ABSTRACT

HAZEL, ROBERT YOUNG An Inertial Sensor-Based Ergonomic Feedback System for a Human-Robot Collaboration Assembly Task: Prototype, Proof of Concept and User Study. (Under the direction of Dr. Xu Xu).

Collaborative robots (Cobots) have garnered significant interest in industry and research in recent years. Research suggests that there will be a significant contingent within industry that requires scenarios where humans and robots share the same workspace. Robotic systems in these scenarios must be able to interface effectively with humans and leverage the advantages that each actor provides. It is important, then, to consider the implications of robots working in close proximity with humans. This thesis focuses on the ergonomic and physical safety implications of human robot interactions in manufacturing assembly. A method is proposed for improving the ergonomics of human-robot interactions in a manufacturing assembly task by using inertial measurement units to monitor Rapid Entire Body Assessment (REBA) scores during a task and using those scores to plan robot motion.

Ten subjects participated in a user study that tested the effectiveness of working on an assembly task using the proposed human-robot collaboration system when compared to working on the task alone. A within-subject design was used so that each participant experienced each of the three treatment conditions: working alone, working with partial robot involvement, and working with full robot involvement. Average REBA score, task performance, perceived workload, and user preference were measured as dependent variables.

The results of this study show that the proposed method reduced average REBA score and perceived physical workload but increased perceived temporal workload. It also showed strong user preference for working with the robot over working alone. The task performance

results were not statistically significant. These findings support the effectiveness of cobot systems in manufacturing and assembly tasks.

An Inertial Sensor-Based Ergonomic Feedback System for a Human-Robot Collaboration Assembly Task: Prototype, Proof of Concept and User Study.

by
Robert Young Hazel

A thesis submitted to the Graduate Faculty of
North Carolina State University
in partial fulfillment of the
requirements for the degree of
Master of Science

Industrial Engineering

Raleigh, North Carolina
2020

APPROVED BY:

Dr. Xu Xu
Committee Chair

Dr. Karen Chen

Dr. Jing Feng

BIOGRAPHY

Robert Hazel's interest in the field of human factors started during an internship in 2016 at the National Space Biomedical Research Institute where he worked as a research assistant on a project studying the cognitive function of astronauts during space flight. After completing his Bachelor of Science in Biomedical Engineering at the University of North Carolina at Chapel Hill in 2017, he decided to pursue a Master of Science degree in Industrial and Systems Engineering with a focus in human factors. After completion of this degree he plans to start a career in industry tackling human factors issues in medical devices with the goal of integrating his undergraduate and graduate training.

ACKNOWLEDGMENTS

I would like to express my thanks to all of the individuals who supported me and provided advice throughout the completion of this thesis.

First, I would like to thank Dr. Xu Xu, my advisor and committee chair, for his support and guidance throughout this process. I would also like to thank Dr. Karen Chen and Dr. Jing Feng for serving on my committee and for offering their advice on matters relate to their areas of expertise. Finally, I would like to thank all of the participants who took time out of their lives to be a part of this research.

This research was made possible by the National Institute for Occupational Safety and Health (NIOSH) through the NIOSH Training Program Grant. I would like to thank them for providing financial support and the opportunity to conduct safety-related research during my graduate training.

TABLE OF CONTENTS

LIST OF FIGURES

1. INTRODUCTION

1.1 Background

Over the past several decades the field of robotics has continued to grow at an amazing rate. The International Federation of Robotics is forecasting robot sales and shipments to have an average growth of 12 percent per year from 2020 to 2022 (Ifr., 2019). Robots have been put to use in many different settings promising efficiency, cost reduction and increased safety with manufacturing being a particularly salient target for innovation (Esmaelian et al., 2016). A commonly held belief is that advanced robotic manufacturing systems will completely replace the human workforce leading to automated factories and many workers losing jobs (Acemoglu & Restrepo, 2019). Some research, however, suggests that there will be a significant contingent within industry that requires scenarios where humans and robots share the same workspace (Kruger et al., 2009; Bley et al., 2004, Pires & Azar, 2018). Many businesses require manufacturing and assembly processes to be flexible and rely on a skilled human worker's ability to judge and adapt to variations in processes. Robotic systems in these scenarios must be able to interface effectively with humans and leverage the advantages that each actor provides. One such advantage that these collaborative robotic systems can provide is increased safety for the human workers by offering assistance and alternative task configurations for occupational workflows, for example, a robot can handle objects for a human or take over risky portions of a task (Cherubini et al., 2016).

