ABSTRACT

TEZCAN, NURCAN. Energy-Efficient and Reliable Data Transfer in Wireless Sensor Networks. (Under the direction of Dr. Wenyue Wang.)

Wireless Sensor Networks (WSNs) have emerged as a new information-gathering paradigm based on the collaborative efforts of large number of sensors. Sensor nodes are low-cost, low-power devices that are equipped with acoustic, seismic, infrared, video, or audio sensors. WSNs come in a wide variety forms covering different geographical areas of interest to collect and transmit real-time data to a gateway node. The existing and potential applications of WSNs span a wide range, including real-time target tracking, homeland security, battlefield surveillance, and biological or chemical attack detection.

Many of these WSN applications requires energy-efficient and reliable communication services to report of conditions within a region where the environmental conditions changes due to an observed event. Although WSNs provide redundant detection and reporting, this does not guarantee end-to-end reliability. For real-time applications such as monitoring where decision, control and update processes are based on the received data, reliable packet delivery is an important issue. An elegant reliability solution should benefit by constructing an energy-efficient topology, in order to be effective within this resource-constraint networking domain. Moreover, solutions should be flexible enough to support wide range of applications where WSNs are lack of centralized coordination and have different types of sensors such as audio, video sensors which bring unique characteristics and challenges coupled with the limitations of wireless environments.

In this thesis, the problem of energy-efficient reliable data transport is addressed targeting wide range of WSN domains that matches the unique characteristics of sensor networks. The proposed protocols fit into different class of wireless sensor networks supporting both centralized and distributed solutions. We first present the design of an asymmetric and reliable transport (ART) mechanism, and evaluated the scheme by simulating and implementing it using realistic scenarios based on a reference home WSN application. Next, an energy efficient two-tier self-scheduling (TTS) paradigm is proposed. Specifically, TTS enables sensor nodes to construct a scalable topology under stringent energy, coverage and reliability constraints. Sensor nodes aim to preserve sensing coverage, while scheduling
themselves into sleep in phases for energy conservation. By incorporating ART reliability mechanism, we show that high precision event detection at the collector node can be achieved with guaranteed event and query delivery performance. TTS has been studied to fit both centralized and distributed WSN domains. In distributed version, sensors are self-organized targeting to generate the scalable topology by self-discovery and self-calculation of their sensing coverage. In addition, self-organization is extended for wireless multimedia sensor networks having directional sensing views. A distributed scheme is designed and simulated for multimedia sensor nodes to compute their directional coverage, through which orientations are calculated for efficient self-organization. Finally, a case study of questioning and improving the reliability of home WSNs is presented and performance of ART in home wireless sensor networks are investigated. The results are promising and provide a basis for future investigations of home WSN applications that requires reliable communication services.
Energy-Efficient and Reliable Data Transfer in Wireless Sensor Networks

by
Nurcan Tezcan

A dissertation submitted to the Graduate Faculty of North Carolina State University in partial fulfillment of the requirements for the Degree of Doctor of Philosophy

Computer Engineering
Raleigh, North Carolina
2008

APPROVED BY:

Dr. Injong Rhee
Dr. Ioannis Viniotis

Dr. Wenye Wang
Chair of Advisory Committee
Dr. Arne A Nilsson
DEDICATION

To my dear parents
Nuriye and Remzi Tezcan;
and my dear love
Mesut Ali Ergin.
BIOGRAPHY

Nurcan Tezcan received the B.S. and M.S. degrees in Computer Engineering from Yeditepe University and Bogazici University, Istanbul, Turkey, in 2001 and 2004, respectively; and currently pursing Ph.D. degree in Electrical and Computer Engineering in North Carolina State University, Raleigh, NC. Her research interests include transport layer protocols, energy-efficient algorithms and performance analysis of wireless sensor networks and next generation wireless networks. She held an Interim Engineering Intern position at Mobile Wireless Group at Intel Corp. during Summer 2008, Tekelec during Fall 2008 and Spirent Communications during Summer 2007. She is a member of the IEEE Computer Society and ACM.
ACKNOWLEDGMENTS

Early in the process of completing my thesis, it became quite clear to me that a researcher cannot complete a Ph.D. thesis alone. Although the list of individuals I wish to thank extends beyond the limits of this format, I would like to thank the following people for their dedication and support:

My Ph.D. adviser, Dr. Wenye Wang, for her enthusiasm and inspiration. Her insights have strengthened this study significantly. I will always be thankful for her wisdom, knowledge, and deep concern.

My cordial thanks also extend to Dr. Ioannis Viniotis, Dr. Arne Nilsson, Dr. Injong Rhee for being on my dissertation defense committee. Their invaluable comments and enlightening suggestions have helped me to achieve a solid research path towards this thesis. I would also like to acknowledge the members of Networking of Wireless Information Systems (NetWis) laboratory due to the excellent atmosphere they created. I am especially thankful to Avesh Agarwal, Fei Xing, Ming Zhao, Shawqi Kharbash, and Yi Xu for their friendship and support.

I wish to thank everybody with whom I have shared experiences in life. Special thanks to my friends Aysegul Ergin, Yagiz Sutcu, Orcun and Ebru Kepez, Inci Ozdemir, Esra Cakir, Gulsen Altun, Namik Temizer, Berke Yelten, Funda Gunes, and Rabia Sarica for helping me get through the difficult times, and for all the support and caring they provided.

I would also like to acknowledge and thank to my dear family, my parents Nuriye and Remzi Tezcan, my sisters, Nur and Cansev, for their understanding and support during these years. At times, it has been good to know they have just been a phone call or an email away.

To my dear love Ali, all I can say is it would take another thesis to express my deep love to him. His great help, patience, encouragement and companionship has turned my years in graduate school into a pleasure. For all that, and for being everything I am not, he has my everlasting love.
# TABLE OF CONTENTS

**LIST OF TABLES** ................................................................. viii

**LIST OF FIGURES** ............................................................... ix

1 **Introduction** ................................................................. 1

1.1 Research Objectives and Solutions ............................................. 4

1.1.1 Asymmetric and Reliable Transport Protocol in Wireless Sensor Networks ........................................ 4

1.1.2 Two-tiered Scheduling for Energy Efficient in Wireless Sensor Networks ........................................ 5

1.1.3 Self-organization of Wireless Sensor Networks .............................. 6

1.1.4 Experimental Study on Critical Factors Limiting Reliability in Home Wireless Sensor Networks ......................... 7

1.2 Thesis Outline ................................................................. 8

2 **ART**: An Asymmetric and Reliable Transport Mechanism for Wireless Sensor Networks ........................................... 9

2.1 Motivation and Related Work .................................................. 9

2.2 Preliminary Definitions ....................................................... 13

2.2.1 Network Description ....................................................... 13

2.2.2 Energy Model ............................................................ 14

2.2.3 Reliability Definitions ..................................................... 15

2.3 Energy-Aware Sensor Classification ......................................... 16

2.3.1 Node Classification Algorithm ........................................... 17

2.3.2 Coverage Set Update ..................................................... 21

2.4 ART Protocol Operations ..................................................... 22

2.4.1 Reliable Query Transfer ................................................ 23

2.4.2 Reliable Event Transfer ................................................ 24

2.4.3 Distributed Congestion Control ........................................ 25

2.4.4 Timeout and Retransmissions .......................................... 27

2.5 Performance Evaluation ..................................................... 29

2.5.1 Performance Metrics and Simulation Setup ............................... 29

2.5.2 Simulation Results ..................................................... 31

2.6 Summary ................................................................. 37

3 **TTS**: Two-Tiered Scheduling for Effective Energy Conservation for Wireless Sensor Networks ........................................... 38

3.1 Motivation and Related Work ................................................. 38

3.2 Preliminary Definitions ..................................................... 40
3.2.1 Coverage and Connected Dominating Sets ........................................... 41
3.2.2 Two-Tiered Scheduling Problem .......................................................... 42
3.3 TTS: Two-Tiered Scheduling Mechanism .................................................. 44
  3.3.1 Establishment of Coverage Tier ......................................................... 44
  3.3.2 Establishment of the Connectivity Tier ............................................... 44
  3.3.3 Updating Coverage and Connectivity Tiers ......................................... 47
  3.3.4 Walk Through the Algorithms By an Example ...................................... 47
3.4 Performance Evaluation ................................................................. 49
  3.4.1 Simulation Results ........................................................................... 49
3.5 Summary .............................................................. 54

4 Self-Organization of Wireless Sensor Networks ........................................ 56
  4.1 Motivation and Related Work .................................................................. 56
  4.2 Self-organization Algorithms for Omni-directional Sensors ...................... 62
    4.2.1 Definitions and Target Applications ............................................... 62
    4.2.2 A Distributed Coverage Calculation Algorithm ............................... 64
    4.2.3 Comparison of Distributed and Centralized Coverage Set Establishment 72
    4.2.4 Simulation Results ................................................................. 74
  4.3 Self-organization for Directional (Multimedia) Sensors ............................ 76
    4.3.1 Definitions and Target Applications ............................................... 77
    4.3.2 A Distributed Algorithm for Multimedia Sensors Self-Orientation .......... 79
    4.3.3 Simulation Results ........................................................................ 88
  4.4 Summary .............................................................. 94

5 Experimental Study on Critical Factors Limiting Reliability in Home Wireless Sensor Networks ......................................................... 95
  5.1 Indoor Wireless Sensor Network Applications ........................................ 96
  5.2 Motivation and Related Work ............................................................... 98
  5.3 Experimental Methodology .................................................................... 101
    5.3.1 Hardware and Software .............................................................. 102
    5.3.2 Metrics ..................................................................................... 104
    5.3.3 Home Layout ............................................................................ 105
  5.4 Factors and Effects ............................................................................... 106
    5.4.1 Physical Diversity ......................................................................... 107
    5.4.2 Node Density .............................................................................. 108
    5.4.3 Home Layout .............................................................................. 110
    5.4.4 External Interferes ....................................................................... 113
    5.4.5 Transmit Power ........................................................................... 114
    5.4.6 Reporting Frequency .................................................................... 115
  5.5 Dissecting PDR .................................................................................... 117
    5.5.1 Time Characteristics of PDR ......................................................... 117
    5.5.2 Contribution of Collision and BER to PDR .................................... 118
    5.5.3 RSSI and LQI ............................................................................ 119
5.6 Improving Event Reliability in Home Wireless Sensor Networks . . . . . . . 120
5.7 Key Findings .................................................. 126
5.8 Summary ...................................................... 127

6 Conclusion .............................................................. 128
6.1 Research Contributions ...................................... 128
6.2 Future Research Directions ................................. 131

Bibliography ............................................................. 133
LIST OF TABLES

Table 2.1 Comparison of existing transport protocols. ........................................... 12
Table 2.2 ART simulation parameters. ................................................................. 31
Table 3.1 TTS notations. ......................................................................................... 41
Table 3.2 An example: node information in the sink............................................. 48
Table 5.1 Summary of critical factors studied that limiting reliability............... 100
Table 5.2 List of sensor nodes. ................................................................................. 102
Table 5.3 Summary of home layouts used in our experiments. ......................... 106
LIST OF FIGURES

Figure 2.1 Successful event detection ratio and event detection delay at the sink node. 11
Figure 2.2 Classification of sensor nodes in ART. 18
Figure 2.3 Walking through algorithm 2.1. 20
Figure 2.4 Example of query loss. 24
Figure 2.5 Example of event-alarm loss. 26
Figure 2.6 Retransmission and congestion control behavior. 28
Figure 2.7 E-Node ratio of coverage set vs. network density \((T_{\Delta U} = 10\ sec)\). 32
Figure 2.8 Effect of update interval on network lifetime. 33
Figure 2.9 End-to-end (E2E) delay and packet loss: ART and MLR. 34
Figure 2.10 Effect of congestion control mechanism. 36
Figure 3.1 Logical view of coverage and connectivity-tiers. 42
Figure 3.2 Sleep schedules of coverage and connectivity-tiers. 43
Figure 3.3 Walk through the centralized algorithms by an example. 48
Figure 3.4 Percentage of on-duty nodes vs time. 50
Figure 3.5 Performance of two-tiered scheduling mechanism. 51
Figure 3.6 Network lifetime. 52
Figure 3.7 Residual energy distribution. 54
Figure 4.1 Illustration of distributed coverage problem. 62
Figure 4.2 Illustration of distributed coverage problem. 65
Figure 4.3 Two examples where perimeter-test is passed for sensor \(s_0\). 67
Figure 4.4 Signaling diagram while constructing dominating coverage set. ............... 71
Figure 4.5 Percentage of on-duty nodes under different node densities. .................. 73
Figure 4.6 Performance of the redundant discovery and elimination algorithms. .......... 75
Figure 4.7 Two dimensional representation of a wireless multimedia sensor network. .. 78
Figure 4.8 Illustration of two dimensional field of view (FoV) of a multimedia sensor node. ................................................................................................................. 79
Figure 4.9 Three major steps in self-orientation of multimedia sensors. ................. 80
Figure 4.10 An example showing the perimeter test for sensor $s_1$. .................... 81
Figure 4.11 Pseudo code of perimeter test. ............................................................. 82
Figure 4.12 Pseudo code of neighbor-distance test. ............................................. 83
Figure 4.13 An example showing the neighbor-distance test for sensor $s_1$. .......... 84
Figure 4.14 An example showing the obstacle-distance test condition for sensor $s_1$. 84
Figure 4.15 Pseudo code of obstacle-distance test. ............................................. 85
Figure 4.16 The general approach of self-orientation algorithm. ......................... 86
Figure 4.17 An example showing the area $A'$ that should be monitored using $oFoVs$. . 88
Figure 4.18 Multimedia coverage. ................................................................. 90
Figure 4.19 Multimedia coverage ratios. ............................................................ 90
Figure 4.20 Highly-occluded sensing field. ...................................................... 91
Figure 4.21 Overlapping FoV ratio. ................................................................. 92
Figure 4.22 Messaging overhead. ................................................................. 93

Figure 5.1 Tmote Sky with PIR sensor connected. ........................................ 101
Figure 5.2 First home layout (H1), three bedroom apartment. .......................... 104
Figure 5.3 Second home layout (H2), one bedroom apartment. ....................... 105
Figure 5.4 Effect of home daily characteristics. ............................................. 107
Figure 5.5 Effect of time of the day on individual link performance. .................. 109
Figure 5.6 Effect of node density: average PDR in a room with 3 nodes, 6 nodes and 9 nodes. .......................................................... 110
Figure 5.7 Effect of home layout: average PDR in H1 and H2. ................. 111
Figure 5.8 Effect of external interferes (AP, electrical devices, etc.). ................. 112
Figure 5.9 Effect of interferes on individual link performance (H1). ................. 112
Figure 5.10 Effect of transmit power................................................. 114
Figure 5.11 Effect of transmit power on individual link performance. ................ 115
Figure 5.12 Effect of reporting frequency............................................. 116
Figure 5.13 Number of dropped packets in four different nodes....................... 117
Figure 5.14 Isolated link performance vs performance under neighbor sensor interference. 118
Figure 5.15 Relation between PDR, RSSI and LQI..................................... 121
Figure 5.16 Example snapshot of PIR sensor reading................................. 122
Figure 5.17 Oscope packet structure.................................................... 123
Figure 5.18 PDR and EDR relation..................................................... 124
Figure 5.19 Performance of event reliability scheme on PDR and EDR in H2 .......... 125
Figure 5.20 Effect of retry (time out) period on EDR................................. 126
Chapter 1

Introduction

With the development of micro electromechanical systems (MEMS), sensors can be made smaller and cheaper [5]. This along with the advances in low power VLSI, digital signal processing and low manufacturing costs have lead to the development of wireless sensor networks (WSNs). These technologies allow for development of small and inexpensive wireless sensor nodes, which can be easily distributed over a large geographic area. The nodes can collect information and relay that information to a center where the information is processed to make an appropriate decision [5]. Due to the large number of nodes, sensor networks can provide coverage of a very large area through the scattering of thousands of sensors.

The existing and potential applications of WSNs span a wide range, including environmental monitoring (temperature, pressure, and pollution levels), situation awareness, intrusion detection and denial of access, to name a few [11, 35, 44, 45]. They can be the first line of defense in many applications where access is limited such as detection of biological hazards, chemical spills, health monitoring, fire detection, etc. In homes and buildings, networks of image sensors could provide greater security. In buildings, motion and light sensors in a building can detect the presence of intruders and command cameras or other instrumentation to track them. Furthermore, sensors for structural health monitoring in airplanes or spaceships can drive instruments to timely take countermeasures against critical mechanical stress or structural faults [7, 58]. Further, we are now able to capture audio-visual information from the environment using low-cost, low-resolution cameras embedded
to the sensor nodes.

WSNs may operate on harsh environments in which transmission distance is very short, and the communication link is highly asymmetric. Also sensors have low mobility and limited processing capability. Actually, the most important constraint is that the battery lifetime of a sensor node is crucial. Since the network may be deployed in inaccessible or hostile environments, battery replacement of a sensor node is undesirable, even not possible.

When a sensor network is deployed, one important question of energy-efficient and reliable data transport, affects the overall performance of the application, thus becoming particularly challenging. Providing redundant detection and reporting does not guarantee end-to-end reliability. For real-time applications such as monitoring where decision, control and update processes are based on the received data, reliable packet delivery is an important issue. Second issue is the energy-efficient self-organization of sensors such that active sensors can cover the whole sensing field, i.e., capable of detect each and every event using their limited sensing ranges. Preserving sensing coverage is also particularly challenging and should be addressed in large number of sensor networks having circular or directional sensing views.

The major communication challenges for the realization of energy-efficient and reliable communications in WSNs can be outlined as follows:

- **Scalability**: WSNs are composed of large number of sensor nodes. Proposed solutions should be designed to consider the large number of sensors, deployed in high density to unattended geographical areas such as a battlefield or an arctic region that have harsh and noisy medium for wireless transmission.

- **Energy constraint**: One of the most important constraints on sensor nodes is on the energy budget. Each node has a battery-limited energy which can not be replaced or re-charged in most cases. Hence, this necessitate energy-awareness in the design of the protocols.

Since sensors have battery-limited power, energy conservation and prolonging lifetime are the key factors [10, 14, 19, 22, 57, 86]. To achieve efficient use of energy we may (i) schedule nodes to go into sleep for reduction in energy consumption (ii) use energy-aware algorithms where residual energy of sensors are taken as decision criteria,
reduce the overhead of retransmissions and control packets and (iv) regulate the excessive traffic which will also avoid probable congestion.

On the other hand, WSNs may be densely deployed which results in overlapping sensing regions. To reduce unnecessary traffic, an efficient way is to classify the sensors to find the set of essential ones for reliability especially large scale networks in terms of the number of nodes. In case of topology changes, essential ones may rotate in time. It may increase the overhead in large scale networks. However, this challenge may be tackled by the central control of the sink.

- **Asymmetric data traffic:** Data flow for downstream (sink-to-sensor) and upstream (sensor-to-sink) traffic is not symmetric in WSNs. For the upstream data flow, all sensor nodes report their perceptual data to the sink node, when they detect an event. Unlike upstream, downstream flow can be characterized as point-to-multipoint and demand-driven.

  The asymmetric data flow also requires asymmetric message size and format in each direction. Since sensor nodes have limited capability and power, the messages reporting the sensed data are much more smaller in size than the messages sent by the sink. Sink may send control code, query-data or query messages depending on the application. Furthermore, messages sent by sink must received in-sequence while single-packet sensor messages have no such restriction. This asymmetric characteristic also makes the traditional transport layer solutions inappropriate in use in WSNs.

- **Omnidirectional/bidirectional sensing coverage:** Another challenging issue in WSNs is the sensing coverage, which reflects the quality of service provided by a particular sensor network. The coverage problem is defined as the sufficient number of active sensors in the network such that any point on the desired region can be monitored. However, the sensing range of a sensor node might be approximately in between 1-30 m, whereas the transmission range of that sensor might be in between 150-300 m [87]. Thus, establishing a connected network may not pose full coverage. Sensing coverage is also heavily depended upon the type of sensors, i.e., omnidirectional sensors (temperature, seismic, etc.) or multimedia sensors such as audio, video.
Multimedia sensors are powerful multi-dimensional sensors that can capture a directional view, usually called Field of View (FoV) which is coupled with unique challenges in the coverage design. To avoid missing events in the sensor field, we have to consider sensing coverage for omnidirectional and multimedia sensors in our design.

In this thesis, our objective is to design and analyze energy-efficient and reliable data transport solutions for WSNs that can be used in centralized and self-organized manner. As the first step of our research, we propose an asymmetric and reliable transport (ART) mechanism, that specifically address and leverage the characteristics of WSNs. In ART, we propose a novel method providing end-to-end event and query reliability using energy-aware algorithms. Second, we focus on designing an effective two-tiered node scheduling scheme (TTS) to reduce energy consumption due to communication and being idle. By this way, only the nodes maintaining the functionality stay active whereas others are scheduled to sleep, e.g., switching to power saving mode. Third, the problem of self-organization is addressed that can establish the communication among nodes via discovery mechanism, preserve sensing coverage, and reliably transfer the sensing measurements to the sink. For this purpose, we design two new algorithms where nodes can self-calculate their sensing coverage and self-oriented for wireless sensor and multimedia networks. Finally, a case study of questioning and improving the reliability of home WSNs is presented and performance of ART in home wireless sensor networks are investigated. The results are promising and provide a basis for future investigations of home WSN applications that requires reliable communication services.

1.1 Research Objectives and Solutions

Here we summarize our objectives which we aim to achieve during the course of this thesis and proposed solutions.

1.1.1 Asymmetric and Reliable Transport Protocol in Wireless Sensor Networks

The major goal of deploying a WSN is to collect accurate and reliable "information" of the sensing field. To understand the problem of reliability in this context, we need
to elaborate on the following question: "What is the information to be delivered reliably on WSN?"

In conventional reliability context, transport service has no additional knowledge on the semantics of the information, thus reliability solutions are per transport message segment based (shortly, message-level). In such transport solutions, end-to-end reliability ensures that each message is individually received by the intended end point successfully. However in WSNs, information of interest is carried into an event which is usually transferred with more than one transport message segment due to the overlapping sensing ranges of many sensor nodes.

Due to above reasoning, a conventional message-level reliability would involve reliable delivery of many redundant event messages in a WSN. This is a very fundamental challenge not only from the perspective of energy conservation, but also from the perspective of delivery latency under congested network conditions. In message-level reliability, many redundant event reports have to be retransmitted even in case of congestion which can make the network more unstable, energy wasting, and potentially non-operational. Hence, a reliable delivery mechanism must provide reliability by operating with the least possible number of transport segment messages in a WSN. In order to achieve such an objective both for queries and event report messages, we propose an Asymmetric Reliable Transport (ART) mechanism adapting to the inherent characteristics of upstream (sensors-to-sink) and downstream (sink-to-sensors) traffic. Simulation experiments have validated that, under the 100% reliable event and query delivery ART performs significantly better than message-level reliability scheme in terms of latency and packet loss [72, 75].

1.1.2 Two-tiered Scheduling for Energy Efficient in Wireless Sensor Networks

In order to achieve efficient energy conservation using our reliability protocol, we propose a node scheduling algorithm that can corporate with reliability protocol to extend the functionality and lifetime of the network. In node scheduling, only the nodes maintaining the functionality stay active whereas others are scheduled to sleep, e.g., switching to power saving mode. Therefore, the energy dissipation in sending/receiving and idle time can be significantly reduced and by updating the sleeping nodes, network lifetime can be prolonged.
The fundamental challenge of scheduling is to maximize the number of sleeping nodes to conserve more energy while maintaining the functionality which are connectivity and coverage in a typical WSN. Besides existing works, we can decompose the two functionalities, coverage and connectivity, such that connected dominating backbone can be built among sensors providing the coverage. Such a decomposition allows us to schedule more nodes to be in power-savings mode, thus conserving more energy.

We then present a two-tiered scheduling approach for effective energy conservation in wireless sensor networks. The effectiveness of this mechanism relies on dynamically updated two-tiered scheduling architecture. We aim to prolong network lifetime, while preserving the major requirements of wireless sensor networks: coverage and connectivity. In this approach, sensors are periodically scheduled into sleep in two phases using weighted greedy algorithms that can be deployed either centralized or distributed. First, we establish a coverage-tier by selecting a set of sensors that fully covers the sensing field. Thus, sensors that are not selected for the coverage-tier, are put into sleep immediately. However, the coverage-tier sensors do not necessarily stay active all the time when events are not reported. Therefore, a second tier, called connectivity-tier, is formed to deliver data traffic to a sink node. Thus sensors, essential to coverage-tier but not in connectivity-tier may periodically sleep and become active only for sending new sensing measurement and receiving queries from the sink to preserve coverage for energy savings. In addition, periodically rotating the coverage and connectivity tiers is performed in order to maximize network lifetime and achieve fairness of energy consumption [70, 71].

1.1.3 Self-organization of Wireless Sensor Networks

When sensor nodes are deployed in a sensing field, they should carry on data transport to the gateway node after constructing an energy-efficient and reliable topology based on local information. One key challenge to construct such a topology is to preserve sensing coverage under stringent energy constraint. Coverage preservation is a necessary functionality and quality of service indicator of a sensor network. Therefore, several research studies have been proposed related to coverage in sensor networks that concerned on how well sensors observe the sensing field in a distributed way [1, 14, 20, 81]. In these studies, each node make its decisions (to be active, sleep, etc.) based on some coverage related
metrics such as the size of intersection or union of the overlapping regions with its neighbors. Even though such metrics are logically correct, it is hard to verify the size of asymmetric overlapping regions for a sensor having limited processing and storage capacity. Hence, the question of “how to calculate coverage distributively?” remains an open issue.

However, sensing coverage calculation using circular sensing ranges, e.g., temperature sensors, seismic sensors are not applicable to multimedia sensors having directional sensing view. More recently, the availability of low-cost multimedia devices has fostered the use of low resolution multimedia sensors for many sensor network applications such as environmental monitoring, and health care, providing detailed visual information from multiple disparate viewpoints. Therefore, the problems relating multimedia sensor nodes to monitor their coverage performance, provisioning self-configurable sensor orientations is an attractive research topic that is addressed in the context of this thesis.

To self-organize the wireless sensor networks, we construct a scalable topology under stringent energy, coverage and reliability constraints. Self-organized sensor networks can use the distributed coverage calculation scheme to achieve full coverage and eliminate the redundant nodes. Sensors are densely deployed in many sensor applications. The number of sensors deployed is usually higher than optimum required due to the lack of precise sensor placement, especially when the interest region is inaccessible. Thus it is possible to turn some sensors off while guaranteeing the complete coverage of the interest region. By this way, the energy dissipation in sending/receiving and idle time can be significantly reduced and by updating the sleeping nodes, network lifetime can be prolonged [74].

1.1.4 Experimental Study on Critical Factors Limiting Reliability in Home Wireless Sensor Networks

Home environments are becoming popular deployment areas for sensor networks for future in-home health care systems such as in-home assistance, smart nursing homes, and clinical trial and research augmentation [66]. In such health-care applications, sensor networking applications, when an emergency event is detected by a set of sensor nodes, and then relayed to a remote nursing station through a special sensor node (i.e., gateway) over the Internet. The information relayed to the gateway node might be a critical information (such as motion pattern as falling, walking, sleeping), thus require high end-
to-end reliability. In the near future, many homes will be equipped with wireless sensor networks that can send collected data to the outside network instantaneously under high reliability requirements.

However, homes are disadvantageous networking environments where several obstacles may render wireless communication impossible between node pairs [51]. Additionally, successful home sensor networks deployments are hindered by the resource constraints of the underlying sensor nodes including power, computation, and communication quality [31]. These limitations render the sensor nodes highly unreliable and susceptible to frequent failures [6]. Sensors must operate with enough reliability to yield high-confidence data suitable for such mission-critical health care applications. In addition, due to limited and irregular sensing ranges, placement of sensors becomes an important and challenging problem which may impact the accuracy of the collected data. Therefore, high end-to-end reliability becomes a vital requirement for health care applications in home environments. We have deployed wireless sensor networks into two different homes investigating the critical factors on reliability of data transport. We then implement our reliability solution to improve the end-to-end reliability of home sensor networks. The results are promising and provide a basis for future investigations of home WSN applications that requires reliable communication services.

1.2 Thesis Outline

This thesis is organized as follows. Chapter 2 introduces a new reliable transport protocol, which achieves reliable and timely event detection with minimum energy expenditure in WSNs. Chapter 3 presents a new two-tiered scheduling scheme for energy conservation for reliable communication of sensor nodes. Chapter 4 presents distributed algorithms to establish coverage tier for wireless multimedia sensor networks and omnidirectional sensor networks. Chapter 5 presents the home WSN applications, investigates the reliability of data transport in home sensor networks and presents the reliability schemes that improves the reliability of home sensor networks. Finally, Chapter 6 summarizes the research results and suggests a number of problems for future investigation.
Chapter 2

ART: An Asymmetric and Reliable Transport Mechanism for Wireless Sensor Networks

In this chapter, a new asymmetric reliable transport mechanisms for wireless sensor networks (WSNs) is presented. An extensive set of simulations is performed in order to quantify the impacts of several network parameters on the overall network performance. This study was first presented in [75, 72]. In Section 2.2, we present the network description and concept of reliability. We introduce a new classification algorithm in detail in Section 2.3. In Section 2.4, we present the design of reliability and congestion control schemes for event and query delivery. Performance evaluation is discussed in Section 2.5.

2.1 Motivation and Related Work

Many applications developed for wireless sensor networks (WSNs) demand for Reliable communication service, since majority of these applications are event-critical applications. There has been a vast body of knowledge on reliable data transfer in wireless networks; however, many of those solutions are not applicable to WSNs due to the fact that they address the problem by offering per message transport reliability. However, densely deployed sensor nodes can generate many redundant messages that essentially indicate the
same event from the area of interest, this message-level reliability usually poses significantly high and unnecessary communication costs.

Consider an example of WSN applications for border surveillance. Many sensor nodes are scattered through a restricted area near a national border to monitor illegal border-crossing activity. Intruders in the area are detected; sensors report them immediately via event messages. Also, a centralized authority (through sink node) may further query the sensors for an up-to-date reading of their measurements, or update them to change detection parameters. In this example, each event such as border-crossing, must be reported successfully, but not necessarily every message. Further, every message from the sink must be reliably delivered to the entire sensing field, again not necessarily every node to achieve reliable information delivery between sensors and the sink.

In WSNs, a reliable delivery mechanism must provide reliability by handling the least possible number of messages in order to achieve significant energy conservation and low delivery latency under congested network conditions. Thus, we carefully define event reliability and query reliability as follows.

Event reliability is defined to be achieved when every critical event report message is received by the sink node. This is the necessary and sufficient condition for sensor-to-sink direction reliability. Query reliability is defined to be achieved when every query of the sink is received by those sensors that cover the entire sensible terrain within the area of deployment, which is necessary and sufficient for sink-to-sensor direction reliability.

To understand the problem with reliable transport service, the impact of unreliable WSN is shown in Figure 2.1 for the scenarios having different event rates. We investigate successful event detection ratio, the total number of events detected by the sensors to the total number of events received by the sink, and event detection delay, time delay between an event detection by the sensor and receiving the first report indicating that event by the sink. Figure 2.1 (a) shows the percentage of events delivered to the sink for a network of size 250 x 250 m, with increasing number of nodes in the absence of reliability. We observe that the percentage of successful events received at the sink decreases dramatically with increasing number of nodes and event rate. Figure 2.1 (b) shows the latency of event detection at the sink for different number of nodes. Here again, we notice that the latency increases as the event rate increases beyond a certain point and that the point at which the
minimum latency occurs shifts for different numbers of sensor nodes. Note that, event loss can be either due to query-loss, where received data would not indicate the latest queried information, or packet-loss.

We have observed that in a network of 250 m x 250 m grid with 200 nodes, the number of events successfully detected by the sink decreases from about 98% when the event rate is about 0.3 events/sec to about 80% when the event rate is increased to 1.0 event/sec. Also, we have observed that the event detection delay jumps from about 0.02 sec for the 200 node scenario to 1.8 sec illustrating the effect of broadcast storm. Therefore, event and query reliability is a critical problem for data services in WSNs.

The reliable transport problem in wireless packet-data networks has been studied in several research works many of which are aimed to improve the performance of TCP over wireless links and ad hoc networks [80]. In [68], a new transport protocol, Ad hoc Transport Protocol, is proposed for operating conditions in ad hoc networks. However, it is designed for point-to-point data transport for mobile nodes, thus consisting procedures such as connection initiation and rate based transmission which cannot be used in WSNs due to energy constraint of sensors.

Existing transport layer protocols designed for upstream or downstream reliability in WSNs are either sink-to-sensor [52, 78] or sensor-to-sink reliable delivery [28, 56, 67]. Table 2.1 shows a detailed comparison of their characteristics.
Table 2.1: Comparison of existing transport protocols.

<table>
<thead>
<tr>
<th></th>
<th><strong>PSFQ</strong></th>
<th><strong>RMST</strong></th>
<th><strong>ESRT</strong></th>
<th><strong>GARUDA</strong></th>
<th><strong>ART</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Reliability</strong></td>
<td>Downstream</td>
<td>Upstream</td>
<td>Upstream</td>
<td>Downstream</td>
<td>Both</td>
</tr>
<tr>
<td></td>
<td>Hop by Hop</td>
<td>Hop by Hop</td>
<td>End to End</td>
<td>Hop by Hop</td>
<td>End to End</td>
</tr>
<tr>
<td></td>
<td>NACK</td>
<td>NACK</td>
<td></td>
<td>NACK</td>
<td>ACK/NACK</td>
</tr>
<tr>
<td><strong>Energy-aware</strong></td>
<td>-</td>
<td>-</td>
<td>Yes</td>
<td>-</td>
<td>Yes</td>
</tr>
<tr>
<td><strong>Loss Rec.</strong></td>
<td>Yes</td>
<td>Yes</td>
<td>-</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td><strong>Cong. control</strong></td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
</tr>
</tbody>
</table>

*Pump Slowly, Fetch Quickly* (PSFQ) [78] is the first transport protocol proposed for downstream reliable data transmission from source to the sensor nodes. This protocol is based on a set of operations including hop-by-hop error recovery, in-network caching and sending repair request via NACKs (Fetch) that is faster than the source transmission rate (Pump). Also, a hop-by-hop error recovery mechanism is used for message loss recovery. Although PSFQ achieves in-sequence transmissions, with specific reference to a re-tasking application, it cannot handle single packet losses, and it also does not consider losses due to the congestion. *GARUDA* [52] is another important work focusing on reliable downstream data delivery based on a virtual infrastructure, that is, a set of local and designated loss recovery servers. This solution also supports multiple reliable semantics such as delivery to sensors in a sub-region of the field. Fast loss recovery is down by using a two-phase loss recovery strategy: the first one involves the core nodes recovering from all lost packets, and then the recovery of lost packets at the non-core nodes.

From the upstream perspective, *Event-to-Sink Reliable Transport* (ESRT) [56] is the first protocol which is motivated by the fact that the sink is only interested in reliable detection of event features from the collective information provided by sensor nodes. Although it considers the event information, rather than each individual data packet, it is designed for sensor-to-sink communications only. The event-to-sink reliability is determined by the number of received data packets. ESRT adjusts the reporting frequency of the source nodes to increase and decrease the reliability. Further, ESRT regulates the reporting rate of sensors in response to congestion detection in the network by using congestion notification bit and reducing event reporting frequency. *Reliable Multi-Segment Transport* (RMST) [67] is another transport layer protocol which is designed to run in conjunction with directed
diffusion. It is a selective NACK-based protocol, which is used for transferring large amounts of data from sensors to the sink. The receiver sensors are responsible for detecting whether a fragment needs retransmission, thus achieving reliable data transfer.

To the best of our knowledge, ART is the first bidirectional transport protocol for reliable event and query transmission in WSNs. The proposed protocol addresses the reliability requirements for both sensor-to-sink and sink-to-sensor data transfer. In addition, incorporating congestion control mechanism shows considerable performance improvement in terms of energy savings and balancing, which further improves network lifetime.

2.2 Preliminary Definitions

2.2.1 Network Description

Let $S = \{s_1, s_2, s_3, \ldots, s_N\}$ be the finite set of sensors which are distributed randomly in a two-dimensional area $A$. Each sensor $s_i$ has a unique id (such as MAC address). We assume that each node is equipped to gather its location information via any lightweight localization technique for wireless networks [27]. Therefore, all sensor nodes and the sink know their location coordinates $(x_i, y_i)$ and sensing range $r_i$. We assume that all nodes have similar processing and communication capabilities. Messages are sent in a multi-hop fashion.

The sensing region $R_i$ of a node $s_i$ is the area with its center at $(x_i, y_i)$ and radius of $r_i$. A subset of sensors, $C \subseteq S$ is called a coverage set if the union of the sensing regions of the $s_i \in C$ covers the entire field $A$ such that $A \subseteq \bigcup_{s_i \in C} R_i$.

The sensors are classified into essential (E) nodes and non-essential (N) nodes (more details about the classification algorithm is described in Section 2.3). This classification process is proceeded by finding a coverage set, denoted by $C$. Let us denote the cardinality of coverage set $C$ as $N$ that is, $N = |C|$. We consider a sensor node as an essential (E) node in $C$ if $s_i \in C$ and it is denoted as $s_i^{(E)}$; otherwise, it is an non-essential (N) node, $s_i^{(N)}$. At any time, a unique coverage set is selected using a weighted-greedy algorithm explained in Section 2.3. The coverage set is valid for a time interval called update interval, denoted by $T_{\Delta U}$. In other words coverage set is determined periodically for every $T_{\Delta U}$.
Also, we assume that sensors are able to monitor their residual energy because many electronic devices are equipped with energy monitoring functions. The energy level of sensor $s_i$ at the beginning of $\gamma$th $T_{\Delta U}$, denoted by $e_i(\gamma \cdot T_{\Delta U})$, is calculated as:

$$e_i(\gamma \cdot T_{\Delta U}) = \frac{E_i(\gamma \cdot T_{\Delta U})}{E_i(0)},$$

where $E_i(0)$ is the initial energy corresponding to a fully charged battery [16], and $E_i(\gamma \cdot T_{\Delta U})$ is the residual energy of sensor $s_i$ at the beginning of $\gamma$th update interval. Hence, $e_i(\gamma \cdot T_{\Delta U}) = 1$ and $e_i(k \cdot T_{\Delta U}) = 0$ correspond to full and empty battery respectively.

In this context, a wireless sensor network is modeled as a directed graph $G(S, E)$, where $S$ is the set of vertices ($|S| = N$), representing the sensor nodes, and $E$ is the set of edges, representing the communications links. We also consider the fact that links may be asymmetric due to radio irregularity [91]. A communication link is symmetric if there exists links from $v_i$ to $v_j$ and $v_j$ to $v_i$, which is determined by using the neighbor discovery scheme given in [91].

### 2.2.2 Energy Model

The energy model of sensors is a function of reception energy consumption per bit $\varepsilon_r$ and the transmission energy consumption per bit $\varepsilon_t$ [42]. If node $s_i$ sends a data packet of length $l$ bits, an amount of $l \cdot \varepsilon_t$ energy will be deducted from sensors’ residual energy, $E_i$. Let $\Omega^{up}$ and $\Omega^{down}$ be the energy consumed in upstream (sensors-to-sink) and downstream (sink-to-sensors) directions, respectively. Then

$$\Omega^{up} = l_u \cdot [N_t \cdot \varepsilon_t + c \cdot N_l \cdot (\varepsilon_r + \varepsilon_t)] \quad \text{and}$$

$$\Omega^{down} = l_d \cdot [N_r \cdot \varepsilon_r + (1 - c) \cdot N_l \cdot (\varepsilon_r + \varepsilon_t)],$$

where $N_t$, $N_r$ and $N_l$ are the numbers of transmitted, received, and relayed packets during one update interval $T_{\Delta U}$ on node $s_i$, respectively; $l_u$ and $l_d$ are the average lengths of upstream and downstream messages, respectively; and $c$ is the ratio of relayed upstream messages over all relayed messages. Hence, residual energy of a sensor $s_i$ at the beginning of the $\gamma$th interval can be written as:

$$E_i(\gamma \cdot T_{\Delta U}) = E_i((\gamma - 1) \cdot T_{\Delta U}) - \Omega^{up} - \Omega^{down},$$

(2.2)
where $E_i((\gamma - 1) \cdot T_{\Delta U})$ is the residual energy at the beginning of the previous update interval.

### 2.2.3 Reliability Definitions

WSNs distinguish themselves from other wireless networks through traffic characteristics, e.g., asymmetric data traffic from sensors-to-sink and sink-to-sensors. Reliability of such networks are categorized as event and query delivery reliability, whereas the least possible number of messages are transmitted in order to achieve energy conservation and low delivery latency. Therefore, we need to clearly define event and query reliability notions in WSNs for downstream and upstream data delivery.

Consider a group of sensors need to send a sequence of messages to the sink node, $s_o$, regarding an event. End-to-end reliable event transfer is achieved when the first message indicating the event (sent by essential nodes) is successfully received by the sink. Note that sensors may send more than one message indicating the same event, even though the successful delivery of the first message is sufficient to achieve the reliable delivery of desired event. However, subsequent messages regarding the same event does not affect event reliability.

Let $v_k$ be the first message that reports event $k$ to the sink. Then, the probability of successful transfer of an event $k$ is given as follows:

$$Pr(success \ of \ v_k) = 1 - \prod_{s_i^{(E)} \in C'} Pr\{\chi(s_i^{(E)}, s_o) = 0\}, \quad (2.3)$$

where $C' \subseteq C$ is the set of essential nodes having sensed the event $k$. $\chi(s_i, s_o) \in [0,1]$ is a link state indicator function; $\chi(s_i, s_o) = 1$ indicates a link between $s_i$ and $s_o$ is up and enables communication, and $\chi(s_i, s_o) = 0$ indicates a down link. Note that, $\chi(s_i, s_o)$ is computed using independent failure probabilities of all links between $s_i$ and $s_o$, and it is a function of the physical medium and the underlying link layer protocols in use.

Consider $K$ events occur in an update interval and they have to be delivered reliably. Then the expected number of successfully delivered events is $\sum_{k=1}^{K} Pr\{success \ of \ v_k\}$. Based on this expected number of successfully delivered events, we define event reliability
metric to be the ratio of successful delivered messages such that:

$$R(v) = \frac{1}{K} \cdot \sum_{k=1}^{K} \text{Pr}\{\text{success of } v_k\}. \quad (2.4)$$

Similarly, sink node has a sequence of queries, \( [q_1, \ldots, q_k, q_{k+1}, \ldots, q_{K'}] \), which are sent to the sensor nodes. Then the End-to-end reliable query transfer is referred to as all queries are received by essential nodes successfully. The probability of the successful transfer of query \( k \) as:

$$\text{Pr}(\text{success of } q_k) = 1 - \prod_{s_i^{(E)} \in C} \text{Pr}\{\chi(s_o, s_i^{(E)}) = 0\}. \quad (2.5)$$

Note that we use only essential nodes in calculating \( \text{Pr}(\text{success of } q_k) \) because sending query to essential nodes is sufficient to process the query in the entire field. If there is a number of \( K' \) queries to be sent during \( T_{\Delta U} \). Then query reliability in an update interval, denoted by \( R(q) \), is defined as:

$$R(q) = \frac{1}{K'} \cdot \sum_{k=1}^{K'} \text{Pr}\{\text{success of } q_k\}. \quad (2.6)$$

Given event and query reliability definitions, we propose the new transport protocol, ART, to achieve 100% query and event reliability. Next, we will explain the sensor classification algorithm and reliability mechanisms of ART, respectively.

### 2.3 Energy-Aware Sensor Classification

The reliability of ART is built upon the classification of sensors as essential (E) nodes and non-essential (N) nodes. We propose to select the E-nodes by using a periodic weighted greedy algorithm running on the sink based on residual energy of sensors. For each update, nodes having higher energy levels are selected as essential to achieve fair energy consumption among sensors.

In order to select the set of E-nodes, we maintain a coverage set, denoted by \( C \), to which E-nodes belong. The challenges involved in this process are (i) how can the coverage set be chosen? (ii) how can the coverage set be updated in order to maintain event and query...
reliability? In addition, we need to discuss whether a sink-based approach is a practical solution.

2.3.1 Node Classification Algorithm

For the first challenge, an ideal solution would be to find the minimum number of sensors that cover the entire field. However, it is an NP-hard problem similar to the well-known set cover problem. The goal in set cover problem is to cover a set with the smallest possible number of subsets given a ground set of elements [1, 61]. Due to this reason, we use a greedy approach to find an approximating coverage set running in polynomial time.

For different purposes, previous studies focused on the problem of finding near-optimal coverage in WSNs [17, 26, 81]. In [26], a greedy approach is proposed to find a connected set of sensors whose sensing regions cover an entire field. Therefore, a near-optimal coverage set is selected to form a connected network. However, our approach is different in two aspects. First, we do not need a connected set, since N-nodes can still be used to forward packets. Second, we choose the coverage set of sensors to maximize the benefit in terms of coverage, i.e., the largest uncovered sensing region is covered with the least sensors. As a result, our approach is to cover the entire field with minimum number of sensors having maximum residual energy.

Figure 2.2(a) shows an example sensor network where sensors are deployed randomly on a rectangular area \( A \). E-nodes and N-nodes are illustrated in different formatted circular dots, i.e., E-nodes with dark circles in Figure 2.2(b). Sensing region boundary of an E-node is plotted with dashed-circles. The union of sensing regions covers the entire sensing field. Therefore, by selecting the E-nodes, we guarantee that (i) when an event occurs, it is detected by at least one E-node and (ii) when the sink sends a query to all E-nodes, the query affects the entire sensing field.

We propose an energy-aware greedy algorithm to find a near optimal coverage set, given in Algorithm 2.1. In each step, Algorithm 2.1 selects one node from the unselected sensors which covers the largest area with highest residual energy level. For this purpose, weight function is defined to represent the weight of a sensing region of a sensor based on its residual energy. For a given region, the weight based on the residual energy level of a sensor is:
(a) An example randomly deployed WSN. 

(b) Same WSN after classification algorithm.

Figure 2.2: Classification of sensor nodes in ART.

\[ w(i, R_i) = e_i \cdot |R_i|, \tag{2.7} \]

where \( e_i \) is the energy level given in (2.1) and \(|R_i|\) is the area of sensing region \( R_i \).

Then, we calculate the benefit of selecting each sensor using the weight function. To do this, we first find the size of the area that can be covered by sensor \( s_i \) and has not been covered yet. Consider the sensor \( s_i \) with sensing region \( R_i \). Let \( R_C \) be the area that sensors of \( C \) covered so far, i.e., \( \bigcup_{s_j \in C} R_j \). Beneficial area of \( s_i \) is defined to be the region inside the sensing field which has not been covered, i.e., \( R_C = R_i \cap A \)/\( R_C \). Hence, benefit function for sensor \( s_i \) is the total weight of its beneficial area, which is given as:

\[ \text{benefit}(s_i) = w(i, (R_i \cap A)/R_C), \tag{2.8} \]

where \( R_i \) is the sensing region of sensor \( s_i \) and \( R_C \) is the total region covered by the sensors in \( C \).

Since Algorithm 2.1 is to find a near-optimal coverage set, let us take a look how the proposed algorithm approximates an optimal coverage set.

**Lemma 1** Algorithm 2.1 gives a coverage set where the total weight of the entire field is \( O(\ln(N)) \)-factor of the optimal solution, where \( N \) is the number of sensor nodes.
Proof 1 Let $\tau$ be the unit area and $A$ be the size of the sensing field in terms of unit $\tau$. Algorithm 2.1 terminates when the sensing area of size $A$ is fully covered. Consider the worst case where all $N$ nodes have the minimum overlapping sensing regions covering the field, then all nodes will be selected as $E$-nodes.

Let each unit area have a price defined as follows:

$$price(\tau) = \{e_i \mid \tau \in R_i, s_i \in C\}.$$  

Algorithm 2.1 attempts to cover the entire field by maximizing the total weight, which is also equal to the summation of the price of each unit area in the sensing field, i.e., $\sum_{j=1}^{A} price(\tau_j)$. At the $j$th iteration, the remaining uncovered area can be covered by a total weight of at most $\frac{OPT}{A-j+1}$, where $OPT$ is the total weight of the optimal solution. Then we can write:

<table>
<thead>
<tr>
<th>Algorithm 2.1 Selecting Essential Nodes</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Input:</strong> $S = {s_1, s_2, s_3, \ldots, s_N}$ is the set of sensors which are distributed randomly on $A$. A sensor has $s_i = (r_i, R_i, e_i, (x_i, y_i))$ where $r_i$ is sensing range; $R_i$ is sensing region; $e_i$ is residual energy level; and $(x_i, y_i)$ is location coordinates.</td>
</tr>
<tr>
<td><strong>Output:</strong> Coverage set, $C$.</td>
</tr>
<tr>
<td><strong>I. Initialize</strong></td>
</tr>
<tr>
<td>$C := \emptyset$</td>
</tr>
<tr>
<td>Let $R_C$ be total sensing region of $C$</td>
</tr>
<tr>
<td><strong>II. Repeat</strong></td>
</tr>
<tr>
<td>Let $S - C = {s_1, s_2, \ldots, s_n}$ be the candidates, $\text{max}_\text{benefit} := 0$;</td>
</tr>
<tr>
<td>for each $s_i \in S - C$</td>
</tr>
<tr>
<td>Calculate the energy-benefit of $s_i$</td>
</tr>
<tr>
<td>$\text{benefit}(s_i) := \sum_{a_j \in (R_i \cap A) \cap R_C} w_i(a_j)$;</td>
</tr>
<tr>
<td>if ($\text{benefit} \geq \text{max}_\text{benefit}$)</td>
</tr>
<tr>
<td>$\text{max}_\text{benefit} := \text{benefit}$;</td>
</tr>
<tr>
<td>$\text{temp} := s_i$;</td>
</tr>
<tr>
<td>end if;</td>
</tr>
<tr>
<td>end for;</td>
</tr>
<tr>
<td>$C := C \cup \text{temp}$;</td>
</tr>
<tr>
<td><strong>Until</strong> $A \subseteq R_C$</td>
</tr>
<tr>
<td><strong>III. Finalize</strong></td>
</tr>
<tr>
<td>Return $C$.</td>
</tr>
</tbody>
</table>
Figure 2.3: Walking through algorithm 2.1.

\[ \sum_{j=1}^{A} \text{price}(\tau_j) \leq \sum_{j=1}^{A} \frac{\text{OPT}}{A-j+1} = \text{OPT} \cdot H_A, \]

where $H_A$ is harmonic number. Therefore, Algorithm 2.1 finds an E-node set that covers the entire field at the cost of $O(\ln A)$-factor of the optimal solution.

Consider a network with a total number of $N$ sensors with sensing ranges $r$. When the sensors are placed such that overlapping sensing areas are minimum, size of sensing field will be at most $\sqrt{27}N(r)^2/2$ under the assumption of full coverage [84]. Thus, the factor of the optimal total weight is obtained as $O(\ln(N))$ for fixed sensing ranges. A loose bound of the running time of Algorithm 2.1 is polynomial with upper bound $O(N^2)$.

Finally, in Figure 2.3, we give an example showing how Algorithm 2.1 finds the coverage set. Figure 2.3 (a) shows an intermediate step of the algorithm while Figure 2.3 (b) depicts the final status. In the first step, all nodes are candidates and the coverage set $C$ is empty. Then, each run of Part II in Algorithm 2.1 chooses an unselected node that has the maximum benefit. Figure 2.3 (a) shows the sensing field after the fourth run of Part II. In this example, sensor $s_9$, $s_6$, $s_2$ and $s_{10}$ are selected based on their benefits and added to set $C$. In the next step, uncovered area is $A/R_9 \cup R_6 \cup R_2 \cup R_{10}$. In Figure 2.3 (a), we show the covered area, $R_C$, in dark. Then, sensor having the benefit will be selected in
the next step until the entire sensing field is fully covered as shown in Figure 2.3(b).

2.3.2 Coverage Set Update

The second challenge is how to update the coverage set. E-nodes should be updated throughout the lifetime of the WSN for two reasons: (i) to handle the unexpected E-node failures, (ii) to acquire fairly distributed energy consumption among sensors.

In general, there are two methods to updating the coverage set. The first method is called global update where all E-nodes are re-selected independent from the current set. In particular, global update is the process of repeating classification algorithm with latest residual energy levels of sensors. By this way, sensors that have overlapping regions and was E-Nodes in the previous round might be an N-node in the next update because more energy has been consumed when they were E-node before. This is used to acquire fairly distributed energy consumption among sensors. However, such a global maintenance may incur high overhead if repeated in short periods and can not handle the unexpected E-node failures during an update interval.

The second method is on-demand local update which can handle E-node failures immediately. Local update is triggered when an unexpected E-node failure is detected by the sink. In this case, N-nodes covering the sensing region of failed E-node are assigned to be an E-Node by the sink. It may not be possible to find one N-node instead of failed E-node; however, it is much efficient instead of global update in any E-node failure.

In ART, we combine local and global such that, in case of an E-node failure new E-nodes are selected locally where global update will be performed for longer predetermined update intervals. Sink can monitor up-to-date energy reserves of sensors using a energy monitoring scheme [82]. Based on this remaining energy of sensors, a new essential set is formed by running Algorithm 2.1. After each global update, sink informs sensors of their type by using a control message. The effects of update interval on network lifetime and energy consumption is discussed in Section 2.5.

Finally, we elaborate on the reasonings behind proposing a sink-based or a centralized algorithm for classification. The main reason behind the centralized approach is the residual energy information of a node on which node selection algorithms are based. For a centralized approach, global information about the state of a sensor network together
with node coordinate information need to be disseminated within the network towards a single node (e.g., sink node). In [1], it is shown that collecting information from a sink node is more power-efficient manner compared to spreading this information to each and every other node within the network. In addition, choosing the sink node as the target of data propagation is reasonable if we consider that the sink node has ample energy and computing power compared to individual sensor nodes. Having the global view of the network at the sink node provisions algorithms for closer-to-optimal coverage set determination as well.

Finally, using a centralized scheme can relieve processing load from the sensors in the field and help in extending the overall network lifetime by reducing energy consumption at individual nodes. The proposed greedy algorithm runs on the sink with an approximation ratio of $lnN$, providing very close-to-optimal coverage sets for most instances of the sensor deployments. Additionally, maintaining the node set selections (i.e., E-node updates) can be realized through low cost information diffusion methods.