The manufacturing industry has been identified by the National Institute for Occupational Safety and Health (NIOSH) as a sector of significant concern for worker safety and health. The NIOSH Strategic Plan: FYs 2019-2023 lists manufacturing and musculoskeletal health as an area of interest and recommends that research be focused on increasing the use of robotics for reducing musculoskeletal disorders. Specifically, NIOSH stated a need to "identify scenarios in which the use of robots and other emerging technologies can contribute to MSDs". The plan also includes a call for research in using sensor technologies to measure risk factors for musculoskeletal disorders in manufacturing.

This research aims to contribute to the field of collaborative robotics as it applies to the NIOSH strategic goals by developing and testing an inertial sensor-based ergonomic assessment system for reducing musculoskeletal injury risk in a manufacturing collaborative robot work scheme. The following sections will review the current literature in musculoskeletal injuries for manufacturing workers, ergonomic assessment tools, and collaborative robotics.

1.2 Work Musculoskeletal Disorders

1.2.1 Types of MSDs

Musculoskeletal disorders (MSD) are injuries and disorders of the muscles, nerves, tendons, joints and cartilage of the upper and lower limbs, neck and lower back that affect the movement of the body or the musculoskeletal system (Chaffin et al., 2006). They are the largest single category of workplace injuries and are the cause of nearly 30% of all worker's compensation costs (BLS, 2018). A systematic review (Costa & Vieira, 2009) of recent longitudinal studies of work-related MSD risk factors was conducted and found that the most commonly reported biomechanical risk factors for causing MSDs were excessive repetition, awkward postures, and heavy lifting. Awkward posture was found to be a risk factor for MSDs of the lower back, neck, hands, and knees. Repetitive work was found to be a risk factor for MSDs of the hands and knees (Costa & Vieira, 2009). This review also discussed the potential interaction between risk factors when more than one is present (e.g. high repetition while in an awkward posture) and how that could lead to the precipitation of work MSDs in many parts of the body (Costa & Vieira, 2009).

1.2.2 Manufacturing and Assembly

Musculoskeletal disorders are an important issue in the manufacturing industry. The incidence rate of MSDs in the manufacturing sector that resulted in days-away-from-work was 33.4 per 10,000 equivalent full-time workers in 2015. The incidence rate for all private establishments during the same year was 29.8 (BLS, 2016). A critical review of work-related musculoskeletal disorders conducted by NIOSH in 1997 found a similarly disproportionate incidence rate of MSDs in the manufacturing sector. It reported that manufacturing had a 27.0 per 10,000 workers incidence rate for injuries and illnesses from repetitive motion resulting in days-away-from-work compared to a rate of 11.5 for all other private industry. The same review also provided evidence that work-related awkward postures are associated with MSDs, in particular for the low back. (Bernard, 1997).

One of the reasons for this discrepancy is that the goal of manufacturing is typically to mass produce many copies of the same items as quickly as possible. This results in the individual workers having to do the same task over and over again for long periods of time, leading to repetitive strain injuries. Awkward postures can also be a frequent problem in manufacturing and for assembly. Workers must bend and twist to place parts onto a larger product which puts them at an ergonomic disadvantage (Falck et al., 2014). Often times, these two risk factors are both present in the same task. Several studies have aimed to improve assembly system ergonomics based on reducing repetitiveness, improving posture, and other factors (Battini et al., 2011, Otto et al., 2011, Mura et al., 2019).