### 2.4 ART Protocol Operations

ART is an asymmetric and reliable transport mechanism which provides end-to-end reliability in two directions based on energy-aware node classification and a congestion control mechanism. In this section, we describe the details of ART protocol operations, which includes three main functions:

1. Reliable query transfer
2. Reliable event transfer
3. Distributed congestion control

After classifying sensors as essential and non-essential sensors, end-to-end reliable communications are provided by using asymmetric acknowledgment (ACK) and negative acknowledgment (NACK) signaling between E-nodes and the sink node. Then, we propose a distributed energy-aware congestion control mechanism which relies on receiving ACK packets from the sink. When congestion is detected, ART simply regulates data traffic by
temporarily squelching the traffic of N-nodes. Note that, when there is no congestion, both E-nodes and N-nodes participate in relaying messages to the sink. However, only E-nodes are responsible in providing end-to-end event and query reliability by recovering the lost messages.

2.4.1 Reliable Query Transfer

Reliable query (sink-to-sensors) transfer is provided using negative acknowledgments sent from E-Nodes to the sink if there is a query loss. Since the queries sent by the sink are in order, sensors can detect the lost message by use of sequence numbers in the query messages. An NACK message is sent if a gap is detected, i.e., an out of sequence number, when sink sends a new query message to the E-Nodes. When an E-Node detects a gap in the sequence number of the new query, it sends an NACK back to the sink to recover the previous query. This procedure is described in Algorithm 2.2.

However, lost query messages can be detected when E-Nodes receive a new query message. This may result in two problems. First, loss of the last query message can not be detected. Consider the last message \(q_k\) with sequence number \(k\) is lost. E-Node may not handle the lost message since there is no consecutive query. Second, the query transmission frequency might be very low such that lost queries can not be recovered before timeout. To differentiate the final query message, we use an extra Poll/Final (P/F) bit which can be set by the sink node. P/F bit is set either when a message is the last query or the next query will not be sent before timeout. And the sink retransmits this message until an ACK is received because ACK mechanism is used in reliable event transfer. Therefore, E-Nodes which receive a query with P/F bit set send an ACK to the sink, indicating the query is received successfully.

An example query transmission scenario is illustrated in Figure 2.4. In Figure 2.4 (a), the P/F bit is not used. When the sink sends queries 1, 2 and 3 consecutively where query 3 is lost. After query 3, the sink decreases the query transmission frequency and sends \(q_4\) after a time period \(T_q\). In this case, \(q_3\) is recovered when \(q_4\) is received. If loss recovery period (i.e., \(T_q\)) is very long, even though \(q_3\) can be recovered, long recovery period may affect the performance. Instead, the same scenario is depicted when P/F bit is set in Figure 2.4 (b), where \(q_3\) is recovered before the next query since an ACK is not received
Algorithm 2.2 Reliable Query Transfer

**Input:** Given a sensor network G; Sink has a set of queries $Q = [q_1, \ldots, q_k, q_{k+1}, \ldots]$.

1. **Sink**: Send the in-sequence queries with sequence numbers 1, 2, .., k.
2. **E-Node**: Receive the messages for $q_k$. Check the sequence number for loss detection.
3. **E-Node**: If a gap is detected in the sequence numbers, send an NACK to recover the lost message.
4. **Sink**: Retransmit $q_k-1$ if a NACK is received.
5. **E-Node**: When the queries are successfully received, check P/F bit. If P/F bit is set, send an ACK to the sink. (details in Section 2.4.3)
   - **Sink**: Retransmits the message with P/F bit is set until the ACK is received.

at the sink. This method is very helpful when the query traffic pattern is not uniformly distributed in which case, the interarrival time between queries are not constant. Then the use of P/F bit makes the transport protocol flexible and reliable.

![Diagram](image)

Figure 2.4: Example of query loss.

### 2.4.2 Reliable Event Transfer

The NACK mechanism used in *query transfer* does not work for reliable event transfer because event information is sent by individual sensors and it is usually out of sequence. Hence, NACKs cannot handle the lost event messages by finding the gap in sequence numbers. However, using an ACK mechanism that requires acknowledgment for
each message may result inefficient use of battery power, which is considered to be a very scarce resource in WSNs.

For event reliability, we propose a *lightly-loaded ACK* mechanism between the E-Nodes and the sink node given in Algorithm 2.3. Each E-Node waits for acknowledgment for only the first message that reports an event, i.e., *event-alarm*. When a new sensing value is obtained, an E-Node decides if it reports an event or not. If it is an *event-alarm*, it simply marks the message by setting the *Event Notification* (EN) bit. Therefore, the sink node sends ACK for the only messages which are marked as event-alarm. EN bit, is used to force the sink to send acknowledgment. Event-alarm rate depends on the distribution of events detected in the sensing field. Similar to downstream communications, only the E-Nodes are responsible for waiting the acknowledgment and may retransmit if necessary.

As an example, in Figure 2.5 an event transfer scenario is illustrated where \( v_3 \) and \( v_6 \) are event-alarm messages and their EN bits are set. In this example, the first event alarm message is received by the sink, and the ACK is transmitted. However, next alarm message \( v_6 \) is lost. Since the sender is responsible for loss detection and recovery, E-Node retransmits \( v_6 \) after retransmission timeouts shown in Figure 2.5. Therefore, loss recovery is triggered only for event-alarm messages by the E-Node, which is very effective in energy saving as shown in Section 2.5.

### 2.4.3 Distributed Congestion Control

Given a WSN consisting of large number of nodes, congestion is an inevitable problem because a large number of sensors may transmit the sensed event at the same time. To detect and avoid congestion, several works has been proposed using different mechanisms in WSNs [33, 56, 79]. In [56], congestion is detected by monitoring the buffers

<table>
<thead>
<tr>
<th>Algorithm 2.3 Reliable Event Transfer</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Input:</strong> Given a sensor network G; An E-Node is sending an event-alarm ( v_k^{EA} ) given timeout ( t_{out} );</td>
</tr>
<tr>
<td>1. <strong>E-Node:</strong> If ( v_k = v_k^{EA} ), set the EN bit, send to the sink, then start timer and buffer ( v_k^{EA} ) until an ACK is received. Otherwise, send it to the sink, delete from the buffer.</td>
</tr>
<tr>
<td>2. <strong>Sink:</strong> Send an ACK if it receives a ( v_k^{EA} )</td>
</tr>
<tr>
<td>3. <strong>E-Node:</strong> If the ACK is not received for ( v_k^{EA} ) retransmit ( v_k^{EA} ) and reset timer.</td>
</tr>
</tbody>
</table>
of sensor nodes. When congestion is detected, sensors inform the sink node to decrease
the reporting frequency of the network. A different method is that congestion detection is
based on local channel monitoring and the congestion is propagated through hop-by-hop
back-pressure messages upstream toward the source [79].

Unlike these existing solutions, in ART, congestion control is handled by the E-
nodes in a distributed manner. It is based on monitoring the ACK packets of event reports.
If an ACK is not received during a timeout period by the E-node, traffic of non-essential
sensors is reduced by sending them congestion alarm messages, which will temporarily make
them stop sending their measurements. When an ACK is received, congestion-safe message
is announced to resume normal operation of the network.

It is possible that lost data packets may not indicate an accurate congestion for
WSN because losses can be caused by link failures or congestion [68]. However, in ART we
monitor only the event-alarm messages which report the sensed events. Congestion often
occurs when events are reported by several sensors [79]. When an event is detected, many
correlated event messages are sent to the sink, especially if the event is sensed in a large
area and the network is dense, e.g., earthquake detection. Thus, monitoring the loss event-
alarm messages is an efficient and simple way to detect congestion. Another advantage of
this mechanism is its ease of use, since we already use a timer for retransmission of event-
alarms. Thus, congestion timeout can be determined in accordance with retransmission
timeout, which will be explained in Section 2.4.4. Each E-node decides and triggers the
congestion control procedure without the centralized control of sink, based on receiving the
ACK of an event-alarm.

In case of congestion timeout, E-nodes make their neighboring N-nodes temporar-
ily passive via congestion alarm messages. Being passive for a sensor here means not sending sensing measurements to the sink. First, an E-node, which detects a congestion, will broadcast a congestion alarm (CA) message. After timeout period, if the congestion is still not relieved, an E-node will resend the CA by increasing the hop-count. This will continue until the congestion is relieved. From the N-nodes point of view, when they receive a CA message, they temporarily stop sending their sensing measurements and decrease the hop-count. The CA message is flooded until the hop-count is 0.

Note that N-nodes may receive multiple CA messages, $CA = [CA_1, CA_2, ...]$, which are sent by an E-node sequentially until the congestion is relieved. Each $CA_j$ includes hop-count denoted by \( hop-count(j) = j \). Because E-Nodes increase hop-count in every CA message, CA messages are flooded up to \( j \)-th neighbors of the E-node. When the ACK of an event is received, E-node sends congestion safe (CS) message similar the CA to resume the normal operation of the network. Congestion safe message is sent with the hop-count value of the latest CA message by the E-node. Therefore, the number of sensors sending their measurements is reduced, thus regulating the excessive traffic for congestion control.

2.4.4 Timeout and Retransmissions

In ART, we use an asymmetric protocol, e.g., NACK for sink-to-sensor and ACK for sensor-to-sink communication. While using NACKs, the sink only retransmits if it receives an NACK for a query message. Therefore, no timer is used. However, while transferring events from sensors to the sink, E-nodes wait ACKs for event-alarm messages. When an E-node sends an event alarm message, it triggers the timer and waits for timeout period to detect congestion or retransmit. Thus, timeout periods becomes particularly important and will be discussed in this section.

ART uses timeouts for both reliable end-to-end delivery and congestion control. We use congestion timeout (CTO) for congestion detection, which is dynamically determined based on round trip time (RTT) similar to adaptive retransmission timeout in TCP. Assume that all sensors have an initial \( RTT \) that is the duration between the time when a message is sent and the time when the ACK of the message is received at the sender. Then, \( RTT(sample) \) is computed dynamically based on the latest RTT by using the time stamp field. Sensors assert the time information in their messages sent back via ACKs by the sink.
Thus, E-nodes can determine the $RTT(sample)$ by comparing the time stamp received by ACK. Then, the estimated RTT is determined by exponential averaging as:

$$RTT(t) = \alpha \times RTT(t-1) + (1 - \alpha) \times RTT(sample)$$

$$CTO(t) = \eta \times RTT(t),$$

where $\alpha \in (0, 1)$ is weight ratio, and $\eta > 1$ indicates the coefficient of delay tolerance of the application.

Retransmission is done after each retransmission timeout (RTO) when necessary. However in ART, we let RTO equal to CTO used for congestion detection. CA messages are sent when the timer expires. Clearly, it is not efficient to retransmit and send the CA message at the same time. Hence

$$RTO(t) = CTO(t) + \xi,$$

where $\xi$ is the one-hop transmission delay. Event alarm messages are retransmitted after $\xi$ of sending the CA message. Note that, different from other wireless and wired transport protocols, retransmission does not block the next data transmissions in WSNs. We continue sending next messages and retransmit the lost message if needed. The detailed time diagram of retransmission and congestion control in ART is shown in Figure 2.6 in which $t$ is the time instant.

- $t = t_0$: Suppose an E-node detects an event at time $t_0$ and immediately reports it by setting the EN bit of the message. And CTO timer starts to count down.
• $t = t_1$: At time $t_1$, CTO timer expires. As shown in Figure 2.6, CTO is greater than the estimated RTT. When the timer expires, the first congestion alarm message is sent by the E-node. The N-nodes which receive the $CA^{(1)}$ do not send their measurements until they receive a congestion safe message.

• $t = t_1 + T_{\Delta t}$: According to Algorithm 2.2, E-node waits until $t = t_1 + T_{\Delta t}$. Then, it retransmits the event-alarm. By retransmissions, the CTO timer is restarted.

• $t = t_2$: During $t = t_1 + T_{\Delta t}$ to $t = t_2$, the E-node continues waiting for the ACK. At time $t_2$, since CTO timer expires, $CA^{(2)}$ is sent by increasing the hop-count. Until receiving an ACK from the sink, retransmission and CA steps will be repeated consecutively similar as $t = t_1$ and $t = t_1 + T_{\Delta t}$.

In ART, only the first message with an event information needs to be acknowledged and retransmitted if necessary. Since this message has a setting bit EN bit, the sink will send an ACK for this message. In other words, event information is guaranteed to reach the sink node, whereas not every message is guaranteed, which is to achieve the objective of event reliability. Therefore, the number of retransmissions is decreased which in turn will reduce the energy consumption.

2.5 Performance Evaluation

The proposed ART protocol is implemented in the ns-2 [47] network simulator. We conducted several simulations using different scenarios in a static sensor network. The performance of ART is evaluated regarding the effectiveness of classification algorithm, energy balance, network lifetime, and node density.

2.5.1 Performance Metrics and Simulation Setup

We use the following metrics to characterize the performance:

• **E-Node ratio**: It is the ratio of the number of E-nodes to the number of sensors in a sensing field. We use E-Node ratio to represent the effectiveness of node classification, i.e., size of coverage set, resulting from our weighted-greedy algorithm in Section 2.3.
• **Network lifetime**: It represents the maximum time interval that a network can maintain its functionality. We consider a WSN as alive when every point in $A$ is covered by at least one sensor.

• **End-to-end delay**: It is the time for a packet to arrive at transport entity of the receiver after transmitted by the transport entity of the sender.

• **Packet loss ratio**: It is the ratio of the number of packets lost to the number of packets generated.

Simulations are performed for randomly placed sensor nodes in a rectangular region. All sensor nodes have a *sensing region* of fixed range, $r$, associated with them. A communication edge exists between two sensors nodes if they are within their transmission range. A sensing field of 300 x 300 m$^2$ is used in simulations. We vary the number of sensors which allows us to study the performance from very sparse to very dense networks. The number of sensors should be sufficient to cover the sensing field for given parameters. Note that only the density of sensors affects the performance of the node classification algorithm, thus there is no need to vary the size of the area.

In the basic scenario, 100 fixed sensor nodes having transmission range of 90 m and sensing ranges of 60 m are used. We use the energy model given in Section 2.2.2 where initial energy of sensors are 3 J.

Before we describe the performance results, we explain the application run on sensors and the sink. In the experiments, we use a mobile tracking application in which the movements of mobile nodes are reported to a sink. Mobility pattern of a mobile (phenomenon) node is generated using Gauss-Markov mobility model [77] at a maximum speed of 20 m/sec. An event is defined to detect the phenomenon node in the sensing area of a sensor.

We follow an *event-driven* data delivery model to transfer data from sensors to the sink. Sensors send data only if they detects an event. If an event is detected in the period of an update interval, a sensor reports the event to the sink by sending consecutive messages. We use the parameter *event-reporting frequency* to customize how frequently a sensor node sends event reports when phenomenon is in its sensing area. Note that, the first report is regarded as the event alarm message. On the other side, the sink uses
Table 2.2: ART simulation parameters.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Area of sensing field</td>
<td>$300 \times 300 \text{ m}^2$</td>
</tr>
<tr>
<td>Number of sensor nodes</td>
<td>100</td>
</tr>
<tr>
<td>Radio range of a sensor node</td>
<td>90 m</td>
</tr>
<tr>
<td>Sensing range of a sensor node</td>
<td>60 m</td>
</tr>
<tr>
<td>Packet length</td>
<td>100 bytes</td>
</tr>
<tr>
<td>Interface Queue length</td>
<td>50</td>
</tr>
<tr>
<td>Transmit power</td>
<td>24 mW</td>
</tr>
<tr>
<td>Receive power</td>
<td>13 mW</td>
</tr>
<tr>
<td>Idle power</td>
<td>13 mW</td>
</tr>
</tbody>
</table>

For a continuous data delivery model, by sending periodic queries to the sensors. Similarly, we use query-reporting frequency, as a simulation parameter to maintain traffic load in downstream direction. Queries sent by the sink do not affect the scenario or sensing period in the simulation. The coordinates of the sink is the center of the sensing field and same for all experiments. CSMA/CA is used as the MAC protocol and AODV is used as the routing protocol [53].

2.5.2 Simulation Results

We start by illustrating the effectiveness of the energy-aware node classification algorithm (Algorithm 2.1), i.e., the size of coverage set for various network densities. We then discuss the effect of update interval, which is an important question to find the value of update interval for a given sensor network. We then show the effect of update interval on network lifetime. Further, performance gains of reliable event and query transfer service are shown over message-level reliable service. These gains demonstrate the unnecessary overhead that is generated when message-level reliability is concerned instead of event and query reliability which is guaranteed by persisted retransmissions for all experiments.

Performance of node classification algorithm. Figure 2.7 plots the ratio of E-nodes for different network densities. Note that, given the fixed area of sensing field, the network density depends on the number of nodes. Among the three, the network with higher density (200 nodes) has the lowest ratio of E-nodes, thus showing that the greedy algorithm is able
to find coverage sets regardless network density with a decreasing E-node ratio as the network density increases. Therefore, the weighted-greed algorithm for node classification is even more effective in reducing the cost of reliability in dense networks. Further, results in Figure 2.7 indicate that the ratio of E-nodes does not vary in time. In every 10 seconds, our algorithm finds a new coverage set which is independent from the previous set. This implies that no matter what changes occurred in an update interval, E-nodes can always be selected.

**Effect of Update Interval on Lifetime.** For performance evaluation of ART protocol, selecting a proper time interval is very important for a given network. A very large value may increase the communication cost, thus reducing residual energy. On the other hand, a very small update interval may cause high variance in sensors residual energy as E-nodes may drain out their battery much faster, thus partitioning the network. Thus, we study the effect of update interval on network lifetime.

However, the optimal interval length should be the one that prolongs, if not maximize, network lifetime. In Figure 2.8 (a) and (b), we plot network lifetime against update interval for various dense networks. We observe that update interval changes the lifetime at most 3% as a result of energy consumption. For example, consider the network having 100 nodes. Lifetime curve has a peak point at interval length 30 for heavy loaded sce-
In this experiment, we also present the performance of networks having different packet load. We generate different packet loads by varying the event-reporting ($f_e$) and query-reporting frequency ($f_q$) parameters. In Figure 2.8, two different packet loads are performed: (i) heavy: $f_e = 0.5$ and $f_q = 5$ and (ii) light: $f_e = 1$ and $f_q = 10$ sec.

**Query and Event Reliability.** The *ideal* reliable service for a WSN is achieved when the 100% query and event reliability is provided. Thus, retransmissions are needed only to recover the loss of event alarm messages and loss of query messages delivered to the E-nodes. We observe that for message-level reliable service, unnecessary overhead will be generated, which implies the ART protocol has gained performance improvement for ideal reliable service is not used. We refer message-level reliable service as *MLR* and compare the performance of our query and event reliability scheme which is referred as *ART* to
Figure 2.9: End-to-end (E2E) delay and packet loss: ART and MLR.
MLR for various network densities and packet loads. Initial roundtrip time ($RTT = 2$ sec), coefficient of adaptive RTT ($\alpha = 0.125$), coefficient of delay tolerance ($\eta = 0.8$) and one-hop transmission delay ($\xi = 0.05$ sec) are used as input parameters.

Figure 2.9 compares the performance of ART and MLR with respect to average end-to-end delay and packet loss ratio. We have simulated three types of traffic load scenarios: (i) heavy: $f_e = 0.1$ and $f_q = 2$ and (ii) moderate: $f_e = 0.5$ and $f_q = 5$ (iii) light: $f_e = 1$ and $f_q = 10$ sec. From Figure 2.9 (a), we find that the end-to-end delay is a function of increasing network density. Notice that under all traffic loads, end-to-end delay of ART is 40% lower than MLR on average. The reasons for reduced delay are twofold: the advantage gained by having classified E-Nodes dealing with retransmissions reduces the amount of data sent, and the advantage gained by using event-based reliability to avoid ACK implosion. Also, end-to-end delay in ART degrades gracefully with decrease in traffic load. Even in heavy packet load, the delay in ART protocol remains below 5 sec. The packet loss ratio is shown in Figure 2.9 (b) where even at heavy load, ART yields less packet losses than MLR scheme.

**Effect of Congestion Control Mechanism.** The congestion control scheme of ART is designed to reduce the effect of congestion, e.g., high packet loss and long delay. The distributed congestion control scheme described in Section 2.4.3 does not guarantee to detect each and every congestion; however, it is very effective in regulating traffic load and maintaining ideal reliability without additional overhead. We used the same type of traffic load scenarios as in Figure 2.9 to observe the effect of congestion control. In Figure 2.10 (a), we observe that end-to-end delay is significantly reduced as the density of the network increases. Moreover, packet loss is reduced up to 50% by using the congestion control mechanism. The reason is that, only E-nodes sensing the phenomena, which avoids the neighboring N-nodes that sense the same event to send their reports if necessary. Note that, in ART, we do not include a scheduling scheme for N-nodes, i.e., N-nodes do not turn off their radio. Even in a congestion alarm, N-nodes participate in relaying the messages to the sink. However, they do not send new sensing measurements, thus the number of messages injected to the network is reduced significantly compared to ART without congestion control.
(a) Effect of congestion control on E2E delay.

(b) Effect of congestion control on packet loss.

Figure 2.10: Effect of congestion control mechanism.
2.6 Summary

As a summary, we introduced a new transport protocol addressing bidirectional end-to-end reliability in wireless sensor networks. The reliable event and query transfer is accomplished between the sink and essential nodes, while incurring low overhead in terms of control messages and retransmissions. Second, for event transfer, a lightweight ACK mechanism is used while NACK solves the reliable query delivery. Third, we incorporated a distributed congestion control mechanism, in which congestion is relieved by regulating traffic from non-essential sensor nodes.

Simulation experiments have validated that, under the 100% reliable delivery between essential nodes and the sink, traffic load in the network is dramatically reduced by the integration of node classification and congestion control. The proposed protocol performs significantly better than message-level reliability scheme in terms of latency and packet loss.

Next, we discuss the ways to reduce energy consumption of sensor nodes while achieving reliable communication. We extend the node classification algorithm and introduce a two-tiered approach to establish a scalable and energy-efficient network topology that works with ART protocol.
Chapter 3

TTS: Two-Tiered Scheduling for Effective Energy Conservation for Wireless Sensor Networks

In this chapter, we present a two-tiered scheduling approach for effective energy conservation in wireless sensor networks. The effectiveness of this mechanism relies on dynamically updated two-tiered scheduling architecture. We aim to prolong network lifetime, while preserving the major requirements of wireless sensor networks: coverage and connectivity. TTS protocol was presented in [70, 71]. In Section 3.2, the problem formulation is and definitions are given. We describe the two-tiered scheduling mechanism in detail in Section 3.3. Following, simulation results are presented in Section 3.4.

3.1 Motivation and Related Work

In a wireless sensor network, a large number of densely deployed sensor nodes, monitor the events of interest queried by the sink [5]. In such dense networks, energy-efficient scheduling is a key factor to extend the functionality and lifetime of the network. That means, only the nodes maintaining the functionality stay active whereas others are scheduled to sleep, e.g., switching to power saving mode. Therefore, the energy dissipation in sending/receiving and idle time can be significantly reduced and by updating the sleeping
nodes, network lifetime can be prolonged.

The fundamental challenge of scheduling is to maximize the number of sleeping nodes to conserve more energy while maintaining the functionality of the WSN. For this purpose, several approaches have been proposed that make use of topological information which can be categorized into three groups: (i) \textit{connectivity preserving} scheduling schemes \cite{15, 17, 29, 85}; (ii) \textit{coverage preserving} scheduling schemes \cite{14, 62, 76}; and (iii) \textit{connectivity and coverage} preserving scheduling \cite{26, 81}. Connectivity preserving schemes have been proposed to put nodes into sleep mode based on their transmission ranges. Network topology is formed based on the connectivity of the network. For example, in GAF \cite{85}, sensing area is divided into grids, thus one sensor stays active for each grid, whereas other sensors are put into the sleep mode. Grid size is defined based on the transmission range of nodes. SPAN \cite{17} is presented as a distributed algorithm to form a coordinator backbone of active nodes. It attempts to minimize the number of coordinators ensuring that enough coordinators are elected so that every node is in radio range of at least one coordinator.

On the other hand, coverage preserving scheduling mechanisms have selected nodes for full coverage based on their sensing ranges \cite{14, 62}. The goal of these methods is to organize sensors to preserve the sensing coverage without blind points in the sensing field. Therefore, only the sensors covering the field stay awake while others are put into sleep mode. For example, the sensing range of a sensor node might be approximately in between 1-30 m, whereas the transmission range of that sensor might be in between 150-300 m \cite{87}. Even though the coverage might imply connectivity under given conditions \cite{81}, more nodes stay active in \textit{coverage preserving schemes} than in \textit{connectivity preserving schemes}. The nodes which are essential to coverage are not needed to stay active all the time. Instead, some may wake up periodically to send their sensing measurement and receive queries, and then go back to sleep. Similarly, when we integrate connectivity and coverage for scheduling, at least, the minimum number of nodes preserving coverage must stay active \cite{26, 81}.

This work differs from existing scheduling mechanisms in various aspects. Recent scheduling schemes have classified sensors as either active or sleeping nodes. In this work, we integrate coverage and connectivity by a tiered approach; thus, nodes having been used for connectivity or coverage have different sleeping behaviors during an update interval. Nodes, which are not selected for coverage or connectivity-tier, are put into \textit{sleep} immediately; nodes
in the coverage-tier are put into semi-sleep because they can wake up for sending data and can go back to sleep mode periodically; nodes in the connectivity-tier stay active in order to forward data traffic. Hence, we enable more nodes to sleep while maintaining the coverage and connectivity of the network.

We propose a two-tiered scheduling mechanism using weighted-greedy algorithms for efficient energy conservation, which can be deployed either centralized or distributed. First, coverage set is established; in each step of the algorithm of establishing the coverage set, an unused sensor, covering the largest uncovered area and having higher residual energy, is chosen as an essential node (E-node) for the coverage set. Nodes in the coverage set can monitor the entire sensing field and periodically wake up to send and receive to/from the sink. Therefore, we guarantee that an event can be detected by at least one node in the coverage set and queries sent by the sink can affect the entire sensing field. The nodes that are not selected for coverage set are called non-essential nodes (N-nodes) and put into sleep mode. Second, connected dominating set is selected among the nodes in the coverage set according to the residual energy and the network connectivity. The essential dominating nodes (ED-nodes), selected from the coverage set, stay active to forward the traffic, whereas others are in sleep mode. In this process, we attempt to reduce maximum number of nodes while ensuring that the remaining network is connected. The algorithms mainly runs on sink which is aware of locations of the sensors through lightweight localization technique designed wireless networks [18].

Further, to balance the energy consumption while scheduling, coverage and connectivity tiers are updated dynamically. In every round, greedy algorithms are re-performed to establish the new set of coverage set and dominating set by maximizing the total residual energy of selected nodes. Then, a dominating node, whose energy consumption is high, might be a non-essential node for the next round. This dynamic update process also helps handling the topology changes due to unexpected node failures.

3.2 Preliminary Definitions

Let \( S = \{s_1, s_2, s_3, \ldots, s_N\} \) be the finite set of sensors, distributed randomly in a two-dimensional area \( A \), where there are sufficient sensors to monitor the field. Each
Table 3.1: TTS notations.

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>S</td>
<td>The set of sensors in the WSN</td>
</tr>
<tr>
<td>C</td>
<td>Coverage set</td>
</tr>
<tr>
<td>D</td>
<td>Connected dominating set</td>
</tr>
<tr>
<td>A</td>
<td>Sensing field of the entire WSN</td>
</tr>
<tr>
<td>( r^s_i )</td>
<td>Sensing range of node ( s_i )</td>
</tr>
<tr>
<td>( R_i )</td>
<td>Sensing region of node ( s_i )</td>
</tr>
<tr>
<td>( r^t_i )</td>
<td>Transmission range of node ( s_i )</td>
</tr>
<tr>
<td>( e_i(t) )</td>
<td>Residual energy at time ( t )</td>
</tr>
<tr>
<td>( e_i(0) )</td>
<td>Initial energy of node ( s_i )</td>
</tr>
<tr>
<td>( l_i )</td>
<td>Lifetime of node ( s_i )</td>
</tr>
<tr>
<td>( L )</td>
<td>Network lifetime of a sensor network</td>
</tr>
</tbody>
</table>

sensor \( s_i \) has a unique identifier (such as MAC address). We also assume that each node is equipped to learn its location information via any lightweight localization technique for wireless networks [18]. Therefore, all sensor nodes and the sink know their location coordinates \((x_i, y_i)\), sensing range \( r^s_i \), and transmission range \( r^t_i \). Transmission range is assumed to be at least as twice as sensing range which is the case for many sensor nodes [81]. All nodes have similar processing and communication capabilities; messages are sent in a multi-hop fashion.

### 3.2.1 Coverage and Connected Dominating Sets

The sensing region \( R_i \) of a node \( s_i \) is the circular area with its center at \((x_i, y_i)\) and radius of \( r^s_i \). A subset of sensors, \( C \subseteq S \) is called a coverage set if the union of the sensing regions of the \( s_i \in C \) covers the entire field \( A \), that is \( A \subseteq \bigcup_{s_i \in C} R_i \). We consider a sensor node to be an essential (E) node in \( C \) if \( s_i \in C \). This E-node is referred to as \( s^{(E)} \). Otherwise, it is a non-essential (N) node, \( s^{(N)} \).

Given the sensor network \( G(S, E) \) with the set of sensors \( S \) and the set of edges \( E \), a connected dominating set (CDS), denoted by \( D \), is a connected set of E-nodes \( D \subseteq C \), where each E-node \( s_i^{(E)} \in (C/D) \) can directly communicate with one of the sensors in \( D \). Our goal is to construct a connected dominating set having minimum number of dominating nodes \( \in D \). We consider a sensor node to be an essential dominating (ED) node in \( D \) if
Non-essential Nodes (N−Nodes)

Essential Nodes (E−Nodes)

Essential Dominating Nodes (ED−Nodes)

Sensing Region

COVERAGE TIER

CONNECTIVITY TIER

Figure 3.1: Logical view of coverage and connectivity-tiers.

\[ s_i \in D. \] This ED-node is denoted by \( s^{(ED)} \).

In this work, time is divided into rounds, denoted by \( T_R \). Each round is composed of classification update interval \( T_{CU} \) and network operation interval \( T_{NO} \). The coverage and the dominating sets are updated periodically every round in \( T_{CU} \). We should ensure that \( T_{CU} \) is much smaller compared to \( T_{NO} \) because short \( T_{CU} \) implies less overhead and better performance of the network. However, a long \( T_{NO} \) may cause high variance in sensors residual energy as E-nodes and ED-nodes may drain out their battery much faster, thus partitioning the network. The effects \( T_{NO} \) on network lifetime and energy consumption is discussed in Section 3.4.

3.2.2 Two-Tiered Scheduling Problem

The main idea of two-tiered scheduling problem is to decompose the main functionalities of the WSN into coverage-tier and connectivity-tier as shown in Figure 3.1. Such a decomposition allows us to schedule more nodes to be in power-savings mode, thus conserving more energy. If the coverage-tier does not exist, the proposed mechanism works like an energy-efficient topology control. On the other hand, if the connectivity-tier does not exist, it becomes a coverage preserving node scheduling scheme.

Particularly, in our two-tiered scheduling architecture, sensors are classified into three groups with different sleeping behaviors. The first group of nodes, called E-nodes, are
selected to maintain the coverage thus, they should be active to send/receive to/from the sink for some periods, and then may go to sleep. Sleeping behavior of E-nodes are called *semi-sleep* because they can be in active/sleep mode during a round as shown in Figure 3.2. The second group nodes are N-nodes which are scheduled to sleep until the next round without serving on the coverage tier. The third group of nodes, ED-nodes, which forward the data to sink are active because they are selected from the coverage set and serve in the connectivity-tier. Figure 3.2 summarizes the sleeping behavior of these different group of sensors. Before describing the details of the proposed algorithms, some important aspects of the two-tiered scheduling scheme are explained as follows:

- Coverage is provided by E-nodes, which periodically wake up to send their measurement to the sink and receive querying from the sink. E-nodes also form a connected network since transmission range is assumed to be at least as twice as sensing range which is the sufficient condition of coverage that implies connectivity [81].

- However, all E-nodes are not necessarily be active all the time. Some E-nodes may be semi-sleep such that they may wake-up for collecting event data from time to time. Therefore, only a small number of them can be active as a backbone to forward the data traffic and delivery tasks sent by the sink. To achieve this, we establish a connected dominating set (CDS) among coverage set where an E-node is either a
dominating node or a direct (one-hop) neighbor of a dominating node. The dominating
nodes always stay active to preserve the connectivity of the network and forward the
data traffic to/from the sink. E-nodes can communicate at least with one ED-node
and send/receive their measurement/query via their neighboring ED-nodes.

- Based on the sensing ranges of nodes, to provide full coverage, sensors should be
densely deployed compared to the schemes which consider the connectivity of the
network for topology control. Our approach is designed for fully covered networks.

- The active/sleep period of E-nodes are predetermined based on the WSN application.
  If the an event can be detected frequently, then the sleep/wakeup period of an E-
  node should be shorter. Therefore, detected event can be reported immediately via
  ED-nodes.

Next, we give the details of the algorithms to perform this two-tiered scheduling
mechanism.

3.3 TTS: Two-Tiered Scheduling Mechanism

In this section, we give the details of the algorithms to perform two-tiered schedul-
ing under the centralized control of the sink. First, we explain how the coverage-tier is
established. Then, we describe the algorithm for connectivity-tier establishment.

3.3.1 Establishment of Coverage Tier

In TTS, we use the similar weighted greedy algorithm in Section 2.3 to establish
the coverage tier. In contrast the other works, we then construct a second tier called
connectivity tier which will be explained in the following section.

3.3.2 Establishment of the Connectivity Tier

In the second phase, we select a connected dominating set $D$ from the coverage set
$C$, where all other nodes in $C/D$ can directly communicate with a dominating node, i.e.,
ED-node. The most effective approach to conserving energy is to establish the minimum
connected dominating set (MCDS), which is NP-hard as well as finding connected dominating set (CDS) [24]. Thus, similar to the coverage set, we use a weighted-greedy algorithm to find a near optimal CDS.

While finding the connected dominating set, we use a similar greedy heuristic method in [12]. However, in our algorithm, we again consider the residual energy as benefit of sensors and aim to maximize the total benefit while conserving connectivity. In this phase, benefit function is based on the residual energy and the degree of connectivity. Therefore, nodes, having higher residual energy and degree of connectivity, may have a better chance of being ED-nodes.

After implementing the Algorithm 2.1, we have a coverage set which is also connected based upon the assumption that coverage implies connectivity when \( r_t \geq r_s \) [81]. Hence, the CDS set for coverage-tier is obtained in the first tier, which is composed of E-nodes. The objective of Algorithm 3.1 is to reduce the number of nodes in the CDS and select dominating nodes, that is, ED-nodes for the connectivity-tier. For this purpose, we start selecting a node having minimum connectivity and decide either to remove it from the CDS or set it as an ED-node.

A node can be removed from the CDS if and only if the remaining set is still connected. For this reason, we start checking nodes with the minimum connectivities. Also, while removing a node, we have to ensure that at least one of its neighbors has already been assigned as a dominating node. Otherwise, we select one of its neighbors to be a dominating node. In this step, we use the connectivity-benefit to select a neighbor having maximum benefit to be set as an ED-node. This operation continues until all possible nodes in CDS are removed.

Let \( N_i \) be the set of one-hop neighbors of sensor \( s_i \). We define the connectivity-benefit of sensor \( s_i \) as:

\[
\text{benefit}^{(D)}(s_i) = e_i \cdot ||N_i/D||,
\]

where \((N_i/D)\) represents the neighbors of sensor \( s_i \) that are not currently included in \( D \).

In the pseudo code of the Algorithm 3.1, \( L \) is used to denote the current CDS and set \( D \) denotes the CDS that will be returned at the end. In each iteration, (line 8), the sink checks if the current CDS is connected or not. That is, we examine whether there is a node in \( L/D \) that can be removed such that \( L - s_i \) is still connected. When a sensor
Algorithm 3.1 Selecting ED-Nodes for Connectivity-Tier.

Input: $\mathbf{C}$

Output: $\mathbf{D}$

\[
\begin{align*}
\mathbf{D} & \leftarrow \{\text{sink}\}, \ \mathbf{L} \leftarrow \mathbf{C} \cup \{\text{sink}\} \\
\text{while} \ (\mathbf{L}/\mathbf{D} \neq \emptyset) & \\
\text{for all} \ s_i \in \mathbf{L}/\mathbf{D} & \text{ do} \\
\text{benefit}^{(\mathbf{D})}(s_i) & = e_i \cdot ||\mathbf{N}_i \cap \mathbf{L}|| \\
\text{end for all} & \\
\text{select} \ s_i \text{from} \ \mathbf{L}/\mathbf{D} \text{ having} \ \min\{||\mathbf{N}_i||\} & \\
\text{if}(\mathbf{L} - s_i \text{ is connected}) & \\
\mathbf{L} & \leftarrow \mathbf{L} - s_i \\
\text{if}(\mathbf{N}_i \cap \mathbf{D} == \emptyset) & \\
\text{select} \ s_j \text{from} \ \mathbf{N}_i \text{ having} \ \max\{\text{benefit}^{(\mathbf{D})}(s_i)\} & \\
\mathbf{D} & \leftarrow s_j \cup \mathbf{D} \\
\text{end if} & \\
\text{end if} & \\
\text{else} & \\
\mathbf{D} & \leftarrow s_i \cup \mathbf{D} \\
\text{end} & \\
\text{return} \ \mathbf{D} & \\
\end{align*}
\]

is added to $\mathbf{D}$, it is assigned as an ED-node. Note that, the sink is a default member of CDS. Algorithm 3.1 terminates when $\mathbf{D}$ and $\mathbf{L}$ are equivalent. After Algorithm 3.1 terminates, nodes in $\mathbf{C}$, are either dominating node in $\mathbf{D}$ or the neighbor of a dominating node.

In the implementation of the algorithm, to check whether the set is connected, we simply use depth-first-search (DFS). We test whether all nodes are visited starting from a random dominating node. The running time of DFS is $O(||\mathbf{C}|| + ||\mathbf{E}'||)$, where $\mathbf{E}' \subseteq \mathbf{E}$ is the set of edges belonging to the E-nodes, $\mathbf{E}' = \{(s_i, s_j) | s_i \in \mathbf{C}, s_j \in \mathbf{C}\}$. Consider the worst case in which any node subtraction from CDS may cause the remaining set disconnected. In this case, all nodes should be added to $\mathbf{D}$ (line 16) before the algorithm terminates. In this case, the running time of Algorithm 3.1 for establishing the CDS is polynomial time with an upper bound $O(||\mathbf{C}||^2)$. 
3.3.3 Updating Coverage and Connectivity Tiers

The energy consumption of ED-nodes may be higher than the E-nodes; and N-nodes may have the lowest energy consumption due to continuous sleep. Thus, to acquire a fair energy consumption among sensors, coverage and connectivity sets should be updated throughout the lifetime of the network.

In TTS, we make use of global update where all E-nodes and ED-nodes are re-selected independent from the current set. In particular, global update is the process of repeating classification algorithms with latest residual energy levels of sensors. By this way, sensors that have overlapping regions and were E-Nodes in the previous round might be N-nodes in the next update because more energy has been consumed when they were E-node before. This is used to acquire fairly distributed energy consumption among sensors.

Sink can monitor up-to-date energy reserves of sensors using an energy monitoring scheme [90]. Based on this remaining energy of sensors, a new coverage and connectivity tiers are formed by running Algorithm 2.1 and Algorithm 3.1. After each global update, the sink informs sensors of their type by using a control message. The effects of the length of rounds on network lifetime and energy consumption is discussed in Section 3.4.

3.3.4 Walk Through the Algorithms By an Example

In this section, we present an example to explain the proposed two-tiered scheduling. Let $S = \{s_1, s_2, \ldots, s_{20}\}$ scattered through a sensing field randomly, having sensing range $r^s$ and transmission range $r^t$ as shown in Figure 3.3 (a).

1. Algorithm 2.1 is performed after receiving the neighboring information and energy levels from sensors. Sink (gateway) node starts selecting the coverage set based on energy levels and location information as shown in Figure 3.3 (b). In this example, the sink first selects $s_5$, then $s_{10}$ followed by $s_8$ based on the coverage-benefit function given in (2.8). Sensing ranges of E-nodes are shown by dashed circles, where the total sensing area of selected nodes, can cover the entire field.

2. Next, the sink schedules N-nodes to sleep, then N-nodes turn their radio off until the next round. At the end of this step, the coverage-tier has been built. In this example,
coverage set \( C \) is composed of sensors \( C = \{s_2, s_4, s_5, s_8, s_{10}, s_{15}, s_{17}, s_{19}\} \), which are represented by solid dots in Figure 3.3 (b).

3. After constructing the coverage set, the neighborhood information is determined using the coverage set selected in the previous step. In the first iteration, the sink has the information given in Table 3.2.

Table 3.2: An example: node information in the sink.

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Communication Neighbors</th>
<th>Node degree</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>4, 5, 19</td>
<td>3</td>
</tr>
<tr>
<td>4</td>
<td>0, 2, 5, 8, 15</td>
<td>5</td>
</tr>
<tr>
<td>5</td>
<td>0, 2, 4, 15, 17, 19</td>
<td>6</td>
</tr>
<tr>
<td>8</td>
<td>0, 4, 10, 15</td>
<td>4</td>
</tr>
<tr>
<td>10</td>
<td>0, 8, 15</td>
<td>3</td>
</tr>
<tr>
<td>15</td>
<td>0, 4, 5, 8, 10, 17, 19</td>
<td>7</td>
</tr>
<tr>
<td>17</td>
<td>0, 5, 15, 19</td>
<td>4</td>
</tr>
<tr>
<td>19</td>
<td>2, 5, 15, 17</td>
<td>4</td>
</tr>
</tbody>
</table>

4. The sink starts selecting the node having minimum number of neighbors in the current CDS, denoted by \( T \) in the pseudo code in Algorithm 3.1, Initially \( T \) is equal to \( C \).
For the example, sink starts with sensor $s_2$ having three neighbors. When we remove $s_2$ from $T$, $T - s_2$ is still connected. Therefore, after setting its neighbor with maximum benefit as dominating node, we can remove $s_2$ from CDS. From $s_4$, $s_5$ and $s_{19}$, $s_5$ has the maximum benefit (assuming all sensors have equal residual energy). Then we add $s_5$ to $D$, and the **Algorithm 3.1** jumps to next iteration.

5. When, **Algorithm 3.1** terminates, we have the dominating set $D = \{s_5, s_{15}\}$ as shown in Figure 3.3 (c). Then sink immediately send schedule nodes in $D$ and $C - D$ to be active sleep and semi-active, respectively.

6. Sink re-performs this operation in every $T_{CU}$ using up-to-date energy levels sent by the sensors.

### 3.4 Performance Evaluation

Simulations are performed in an 250 m x 250 m area consisting of different numbers of sensors distributed randomly. In the basic scenario, 100 fixed sensor nodes having transmission range of 100 m and sensing ranges of 25 m are used. We use the radio power consumption parameters in [30]. The energy consumption of turning the radio on/off is again negligible. The buffer size of sensor nodes is chosen as 50 and the packet length is 100 bytes. Our protocols run on the 802.11 MAC with power saving support.

In our experiments, we use a mobile tracking application as explained in Section 2.5. All experiments results are provided after averaging 10 random topologies.

#### 3.4.1 Simulation Results

In this work, one of our goals is to reduce the number of on-duty nodes, E-nodes and ED-nodes. For this purpose, we first measure the number of E-nodes and ED-nodes for each round. In the basic scenario, we take the ratio of transmission range over sensing range ($r^t/r^s$) as 4, that holds for most commercially available sensor nodes [88]. Figure 3.4 shows the percentage of on-duty nodes of three networks of different node densities. To cover a 250 m x 250 m area with sensing range of 25 m, we classify random placement of
100 nodes as low density (1600 sensors/km²), 300 as medium (4800 sensors/km²), and 500 as high density (8000 sensors/km²).

From Figure 3.4, we can observe that among these three scenarios, the network having 500 nodes has the lowest ratio of E-nodes and ED-nodes, thus showing that the greedy algorithms perform even better in densely deployed network. In low density scenario, we observe that the E-node ratio is at most 63%, whereas the ED-node ratio is around 5%. This indicates that only 5 nodes among 100 is active over time, which may dramatically effect the network lifetime. Also results indicate that the ratio of on-duty nodes remains stable in time. In the simulation, $T_{NO}$ is 10 sec. Therefore, the sink re-generate the coverage-tier and connectivity-tier using new energy values every 10 sec to balance the energy consumption.

Moreover, we also evaluate the number of on-duty nodes of higher sensing ranges. When the ratio of $(r^t/r^s)$ is getting smaller, the number of E-node decreases dramatically up to 18%, while ED-node ratio remains the same. Figure 3.5 (a) shows the ratios of on-duty nodes in a low dense network which decrease monotonically as the ratio of $r^t$ and $r^s$ decreases. In other words, the number of on-duty nodes in a sensor network depends heavily on the ratio of transmission range and sensing range of each sensor.

Here, we evaluate the energy consumption of the proposed two-tiered scheduling
(a) Percentage of on-duty nodes vs. the ratio of $r^t$ to $r^s$.

(b) Energy Consumption per Round.

Figure 3.5: Performance of two-tiered scheduling mechanism.

approach, comparing with *alwaysActive* scheme, where nodes are not scheduled to sleep. The reason is that there is not much performance evaluation in the prior works integrating coverage and connectivity [26, 81] in terms of energy conservation. Instead, they have evaluated the coverage percentage, achieved coverage degree and size of the coverage sets. In our experiments, we show that two-tiered scheduling provides a considerable energy consumption compared to *alwaysActive* scheme while fully monitoring the sensing field.

In Figure 3.5 (c), we show the average residual energy dissipation per round. By two-tiered scheduling, labeled as *TTS*, the average energy dissipation is reduced around 40% compared to *alwaysActive* scenario. Energy dissipation values, depicted in this figure, are the average of the corresponding round. For example in the 3rd, the average energy consumption is around 3 J in two-tiered scheduling, while it is 6 J in *alwaysActive* scenario. The reason for this performance lies on the tiered approach in which on-duty nodes can be put into semi-sleep state for the coverage, which results in more energy savings.

Further, we show the effect of the two-tiered scheduling on the network lifetime. The key factors prolonging the network lifetime are (i) the energy conservation, which can be achieved by putting more sensors into sleep mode and (i) balanced energy consumption among sensors. A non-uniform residual energy consumption within the entire sensor net-
network may lead to network partitioning and shorten the network lifetime. Severity of such non-uniform energy consumption is alleviated by updating the coverage and connectivity tiers.

First, we demonstrate the network lifetime in Figure 3.6 (a) compared to *alwaysActive* scheme with the initial energy of 1 J. We consider a WSN as *alive* when the sensing field is fully covered. In other words, a network is alive when every point in $A$ is covered by at least one sensor. According to this, we observe that network lifetime is prolonged significantly in two-tiered scheme compared to *alwaysActive*, especially in high density networks. Even in low density network with 100 nodes, network lifetime is prolonged up to 28% which shows the effective energy savings of proposed tiered approach. We estimate a similar effect on lifetime for distributed implementation of TTS, since we observe very close on-duty node ratio compared to the centralized TTS.

It is worthy of mention that in CCP, network lifetime is measured in terms of coverage percentage. CCP with connectivity feature keeps the coverage above 90% (lifetime threshold) until 470 sec with node density 200. However, the sensors are deployed with a
much higher initial energy selected randomly within the range from 200 J to 300 J. Also, the power consumption of Tx, Rx, Idle and Sleeping in CCP are for 802.11 network card, which is not common for a sensor node [30]. Compared to CCP, network lifetime can be prolonged by TTS up to 132 sec in a similar dense network with the given Mica2 power consumptions and initial energy of 1 J. This signifies that, two-tiered scheduling approach with semi-sleep behavior of coverage-tier nodes has great impact on prolonging the network lifetime.

Meanwhile, we notice that energy savings resulted from the proposed two-tiered scheduling is accompanied by the overhead of updating the coverage and connectivity sets. At the beginning of each round, the sink re-schedules the sensors. Without updating, although we conserve energy, nodes in active state (ED-nodes) will die faster, which causes shorter network lifetime due to the waste of unused energy of sleeping nodes. For this purpose, in Figure 3.6 (b), we plot network lifetime against network operation interval, $T_{NO}$, for various dense networks. When $T_{NO}$ is longer, the sink updates the coverage-tier and connectivity-tier less frequently, thus conserving energy. However, this does not result in prolonging the network lifetime. We observe that $T_{NO}$ changes the network lifetime at most 5% as a result of energy consumption and residual energy distribution. This shows that even with the overhead of updating, the network lifetime can be expanded significantly by using two-tiered scheduling mechanism.

As a matter of fact, updating E-nodes, which provides balanced energy distribution among sensors, is also effective in prolonging lifetime. To show the energy distribution, we depict the residual energy of sensors in Figure 3.7 where x-y plane represents the sensing field. Nodes are positioned their actual locations as in the simulation and z-axis represents their residual energy. In Figure 3.7 (a), coverage-tier and connectivity-tier are updated in every round based on their new residual energy levels. However, in Figure 3.7 (b) coverage-tier and connectivity-tier are established at the beginning without updating or rotation over time. Note that the surface in Figure 3.7 (a) does not fluctuate dramatically as in Figure 3.7 (b), indicating that the residual energy of sensors in Figure 3.7 (a) is close to each other. Therefore, by rotating nodes, the balance or the fair energy consumption of sensors is achieved and the lifetime of a sensor network is extended.
3.5 Summary

As a summary, we presented a two-tiered approach addressing the efficient scheduling issue in wireless sensor networks. In order to prolong network lifetime, we schedule sensors to be in power saving mode, while preserving coverage and connectivity. We decomposed the coverage and connectivity functionalities of a sensor network into two-tiers; thus, nodes having been used for connectivity or coverage have different sleeping behaviors. We first established the coverage-tier based on their sensing areas of sensors by a weighted greedy algorithm. Nodes in the coverage-tier can monitor the entire sensing field and periodically wake up to send and receive to/from the sink, whereas dominating nodes selected for the connectivity-tier stay active to forward the data traffic.

Simulation experiments have validated that a significant energy saving is achieved by the proposed scheduling algorithms while providing full coverage and connectivity. Algorithm for finding the coverage set, selected 30% of nodes on average in medium dense networks. Among the coverage set, on average 2% of nodes are always active as dominating nodes. Furthermore, we showed that energy consumption is balanced and the network lifetime is prolonged around 30% by rotation of coverage and connectivity tiers.

Next, we discuss an alternative distributed implementation of the algorithms where
sensors use local neighboring information to establish the coverage and connectivity sets. We then extend the implication of our algorithms to directional (multimedia) sensor networks and present an approach for maximizing directional sensing coverage.
Chapter 4

Self-Organization of Wireless Sensor Networks

In this chapter, we address the problem of finding an optimal coverage set by effectively eliminating redundant nodes without using centralized control and accurate location information. Using a fully distributed approach, we propose an effective redundant node elimination method that considers even the smallest overlapping regions to establish a coverage set. This work was presented in [73]. We then study the problem of self-orientation in Wireless Multimedia Sensor Networks (WMSNs), that is finding the most beneficial orientation for all multimedia sensors to maximize multimedia coverage. We propose a new algorithm to determine a node’s multimedia coverage and find the sensor orientation that minimizes the negative effect of occlusions and overlapping regions in the sensing field. Multimedia coverage work was presented in [74]. In Section 4.2, omni-directional coverage algorithms are proposed. We summarize the challenges on multimedia converge, define the multimedia coverage problem, and propose a new distributed algorithm for multimedia coverage calculation in Section 4.3.

4.1 Motivation and Related Work

Once a sensor network is randomly deployed, sensor nodes should have the ability to *self-organize*, i.e., to dynamically construct and maintain the network topology befit-
ting the purpose of the application without any centralized or human assistance. The self-organized sensor network is expected to establish the communication among nodes via discovery mechanism, reconfigure the topology, and reliably transfer the sensing measurements to the sink, while achieving these functions via low power operations.

When sensor nodes are randomly distributed into a sensing field, they start to form a network by constructing an energy-efficient and reliable topology based on local information. One key challenges to construct such a topology is to preserve sensing coverage under stringent energy constraint. Coverage preservation is a necessary functionality for all mission-critical sensor networks and used to measure the quality of service a sensor network can provide. Therefore, several research studies have been proposed related to coverage in sensor networks that concerned on how well sensors observe the sensing field in a distributed way [1, 14, 20, 81]. In these studies, each node make its decisions (to be active, sleep, etc.) based on some coverage related metrics such as the size of intersection or union of the overlapping regions with its neighbors. Even though such metrics are logically correct, it is hard to verify the size of asymmetric overlapping regions for a sensor having limited processing and storage capacity. Hence, the question of “how to calculate coverage distributively?” remains an open issue.

In particular, finding an optimal coverage or connectivity set can be implemented using either centralized [1, 14, 63] or distributed algorithms [26, 13, 43, 76, 81]. Centralized solutions basically organize sensors to preserve the sensing coverage without leaving blind points in the sensing field by use of a central authority (the sink) and global location information of sensors. Even though they find near-optimal solutions, they can not be applied to high-dense sensor networks with large number of sensor nodes due to the communication expense of having global information at the sink. Therefore, many distributed solutions have been proposed [26, 13, 43, 76, 81] where coverage is achieved by forming connected set-covers in a distributed manner for each query [26]. In [14], rather than sensing field, a set of targets with known locations are necessarily covered by each set cover. Therefore, only active nodes in the set-cover send and receive data. On the other hand, in [76], a distributed scheduling algorithm has been proposed where each node turns itself off using local neighbor information where all nodes have identical sensing range that is the same as their transmission range. However, the sensing range of a sensor node might be approximately
In between 1-30 m, whereas the transmission range of that sensor might be in between 50-300m [87].

In this research, we propose a new self-organization approach for wireless sensor networks by using a new self-calculation of coverage (SCC) method, which is a fully distributed solution used under stringent energy and reliability constraints. We consider to preserve coverage such that nodes can be self-organized to form the minimum coverage set with essential nodes based on relative locations and unit disk sensing ranges. Using SCC method, each node calculates its sensing coverage by studying necessary and sufficient conditions. This makes our coverage based approach realistic and lightweight in terms of computational cost. In SCC, a node starts with examining the orientation of neighbors that share a sensing area in common. Then it checks whether these sensing neighbors are close enough to monitor its entire range. Since sensors can rapidly run out of energy, nodes can self-monitor their coverage performance using SCC, thus being able to self-organize in an energy-efficient way.