The musculoskeletal risks that assembly workers face is often variable and highly dependent on the specific product that is being manufactured. Some products may require heavy lifting, some might require complex skill-based actions, and others might require very simple motions. To address this, a lot of researchers have focused on ergonomic analysis and interventions for specific use cases such as automotive manufacturing (Anghel et al., 2019) or agricultural equipment manufacturing (Gonen et al., 2016). There has also been a lot of work towards incorporating ergonomic risk considerations into optimization techniques for assembly line balancing and workstation design (Bortolini et al., 2017, Bautista et al., 2015). The overarching goal of this research is to integrate ergonomic assessment with collaborative robotics schemes to address musculoskeletal injury risks in assembly workers.

1.3 Ergonomic Assessment Tools

1.3.1 Background

Many different methods have been developed for evaluating ergonomics in work settings that come in many different forms. There are analytical methods such as Rapid Upper Limb Assessment (RULA), Psychophysical Upper Extremity Data, the NIOSH Lifting Equation, and the Strain Index. There are self-reports from workers that can be used to collect information on occupational exposures, observational methods that can be used for recording general exposure information and also for assessing postural information, and methods that rely on monitoring instruments and sensors (David et. al., 2005). Some researchers have developed digital ergonomic evaluations that use musculoskeletal disorder factors to assess ergonomic risk (Maurice et. al., 2016). The focus in this work will be on a popular ergonomic assessment tool called Rapid Entire Body Assessment (REBA). REBA was chosen because of its ability to evaluate the entire body and because of its prevalence in industry among ergonomics practitioners (Lowe et. Al., 2019).

1.3.2 Rapid Entire Body Assessment

Rapid Entire Body Assessment (REBA) was developed to be a postural analysis system that is sensitive to musculoskeletal risks in a variety of tasks (Hignett and McAtamney, 2000). It divides the body into segments and references movement planes to provide a scoring system for posture. This is a pen and paper method where the practitioner observes a subject and records information on a worksheet. Scores are created for the neck, trunk, legs, upper arm, lower arm, and wrist. These scores, when combined with additional scores for activity, coupling (grip), and the load weight, makeup the final REBA score. A web-based survey conducted in 2017 found that REBA is used by 68.4% of US-based ergonomics professionals which, in the category of observational tools, is exceeded by only Rapid Upper Limb Assessment at 78.6% (Lowe et. al., 2019). REBA method was chosen for this research because of its prevalence in industry and its ability to assess the whole body as opposed to just the upper extremities.

1.3.3 Automated Ergonomics Assessment Tools

In recent years, there has been some emphasis on using digital simulation tools for ergonomic analysis as a proactive approach (Maurice et. al., 2016). A common digital, automated tool for ergonomic assessment is digital human models which reconstruct the body and simulate motions during tasks. Models can be useful during the design process for workstation to try and eliminate ergonomic issues before any work has happened (Naumann et al., 2007).

Another form of automated tools is the use of wearable sensors. A systematic review of wearable monitoring devices of biomechanical risk assessment (Alberto et al., 2018) found that “too few researchers foresee the use of wearable technologies for biomechanical risk assessment” and argue that there are many factors that prompt the use of this technology. In this review of 30 articles, inertial measurement units (IMUs) were used in only five studies.

1.3.3.1 Inertial Measurement Units for Automated Tools

This work focuses on using IMUs to sense body motion and facilitate an automated ergonomic assessment tool. IMUs measure linear acceleration, angular velocity, and the magnetic field vector in their local three-dimensional coordinate system. Some commercial IMU systems are equipped with algorithms that can estimate sensor orientation and position with respect to a global fixed coordinate system, the XSENS IMU system was chosen for this research for that reason (Xsens, 2019). Optical motion tracking systems are the gold standard in ergonomics research because of their ability to generate high quality motion data but IMUs have several important advantages. First, they do not suffer from the issue of occlusion (Tian, et al., 2015). Occlusion could be a major issue in a manufacturing setting because of the high amount of activity and large pieces of equipment that tend to be present in factories. In addition, marker-based motion tracking systems, which are popular in biomechanical research, are too difficult to install on a shop floor for practical applications (Fang et al., 2017). This is another distinct advantage of IMUs for body motion tracking of manufacturing assembly workers. Finally, IMUs are light weight, small in size, have low power consumption, are portable, and are low cost.