On the other hand, sensing coverage calculation using circular sensing ranges, e.g., temperature sensors, seismic sensors are not applicable to multimedia sensors having directional sensing view. More recently, the availability of low-cost multimedia devices has fostered the use of low resolution multimedia sensors for many sensor network applications such as environmental monitoring, and health care, providing detailed visual information from multiple disparate viewpoints. Therefore, the problems related to multimedia sensor nodes to monitor their coverage performance, provisioning self-configurable sensor orientations is an attractive research topic that is addressed in the context of this thesis.

The need for using such multimedia sensors is usually driven by the necessity of providing comprehensive information pertaining to a specific region of interest. To be able to support the demand for monitoring, we focus on wireless multimedia sensor nodes with directional sensing views. Performance of directional sensing is very much dependent on the obstacles present in the environment. Therefore, finding the most favorable orientation for the multimedia sensors is an important and challenging problem. For example, deploying a large number of low-resolution image sensors is recently shown to be a good alternative to having a single high resolution camera [54]. Distributed methods for camera sensor networks also show gains from using a large number of low-power image sensors [54, 55]. In
such multimedia sensor networks having large number of nodes, inherent disadvantages due to physical obstacles in an environment (e.g., trees, buildings, lakes, etc.) can be turned into a multi-modality advantage, with the flexibility to adjust orientations of the multimedia sensors attached to the wireless nodes.

Maintaining and maximizing the coverage of an area have been studied in great depth in the fields of multimedia, robotics and wireless sensor networking. From the perspective of sensor networking, considerable work is present for the omni-directional coverage problem [14, 26, 62, 76] that aims to cover a plane by arranging circles on the plane. However, the proposed solutions for omni-directional coverage can not be used for the coverage of bidirectional and field-of-view sensors such as low-resolution video cameras. A common limitation of these existing protocols [14, 81, 87] is that the collected information on phenomena (e.g., temperature, concentration of a substance, light intensity, pressure, humidity, etc.) are assumed to come from an omni-directional sensing. However, multimedia sensors, (i.e., low-resolution cameras, microphones, etc.) have the unique feature of capturing direction-sensitive multimedia content. Especially, video sensors can only capture useful images when there is line of sight between the event and the sensor [4]. Hence, coverage models developed for traditional wireless sensor networks are not sufficient for deployment planning of a multimedia sensor network.

In [64], a preliminary investigation of the coverage problem for video sensor networks is addressed. The concept of sensing range is replaced with the camera’s field of view, which is the maximum volume visible from the camera when sensors are placed on the floor. All camera nodes are assumed to be situated on a plane (at the ceiling of the monitored room), and they shoot the images of the scene from a parallel plane. Such a ceiling placement, however, may only fit specific indoor applications. Then, authors proposed a routing scheme for the video sensors based on cameras’ field of view metrics. Video sensors are directed to the floor, and coverage is determined by disk shaped scenes on the floor, without considering effects of any occlusions. On the other hand, a wide range of multimedia applications require outdoor placement of multimedia sensors. Several projects on habitat monitoring use acoustic and video feeds from the multimedia sensors scattered in the environment. Similarly, a large number of video sensors are already used by oceanographers to observe sandbars via image processing techniques.
In addition, triangular view regions are used for computing multimedia coverage of sensor networks in [2]. The major goal of this work is to find the minimum observed distance to any multimedia sensor that any target traveling through the field must have, even if the target optimally tries to avoid the sensors. Sensors are assumed to have a isosceles triangular coverage (field of view) placed on a square field. Using mathematical modeling, worst-case breach coverage is calculated using a polynomial time algorithm. One limitation of this work is the lack of occlusions which is the most common problem of multimedia sensors. Any obstacle in the FoV (Field of View) region result in occlusion which should be considered while calculating the worst-case breach coverage. Second, the proposed algorithm determines the closest observable distance to a sensor that any target must have for a given a deployment. Differing from this study, our goal is to determine and then increase the multimedia coverage of each individual sensor and in total by designing a local algorithm to self-orient the pose of the sensors.

In terms of occlusion effect, [54] has several investigations for wireless camera networks. The paper shows that deploying a large number of low-resolution image sensors is a better alternative compared to a single high resolution camera in highly-occluded environments. Therefore, distributed methods for camera sensor networks have gains over using a large number of low-power image sensors [54, 55]. They observed that a collection of low resolution (short sensing range) sensors outperforms a single sensor with equivalent coverage as the degree of occlusion in the environment increases [54].

On the other hand, the geometric variations of the classic camera placement problem are also related to our problem. However, none of these variations in the literature addressed cameras as individual multimedia sensor nodes which can communicate to each other. In [48], an in-depth theoretical analysis of the problem is shown to maximize camera coverage of an area, where the camera fields of view do not overlap. In [21], the art gallery framework is further refined by introducing a resolution quality metric. In addition, Isler et al. extended the formulation of the minimum guard coverage art gallery problem to incorporate the minimum-set cover problem. They derived reduced upper bounds for two cases of exterior visibility for two- and three- dimensions [34]. In the field of robotics, a system was developed to perform dynamic sensor planning for a camera mounted on a moving robotic arm in order to compute optimal viewpoints for a preplanned robotic grasping
task. In [69], a planning method was presented to determine optimal camera placement given task-specific observational requirements such as field of view, visibility, and depth of field. Our research differs from the existing works since it calculates the optimal orientation of sensor nodes using local information only after the initial deployment. In addition, our method considers a large number of sensor nodes with multimedia sensors having much lower resolution than the multimedia devices discussed in [69, 34].

In this work, we also include a new distributed method to find the most beneficial orientations for the sensors used in a multimedia sensor networks. We specifically consider (i) minimizing the effects of occlusion in the environment and (ii) improving the cumulative quality of the information sensed from the region of interest. Let us consider a WMSN with a large number of scattered nodes, each having neighbors with which it can communicate directly. Using a distributed method outlined in this paper, each node can discover its neighbors and examine possible overlapping sensing regions as well as the obstacles in the environment. In our scheme, each sensor node determines the most beneficial orientation for its multimedia sensor so that the entire image of a field can be constructed using low-resolution snapshots from multiple sensors. Our approach enables multimedia sensor nodes to monitor their coverage performance, provisioning self-configurable sensor orientations in an efficient way.

The proposed algorithm also decreases the obstacles’ detrimental effect on the quality of the sensed information while maximizing total covered area. As discussed in [3, 25], WMSNs have stringent constraints of limited communication bandwidth, processing capability, and power supply to deliver multimedia context. It is crucial to capture the most recent occlusion-free multimedia context from the environment. This helps newly designed WMSN protocols [25] delivering efficient multimedia context with the limited bandwidth resource.

Next, we first explain self-organization algorithm for omni-directional sensors, then discuss the bidirectional (multimedia) sensor extension of self-organization.
4.2 Self-organization Algorithms for Omni-directional Sensors

4.2.1 Definitions and Target Applications

Let $S = \{s_1, s_2, s_3, \ldots, s_N\}$ be the finite set of sensors, distributed randomly in a two-dimensional area $A$, where there are sufficient sensors to monitor the field. Each sensor $s_i$ has a unique identifier (such as MAC address). All sensor nodes know their sensing range, denoted by $r$, which is assumed to be identical for all sensors, and their transmission range, $t$. In this paper, we assume that transmission range is greater or equal to the sensing range, i.e., $r \leq t$ [87]. We use virtual coordinates and virtual distances given in [41]. A sensor discovers its neighbors in its transmission range by periodically sent hello messages and collect received signal strength (RSS) measurements of its neighbors. By this way, each sensor places its one-hop neighbors to a virtual coordinate system centered at itself [41] and calculates the virtual distances.

The following notations will be used in the paper:

1. $S_i$, the sensing region of a node $s_i$ is a circular area centered at $(vx_i, vy_i)$ and radius
of \( r \), where \((vx_i, vy_i)\) is the virtual coordinates of \( s_i \).

2. \( T_i \), transmission neighbors of sensor \( s_i \) with which \( s_i \) can communicate directly.

3. \( C_i \), coverage neighbors of sensor \( s_i \) which have a common sensing area with \( s_i \). We classify the coverage neighbors of a sensor as 1-hop and 2-hop based on virtual distances.

4. For each sensor pairs \( s_i \) and \( s_j \) that have common sensing area, we associate a triple \((P^1_{ij}, P^2_{ij}, \theta_{ij})\) where \((P^1_{ij}, P^2_{ij})\) are the two intersections between \( s_i \) and \( s_j \) arranged in the counterclockwise order, and \( \theta \) is the effective angle.

Let us denote the virtual distance between \( s_i \) and \( s_j \) by \( vd(i, j) \), i.e., \( vd(i, j) = \sqrt{(vx_i - vx_j)^2 + (vy_i - vy_j)^2} \). If \( vd(i, j) < r \), then sensor \( s_i \) records the sensor \( s_j \) as its 1-hop coverage neighbor, which means the \( s_j \) is inside its sensing range, \( s_j \in C^{1\text{-Neigh}}_i \). If \( vd(i, j) < 2r \), then sensor \( s_i \) takes the sensor \( s_j \) as its 2-hop coverage neighbor, that is not in its sensing range but shares a sensing area in common, then, \( s_j \in C^{2\text{-Neigh}}_i \), where \( C^{1\text{-Neigh}}_i \cup C^{2\text{-Neigh}}_i = C_i \subseteq T_i \).

**Definition 1** Let \( S_i \) be the sensing region of sensor \( s_i \). If \( S_i \subseteq \bigcup_{s_j \in C_i} S_i \cap S_j \), we call sensor \( s_i \) is a redundant sensor, since its sensing region can be covered by its coverage neighbors, \( C_i \).

A subset of sensors, \( C \subseteq S \) is called a coverage set if the union of the sensing regions of the \( s_i \in C \) covers the entire field \( A \), that is \( A \subseteq \bigcup_{s_i \in C} S_i \). We consider a sensor node to be an essential node (E-node) in \( C \) if \( s_i \in C \). Otherwise, it is a redundant node (R-node). Our goal is to construct a coverage set having minimum number of E-nodes.

After constructing the coverage set, we find a subset of the coverage set, called connected dominating set, \( D \), such that each E-node \( \in (C/D) \) can directly communicate with one of the sensors in \( D \). We consider a sensor \( s_i \) to be an essential dominating (ED) node if \( s_i \in D \).

Next, we present the distributed coverage calculation and redundant node discovery algorithm to construct the coverage and dominating coverage sets.
4.2.2 A Distributed Coverage Calculation Algorithm

In this work, we present a realistic and lightweight method, called self-coverage calculation (SCC), for sensors to calculate their sensing coverage based on local sensing neighbors, which is the ultimate condition to select a coverage set. In particular, our SCC method is composed of three conditions. The first condition, called perimeter-test, checks whether there are enough sensing neighbors. This is a necessary condition based on the assumption of densely deployed nodes [32]. The second condition is called center-test to exercise whether the sensor itself can be covered by at least one of its neighbors. Finally, the third condition is called distance test, that checks if sensing neighbors are close enough, so that there may not be uncovered area inside the sensing region.

Assume that sensor \( s_i \) will use SCC to determine if it is a candidate redundant node, which means its sensing coverage is fully monitored by its neighbors. Here, we explain SCC conditions in detail as follows:

**Perimeter-test:** First condition in SCC is to determine whether the perimeter of its sensing region is fully covered by its neighbors. By examining each 1-hop and 2-hop sensing neighbor, a sensor can determine the intersection points as illustrated in Figure 4.2. If intersected arcs in total are sufficient to enclose its perimeter from 0 to \( 2\pi \) [32], the perimeter is enclosed, which refer that “perimeter-test” is passed. The uncovered arc in the perimeter indicates that sensing neighbors can not fully cover the unit-disk sensing region. In this case, sensor can not be eliminated as a redundant node, this refer to fail in the perimeter-test.

We show an example of the perimeter-test in Figure 4.2, where sensor \( s_0 \) has 4 sensing neighbors. Using the coordinates of its sensing neighbors, sensor \( s_0 \) can find the intersection points of the arcs [9]. Let the line segment from 0 to \( 2\pi \) in Figure 4.2 denote the perimeter of \( s_0 \). After we list the arcs and then scan the perimeter in as shown in Figure 4.2, we can see that the entire perimeter is enclosed by \( \widehat{P^2_{01}P^1_{04}} \) (node \( s_3 \)), \( \widehat{P^1_{04}P^2_{04}} \) (node \( s_4 \)), \( \widehat{P^1_{01}P^2_{01}} \) (node \( s_1 \)) and \( \widehat{P^1_{02}P^2_{02}} \) (node \( s_2 \)).

Although, perimeter-test ensures that a sensor has sufficient number of sensing neighbors, this does not guarantee the full coverage of the sensing region. There may have some uncovered area in the middle of the region. Thus, we propose a center-test and a
distance-test, so that a sensor ensures that neighbors are close enough to the center and provide full coverage.

**Lemma 2** Let \( S_i \) be the sensing region of sensor \( s_i \) and \( C'_i \) be a subset of sensing neighbors of node \( s_i \). Then, \( S_i \) is fully covered by its sensing neighbors in \( C'_i \) if and only if any point \( P_i \) on the perimeter is covered by the arc denoted by \( \hat{P}_{ij} \), i.e., \( S_i \subseteq \bigcup_{s_j \in C'_i} S_i \cap S_j \) where \( s_j \in C'_i \).

**Proof 2** Since the perimeter circle that surrounds the sensing region \( S_i \) is also in \( S_i \), any arc \( \hat{P}_{ij} \) on this perimeter circle must also be covered by one or more sensors in \( C'_i \).

**Center-test:** When a sensor passes the perimeter-test, we ensure that it has the necessary sensing neighbors that can cover its sensing region. However, this is not sufficient to claim that the sensing region is fully covered. For instance, Figure 4.3 shows an example where perimeter-test is passed but distance test fails. In Figure 4.3, even there are 5 sensing neighbors that covers the perimeter, there is an uncovered area in the middle of the region. Therefore, we need to ensure that the center of a sensing region can be covered by at least one of a node’s sensing neighbors.
In this step, sensor \( s_i \) chooses one of its sensing neighbor \( s_j \) as primary neighbor which satisfies \( d(i, j) \leq R_s \), where \( d(i, j) \) is the distance between \( s_i \) and \( s_j \). One necessary condition is that there should be at least one primary neighbor to cover the center point of a sensing region. If there is no primary neighbor as in Figure 4.3 (a), i.e., distances between all sensing neighbors of the \( s_0 \) are greater than \( R_s \), then neighbors are not sufficient to achieve full coverage. Therefore, center-test is a necessary condition in finding a coverage set.

In Figure 4.3 (b), the primary neighbor of \( s_0 \) is \( s_4 \), where \( d(0, 4) = |OP| \leq R_s \). In case there are multiple sensors satisfying \( d(i, j) \leq R_s \), we select the one having the minimum distance as the primary neighbor.

**Corollary 1** For each \( s_i \), there exists a subset, \( C'_i \subseteq C_i \), such that \( S_i \supseteq \bigcup_{s_j \in C'_i} S_i \cap S_j \) if and only if \( 1 \leq |C'_i \cap C_i^{1-N}| \).

**Proof 3** Consider a sensor \( s_i \) having sensing neighbors \( C_i \). Let all sensing neighbors are 2-hop neighbors, i.e., \( \forall s_j \in C_i, s_j \in C_i^{2-N} \). In this case, all sensing neighbors should be outside its sensing range, where \( \forall s_j \in C_i, d(s_i, s_j) > R_s \). If all \( s_j \in C_i \) are more than \( R_s \) away from the sensor \( s_i \) itself, there is a gap in the inner region where sensor is located that cannot be covered by any neighbors. By this contradiction, we show if there is no 1-hop sensing neighbor of \( s_i \), sensing region \( S_i \) can not be covered by \( C_i \).

**Distance-test:** When a sensor passes the perimeter-test, and center-test, it is still possible that there are uncovered area of a sensor’s coverage. The motivation of distance-test is to verify that sensing neighbors are close enough to the center and satisfy full coverage, which is based on the selection of primary neighbor in the center-test.

Let \( s_p(i) \) be the primary neighbor of \( s_i \). In this test, we check if for all \( s_j \in C_{Neigh} \), the following condition satisfies:

\[
d(i, j) \leq R_s + d(i, p).
\] (4.1)

In Figure 4.3 (b), to illustrate the distances between \( s_0 \) and neighbors clearly, we draw an extended coverage range of node \( s_0 \), where the center is \( s_0 \) and the radius is \( R' = |OB| = R_s + |OP| \). We called the original sensing range of \( s_0 \) as \( R \) and the extended
(a) Distance test: fail.  
(b) Distance test: pass.

Figure 4.3: Two examples where perimeter-test is passed for sensor $s_0$.

range as $R'$ in the Figure 4.3 (b). The condition in (4.1) can be verified by two extreme cases: for $d(i, p) = 0$, that is, node $s_p$ and node $s_i$ are in the same location, then the radius of the extended coverage, $R' = R_s$, which is exactly the same as $s_i$, that is, there is no extension of coverage from node $s_p$; for $d(i, p) = R_s$, that is, node $s_p$ is on the perimeter of node $s_i$, then $R' = R_s + R_s = 2R_s$, which means that the extended coverage is enlarged one time. Therefore, the extended coverage shows the maximum distance that the primary neighbor can reach. If all sensors in the sensing neighborhood of $s_i$ are closer than $R_s + d(i, p)$, then we say that full coverage is achieved and distance-test is passed.

Therefore, the first condition, perimeter-test is a necessary condition to cover the perimeter; and the second condition, center-test is also a necessary condition to cover the center. The third condition, distance-test is very effective for the full coverage after many tests, though it is an approximate condition for coverage calculation.

Therefore, sensors that have passed the perimeter, center, and distance-tests, are marked as $R$-nodes and will be eliminated to find an optimal coverage set which will be explained in the next section.

Using the proposed method, a sensor $s_i$ can be covered by at least three sensing
neighbors. If only 1-hop sensing neighbors are considered then all three neighbors are needed to be closer than $R_s$ similar to the coverage calculation methods in [13, 81]. On the other hand, if we also consider 2-hop sensing neighbors, then only a single 1-hop sensing neighbor together with two 2-hop sensing neighbors can be sufficient to cover $S_i$. Note that two sensors cannot be at the same location.

**Lemma 3** If $\bigcup_{s_j \in C_i} S_i \cap S_j \supseteq S_i$, then there must exist a subset of $C_i$, denoted by $C'_i$, such that $\bigcup_{s_j \in C'_i} S_i \cap S_j = S_i$. So, we can write $3 \leq |C'_i|$, where $C'_i$ satisfies either

- $1 \leq |C'_i \cap C^1_{1-N}|$ and $2 \leq |C'_i \cap C^2_{1-N}|$, or
- $C'_i \subseteq C^1_{1-N}$.

**Proof 4** From Corollary 1, we know that at least one sensor in $C^1_{1-N}$ is needed for full coverage. The angle $\theta_{ij}$ of the arc that is not covered by any sensor $s_j$, $s_j \in C^1_{1-N}$, satisfies $\theta_{ij} > \pi$. Since all arcs that constitute the $2\pi$ perimeter must be covered for full coverage (see Lemma 2), the uncovered arc can be covered by sensors in $C^2_{1-N}$. However, the angle $\theta_{ik}$ of the arc covered by any sensor $s_k$, $s_k \in C^2_{1-N}$, satisfies $\theta_{ik} < \frac{2\pi}{3}$. Hence for full coverage, at least two sensors in $C^2_{1-N}$ are needed.

Now let us consider the second case where only 1-hop sensing neighbors are used. The angle $\theta_{im}$ of the arc covered by any sensor $s_m$, $s_m \in C^1_{1-N}$, satisfies $\theta_{im} < \pi$. Similar to the first case, each sensor in $C^1_{1-N}$ can only cover less than $\pi$, therefore at least three sensors are needed in $C^1_{1-N}$ for full coverage.

In this section, we will explain how coverage and connected dominating sets are constructed in a distributed fashion. First step is to discover the possible redundant nodes, which is explained in the previous section. However, each redundant node can not be removed from the coverage set unless its necessary coverage neighbors are in the coverage set. Therefore, we use an energy-aware redundant elimination method, where sensors calculate their benefits of being in the coverage set in terms of energy and then start sending announcement messages to build the coverage set. After coverage set is established, dominating coverage is dynamically constructed starting from the sink. Here, we give the details of the steps that each sensor follows.
To construct the coverage set, we first need to determine essential nodes to preserve coverage and eliminate the redundant ones. If sensor $s_i$ calculates that its coverage neighbors, $C_i$, are not sufficient to monitor its sensing region, then it is mandatory member of the coverage set, i.e., if $S_i \not\subseteq \bigcup_{s_j \in C_i} S_i \cap S_j$, then $s_i \in C$.

In this case, a sensor broadcasts an $I$-AM-ESSENTIAL message and become a member of coverage set. Otherwise, it is a candidate of being redundant node and follows the benefit calculation step that determines its benefit to be in the coverage set. Any sensor that is not a mandatory E-node has to calculate its benefit. Our goal is to choose the coverage set of sensors to maximize the benefit in terms of coverage and the residual energy, i.e., the largest uncovered sensing region is covered with the least sensors having maximum residual energy.

Consider the sensor $s_i$ with sensing region $S_i$. If $S_i$ is fully covered by the current E-nodes, i.e., $S_i \subseteq \bigcup_{s_j \in C_E} S_i \cap S_j$, then sensor $s_i$ sends an $I$-AM-REDUNDANT message and go to sleep mode. Otherwise, it calculates and broadcasts its benefit, which is:

$$benefit(s_i, t) = \frac{e_i(t)}{S_i \cap S_{C_E}},$$

(4.2)

where $S_{C_E}$ is the total region covered by the mandatory E-node neighbors of sensor $s_i$, and $e_i(t) \in [0, 1]$ is the residual energy level. Nodes having higher residual energy, and smaller covered area will have a better chance of being in coverage set whereas others will be eliminated as redundant nodes.

In this step, mandatory nodes have already announced and each node is aware of its benefit and its neighbors benefit. Then, nodes start to broadcast $I$-AM-ESSENTIAL messages after a short back-off time, denoted by $T_{\text{back-off}}$, where $0 < T_{\text{back-off}} \leq CB_{\text{MAX}}$. $CB_{\text{MAX}}$ denotes the maximum back-off and is determined based on the average one-hop latency during neighbor discovery. We assume that sensors have globally synchronized clocks [39]. A sensor determines its back-off time based on its benefits, i.e., a node having the maximum benefit will have the shortest back-off time, thus announcing the $I$-AM-ESSENTIAL message earlier.

When a sensor receives $I$-AM-ESSENTIAL message from its coverage neighbor, it should update its benefit since its covered region, $S_i \cap S_{C_E}$, might increase by newly
announced E-node neighbors. If \( S_i \cap S_{CE_i} \supseteq S_i \), sensor reset its back-off timer, sends an **I-AM-REDUNDANT** message and go to sleep. Otherwise, the benefit will decrease proportional to the covered area which may also prolong the back-off time. Coverage tier is established at the end of \( CB_{MAX} \). Next, we will discuss how the dominating coverage is established to preserve connectivity using minimum number of nodes.

In sharp contrast to earlier studies [26, 81], we decompose the coverage and connectivity features of the WSN in this work. After establishing the optimal coverage set, all E-nodes are not necessarily be active all the time. Only a small number of E-nodes can work as a backbone to forward the data traffic and delivery tasks sent by the sink. To achieve this, we establish a dominating coverage set among coverage set where an E-node is either a dominating node or a direct (one-hop) neighbor of a dominating node. The dominating nodes always stay active to preserve the connectivity of the network and forward the data traffic to/from the sink. E-nodes can communicate at least with one ED-node and send/receive their measurement/query via their neighboring ED-nodes.

Following, we need to construct a dominating set among the nodes in the coverage set. We use a greedy approach similar to the centralized algorithm, i.e., sensors are removed one by one as long as the remaining set is connected. However, when such a greedy approach is run by sensors, a distributed algorithm, e.g., distributed breadth-first search, is necessary to ensure that the remaining network is connected in each iteration. In a large-scale sensor network, distributed breadth-first search may incur high overhead due to its computational complexity, i.e., \( O(D \log^3 N) \), where \( D \) is the diameter of the network [12]. Therefore, we propose a dynamic dominating set construction approach triggered by the sink.

During dominating set construction, sensors broadcast three types of messages.

- **JOIN-Backbone**: It indicates that there is no dominator in the neighborhood, thus sensor may become a dominating node.

- **CANDIDATE-Backbone**: A sensor broadcasts this message after receiving **JOIN-Backbone**.

- **NOT-IN-Backbone**: This message is sent by sensors which are already connected to a dominating node and they decide not to be dominating nodes.
Our dominating set construction starts from the sink by sending a broadcast \textit{JOIN-Backbone} message. The idea is that sensors which will forward the message, are included to the connectivity set as a dominator. In the first step, \textit{JOIN-Backbone} message is received by the neighbors of the sink, which are called candidate dominator. A candidate dominator, again sets a back-off time $t \in [0, DB_{MAX}]$ to forward the message, where $DB_{MAX}$ denotes the maximum back-off while establishing connectivity-tier and is determined based average one-hop latency, and the node density. Back-off time will be inversely proportional to residual energy level and the degree of connectivity. In this context, degree of connectivity is the number of neighbors which have not sent a \textit{JOIN-Backbone} or \textit{NOT-IN-Backbone} message. For example, sensor $s_i$ has 4 neighbors among which two of them have sent a \textit{NOT-IN-Backbone} message, whereas the other neighbor has sent a \textit{JOIN-Backbone} message. This implies that two neighbors are connected to ED-nodes and one neighbor has already become an ED-node. In this case, degree of connectivity of $s_i$ is 1 in calculating its benefit. Similar to the previous step, a node having greater benefit has shorter back-off time, thus forwarding \textit{JOIN-Backbone} message earlier to be an ED-node.

When a node receives a \textit{JOIN-Backbone} message, it (i) updates its its connectivity is decreased; because one of its neighbors becomes a dominator; (ii) sets/updates its back-off time based on newly calculated benefit; and (iii) broadcasts a \textit{CANDIDATE-Backbone} message. By receiving \textit{CANDIDATE-Backbone} messages during the back-off time, candi-
date dominators can be noticed if their neighbors are also candidates. If all neighbors of a candidate node is either dominator or candidate dominators, it can safely give up of being dominator, since all its neighbors are already received a \textit{CANDIDATE-Backbone} message. In this case, a sensor node sends a \textit{NOT-IN-Backbone} message indicating that it will not be an element of dominating coverage.

At the end of a back-off period, a candidate which has not been self-removed, forwards \textit{JOIN-Backbone} message and becomes an ED-node. Following the forwarded \textit{JOIN-Backbone} message, new candidates appear and send \textit{CANDIDATE-Backbone} messages. This process continues until all nodes have received at least one \textit{JOIN-Backbone} message. Note that, a sensor updates its benefit after receiving \textit{JOIN-Backbone} or \textit{NOT-IN-Backbone} messages.

An example signaling diagram is shown in Figure 4.4. Assume that sensor $s_1$ has one hop neighbors $s_2, s_3, s_4$, and two-hop neighbor $s_5 \in C$. When $s_1$ receives \textit{Join-BACKBONE} message and broadcast to its neighbors, thus become an ED-node. Signaling diagram illustrates the messages while constructing dominating coverage set.

The energy consumption of ED-nodes may be higher than the E-nodes; and R-nodes may have the lowest energy consumption due to continuous sleep. Thus, to acquire a fair energy consumption among sensors, coverage and connectivity sets should be updated throughout the lifetime of the network.

In this paper, we make use of \textit{global update} where all E-nodes and ED-nodes are re-selected independent from the current set. In particular, global update is the process of repeating algorithms with latest residual energy levels of sensors. By this way, sensors that have overlapping regions and were E-Nodes in the previous round might be R-nodes in the next update because more energy has been consumed when they were E-node before.

\subsection{Comparison of Distributed and Centralized Coverage Set Establishment}

In this section, we compare the distributed approach, centralized approach and CCP \cite{81} in terms of on-duty node ratio in Figure 4.5 because it is an immediate measure to evaluate the effectiveness of scheduling mechanisms. The lower the on-duty node ratio, the more nodes can be put into sleep, thus increasing the network lifetime. Here, \textit{on-duty}
nodes refer to the nodes which are not scheduled to sleep. We show that the number of on-duty nodes in centralized approach and distributed approach are lower than the number of on-duty nodes in CCP, i.e., scheduling scheme that integrates coverage and connectivity. In Figure 4.5, ratio of ED-nodes and E-nodes are illustrated on a single column where ED-node ratio is on the bottom with having different patterns.

In CCP, results for 1-degree coverage show that 20% of 100 nodes should be active which have been randomly deployed on a 50 m x 50 m area with sensing range of 10 m. However, in centralized approach, on average 1% of nodes are always active and 23% are periodically active/sleep in the same dense network. Similarly, distributed approach performs better than CCP. Event hough, the ratio of E-nodes is higher than the ratio of on-duty nodes in CCP, E-nodes are not active all the time, instead having semi-sleep behavior.

![Percentage of on-duty nodes under different node densities.](image)

In Figure 4.5, we can observe that the ratio of E-nodes and ED-nodes decreases in both centralized approach and distributed TTS as the node density increases, which shows
that the proposed algorithms can establish a near optimal coverage set and CDS regardless of node density.

On the other hand, when we compare the centralized approach and distributed approach, we observe that centralized approach performs 10% better at most in terms of on-duty node ratio. However, the cost for deploying the centralized algorithm in sensor networks may be different from that for distributed approach, which may vary greatly between applications.

4.2.4 Simulation Results

The performance of our approach is evaluated using simulations that are performed in an 250 m x 250 m area consisting of different numbers of sensors distributed randomly. In the basic scenario, 100 fixed sensor nodes having transmission range of 100 m and sensing ranges vary from 15 m to 40 m are used. We use the radio power consumption parameters in [30]. The energy consumption of turning the radio on/off is negligible. The buffer size of sensor nodes is chosen as 50 and the packet length is 100 bytes.

In the first experiment we investigate the performance of our coverage calculation under three metrics: the total number of locally detected redundant sensors, the total number of nodes for coverage (E-nodes), and the total number of nodes to preserve connectivity (ED-nodes). To cover a 250 m x 250 m area with sensing range of 30 m on average, we use random placement of 100 to 300 nodes. We evaluate the number of redundant and E-nodes of higher sensing ranges. When the ratio of sensing range is increased, the number of redundant nodes is increased up to 70% where the number of E-nodes and ED-nodes remains the same. Figure 4.6 (a) shows the number of nodes in a low dense network (N=100) and higher density with N=200. Finally, we evaluate the possible energy saving when the coverage set is used, where R-nodes are scheduled to sleep to save energy and only E-nodes and ED-nodes are active. In Figure 4.6 (b), we demonstrate the network lifetime compared to the scheme when all nodes are active. We consider a WSN as alive when the sensing field is fully covered. In other words, a network is alive when every point in A is covered by at least one sensor. According to this, we observe that network lifetime is prolonged significantly when R-nodes are scheduled to sleep while preserving coverage and connectivity, especially in high density networks. Even in low density network with 100 nodes, network
Figure 4.6: Performance of the redundant discovery and elimination algorithms.
lifetime is prolonged up to 28% which shows the effective energy savings of using coverage and dominating coverage sets.

4.3 Self-organization for Directional (Multimedia) Sensors

Let us consider a WMSN with a large number of scattered nodes, each having neighbors with which it can communicate directly. Using a distributed method outlined in this research, each node can discover its neighbors and examine possible overlapping sensing regions as well as the obstacles in the environment. In our scheme, each sensor node determines the most beneficial orientation for its multimedia sensor so that the entire image of a field can be constructed using low-resolution snapshots from multiple sensors. Our approach enables multimedia sensor nodes to monitor their coverage performance, provisioning self-configurable sensor orientations in an efficient way.

Our practical and efficient algorithm also ensures that the obstacles’ detrimental effect on the quality of the sensed information is minimized while total covered area is maximized. However, in some applications, there may have some specific area in the sensor field that must be observed, i.e., areas having higher priority of observability such as observing human activity recognition tasks. The areas where the human activity takes place have much intention to be observed and need to have overlapping images in some cases. Therefore, we extend our method to consider the following scenarios: (i) the entire sensor field needs to be maximally covered (ii) the sensor field has selected high priority regions that multiple sensors should observe.

we summarized the contributions of this paper as follows: (i) the proposed algorithm is fully distributed using local information: thus communication overhead is incurred only between neighboring nodes; (ii) with the flexibility to adjust orientations of the multimedia sensors, multimedia sensor nodes update the orientation of multimedia sensors on the fly to increase the multimedia coverage significantly, (iii) overlapped and occluded regions in the sensing field can be decreased by collecting the current pose of neighboring nodes and (iv) coverage is increased even for sparse networks by using self-orientation instead of random orientations, for arbitrary obstacles in the sensor field.
4.3.1 Definitions and Target Applications

As audio-visual sensors take their places on wireless nodes, circular sensing range assumption loses ground significantly since a typical audio or video sensor has a sectoral perception and affected by surrounding obstacles heavily [4]. Therefore, we envision that sensing coverage planning for the wireless multimedia sensor networks (WMSN) will be different from what first-generation sensor networks demanded. Multimedia nodes are densely deployed, providing detailed visual information from multiple disparate viewpoints. Low resolution sensors can be used for many WMSN applications such as environmental monitoring, and health care. A sensor resolution of 128x128 is usually enough for typical applications, whereby 320x240 might be required for some applications requiring object recognition [83]. Each camera node is responsible for extracting necessary data out of the captures video stream and sending it to a base station. Multimedia sensors, such as cameras, are powerful multi-dimensional sensors that can capture a directional view, usually called Field of View (FoV). The most commonly used low-resolution camera module is equipped with a lens providing a 45° FoV [69]. For example, the human eye without any rolling movement can only see objects lying inside a cone having a 25° half-angle [69]. To obtain a much wider view of the surroundings, fisheye lenses with a FoV of 150° FOV are developed [55].

In this work, we assume sensors nodes have a fixed lenses providing field of view with angle $\Theta$, and they can only pan to adjust their FoV. In Figure 4.7, two dimensional representation of a wireless multimedia sensor network having four low-resolution sensors is shown. In the left figure, nodes’ orientation is randomly determined. The right one illustrates the same area with slightly changes orientation. Gray areas are the visible regions by the sensors. We use the term “camera sensors” to represent wireless multimedia sensors, having directional view for simplicity.

A sensor is called self-orienting, if it is capable of adjusting its pose at the point of deployment (low-cost camera sensors [46] that are capable of panning). We claim that sensor networking can be used to find the most beneficial sensor pose, via neighbor information exchanges for maximizing multimedia coverage through occlusion-free viewpoints. We use the term viewpoint to represent a sensor’s pose at its fixed location.

A multimedia sensor network with $N$ sensors is represented with its individual sensors, $S = \{s_1, s_2, \ldots, s_N\}$, deployed in a polygonal sensing field, denoted by $\mathcal{A}$. For each
sensor \( s_i \), we assume that its location \((x_i, y_i)\), and orientation parameters to determine the FoV are known. Let us denote the distance between \( s_i \) and \( s_j \) by \( d(i, j) \), where
\[
d(i, j) = |\sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}|.
\]
If \( d(i, j) < 2R_s \), then sensors \( s_i \) and \( s_j \) are FoV neighbors, sharing a sensing area in common. These sensors use the FoV neighbor information to compute non-overlapping viewpoints. A communication link exists between sensor \( s_i \) and sensor \( s_j \) if a single-hop transmission from \( s_i \) to \( s_j \) and \( s_j \) to \( s_i \) can be performed successfully. Sensors \( s_i \) and \( s_j \) are transmission neighbors, if there is a symmetric link between them. Each sensor \( s_i \) is associated with quad \((x_i, y_i, T_i, C_i)\), where \( T_i \) represents transmission neighbors, and \( C_i \) represents the set of FoV neighbors.

In this context, some definitions that will be used in the rest of the paper are as follows:

**Definition 1 Field of View (FoV):** The term field of view refers to the directional view of a multimedia sensor and it is assumed to be an isosceles triangle (two-dimensional approximation) as shown in Figure 4.8 (a), where \( \alpha \) is the vertical angle to the boundary edge of FoV , \( \Theta \) is the FOV vertex angle, and \( R_s \) is the maximum multimedia sensing range. We represent a field of view of a sensor \( s_i \) as \( \Lambda_i^{\alpha_i} \), where the parameter \( \alpha_i \) is the vertical angle to the boundary edge of FoV showing the pose of the sensor \( s_i \). Any \( \Lambda_i^{\alpha_i} \) has a FOV vertex angle, denoted by \( \Theta_i \), and \( R_s \), which is the equal side length of FoV representing the maximum multimedia sensing range.

- **Definition 1.1 Visible FoV (vFoV):** Visible FoV is the set of all points in the FoV of a sensor node which is visible to the sensor itself, i.e., has not been blocked by any obstruction within FoV, \( \forall obs_j \) in \( A \), if \( A(obs_j) \cap \Lambda_i^{\alpha_i} = \emptyset \), then \( \Lambda_i^{\alpha_i} \Rightarrow v\Lambda_i^{\alpha_i} \), where \( obs_j \) is an obstacle in the sensing field \( A \) and \( A(obs_j) \) is the area where the \( obs_j \) is located.
Defining 1.2 Occluded FoV (oFoV): The complement of the visible region within FoV is the occluded FoV (as shown with the dark shaded region behind wall in Figure 4.8 (b)), \((v\Lambda_i^{\alpha_i})' \Rightarrow o\Lambda_i^{\alpha_i}\).

Defining 1.3 Overlapping FoV (xFoV): The set of points in a visible FoV is referred to as overlapping FoV if it intersects with any of the neighboring sensor’s visible FoV, \(\forall s_j \in C_i\), if any \(v\Lambda_i^{\alpha_i} \cap v\Lambda_j^{\alpha_j} \neq \emptyset\), then \(\Lambda_i^{\alpha_i} \Rightarrow x\Lambda_i^{\alpha_i}\).

Definition 2 FoV disk: The FoV disk associated with a sensor defines the set of all possible regions, to which the sensor can adjust its pose. For simplicity, we assume that the orientation of all sensors can be anywhere in between \([0^0, 360^0]\); thus, FoV disk is a circular disk having a radius of \(R_s\), i.e., the maximum distance to capture with a given resolution.

Definition 3 Multimedia sensors self-orientation problem (MSSP): Given a multimedia sensor network deployed on a sensor field \(\mathcal{A}\), the multimedia self-orientation problem is defined as finding the optimal sensor orientations to achieve the maximum total visible FOVs on the field \(\mathcal{A}\).

4.3.2 A Distributed Algorithm for Multimedia Sensors Self-Orientation

In this section, we will explain the details of the self-orientation procedure for a multimedia sensor network. Our algorithm has three major phases: (i) initial messaging; (ii) distributed FoV detection; and (iii) self-orientation algorithm as shown in Figure 4.9.
Figure 4.9: Three major steps in self-orientation of multimedia sensors.

Each phase has specific tasks and uses a set of messages. Next, we walk through each phase in detail.

**Initial Messaging Phase**

Each sensor needs to determine its location, which can be done using a suitable lightweight localization technique designed for wireless sensor networks such as time-based positioning scheme [18] or range-free localization scheme [27]. Sensor nodes then exchange messages between neighbors to collect this neighborhood information. All sensors broadcast a `HELLO_MSG` indicating their unique sensor IDs and their location coordinates. We assume that stationary sensors having identical FoV ranges are located in the sensing field. Finally, each sensor processes the `HELLO_MSG` and indent overlapping FoV neighbors. Initial messaging phase ensures that every sensor is aware of its neighbors and their locations. Here, we present a new method to compute FoV of multimedia sensors. To the best of our knowledge, our work will be the first to provide a distributed algorithm to maintain orientation of wireless multimedia sensors for increased sensing efficiency. The method is composed of three tests, in which each sensor detects its maximum visible FoVs. The first test, namely *perimeter test*, checks the existence of a visible FoV within $[0^0, 360^0]$. If a sensor fails to find a visible FoV during the perimeter-test, it moves to the second test called *neighbor-distance test* which examines the distance with FoV neighbors. Finally, the third test, called *obstacle-distance test*, is performed if the sensor fails from the neighbor-distance test. It compares the occluded FoVs to find the largest visible FoV. Here, we explain these three tests in detail as follows:
Figure 4.10: An example showing the perimeter test for sensor $s_1$.

**Perimeter Test**

In perimeter-test, each sensor scans its FoV disk perimeter to determine whether a visible FoV (which can not be captured by any other FoV neighbor) exists in its FoV disk. The reason is that FoV disk perimeter can effectively show occlusions and possible overlapping regions. The intersection points of any tangent touching an existing obstacle on the perimeter can be used to determine the size of occlusion. For example in Figure 4.10, FoV disk of sensor $s_1$ is illustrated. There are two obstacles inside its FoV disk which are close enough to $s_1$ that may result in occlusion. The intersections of the tangents on the perimeter are shown with points $F$ and $G$ for the first obstacle (obs1); $H$ and $A$ for the second obstacle (obs2). Therefore, a sensor $s_i$ can determine that if any $\Lambda_i^{\alpha_i}$ with $\Theta_i$ implies $\Theta_i \cap (\angle FOG) = 0$ or $\Theta_i \cap (\angle HOA) = 0$ then $\Lambda_i^{\alpha_i}$ is a visible FoV and we refer arcs $\widehat{FG}$ (counter clock-wise) and $\widehat{HA}$ as occluded arcs on the FoV disk of $s_1$.

Perimeter-test not only finds the non-occluded FoV but also helps to determine non-overlapping FoVs in a FoV disk. In this step, sensors do not know the orientations
of their FoV neighbors. However, they can determine possible overlapping FoVs inside their FoV disks. Similar to occluded arcs, each sensor finds possible overlapping arcs on its perimeter using the location information received from its neighbors. To do this, we simply determine the intersection points of the arcs and scan the perimeter as illustrated in Figure 4.10. For example, sensor $s_1$ has an overlapping arc $\hat{BD}$ and $\hat{CE}$ as shown in Figure 4.10.

By examining each FoV neighbor and obstacles, a sensor decides if intersected arcs and occluded arcs in total are sufficient to enclose its perimeter from $0^0$ to $360^0$ [32]. If there exists a $v\Lambda_i^{\alpha_i}$ and $o\Lambda_i^{\alpha_i}$ with $\Theta_i$ such that $\Theta \geq \Theta_i$, we refer that “perimeter-test” is passed. This means that the sensor has a visible FoV which has not been captured by any other sensor in any orientation. Since our goal is to maximize the visible FoV in the total sensing region, sensors which pass the perimeter-test will adjust their pose to $\alpha_i$. On the other hand, sensors that do not pass the perimeter-test continue the FoV detection with the neighbor-distance test, which will be explained in the following subsection.

**Neighbor-Distance Test**

Passing the parameter test implies that a sensor has visible FoV, which can not been covered by its neighbors in any orientation (non-overlapped in any case). In neighbor-distance test, however, we examine whether a sensor has non-occluded FoV which might be overlapped. If a sensor has a $v\Lambda_i^{\alpha_i}$ with an angle $\Theta_i \geq \Theta$ in its perimeter, it is assumed to pass the neighbor-distance test, otherwise it moves to obstacle-distance test. Sensors that
Figure 4.12: Pseudo code of neighbor-distance test.

```plaintext
neighbor_distance_test () {
    while scan perimeter \((0^\circ, 360^\circ)\) for any arc \(\overrightarrow{P_mP_n}\)
        if \{\text{non-occluded}(\overrightarrow{P_mP_n}) == TRUE \} and \{ \(\overrightarrow{P_mP_n}\) > \(\Theta\)\}
            return PASS;
        for each \{\text{FoV neighbor } s_j\}
            find the distance \(d(i, j) = |\sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}|\)
            compute \(s_j\) with minimum \(d(i, j)\);
        else { return FAIL; }
}
```

have passed the neighbor-distance test then find the largest visible FoV among non-occluded FoVs using neighbor’s distances.

Even though the final orientations of the neighbors are not known, FoV neighbors might have overlapping FoVs. In this case, sensors need to find the smallest overlapping FoV by scanning non-occluded arcs and calculating the distances between each neighbor. A closer neighbor implies a larger overlapping FoV. In Figure 4.13, FoV disk of sensor \(s_1\) and its neighbors are shown. Since perimeter of \(s_1\) is enclosed by an occluded arc \(\overrightarrow{FH}\) and possible overlapping arcs \(\overrightarrow{FA}, \overrightarrow{BC}, \overrightarrow{DE},\) and \(\overrightarrow{GA}\), sensor \(s_1\) fails the perimeter-test. However, it passes the neighbor-distance test, since arc \(\overrightarrow{HF}\) is non-occluded which is greater than \(\Theta\), FoV angle of the camera sensors which is assumed to be fixed. Among the neighbors \(s_2, s_3, s_4\) and \(s_5\), sensor \(s_2\) has the largest distance to \(s_1\), denoted by \(d(1, 2)\), indicating smallest possible overlapping FoV, shown as dark shaded areas inside the FoV disk.

**Obstacle-Distance Test**

Finally in obstacle-distance test, sensors with no vFoV \((\Theta_i \geq \Theta)\) are examined. Figure 4.14 shows and example sensor \(s_1\) surrounded by four obstacles. Since there is no non-occluded arc in the perimeter greater than \(\Theta\), the final orientation of sensor \(s_1\) will not have a visible FoV. However, by finding the distances between the obstacles and the sensor node, occluded FoV can be minimized keeping the visible FoV maximized. Similar to neighbor-test, a closer obstacle means a larger occluded FoV. In such conditions, a sensor scans the perimeter to find the most beneficial arc \(\Theta\), to maximize the visible FoV.
Figure 4.13: An example showing the neighbor-distance test for sensor $s_1$.

Figure 4.14: An example showing the obstacle-distance test condition for sensor $s_1$. 
obstacle_test() { 
  for each {obstacle obst_k inside FoV disk} 
    find the distance $d(i, k)$, where $d(i, k) = |\sqrt{(x_i - x_k)^2 + (y_i - y_k)^2}|$ 
  return obst_k with minimum $d(i, k)$ } 

Figure 4.15: Pseudo code of obstacle-distance test.

Note that the perimeter of FoV disk may not be fully-occluded or fully-overlapped. For example, In Figure 4.14, arc $\overparen{AB}$, $\overparen{CD}$ and $\overparen{EF}$ are non-occluded and non-overlapped arcs, but smaller than $\Theta$. In such cases, these small segments can be included to the FoV. In the Figure 4.14, the FoV of sensor $s_1$ is shown in shaded region which includes the arc $\overparen{CD}$ and some occluded regions with larger distance from obstacles.

Next, we explain how to use FoV detection test algorithms. Note that, taking the advantage of local information exchange, multimedia sensors update their neighbor list and orientations periodically. Thus, all tests are performed using up-to-date FoV neighbors and their orientation decisions. Under the $360^\circ$ pan-capability assumption, multimedia sensors will determine their pose for self-orienting by using their local one-hop neighborhood information. The dimensions and the locations of the obstacles are assumed to be known by sensors before self-orientation. We do not consider the multimedia sensors as obstacles with respect to the other multimedia sensors due to their small size.

Based on the test for distributed FoV detection, we propose a heuristic algorithm described in Figure 4.16.

**STEP 1:** Algorithm starts with sensors’ \texttt{HELLO\_MSG} that indicates the location of the sensors. For self-orientation, sensors must build a list of FoV neighbors that are close enough to have an overlapping FoV. A received \texttt{HELLO\_MSG} is then used to update the neighbor lists. Note that, we assume that the maximum sensing range, $R_s$, is equal or smaller than the transmission range of the multimedia sensors.

**STEP 2 and STEP 3:** After exchanging \texttt{HELLO\_MSG}, each sensor has an up-to-date FoV neighbor list with their locations and priori-known obstacle locations. Next step is performing the perimeter test. This test checks if a sensor $s_i$ has a visible FoV, $v\Lambda_i^{\omega_i}$, which can not be captured by any other FoV neighbor in a FoV disk. Thus, when perimeter test is passed, the sensor $s_i$ can self-orient to $v\Lambda_i^{\omega_i}$ and finalize the self-orienting algorithm.
0. for each sensor \( s_i \) do {
1. broadcast HELLO_MSG for exchanging location information and finding FoV neighbors.
2. perform \( \text{perimeter\_test()} \)
   if (perimeter\_test == PASS)
     self-orient to pose \( \Theta_i^* \) then broadcast \( \text{POSE\_ADV\_MSG} \).
   return();
   else {
3. update FoV neighbors based on \( \text{POSE\_ADV\_MSG} \) received.
4. perform \( \text{neighbor\_distance\_test()} \)
   if (neighbor\_distance\_test == PASS)
     find candidate pose and broadcast \( \text{CANDIDATE\_ADV\_MSG} \)
5. update FoV neighbor based on \( \text{CANDIDATE\_POSE\_MSG} \) received.
   send ACK\_POSE\_MSG for each \( \text{CANDIDATE\_POSE\_MSG} \)
   self-orient to pose \( \Theta_i^* \) then broadcast \( \text{POSE\_ADV\_MSG} \)
   return();
   else {
6. perform \( \text{obstacle\_distance\_test()} \)
   self-orient to pose \( \Theta_i^* \) and broadcast \( \text{POSE\_ADV\_MSG} \)
   return();
   }
}
}

Figure 4.16: The general approach of self-orientation algorithm.

On the other hand, sensors failing the perimeter test will continue the algorithm with the neighbor-distance test.

In particular, perimeter test shows the existence of at least one \( vFoV \) that can not be observe by others in any orientation. However, there may be more than one visible FoVs that result in passing perimeter test. Then sensors change their pose to the most beneficial \( vFoV \). Here, the term beneficial corresponds to having smallest panning angle to a self-orienting multimedia sensor. Therefore, a sensor selects a \( v\Lambda_i^\alpha \) with a vertical angle of \( \alpha_i \) to the boundary such that \( |\alpha_i - \alpha_0| \) is the smallest among all possible \( vFoV \)s, where \( \alpha_0 \) is the current vertical angle. After changing the pose, a sensor should advertise its decision to all its neighbors with a \( \text{POSE\_ADV\_MSG} \) and finalize the self-orienting procedure.

In step 3, sensors that fails from the perimeter test update their neighbor list based on the \( \text{POSE\_ADV\_MSGs} \) they received. If a sensor receives a \( \text{POSE\_ADV\_MSG} \) from a FoV
neighbor, it updates its neighbor list by adding the pose of its neighbor for the next steps. **STEP 4 and STEP 5:** In step 4, sensors invoke neighbor-distance test to find a occlusion-free FoV. By passing the neighbor distance test, a sensor determines the existence of a visible FoV in the FoV disk. From the visible FoVs, it selects the pose toward the FoV neighbor $s_d$ with maximum distance, using candidate pose selection procedure in step 5 and sends its candidate pose by a **CANDIDATE_ACK.MSG** to the neighbor $s_d$. This message indicates the candidate pose of the sensor to its neighbors.

Since sensor nodes perform the self-orienting simultaneously, sensors then receive **CANDIDATE_ACK.MSG** from their neighbors who have passed the neighbor-distance test, thus replying with a **ACK_POSE.MSG** if no $x$FoV occurs. Whenever a sensor receives **ACK_POSE.MSG**, it indicates that the sensor can select this pose safely and finalize the self-orienting procedure. Otherwise, a sensor should repeat the step 5 with the second minimum distance neighbor. **STEP 6:** Finally, in step 6, sensors that failed from perimeter and neighbor distance test perform the last test, obstacle-distance test. Since they have failed from the previous tests, no visible FoV exists in their FoV disk. Thus, in step 6, sensors will select an occluded FoV with maximum coverage; that is, the pose toward the obstacle with maximum distance similar to the neighbor-distance test. If there is a visible FoV with an angle smaller than $\Theta$, the final pose will be selected from the small vFoV including occluded FoV to maximize the visible region that the sensor will capture.

**Property 1** Self-orienting algorithm uses $O(N)$ messages which takes $O(N)$ time. Every node sends a **HELLO.MSG** and **POSE_ADV.MSG** once. And sensors which execute neighbor-distance test exchange one **CANDIDATE_POSE.MSG** and one **ACK_POSE.MSG**. Thus, the total number of these messages is $O(N)$.

At the end of this algorithm, each sensor selects its pose and self-orient to maximize total visible FoVs on the sensing field $\mathcal{A}$. However, in some applications, e.g., mobile tracking using camera sensor networks, a system may require overlap in the coverage of cameras in the sensing field. For example, the overlapping coverage can help to localize
objects [37], especially moving objects. In such applications, sensors should self-orient for occlusion-free but overlapping FoVs which can be achieved by simple modifications in our algorithm, which will be discussed in the next section.

In some applications, multimedia sensors are used to monitor specific target regions with high accuracy. In these cases, overlapping FoV are often necessary to have multiple views of the same region from different sensors. In the previous section, we propose a heuristic algorithm to maximize total visible FoVs by eliminating overlapping FoVs. However, our method can easily be modified to allow overlapping FoVs; thus, it can be used in a wide range of multimedia sensor network applications.

Let us assume that a polygonal region $A'$ is monitored by overlapping camera views as shown in Figure 4.17, given that sensors are aware of the boundaries of this region $A'$. Each sensor calculates the intersection points of $A'$ and its FoV disk such that in perimeter test, any non-occluded arc overlapped with $A'$ is selected without considering the neighboring overlapped regions. By this way, our algorithm can not only be used to maximize the visible coverage but also serve for any application where overlapping FoV is necessary. In Figure 4.17, an example area $A'$ is shown that should be monitored using oFoVs. In this example, camera sensors 2, 3 and 4 self-orient to capture $A'$.

Next, we show our extensive simulation results for different scenarios.

4.3.3 Simulation Results

We have used Ns-2 simulator [47] for the performance evaluation of our algorithms. Simulations have been performed for randomly placed sensor nodes in a rectangular two-
dimensional terrain. All sensor nodes have been configured with an FoV vertex angle \( \Theta = 60^0 \), and an \( R_s \) of 30m. Communication between two sensors are assumed to be possible (i.e. an edge exists between two sensors nodes in the connectivity graph), if the distance between the transmitter and receiver is no more than 60m. A sensing field spanning an area of 250x250m^2 has been used on which the number of sensors were varied to study the system performance from sparse to dense deployments. In the basic scenario, 50 static multimedia sensor nodes are deployed with self-orientation capabilities. Initial orientation of these sensors are randomly determined. The sensing field \( A \) has several predefined rectangular obstacles which adversely affect the visible viewpoints of multimedia sensors.