Some researchers have used IMUs to develop automated ergonomic assessment tools. One such method used IMUs and other sensors to continuously compute scores via the RULA method (Vignais, et al., 2013). Peppoloni et al., 2015 developed a system for assessing biomechanical risk in repetitive work that automatically computed RULA and Strain Index scores using. This system was able to estimate RULA scores that were congruent with scores given by human ergonomists using traditional methods (Peppoloni et al., 2015). Another study suggested that using an IMU based lift recognition tool that is designed according to the Revised NIOSH Lifting Equation could be useful in estimating ergonomic risk (Rabavolo et al., 2017). Limited research was found during this literature review that aimed to create an automated REBA tool using IMUs. REBA's ability to analyze the whole body, as opposed to RULA's limitation to just the upper body, could be important for the analysis of many tasks that require coordinated movement of the upper and lower body. This work focuses on developing a prototype of an automated REBA scoring tool using IMUs that would fill a technological gap by aiding in analyzing ergonomic risk more accurately and more quickly. Furthermore, this research integrates the developed tool with a collaborative robot system for a manufacturing assembly task application.

1.4 Collaborative Robotics

1.4.1 Background

A collaborative robot, often referred to as "cobot", is a robot that was designed to share a workspace and physically interact with a human (Djuric et al., 2016). These robots are uniquely designed to be flexible and safe so that they can efficiently work with humans. Collaborative systems aim to achieve intuitive human-robot interactions by taking advantage of each partner's strengths – for example, the human's cognitive ability and the robot's physical power generation capacity (Ajoudani et al., 2017). Cobots have garnered a lot of attention in both research and industry as a viable configuration for many types of manufacturing operations. ABI research has published market research asserting that revenue for collaborative robot arms will produce 10.276 billion USD by 2030, up from 446 million USD in 2018 (ABI, 2019). There are many commercially available cobot solutions that have made their way into factories (Djuric et al., 2016) and there has been a strong push for innovative research on these systems.

1.4.2 Collaborative Robots in Industrial Settings

There has been a specific interest in using collaborative robots in industrial and manufacturing settings. A review of cobots in industrial settings (Villani et al., 2018) found that the two most important challenges of implementing these devices are safety and intuitive ways to program and interact with robots. This review identified four major goals for future research in collaborative robots, two of which will be addressed in this research: that robot performance should be optimized in terms of safety and that there needs to be adaptive robot solutions that account for differing capabilities among human users. Other researchers have looked specifically at how cooperation between humans and robots can improve the efficiency, safety and quality of assembly systems (Kruger, et al., 2009 & Koskinen et al., 2009) and reduce physical strain in assembly systems (Cherubini et al., 2016). Specific industry sectors include, but are not limited to, automotive (Akella et al., 1999) and oil and gas (Heyer et al., 2010).

1.4.3 Ergonomics and Collaborative Robots

One of the areas that collaborative robotics has made a positive impact on is ergonomics. The most obvious way that robots can improve the ergonomics of human workers is that they can take over the parts of a task that have a high ergonomic risk such as heavy lifting. Ergonomics can be improved by optimizing task assignments and schedules for human-robot teams (Pearce et al., 2018).

Other work, however, has focused on developing smart robotic systems that can improve the ergonomics of their human co-workers by optimizing motion planning during interactions. One approach is to use previous knowledge about ergonomic indicators and risks to inform the design of cobot systems. Maurice et al. used digital human simulations coupled with evolutionary algorithms to analyze ergonomic indicators in cobot co-manipulation tasks in order to optimize the robot design (Maurice et al., 2016). The same research group recently developed an industry-oriented dataset intended for use by researchers for developing algorithms for classifying, predicting or evaluating human motion and optimizing ergonomics in human robot collaborations (Maurice et al., 2019). Research by Parastegari aimed to optimize object handover between a robot and a human by studying object handover between two humans and using the results to model robot control (Parastegari, 2018).