In our simulations, we consider total coverage and messaging overhead as the two key metrics to evaluate the performance of our self-orienting algorithms. We assume that sensors are configured with their deployment locations (or capable of determining the same). Also, global access to obstacle locations on a calibrated coordinate system is available for the sensors. Sensors perform the tests in sequence and those who send the \texttt{POSE ADV MSG} self-orient their viewpoints to appropriate final FoV. When the initial messaging phase starts, sensor nodes set a timer and broadcast \texttt{HELLO MSG}. Value of this timer is determined using the average degree of connectivity of the sensor. When expired, each sensor node updates its coverage and transmission neighbor list. This \( O(N) \) message complexity operation is repeated periodically (i.e., for each phase) throughout the lifetime of the network.

In the simulation, each sensor scans the perimeter of the FoV disk to determine possible \( o \)FoVs and \( x \)FoVs. This is a low computational cost operation even for low-capacity multimedia sensors. Once the \( \Lambda^o_{si} \) of \( s_i \) is determined, the size of the visible \( v \Lambda^o_{si} \subseteq \Lambda^o_{si} \) is calculated to find the total visible FoV. However, \( v \)FoV might be an arbitrary polygon due to several obstacles, and calculating exact shapes require a complex geometric library support. Therefore, total visible FoV is calculated in a bitmap fashion using 62500 bins (i.e. 1m \( \times \) 1m bins for each point) on the 250mx250m field \( A \). Bins that fall into a sensor’s triangular FoV are tested for line of sight (LOS) view (i.e., line segment from the bin corresponding to the FoV point to the camera sensor should not intersect with any obstacle on the field). Using this test for all FoV points of all sensors, we determine the total vFoVs in all scenarios.

**The effect of self-orientation on coverage:** In Figure 4.18 (a), an experiment outcome with random orientation is illustrated, resulting 21.09\% overall coverage of the field. Al-
Figure 4.18: Multimedia coverage.

(a) Random orientation.  
(b) Self-orientation algorithm.

<table>
<thead>
<tr>
<th>Nodes</th>
<th>Obstacles</th>
<th>Multimedia coverage gain %</th>
</tr>
</thead>
<tbody>
<tr>
<td>50</td>
<td>4</td>
<td>8.93%</td>
</tr>
<tr>
<td>50</td>
<td>8</td>
<td>6.06%</td>
</tr>
<tr>
<td>100</td>
<td>4</td>
<td>16.39%</td>
</tr>
<tr>
<td>100</td>
<td>8</td>
<td>12.08%</td>
</tr>
<tr>
<td>150</td>
<td>4</td>
<td>9.3%</td>
</tr>
<tr>
<td>150</td>
<td>8</td>
<td>7.8%</td>
</tr>
</tbody>
</table>

Figure 4.19: Multimedia coverage ratios.
though sensors had the capability to exchange information regarding their neighbors and obstacles, due to the lack of proper coordination, several sensors went overlapping. Mostly occluded FoVs are serious waste of resources. However, in Figure 4.18 (b), sensors were programmed to determine their FoV disk, scan their coverage neighbors, obstacles and communicate with their neighbors to decide on the optimal pose. We observed that by using our approach in a 50 node network, a coverage ratio of 29.88% could be achieved, which is very close to the maximum possible coverage with 50 sensors of 30m range on this field. A set of resultant coverage gain (%) of self-orienting algorithms are also given in Figure 4.19 for different scenarios. Here, coverage gain is defined as the increase (in %) when self-orientation algorithm is used compared to random orientation in the same deployment. The results are the average of five iterations of each test.

**The effect of resolution vs. node density:** In Figure 4.20, a sensing field with several obstacles (represented by black rectangular areas) and 50 multimedia sensors is shown. Each multimedia sensor is illustrated with a "small diamond" and its vFoV is shown with a dark shaded area. We observe that in highly occluded environments, a small number of
high resolution camera sensors\textsuperscript{1} perform much worse than a large number of low-resolution camera sensors. In Figure 4.20 (a), a sensing field with randomly placed 8 obstacles of different sizes is given. This field has 50 low-resolution camera nodes deployed with 30\textit{m} range. On the other hand, in Figure 4.20 (b), the same sensing field is installed with 10 high-resolution camera nodes of 100\textit{m} range. Triple-ranged camera sensors in Figure 4.20 result in about 10\% degraded total coverage compared to the low-res sensors. Note that the FoVs for the network in Figure 4.20 are set using the self-orienting algorithm explained earlier.

\textbf{The effect of self-orientation on overlapping area:} Self-orienting algorithm not only determines occlusion-free viewpoints for sensors but also avoids overlapping FoVs using neighbor-distance test, as explained in Section 4.3.2. For example, in Figure 4.18, coverage ratio gains up to 41\% were obtained by using self-orientation. Preventing overlapping FoVs contributed 12\% of the the total increase in coverage. In Figure 4.21, we show the ratio of overlapping FoV when self-orienting algorithm is used. We observe that increase in the

\textsuperscript{1}Note that in this context, a high-resolution camera refers to the one that can capture information from a larger sensing area.
number of nodes causes dramatic increase in the total overlapping area. Self-orientation results in at most 9% overlapping area, whereas random orientation results in overlapping areas up to 29%.

**The overhead of self-orientation algorithm:** For the first test we present, multimedia sensors with a 30m range on a field of 250x250m are used. In Figure 4.22, we show the ratio of total number of messages used by the self-orienting algorithm to the total number of control messages, including routing. As we explained in Section 4.3.2, our algorithm uses $O(n)$ messages which is 6% of all control messages on average when $N = 50$. The ratio increases only up to 35% of total control traffic when $N = 200$ and $R_s = 60m$, indicating a very dense network with high degree of connectivity.

From the presented experiments, our observations on multimedia coverage and self-orientation can be summarized as follows:

- Increasing the node density does not increase the coverage ratio proportionally, on the contrary, it results in large overlapping areas.

- In highly occluded fields, many low-resolution cameras constitute a much better al-
ternative to few high-resolution camera nodes

- Self-orientation is a very effective way to increase coverage ratio while avoiding occlusions and overlapping FoVs.

4.4 Summary

As a summary, we proposed a self-orienting algorithm for multimedia wireless sensor networks in order to attain occlusion-free coverage. We find that (i) the proposed algorithm uses local information; that is, communication overhead is incurred only between neighboring nodes with a complexity of $O(N)$, (ii) the proposed algorithm is fully distributed, which can operate after initial deployment and update the orientation of multimedia sensors on the fly, (iii) the proposed algorithm can support prioritized or accurate observation that require more than multiple inputs from more than one sensor node, and (iv) coverage can be increased even for sparse networks by using self-orientation instead of random orientations, for arbitrary obstacles in the sensor field.

Next, a case study of questioning and improving the reliability of home WSNs is presented and performance of ART in home wireless sensor networks are investigated.
Chapter 5

Experimental Study on Critical Factors Limiting Reliability in Home Wireless Sensor Networks

In this chapter, an experimental study investigating and improving reliability of home wireless sensor networks (WSNs) is presented. An extensive set of experiments is performed in order to quantify the factors having impact on the reliability of home WSNs. Existing works do not consider effects of real physical limitations and factors on reliable packet delivery. In addition, our experimental study provides both packet reliability and event reliability measurements, where event reliability shows the real implications of data loss with respect to accuracy of the data collected. Our measurements, conducted with Tmote Sky, confirm that guaranteeing end-to-end reliability in a home environment is challenging due to highly asymmetric links, home-specific interference and dynamic structure of home environments.

In Section 5.1, we summarize the home sensor network applications. In the next section, we discuss the experimental methodology for our experiments, and then describe
hardware and software instruments and metrics. Critical factors and their effects on reliability of home sensor networks are summarized in Section 5.4. In Section 5.5, we discuss our experimental results regarding observed packet drop rate (PDR). Finally, we present the experimental results and reliability improvements when ART protocol (given in Chapter 2) is used in a sensor networks deployed in home environment in Section 5.6.

5.1 Indoor Wireless Sensor Network Applications

Wireless sensor networks (WSNs) are creating a new class of indoor applications which connect users with the real world to help conduct scientific field studies, raise business bottom lines, and improve everyday life. An interesting indoor application of such wireless sensor networks is visually (or virtually) tracking the person’s daily interaction with his/her habitat and monitoring the indoor conditions by the help of the sensors embedded throughout the home, building, etc. An example of such applications is on Aging Services Technologies with a specific focus on In-Home Health Care Solutions for people of ages 65 and older. For these applications, deployed sensor nodes often need to detect a wide variety of activities (people may routinely perform dozens to hundreds of relevant activities a day, for instance) performed in many different manners, under many different environmental conditions, and across many different individuals. The particular aspects of the activity that are of interest also vary widely across applications (e.g., user motion, whom the user interacts with, task progress, object usage or space usage). Hence, reliable data delivery of a sensor node across a variety of activities and individuals and their variations has proved to be difficult to engineer. The current methods available for tracking activities are time and resource consuming manual tasks, relying on either paid trained observers (i.e., a job coach who periodically monitors an individual performing their job or a nurse monitoring an elderly patient) or on self-reporting, namely, having people complete an activity report at the end of the day. However, these methods have significant deficiencies in cost, accuracy, scope, coverage, and obtrusiveness. Paid observers such as job coaches and nurses must typically split their time among several clients at different locations; in addition the constant involvement of humans makes the process very expensive. Self-reporting is often inaccurate and of limited usefulness due to patient forgetfulness and both unintentional
and intentional misreporting, such as a patient reporting more fitness activities than they actually completed.

A home sensor network would help not only to reduce the errors that arise from self-reporting and sparse observational sampling, but also to improve the quality of service that coaches and caregivers can provide, as they would spend less of their time performing bookkeeping duties. In addition, unobtrusive monitoring enables people to go about their daily lives in an unimpeded manner, while providing their caregivers with a more accurate assessment of their real life activities, rather than of a small sample. Such a home WSN does have another clear benefit over existing methods such as surveys, in that it provides a continuous activity log along with times and durations for a wide range of activities. This applications for aging-in-place naturally brings in the need for deployment of an “in-home” wireless sensor network. However, indoor environment is not a benign networking environment where several obstacles may render wireless communication impossible between node pairs. In addition, due to limited and irregular sensing ranges, placement of sensors becomes an important and challenging problem which may impact the accuracy of the collected data.

Another indoor application of WSNs is in-control building application where sensors deployed throughout a building that monitor conference room occupancy and environmental statistics and provide access to room reservation status. Such an application solves potential problems in a work environment that monitor occupancy of conference rooms and environmental parameters throughout our building. These are illustrative examples from the class of in-building sensing applications for which one of the biggest hurdles towards deployment is energy provisioning. Even in buildings, where power outlets are relatively abundant, it is not always feasible to locate sensors near these outlets. While a few nodes may be wall powered, many require battery power since running new wires to sensors is expensive and time consuming. This class of applications requires self-configuring energy-efficient protocols that allow the network to survive many months, or even years, when a large number of nodes operate on constrained battery power. Nodes should be able to spend significant portions of their time sleeping to save energy, yet still maintain communication.

In our experimental study, our major target is indoor home environments since there are significant number of sensor network applications for houses. Homes are poten-
tial environments to deploy sensor networks not only for health care applications but also intelligent/smart home applications that provides remote control of houses using sensors. In our experiments, sensors are deployed in typical home layouts and experiments are performed real-time in fully furnished, human interactive environments. Our experimental study in home networks can provide a basis for future investigations of other indoor (office) experiments by showing the limitations of indoors for sensor communications.

5.2 Motivation and Related Work

Wireless sensor networks is widely deployed in home environments in a non-obtrusive fashion and provide remote and continuous monitoring of the environment for potential target events. Many future medical systems now benefit the most from wireless sensor networks in the applications areas of in-home assistance, smart nursing homes, and clinical trial and research augmentation [66]. In such health-care sensor networking applications, an emergency event is detected by a set of sensor nodes, and then relayed to a remote nursing station through a special sensor node (i.e., gateway) over the Internet. The information relayed to the gateway node might be a critical information (such as motion pattern as falling, walking, sleeping), thus requiring high end-to-end reliability. In the near future, many homes will be equipped with wireless sensor networks that can send collected data to the outside network instantaneously which will work under high reliability requirements.

However, homes are disadvantageous networking environments where several obstacles may render wireless communication impossible between node pairs [51]. Additionally, successful home sensor networks deployments are hindered by the resource constraints of the underlying sensor nodes including power, computation, and communication quality [31]. These limitations render the sensor nodes highly unreliable and susceptible to frequent failures [6]. In addition, due to limited and irregular sensing ranges, placement of sensors becomes an important and challenging problem which may impact the accuracy of the collected data. Motivated by these facts, sensors must operate with high end-to-end reliability to yield high-confidence data suitable for such mission-critical health care applications. In this context, end-to-end reliability is achieved with guaranteed data delivery of every critical event report message to the gateway (sink) node. In our experimental study, we use two
metrics to measure end-to-end reliability: (i) packet drop ratio (PDR), which is the ratio of the number of packets lost in gateway node to the number of packets generated in the sensor nodes; and (ii) event drop ratio (EDR), which is the ratio of the number of events lost in gateway node to the number of events detected in the sensor nodes. To the best of our knowledge, there are research efforts that investigate PDR and link quality for controlled indoor environments, where sensors deployed closely to eliminate external interferers and physical effects. However, none of these works consider the effects of real physical limitations and factors on reliable packet delivery. In addition, our experimental study provides both PDR and EDR measurements, where event reliability shows the real implications of data loss with respect to accuracy of the data collected.

In [23, 38], empirical studies have provided us an understanding of the complex non-ideal behavior of low-power wireless links. The bulk of these studies focuses on wireless link quality in outdoor and office environments which do not reflect the fundamental problems of real home environments. In [23], packet loss is studied on a large-scale testbed grid on an unobstructed parking lot. This research also focuses on the loss and asymmetry of packet delivery at both the link layer and the MAC layer. Measurements of infrastructure-based wireless networks have been studied in [40, 36, 50]. However, [36] focus more on the patterns of user mobility and their impact on traffic. On the other hand, [50] investigates interference among links in a static, IEEE 802.11, multi-hop wireless network. More related to our work is [89], where packet loss is studied in indoor and habitat environments for wireless sensor networks. However, indoor experiments of this paper have limited investigation of the effect of physical diversity in home environments and interference. For example, an experimental characterization of home wireless networks has been studied in [51] deploying 802.11a and 802.11b technologies with different home environments. Our work complements their work by deploying a wireless home sensor network requiring adequate deployment to achieve sensing coverage throughout the home with low-rate Tmotes.

Firstly, we aim to understand the critical factors affecting limiting reliable packet delivery in home wireless sensor networks. Therefore, it helps us to quantify the detrimental effects of these factors. Secondly, we aim to suggest enhancements that may help boost the performance to acceptable levels using ART [72] protocol. We first postulate the potential reasons hampering packet delivery rates with current CSMA-based MAC layer used by the
Table 5.1: Summary of critical factors studied that limiting reliability.

<table>
<thead>
<tr>
<th>Factors studied</th>
<th>Description</th>
<th>Related work</th>
</tr>
</thead>
<tbody>
<tr>
<td>Physical diversity</td>
<td>living home behavior, e.g., placement of furniture, number of people in the house, time of the day, etc.</td>
<td>N/A</td>
</tr>
<tr>
<td>Node density</td>
<td>number of nodes deployed per sq ft.</td>
<td>[40, 51, 89]</td>
</tr>
<tr>
<td>Home layout</td>
<td>size of the house, number of rooms, layout of the rooms, kitchen and electrical devices.</td>
<td>[51] for 802.11</td>
</tr>
<tr>
<td>External interferer</td>
<td>electronic devices in the house, e.g., AP (802.11), washer, dryer, microwave, etc.</td>
<td>[50] for AP only</td>
</tr>
<tr>
<td>Transmit power</td>
<td>tx power level of sensor nodes.</td>
<td>[23, 31, 38, 51, 89]</td>
</tr>
<tr>
<td>Reporting frequency</td>
<td>frequency of sending data to gateway node.</td>
<td>[6, 31, 51, 89]</td>
</tr>
</tbody>
</table>

In particular, we present an experimental work to specifically questioning the end-to-end reliability of real home environments having a specific layout, network topology and traffic scenario. Our measurements, conducted with Tmote Sky, confirm that guaranteeing end-to-end reliability in a home environment is challenging due to highly asymmetric links, home-specific interference and dynamic structure of home environments. We measure packet drop rate in a real-time and event-based application scenario. We show that despite the small size of home sensor wireless networks, data transport between any two sensor nodes is not guaranteed or necessarily predictable, regardless of transmission power or rate. Rather than the physical distance, actual location of the sensor node (kitchen, living room, etc.) has severe impact on packet loss. In addition, we observe the home-specific interference (AP, microwave, dryer) can increase packet loss up to 25% of the near by Tmotes. We also observe asymmetry in the packet loss during the operational time of the day, depending upon the the number of people in the house, interference of household devices and physical changes.

In the next section, we discuss the experimental setup and methodology in detail.
5.3 Experimental Methodology

A number of questions arise when studying the deployment of home sensor networks specifically for high reliability-demanded applications. Home itself is like a living organism. Furniture might move, neighbor might start to emit noise at certain hours, heat can change etc. Further, there are several electronic devices that might cause external interference to the wireless sensor network. Not only this, different house may have different effect on reliability of wireless communication. Size of the house, number of the rooms and their layout might be other critical factors.

In this paper, our primary goal is to observe theses critical factors of such home environmental limiting the reliable communication. We also study the application specific properties on the design of home wireless sensor networks, e.g., short range of radio and the effect of transmission power and traffic rate in a home wireless sensor network. Table 5.1 is a summary of critical factors that are studied in the scope of this experimental work. Results ans impacts of each factor will be presented in the following sections.

For the rest of this section, we discuss the hardware and software used, specifications of home layouts and the metrics used in the experiments.
Table 5.2: List of sensor nodes.

<table>
<thead>
<tr>
<th>Sensor node</th>
<th>Microcontroller</th>
<th>Program and data memory</th>
<th>Support</th>
</tr>
</thead>
<tbody>
<tr>
<td>Eyes</td>
<td>MSP430F149</td>
<td>N/A</td>
<td>PeerOS</td>
</tr>
<tr>
<td>IMote</td>
<td>ARM core 12 MHz</td>
<td>64K SRAM</td>
<td>TinyOS</td>
</tr>
<tr>
<td>KMote</td>
<td>TI MSP430</td>
<td>10k RAM</td>
<td>TinyOS and SOS</td>
</tr>
<tr>
<td>Mica</td>
<td>Atmel ATMEGA103</td>
<td>128+4K RAM</td>
<td>TinyOS</td>
</tr>
<tr>
<td>Mica2</td>
<td>ATMEGA</td>
<td>4K RAM</td>
<td>TinyOS, SOS and MantisOS</td>
</tr>
<tr>
<td>MicaZ</td>
<td>ATMEGA 128</td>
<td>4K RAM</td>
<td>TinyOS, SOS, MantisOS and Nano-RK</td>
</tr>
<tr>
<td>Rene</td>
<td>ATMEL8535</td>
<td>512 bytes RAM</td>
<td>TinyOS</td>
</tr>
<tr>
<td>SunSPOT</td>
<td>ARM 920T</td>
<td>512K RAM</td>
<td>Java Squawk, J2ME Virtual Machine</td>
</tr>
<tr>
<td>Telos</td>
<td>Motorola HCS08</td>
<td>4K RAM</td>
<td>N/A</td>
</tr>
<tr>
<td>TelosB</td>
<td>MSP430</td>
<td>10k RAM</td>
<td>Contiki, TinyOS, SOS and Mantis</td>
</tr>
<tr>
<td>T-Mote Sky</td>
<td>MSP430</td>
<td>10k RAM</td>
<td>Contiki, TinyOS, SOS and Mantis</td>
</tr>
</tbody>
</table>

5.3.1 Hardware and Software

Before we discuss the experiments, we discuss our experimental platform and the experimental instrumentation. We use Tmote Sky [60] in this study as the experimental platform as shown in Figure 5.1 (a). It is widely available and has been used in wireless sensor network research. List of a comparison of available sensors nodes are given in Table 5.2. As given in this table, Tmote Sky is the latest product of the Telos family which has also USB connector thus easily reprogrammable and support of TinyOS.

Each Telos mote has a MSP430 F1611 microcontroller featuring 10KB of RAM, 48KB of flash, and 128B of information storage. In our experiments, the radio has a typical bit rate of 250Kbps. The low-level radio interface also supports the measurement of received signal strength and link quality indicator. Finally, the Tmote Sky comes with an event-driven operating system called TinyOS 1.x [49]. TinyOS is an open-source operating system designed for wireless embedded sensor networks. It features a component-based architecture which enables rapid innovation and implementation while minimizing code size as required by the severe memory constraints inherent in sensor networks. TinyOS’s component library
includes network protocols, distributed services, sensor drivers, and data acquisition tools. TinyOS has been ported to over a dozen platforms and numerous sensor boards. A wide community uses it in simulation to develop and test various algorithms and protocols. The TinyOS system, libraries and applications are written in nesC, which is an extension to the C programming language designed to embody the structuring concepts and execution model of TinyOS which have very limited resources.

TinyOS’s networking stack includes a default physical layer that supports single-error correction and double bit error detection (SECDED) capabilities. On top of this, its default MAC layer implements a simple unslotted CSMA/CA mechanism in nonbeacon-enable network. The results presented are the packet reception rate for a series of packets sent from sensor nodes to the sink node. The radios were tuned to 802.15.4 channel number 11. Packets were generated at the rate of a packet per second for the tests consisting of 10 consecutive sensor readings.

To generate an event-based traffic, we used analog peroelectric infra-red (PIR) sensors [59] connected on Telos motes. In-home health care applications, wireless sensor networks are mostly use for visually (or virtually) tracking the person’s daily interaction with his/her habitat and monitoring the indoor conditions. While tracking the elder in home, a PIR sensor detects the movement and report to the gateway or a body sensor carried by elder may send beacons the existence of the elder. The motion sensors on sensor boards are PIR sensors. They sense changes in the thermal field over the region. During the time when an object is moving through, the variations of the thermal field result in unbalanced infra-red signals detected by the lens pairs in the PIR sensor, leading to positive detections. The PIR analog signal was monitored through Tmote’s ADC7 port by selecting ADC7 through the ADG715 switch as shown in Figure 5.1 (b). Tmote Sky has two expansion connectors and a pair of onboard jumpers that may configured so that additional devices (analog sensors, LCD displays, and digital peripherals). After we connected the PIR sensor to the digital I/O pin 1, we use MSP430GeneralIO interface to get the output from sensor. An important detail is that GIO1 is designed to have interrupt capability. Thus, we catch up the motion by the voltage change in the output of PIR sensor triggers an interrupt.

Tmotes were programmed to send the PIR reading to the sink in one-hop while marking each packet when PIR reading has exceeded the threshold. We have used a simple
star topology in this work leaving the effect of topology for our future work.

5.3.2 Metrics

We use the following metrics to characterize the reliability performance of home sensor networks:

- **Packet drop ratio (PDR):** It is the ratio of the number of packets lost to the number of packets generated. There are many, many factors that govern PDR in a wireless communication system: the environment, the network topology, the traffic patterns and, by extension, the actual physical phenomena that trigger node communication activity. In this work, we evaluate the critical factors limiting PDR, which is a first-degree indicator of reliability in a WSN.

- **Event drop ratio (EDR):** It is the ratio of the number of events lost to the number of events occurred. From the perspective of event reliability, PDR is not sufficient to indicate event reliability. Thus, EDR is used to evaluate event reliability performance of a WSN.
Figure 5.3: Second home layout (H2), one bedroom apartment.

- Received signal strength indication (RSSI) and Link quality indicator (LQI): They are used to estimate the link conditions where RSSI is the strength of a received RF signal and LQI is effectively a measure of chip error rate.

5.3.3 Home Layout

In this work, two different houses are used to perform experiments. First house, denoted by H1 in Figure 5.2, is a typical one-floor apartment with three bedrooms in Raleigh, North Carolina. We show H1 home layout with a sensor placement of 7 and 13 nodes in Figure 5.2 (a) and (b), respectively. The house is fully furnished and used by three people during the data collection process. As shown in Figure 5.2, H1 has a living room and three bedrooms with similar sizes. Dining room and kitchen is smaller in size and there is an 802.11 network in the house where the access point is located in the leftmost bedroom nearby sensor node 4. Additionally, a microwave and a dishwasher was located in the kitchen and a washer and dryer in the small laundry pantry near the kitchen. Each room is used by one person the use of household devices are not restricted during the experiments. We have deploy 7 to 13 sensors which are equipped with PIR sensors in the labeled location
Table 5.3: Summary of home layouts used in our experiments.

<table>
<thead>
<tr>
<th>House</th>
<th>Size</th>
<th>Rooms/Bath</th>
<th>Node density</th>
<th>AP</th>
<th>Washer/dryer</th>
</tr>
</thead>
<tbody>
<tr>
<td>H1</td>
<td>1100 sq ft</td>
<td>3/2</td>
<td>84-157 sq ft/sensor</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>H2</td>
<td>777 sq ft</td>
<td>1/1</td>
<td>59 sq ft/sensor</td>
<td>Yes</td>
<td>No</td>
</tr>
</tbody>
</table>

in the house. We have located three sensors in the living room, one in the dining room and one for each bedroom in the basic setup. Wireless nodes are located in an average height of 30” from the floor in the living room and 95” in the bedrooms.

In addition, we repeated some of our tests in a smaller house in Portland, Oregon, denoted by H2, having one bedroom and a living room as shown in Figure 5.3. Similarly we deployed 13 sensors to the positions with a star topology as illustrated in Figure 5.3 (a). Second house is also fully furnished where one person accommodates. Our major goal to use two different houses is to determine effects of house layout, placements of sensors and furniture and size of the houses. Experimental results for both houses will be discussed in the following sections.

Next, critical factors limiting reliability are discussed using extensive experiments.

5.4 Factors and Effects

In this section, we describe our experiments to understand the reliability characteristics of home wireless sensor networks. Our goal is to exploit a realistic home environment to catch real problems that can be raised in a typical home wireless sensor network using an experimental approach. We have questioned the reliability of the home sensor network using the packet dropped ratio (PDR) in various conditions. The link quality and packet delivery ratio of sensor networks have been already investigated for well-known distance and locations with controlled interference [38, 89]. However, home environment has many uncontrolled interference that will effect the link quality, thus reliable communication of sensor nodes. Many home WSN application do not tolerate high PDR due to sensitivity of the collected data, e.g., health care applications [66]. Therefore, in this section, we investigate the critical factors limiting the reliability of the network such as of (i) physical
5.4.1 Physical Diversity

The major goal of this experiment is to observe overall effect of physical diversity on PDR of home WSNs. In this context, physical diversity is the effect due to mobile people in the house, (hollow wooden-type) doors, and furniture. As we stated, homes look like living organisms, thus there are home-specific factors that might effect wireless communications among sensor nodes. Even though there have been research effort on radio coexistence and interference [50], to the best of our knowledge none of these studies have investigated physical diversity factors of home environments from reliability perspective.

We measure packet drop rate (PDR) performance of a real (living) home environment compared to the same home where there is no people, no electronic devices on and all the doors (hollow wooden-type) are left open. Home sensor network setup consists of seven nodes as shown in Figure 5.2 (a). Sensors send periodic messages per second to the sink node labeled in Figure 5.2 (a). As observed in Figure 5.4, PDR is highly influenced by the
physical diversity of home environments and many links are highly asymmetric. We observe an average PDR of around 5% in a real home environment which drops to 2.5% when the effect of physical diversity is minimized. This shows that, previous experimental studies performed in fully-controlled indoor environments (empty rooms with no people) may not reflect real problems that cause higher PDR in the sink node. Next, we investigate each factor with extensive experiments to understand the limitations of reliable data transport.

We then repeat our experiments during the different time intervals of the day to observe the physical diversity in the day as shown in Figure 5.5. Figure 5.5 reveals the dependence of PDR to the time of the day, due to varying interference throughout the day. In Figure 5.5 (a), we observe slight differences in PDR for each node except node 7 which has a PDR of 15% during the daytime in house 1. Unexpected high PDR in node 7 occurred in due to the high mobility in the room where sensor node was located on experiment time. Similarly, we illustrate the time intervals for selected nodes in house 2 in matching locations. Figure 5.5 (b) confirms that PDR of each node varies during the day with the effect of physical diversity factors in the houses. Position of furniture, doors and the number of people in the house are dynamically changing during the day in a house which may effect PDR as shown in Figure 5.5.

5.4.2 Node Density

Node density is an important factor on reliable data transport in home sensor networks. Less number of nodes may decrease the probability of concurrent transmission, thus collisions in MAC layer. On the other hand, there should be enough sensors of coverage in the house to capture all desired events. Even though high coverage can be achieved with smaller number of sensors, increasing node density has bigger impact in indoor environments compared to outdoor environments [89]. Experiments were performed in the house in Raleigh (H1), with increasing number of nodes balanced into the rooms proportional to their size.

We evaluate the effect of node density, number of nodes per square feet, with the experiment results shown in Figure 5.6. As shown in Figure 5.6 doubling the number of nodes induces an disproportional increase in average PDR. Increasing the number of nodes
Figure 5.5: Effect of time of the day on individual link performance.
by 100% results in only a 0.5% increase in PDR. However, when we increase the number of nodes to 9 in the room result in 2.35% increase in PDR which is much higher compared to 0.5%. These experiments suggest that node density would increase the deployment efficiency of the network vastly. Furthermore, sensor nodes has a threshold indicating the number of nodes.

5.4.3 Home Layout

Using small networks of sensors deployed in two homes, one in Raleigh (H1) and one in Portland (H2), we study the performance of data transport in home environments. Home layout factors are related to the house, such as number of rooms, size of the house, location of each room, closets and kitchen, etc. Effect of home layout was only investigated in [51] which is an experimental study on characterizing wireless home networks using APs. Even though [51] provides comparison using three different home layouts for their experiments, performance results indicates the link performance between a mobile node and AP, where the air link interface is 802.11. However, in WSNs, sensor nodes has smaller transmission range and the air interface of 802.16.4 have different than 802.11, which has
different requirements.

Across homes, results differ substantially. Figure 5.7 presents average packet drop rates across two homes. The larger home, H1, has worse performance than the smaller home, H2, particularly at less number of nodes. H1 and H2 differ in that H1 is a three-bedroom apartment condo, while H2 has one bedroom as shown in Figures 5.2 and 5.3. The major reason that we observe a higher average PDR in the larger house is that physical diversity factors has more effect on more crowded house 1 in Raleigh, and also house 2 has simpler layout compared to house 1. While some of the observations above could suggest that size play a significant role in performance, PDR cannot be predicted based on such features alone. The key parameter is precise location of the sensor, rather than home size or distance between nodes. We will investigate the PDR of each individual sensor in the following sections.
Figure 5.8: Effect of external interferes (AP, electrical devices, etc.).

Figure 5.9: Effect of interferes on individual link performance (H1).
5.4.4 External Interferes

In this set of experiments, we design to study the effect of external interference factors of home environments. Deploying a wireless sensor network in a house is required to operate our network with several electronic home devices. Typical home devices are AC, microwave, washer and dryer, TV, other electronic devices such as laptop and 802.11 network, which are called external interferer.

We first show the effect of 802.11 network, and other home appliances on the average PDR. When all electronic devices, home appliance and access point for 802.11 are off, average PDR is observed around 2.8%. We then turn on the access point and observe an average 2.4% increase in PDR due to coexistence of 802.11 network. In particular, 802.11 Wireless LAN and 802.15.4 sensor networks in the 2.4GHz ISM band have very different transmission characteristics that result in asymmetric interference patterns. The output power of 802.15.4 devices is typically as low as 0 dBm, whereas the output power of 802.11g devices is 15 dBm or above. Moreover, external interference in home environments can be even increased by use of home appliances. When all electronic devices are on, we observe up to 7.7% PDR on average.

In Figure 5.9, we investigate the packet drop ratio of individual sensor nodes in similar three scenarios: (i) all electronic devices in the house are off (labeled as 'None'); (ii) only the access point (AP), 802.11, is on (labeled as 'AP-up'); and (iii) all devices including microwave, washer, dryer, TV, AP, dishwasher, AC are on (labeled as 'all-up'). The experiment results in Figure 5.8 is the average PDR taken within two-hour slots taken at 5 different time of the day in house 1 (Figure 5.2 (b)). In this experiment, we observe that individual PDR of a sensor node can be increased up to up to 15% by the effect of home appliances. Sensor 6 and 11 are the nodes (nearby the kitchen) with highest PDR when all devices on. This shows the devices such as microwave and dryer can have more interference and may lead high packet loss for the nodes in the kitchen. One of our observation is that nodes are highly sensitive to its location which may lead to sub-optimal performance in terms of reliability.
In this set of experiments, we observe the effect of transmit power of sensor nodes on PDR in a home sensor network. Results showing in Figure 5.10 are collected using the deployment layout depicted in Figure 5.2 (b). Sensor nodes communicate to the sink node by sending continuous traffic for their data read from PIR. In Figure 5.10, we show the average PDR for transmit power of 0 dBm and -20 dBm.

In Tmote Sky, we can change the transmit power while compiling and installing the code to the mote. To do this, we predefine a preprocessor directive called CC2420_DEF_RFPOWER and define compile flags (CFLAGS) before compiling our application. We can specify a power index from 1 to 31. The valid values are 1 through 31 with power of 1 equal to -25 dBm and 31 equal to max power (0dBm). Therefore, we conducted experiments by setting the transmit power level 11 and 31 corresponds to -20 dBm and max power 0 dBm.

Experiments in Figures 5.10 and 5.11 are performed for layout 2 (H2), using 13 nodes deployed as in Figure 5.3. We observe that on average setting the transmit power to max value increases the average PDR to 4.8% in Figure 5.10. One reason that home is small enough to have transmission coverage even with the default transmit power. Thus, setting up the transmit power to the maximum value, not increases the performance, but...
decreases the PDR due to increasing interference.

Next, we show the individual link performance of the nodes in H1 and H2, when transmit power is changed. As shown in Figure 5.11, PDR is individually increased in all nodes by putting more transmit power on each sensor node. However, we see that some nodes have more significant increase in PDR. For example, node 7 in house 1 and nodes 1, 2 and 3 in house 2 affected more than the others due to their location in the house. As we have discussed in the previous sections, how much sensor is individually limited by the transmit power factor is highly depended to precise location of the sensor.

5.4.6 Reporting Frequency

Lastly, we evaluate the effect of reporting frequency on PDR in house 2 with 13 sensors (Figure 5.3). Compared to other factors, reporting frequency is the most effective factor that increases the PDR proportional to an increase in reporting frequency. In particular, reporting frequency shows how often a sensor collects measurement from the environment. We have used two sampling frequencies: (i) in every 10ms and (ii) in every
100 ms. Therefore, each sensor continuously collects data with this rate and sends to the sink node a message containing 10 measurements at one time. In terms of data traffic, sensors send 1 message/sec when reporting frequency is 100 and 10 messages/sec when the reporting frequency is increased to 10ms.

In Figure 5.12, average PDR is increased 100% when reporting frequency is increased to 10 message/sec. We observe similar amounts of increase in PDR in all nodes. We also try to increase the reporting frequency such that each node is set to send 100 messages/sec, however due to memory limitations of sensor nodes, this does not work even with 13 nodes in the house. We observe that all factors investigated in this section have a severe effect on average PDR and may have varying effects on the individual link performance based on the precise locations of the sensor nodes. We argue that many event-critical applications used in home sensor networks cannot tolerate PDR higher than 1.5-2%, since it may cause severe event loss and degrade the reliability of sensor network.
5.5 Dissecting PDR

In the previous section, we investigate the critical factors effecting the PDR of each individual node. Due to one of these factors, PDR can be increased, resulting a significant degrade in the reliability of data transport. In this section, we want to dissect PDR in detail by questioning: "why and in which layer is the packets dropped?"

5.5.1 Time Characteristics of PDR

First, we observe how PDR is changed in time for specific nodes in the homes. In Figure 5.13, we show the individual number of dropped packets for nodes 2, 4, 6 and 7 during a three-hour period in house 1; similarly, nodes 1, 3, 7, and 13 from house 2. Selected nodes are located as in Figure 5.2 (b) and 5.3 (a). We choose the nodes in critical location, e.g., different rooms, near by the home appliances, etc. to observe the characteristics of PDR in time. In this experiment, total number of dropped is shown for each house where
sensors have continuous 1 message/sec traffic scenario.

As shown in Figure 5.13, number of packets dropped of each node is not consistent. Node 2 has at most 4 packets dropped in 15 min. while node 6 has dropped more than 30 packets in Figure 5.13 (a). Similarly, node 7 has the largest number of packets dropped in house 2. When see that in both houses, nodes located in the kitchen, node 6 in house 1 and node 7 in house 2, might have higher packet drop rate. On the other hand, nodes located in the bedrooms, i.e., node 7 in house 1 and node 3 in house 2, have smaller packet drops during our experiments. This shows that again nodes with specific locations might differ in PDR and the number of dropped packets may change dramatically which also results in missing significant amount of event information.

5.5.2 Contribution of Collision and BER to PDR

After, investigating time characteristics of dropped packets of individual nodes, we study the PDR at the two layers of the communication stack. At the physical layer and in the absence of interfering transmissions, PDR is largely a function of the environment, the particular physical layer coding scheme, and perhaps individual receiver characteristics. At the medium access layer, interfering transmissions contribute to high packet drop.

In this experiment, we conduct an experiment showing contributions of physical
layer BER and MAC layer collision to the PDR. To do this, we have selected 4 nodes in the house 2 and run experiments to capture PDR of these nodes in two scenarios: (i) only the selected node is actively transmitting data; and (ii) all nodes are actively transmitting data. The reason to isolate the nodes is to understand the effect of MAC layer collision. In isolated scenario, MAC layer has no function, thus PDR observed in the nodes are contributions of physical layer.

5.5.3 RSSI and LQI

In this section, we focused on the relation between PDR, RSSI and LQI in home sensor networks. We have conducted experiments using two useful radio hardware link quality metrics: (i) received signal strength indicator (RSSI) and link quality indicator (LQI). Specifically, RSSI is the estimate of the signal power, while LQI can be viewed as chip error rate.

It is well-known that when an electromagnetic signal propagates, it may be diffracted, reflected and scattered. Reflection occurs when an electromagnetic signal encounters an object, such as a building, that is larger than the signal’s wavelength. Diffraction occurs when the signal encounters an irregular surface, such as a stone with sharp edges. Scattering occurs when the medium through which the electromagnetic wave propagates contains a large number of objects smaller than the signal wavelength. These effects have two important consequences on the signal strength. First, the signal strength decays exponentially with respect to distance. Second, for a given distance, the signal strength is random and log-normally distributed about the mean distance dependent value, thus causing variance in RSSI and LQI. We will then investigate the relation between these radio hardware link quality metrics and PDR to understand the effect of physical layer.

To observe the behavior of RSSI in a home sensor network, we use a TinyOS application that samples RF energy by reading the RSSI and LQI register of the CC2420 radio. For individual link performances, RSSI as a promising indicator when its value is above the sensitivity threshold of CC2420 (-87 dBm). At the edge of this threshold, however, it does not have a good correlation with PDR. This might be due to local noise variations at different nodes. LQI when averaged over many packets has better correlation with PDR.
In our experiment, we show the RSSI, LQI and PDR results collected from nodes 1 and 7 in house 2 in Figure 5.15. In Figure 5.15 (a) we show the PDR of two nodes for 15 min. time intervals. Simultaneously, we record the RSSI and LQI values during the experiments and illustrated them in 5.15 (b) and (c). When we investigate the total dropped packets of node 7, we see that largest packet drop occurred in t=75 min. At t=75 min., there is no sharp decrease in the RSSI value in node 7, however its LQI was significantly dropped to 106.4. This shows that in this experiment, LQI has better correlation with PDR. Similarly, for node 1, increasing LQI value results in decreasing in number of dropped packets, even though the RSSI value remains same.

5.6 Improving Event Reliability in Home Wireless Sensor Networks

The reliability of data transport is a key requirement for a home sensor network to function properly. In case of a critical event detection, if there is high packet loss, the collected data may become erroneous, and critical events may be lost. To avoid such problems, reliable data transport becomes important. Our experimental study given in Section 5.4 shows that wireless channels are often lossy and high PDR occurs due to given factors. In presence of such channel loss and collisions, we showed that achieving high reliability becomes more difficult in home environments.

In this section, we will demonstrate how ART protocol (given in Section 2.4.2) improve reliability of home sensor networks. As we described in Section 2.4.2, we focus on the following question while designing ART protocol: “What is the information to be delivered reliably on WSN?” In conventional reliability context, transport service has no additional knowledge on the semantics of the information, thus reliability solutions are per transport message segment based (shortly, message-level). In message-level reliability, many redundant event reports have to be retransmitted which can make the network more unstable, energy wasting, and potentially non-operational. In contrast, ART provides reliability by operating with the least possible number of transport segment messages in a WSN consid-
Figure 5.15: Relation between PDR, RSSI and LQI.
erring event reliability rather than message-level reliability. Event reliability is defined to be achieved when every critical event report message is received by the sink node.

In this context, we first give event definition in our experiments. An event is defined as the occurrence of any motion captured by PIR sensor connected to the sensor node. Motion is detected when a high data value (i.e., exceeds threshold) read in ADC port where PIR connected. We determine threshold by calibrating the PIR sensors. Figure 5.16 shows an example PIR reading of a sensor node in time. We use oscilloscope [8] application to display the PIR readings. It consists of a single module that reads data from the PIR sensor. For each 10 sensor readings (each measured in every 100 ms), the module sends a packet to the serial port containing those readings. The mote only sends the packets over the serial port. Application GUI parses the sensor readings from each packet, and draws it on the graph as shown in Figure 5.16. PIR measures values between $0x0000$ and $0x100$ when there is no motion, whereas values between $0xF20F$ and $0xF30F$ indicate motion, by all means event.

Our major goal is to improve reliability of home sensor networks by targeting event reliability. Event reliability is assured when each and every message containing event data is successfully received by the sink. Any missing packet that contains event information is referred as event drop, and measured by the metric called event drop rate (EDR).

In particular, we have investigated PDR in previous sections rather than EDR.
The reasons behind are two folds: (i) EDR and PDR have closely associated with each other, and one can be calculated when given other if moving pattern scenario is concrete; (ii) however in reality, concrete moving pattern can be produced only in automated testing environments, not possible in our testbed. Thus, PDR is one of the best indicator showing the reliability of home sensor networks. For example, when there is a continuous-moving object, each and every message contains event data, thus PDR is equal to EDR in such scenarios.

To evaluate the feasibility of ART and to make our design of ART concrete, we implemented our ART abstraction of event reliability in TinyOS. The main structure for transmitting messages is shown in Figure 5.17. The message includes control information as members of the structure: destination, sequence number, data contains 10 consecutive PIR readings, and event counter. Each sensor has its own event counter, which is incremented when any PIR readings exceeds threshold. We set the threshold to 0x0F00 as of preventing false alarms. Since PIR sensor has discrete readings in this application, event notification (EN) bit is not required. Sink node is able to track the number of event readings that sent within the message and compare the event counter to detect event loss.

ART is implemented for sending acknowledgment for any message containing event reading by the sink. Acknowledgement includes packet information except payload. Sensor nodes has designed to have a limited buffer for retransmission which was set to 3 in our experiments. For retransmission timer expiration, an average RTT was observed as 100ms. Thus in our basic set of experiments, timer is set to 100ms.

We evaluate the performance of ART with the following experiments: (i) PDR and EDR comparison for a random moving pattern is given in Figure 5.18; (ii) event reliability performance gain is shown in Figure 5.19; and (iii) effect of retry value is investigated in
In Figure 5.18, example PDR and EDR values are given for three random, non-repeatable moving patterns: (i) one person, low mobility; (ii) one person, high mobility; and (iii) two people, low mobility. First of all, PDR values shown in the figure are independent from the moving pattern. Factors having effect on PDR was already extensively investigated in the previous section. Thus, slight changes in PDR for different patterns can be explained as the behavior of physical diversity and interferes effects. On the other hand, EDR highly depends upon moving pattern of the people in the house. Higher mobility indicates more sensor readings carrying out event information. Since we count each reading as an event, packet loss of an event might even cause multiple event loss. As we increase the number of people and mobility in the house, EDR increases correlated with PDR, and even exceeds PDR in highly mobile scenarios as shown in Figure 5.18. This experiment shows there is a high correlation between PDR and EDR and EDR is effected by the application specific parameters, e.g., mobility pattern. However, these parameters are close enough that can be estimated in a basic moving pattern of a single person having low mobility.

Similar to our simulation work, we compare the performance of ART protocol and message level reliability (MLR) with respect to EDR and PDR. In MLR, all messages are acknowledged regardless of event information. From Figure 5.19, we find that PDR can be
reduced up to 50% in all ACK (MLR) approach and 40% when ART is used. The reason is ART does not force to retransmit all messages but the event messages. PDR calculation in this experiment is based on unique identifier (combination of sequence number and source address) of each packet. Any missing packet received by retransmission decreases the PDR. On the other hand, we observe a proportional decrease in EDR using reliability schemes. Compared to no-ACK approach, EDR significantly reduced by ART, which also performs up to 30% better than MLR.

In comparison to our simulation result given in Section 2 Figure 2.9 (a), we observe a higher packet loss rate but similar improvement when MLR and ART are used. Observing higher PDR value is obvious since several effects such as external interferer, home layout, etc. can not be considered in simulation work.

Finally, we investigate the effect of retry (time out) value on the performance of ART. In Figure 5.20, three different values of retry are shown on EDR. As we stated, an average RTT is observed around 100ms when there is no reliability scheme. We observed that retry value of 300 ms performs the best among 100ms and 1 sec.
Figure 5.20: Effect of retry (time out) period on EDR.

5.7 Key Findings

We summarize the key finding and observation of our experimental study as follows:

- Effects of people at home and external interferers (i.e. appliances) are non-negligible.

- Number of dropped packets doubled when all appliances were actively used.

- Home layout have strong influence on reliability.

- Transmit power affects reliability significantly, only 20dBm increase doubled number of dropped packets for some links.

- Increasing the number of nodes or sensor reporting frequency causes more collisions thus increase PDR, e.g., doubling the number of nodes from 3 to 6, increased average PDR 11 times.

- Majority of losses are due to collisions, only weakly-connected nodes have traffic-independent channel induced errors. On average, one in every 300 packet loss is due to bit errors in channel.

- LQI has better correlation with PDR, compared to RSSI.
• Using ART protocol in a typical home environment recovers event losses significantly, up to 80% increase in the number of reported events when ART is used over the baseline communication protocol.

5.8 Summary

In this work, we study an experimental setup of a wireless home sensor network in order to question the critical factors limiting the end-to-end reliability under different constraints. We have studied the effect of physical diversity, home layout, node density and transmission power, reporting frequency and the impacts of those factors on the end-to-end reliability.

In our testbed, we configure and use passive infrared sensors (PIR) sensors to generate an event traffic and implement ART protocol to improve the event reliability of the home sensor networks. As sensor detects an event, it uses the proposed reliability schemes to achieve event level reliability. This work is also used for assessment of the physical effects on scheduling and self-organization algorithms and give an in-depth view on the physical limitations of the proposed mechanisms.
Chapter 6

Conclusion

In this thesis, reliable and energy-efficient data transport in wireless sensor networks (WSNs) are investigated targeting wide range of WSN domains that matches the unique characteristics of sensor networks. Specifically, the following four areas are investigated under this research:

- Asymmetric and reliable transport in WSNs
- Two-tiered scheduling for energy efficient in WSNs
- Self-organization of WSNs
- Experimental study on critical factors limiting reliability in home WSNs

6.1 Research Contributions

Here we summarize our contributions and key findings in the course of this thesis and proposed solutions.

- Asymmetric and Reliable Transport Protocol in Wireless Sensor Networks:
  In this work, we introduced a new transport protocol addressing bidirectional end-
to-end reliability in wireless sensor networks. The reliable event and query transfer is accomplished between the sink and essential nodes, while incurring low overhead in terms of control messages and retransmissions. Second, for event transfer, a lightweight ACK mechanism is used while NACK solves the reliable query delivery. Third, we incorporated a distributed congestion control mechanism, in which congestion is relieved by regulating traffic from non-essential sensor nodes.

Simulation experiments have validated that, under the 100% reliable delivery between essential nodes and the sink, traffic load in the network is dramatically reduced by the integration of node classification and congestion control. The proposed protocol performs significantly better than message-level reliability scheme in terms of latency and packet loss.

- **Two-tiered Scheduling for Energy Efficient in Wireless Sensor Networks:**
  In this work, we present the design and results of our two-tiered node scheduling scheme (TTS) for effective energy conservation. In order to prolong network lifetime, we schedule sensors to be in power saving mode, while preserving coverage and connectivity. We decomposed the coverage and connectivity functionalities of a sensor network into two-tiers; thus, nodes having been used for connectivity or coverage have different sleeping behaviors. Preliminary results show that, higher ratio of nodes may put into sleep to have a significant energy savings.

  In ART and TTS, we described our classification algorithm with centralized control at the sink node in previous sections since it can provision for closer-to-optimal coverage set determination. Choosing the sink node as the target of data propagation is reasonable if we considers that the sink node has ample energy and computing power compared to individual sensor nodes.

- **Self-organization of Wireless Sensor Networks:** In addition, we propose a distributed coverage calculation model for self-organizing networks. The major challenges in distributed implementation are (i) we need additional messages so that sensor nodes can exchange their location information and find their neighbors; (ii) sensors should calculate their coverage area and should determine whether their sensing regions are overlapping with neighbors; (iii) algorithms should be well modified such that, by use
of local information, nodes can make decisions to be in coverage and connectivity sets. Therefore, *self-organizing* sensor network forms a topology with minimum energy cost of sensors which is sufficient to cover the entire sensible terrain.

Further, we proposed a self-orienting algorithm for multimedia wireless sensor networks in order to *maximum field occlusions* and to attain occlusion-free coverage. We find that (i) the proposed algorithm uses local information; that is, communication overhead is incurred only between neighboring nodes with a complexity of $O(N)$, (ii) the proposed algorithm is a fully distributed, which can operate after initial deployment and update the orientation of multimedia sensors on the fly, (iii) the proposed algorithm can support prioritized or accurate observation that require more than multiple inputs from more than one sensor node, and (iv) coverage can be increased by up to 30% for even sparse networks by using self-orientation instead of random orientations, for arbitrary obstacles in the sensor field.

- **Experimental Study on Critical Factors of Reliability in Home Wireless Sensor Networks:** Finally, a case study is designed to evaluate the performance of the proposed reliable transport mechanism in a real sensor testbed for a target application. Possible target applications where sensor networks are widely used can be in-home assistance, smart nursing homes, and clinical trial and research augmentation [66]. Sensors must operate with enough reliability to yield high-confidence data suitable for such mission-critical health care application. In addition, due to limited and irregular sensing ranges, placement of sensors becomes an important and challenging problem which may impact the accuracy of the collected data.

In this work, we first present an experimental work to examine the network reliability and reachability. A number of questions arise when studying the deployment of wireless sensor networks for health care applications. What is the optimal number and distribution of sensors to achieve reliability? What are the application specific limitations on the design of home wireless sensor networks, e.g., weight of the body sensor, short range of radio? After setting up our testbed, we investigate the critical factors on reliability of home sensor networks and implement our reliable and energy-efficient services to verify our simulation results. In our simulations, we use an event-based
scenario, which triggers to send a packet when an event is detected. Similarly, in our testbed and implementation work, we configure and use passive infrared sensors (PIR) sensors. PIR detects changes in infrared radiation which occur when there is movement by a person (or object) which is different in temperature from the surroundings. As sensor detects temperature differences, it is well suited to detecting the motion of people by their body temperature. After reading the PIR data, sensor nodes uses the proposed reliability schemes to achieve 100% event detection in home environment. This work is also used for assessment of the physical effects on scheduling and self-organization algorithms and give an in-depth view on the physical limitations of the proposed mechanisms.

6.2 Future Research Directions

- **Reliability Analysis of Body Area Sensor Networks:** Body area sensor network (BASN) is a base technology for permanent monitoring and logging of vital signs is a proven method of supervising the health status of patients suffering from chronic diseases, such as Diabetes and Asthma. Another prominent area of application for long-term logging of patient data is cardiology, where 24-hour-ECGs are required for therapy control and as early indicators for impending heart attacks. The basic concept of this network is the fusion of both ideas: a set of mobile, compact units which enable transfer of vital parameters between the patients location and the clinic or the doctor in charge. The vital signs data flow passes a chain of BAN modules from each sensor to a main body station, which consolidates the data streams of all sensor modules attached. It transmits the data to a home base station, from where they can be forwarded via telephone line or Internet.

Considerable attention is needed to spend on a high level of reliability for the new BASN transmission protocol. Finally, it must be guaranteed that patient data are derived from each patients dedicated BASN system and cannot be mixed up with data from other patients or BASN systems at the same location. BASN is not only appropriate for communication in hospital and at home but has further applications.
Potential areas of use are sleep laboratories, monitoring of new-borns or wireless hearing aids.

- **Analytical Modeling of Sensor Networks**: To meet the requirements and constraints of practically deployable WSN applications, an analytical sensor network modeling should be developed based on general features identified through a careful analysis of existing and envisioned WSN applications. This analytical model can facilitate the design of WSNs by characterizing them according to these general features and providing a set of performance objectives. The specification of each network’s performance requirements within this analytical model can also enable the design of efficient communication protocols.

- **Integration of WSNs with Next Generation Wireless Networks**: In WSNs, to achieve anywhere, anytime seamless service to the end users, it is required to integrate sensor nodes with the next generation wireless network architectures. However, the memory, power and processing constraints of WSNs, coupled with the limitations of wireless environments, call for unified and adaptive communication protocols. The impact of these protocols on the overall performance of the integrated architecture of WSNs and next generation wireless network should also be investigated through extensive field experiments.
Bibliography


[47] *The Network Simulator (ns-2).*