While the optimization of robot design and motion control algorithms is an important factor in developing ergonomically sound human-robot systems, it may also be important for Cobots to be able to adapt their behavior to individual humans and scenarios. For example, a posture that is ergonomically low risk for one individual may not be low risk for another individual if there is a significant difference in anthropomorphic measurements (Dianat et al., 2018, Bestick et al., 2015). To combat this issue, many researchers have been working on developing systems that use personalized or real time estimations of the human partner’s actions to inform robot actions. Kim et al. developed an online optimization technique that uses center of pressure and overloading joint torque measurements to adjust robot trajectories in an attempt to achieve more ergonomic body poses during a human robot interaction (HRI) task (Kim et al., 2018). Marin et al. created a system that optimized robotic behavior with respect to ergonomic scores based on full musculoskeletal reconstructions (Marin et al., 2018). Another study by Busch et al., used an optical motion tracking system to track human motion and create REBA scores to optimize ergonomic poses in human robot interaction tasks (Busch et al., 2018). There were, however, gaps in the literature in investigating the use of inertial measurement systems for personalized ergonomic optimization despite the advantage of IMUs discussed in section 1.3.3.1. There is also a need for continued efforts to examine novel techniques in specific task scenarios such as manufacturing assembly.

1.5 Motivation

Given the prevalence of musculoskeletal injuries, in particular among manufacturing and assembly workers, it is important to research and develop new tools that might reduce the risk of physical injury. The objective of this project was to develop a prototype tool for assessing full body ergonomics in human robot collaborations and to test its effectiveness in reducing physical injury risk for a manufacturing assembly task using a cobot.

The first goal of this research was to develop a tool capable of automatically assigning Rapid Entire Body Assessment scores to body postures using data from inertial measurement units. Various methods have been used in the literature to assess ergonomic risk of various parts of the body but few have used IMUs for full body postural evaluation despite the advantages that IMUs may have in practical applications. This research proposes a method using IMU sensors for ergonomic analysis during a cobot task.

The second goal of this research was to test the effectiveness of this tool in reducing physical ergonomic risk in a manufacturing assembly task when integrated with a cobot. There is limited research in testing cobot schemes for specific tasks within specific industries, despite the fact that each task and occupation has unique needs. A task scenario designed to be representative of a manufacturing assembly task was used for this test. The task design was based on principles found in Design for Manufacturing and Assembly, a common guideline in manufacturing engineering. Body motion data from the prototype automated REBA assessment tool was used to inform the motion control of the cobot so that the robot's actions encouraged good ergonomic positions for the human co-worker.

The following four primary research questions were the focus of this experiment. (1) Can ergonomic risk be reduced by using the automated REBA assessment tool to inform robot motion in a cobot task? (2) Does this cobot scheme have an effect on task performance? (3) Does the participants' perceived workload differ between completing the task with the cobot scheme versus without it? (4) Do participants prefer to work with or without the cobot?

2. METHODS

This section covers all of the methodology used in the development of this research. It covers the process behind creating an automated ergonomic assessment tool using inertial sensors, integrating that tool with a cobot, and the details of setting up, conducting and analyzing the results of an experiment utilizing these tools.

2.1 Development of an Inertial Sensor-Based Ergonomic Assessment Tool Prototype

This part of the methods section will detail the methods used to develop an ergonomic postural assessment tool using inertial sensors. It will cover the technology used, the development process, and the validation and prototyping process.

2.2.1 Technology

This development of this tool took place in the Biomechanics Laboratory in the Edward P. Fitts Department of Industrial and Systems engineering at North Carolina State University. The Xsens MVN Awinda inertial motion capture system was used for full-body motion capture. The Xsens system is a portable, full-body, inertial kinematic measurement system that incorporates synchronized video data. The suit uses 17 wireless sensors that are fitted to the body using a Lycra suit and adjustable straps (Figure 1). It provides an output of 3D orientation data for each sensor, center of mass, and joint angle data. The data from the sensors was exported to and processed in MATLAB.

Figure 1. Participant wearing the XSENS sensor suit with LYCRA straps and shirt. The orange rectangles are the IMU sensors.

2.2.2 Development Process

As discussed in section 1.4, Rapid Entire Body Assessment (REBA) is a method of ergonomic postural scoring. In current practice this method is typically done by a trained ergonomist using a pen and paper worksheet (Appendix A). The ergonomist observes a person doing a task and visually estimates the angles between various segments of the body. Often, the ergonomist will also record a video of the task and measure angles in the replay using an on-screen protractor overlay. There are three primary limitations to this method. First, visually estimating body posture or measuring angles on video recordings is not very accurate. Second, the ergonomist must choose which instances during the task to analyze because the pen and paper method is designed to evaluate posture in stationary instances. Finally, the worksheet requires the user to tabulate and add many pieces of information and therefore takes time. The main goal of this part of the project was to create an automated version of REBA in MATLAB using the Xsens inertial sensor system that is accurate, capable of scoring posture for every body position in a given task, and time efficient.

The Xsens system uses 17 sensors placed strategically on the body using Velcro straps and Lycra suit in order to record full body motion. The location of the sensors is shown in Figure 2 The data from these sensors was exported in a .mvnx file format and used to determine the required inputs for the REBA score sheet. This included data for the neck, trunk, legs, upper arm, lower arm, and wrist. The inputs were the angles between certain body segments (this is illustrated in the worksheet seen in Appendix A) and whether or not particular segments were twisted or bent relative to standard anatomical position.

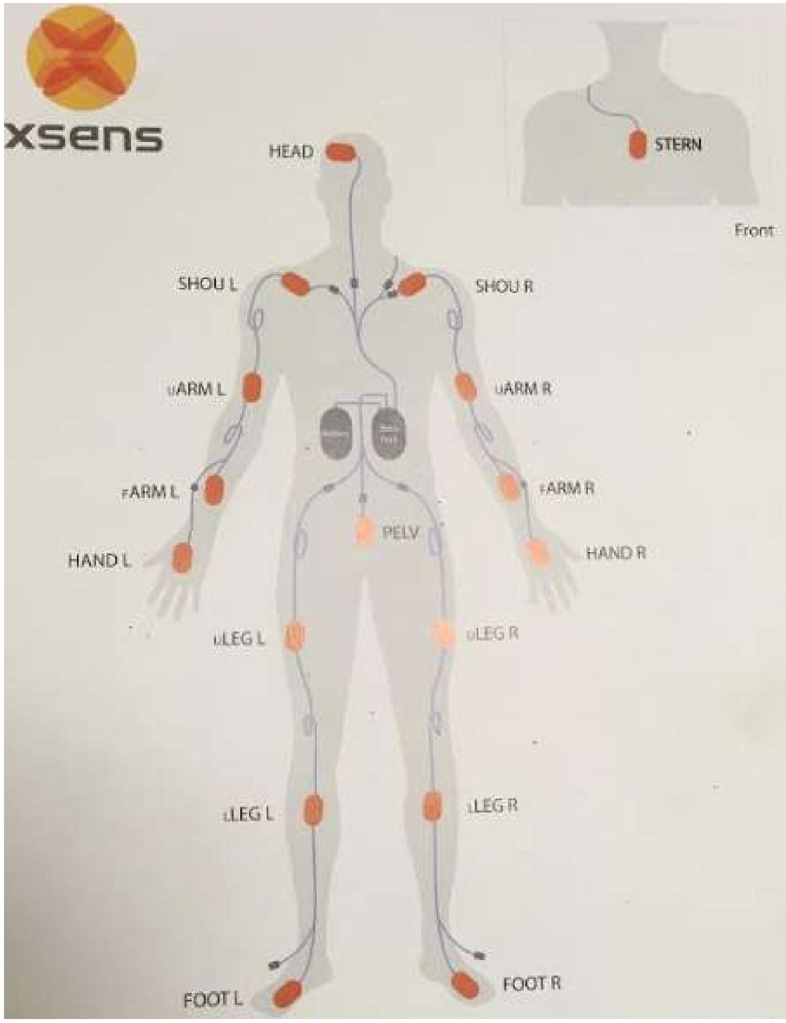


Figure 2. Diagram of the Xsens inertial sensor setup.

The Xsens system has built in software that calculates and outputs the angles between pre-defined body segments along the X, Y, and Z axes. This was used to calculate many of the measurements needed for REBA scoring. The Xsens system outputs convenient angle measurements for the knee, shoulder, elbow, and wrist which corresponded with the REBA worksheet leg, upper arm, lower arm, and wrist measurements, respectively. The Z axis angle measurement was used to determine flexion, the Y axis was used for abduction, and the X axis was used for twisting motions. The REBA method specifies what score to give a posture based on angle for flexion movements. These angle ranges and accompanying scores were transcribed directly from the worksheet. The method does not, however, specify the extent to which a limb is abducted or twisted. It simply says to add a point to the score if the relevant body part is twisted or abducted at all. In practice, this part of the scoring is up to the ergonomist's judgment. Due to the sensitivity of the inertial sensors, it was not practical to increase the score in this manner because the system would rarely, if ever, measure the abduction and twisting angles to be exactly zero. Therefore, the angle thresholds for twisting and abduction were set to 30 degrees for arm abduction and 30 degrees for wrist twisting. The scores for the neck and trunk did not have convenient angle measurement outputs and therefore required a different approach.

Measurements for the neck angle were not directly provided by the Xsens system so the neck score was calculated using the angle between the head sensor segment and the first cervical vertebra segment (C1), which was determined using XSEN's calculations of the upper back position. The Z axis was used for flexion, the Y axis was used for twist, and the X axis was used for bending. Scoring for flexion was calculated in accordance with the REBA worksheet while twisting and bending were based on a +/- 10 degrees threshold. For the trunk, the REBA method is concerned with the angle between the trunk and the vertical axis. A vector for the trunk was created between the C1 vertebra and the pelvis and a second vector was created to represent the Y axis. The angle between these two vectors was used for trunk flexion and was calculated as follows:

$$angle = arccosine(\frac{(\vec{u} \cdot \vec{v})}{(\|\vec{u}\| \cdot \|\vec{v}\|)} \text{ (Equation 1)}$$

Where u is the trunk vector and v is the vertical vector. The scoring for this flexion angle was based on the REBA worksheet. The twisting for the trunk was measured using the angle around the Y axis for the segment between the L1 and T12 vertebrae and bending was measured using the angle around the X axis of the same segment. The thresholds for twisting and bending were set to +/- 2 degrees and +/- 3 degrees, respectively.

Some of the information that is pertinent to the REBA score could not be measured by the Xsens system so it was included as user entered inputs. The inputs for this tool were load weight, coupling score, activity score, and handedness. The load weight refers to the weight of the object being manipulated in the task. The coupling score refers to how well the subject can grip the object that they are manipulating. The action score accounts for repeated small range actions, actions that result in rapid postural changes, and long static holds. The handedness input simply asks which hand is the dominant hand (left or right) of the subject who is being evaluated. When running the program, the user is asked to enter this information based on the task that they are evaluating. In addition, because the REBA method only evaluates one side of the body at a time, this tool was designed to evaluate both sides of the body and report the one with higher ergonomic risk.

The final REBA score is calculated by using all of the flexion, twisting, and bending measurements and referring to the corresponding score tables on the worksheet. Tables A, B, and C from the REBA worksheet were recreated in the MATLAB script. This information was then combined with the user inputs to calculate a final REBA score. The final product of this development process was a MATLAB tool that can analyze .mvnx inertial sensor data files and produce a REBA posture score for each individual frame captured at 60 Hz. Source code can be found in Appendix I.

2.2.3 Validation

The automated REBA scoring tool was validated by comparing the REBA score outputs to REBA scores calculated using the pen and paper method. A test trial was recorded with the

Xsens system where the user performed a basic lifting task. The recording had 1276 frames, 10 of which were chosen at random to be evaluated. A visual representation of the body motion was captured for each of the 10 frames using the Xsens synchronized video functionality and the posture in each frame was given a REBA score using the pen and paper method. An example of the REBA worksheet for this evaluation for one such frame is shown in Figure 3.

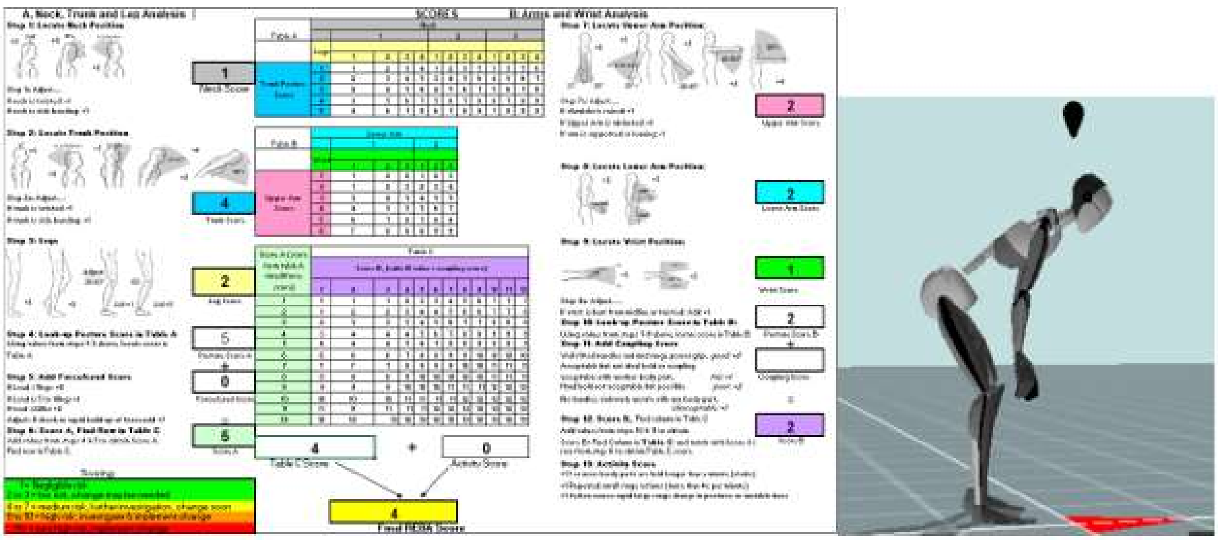


Figure 3. Filled out REBA worksheet for the 10th selected frame of the validation test trial (left) and the synchronized video from the Xsens software of the same frame (right).

The dataset was then analyzed using the automated REBA scoring tool and the automatically calculated REBA scores were extracted for each of the 10 frames. The results of the validation procedure are shown in Figure 4. The two methods produced similar REBA scores. The 1st, 5th, 6th, and 9th frames produced some inconsistencies in scoring with the 6th frame having the largest difference of 2 points. This discrepancy was most likely because the pen and paper method relies on the user to estimate angles between body parts visually while the automated REBA scoring tool can calculate angles with more precision. In addition, the REBA method is designed with absolute thresholds for angles. To illustrate this point, imagine a scenario where a participant is standing at a posture with their upper arms raised to approximately 45 degrees. A person using the pen and paper method might visually inspect the participant and see that the angle is approximately 45 degrees but because the REBA method lists 45 degrees as the threshold between scores, they must choose either below 45 (for an upper arm score of 2) or above 45 (for an upper arm score of 3). Ultimately, they choose below 45 for a score of 2. The automated REBA scoring tool, on the other hand, might have measured the angle to be 46 degrees and thus assigns an upper arm score of 3. The 1 degree difference in angles is typically imperceptible to even a trained eye and is likely a major source of the observed inconsistency in REBA scoring between the two methods.

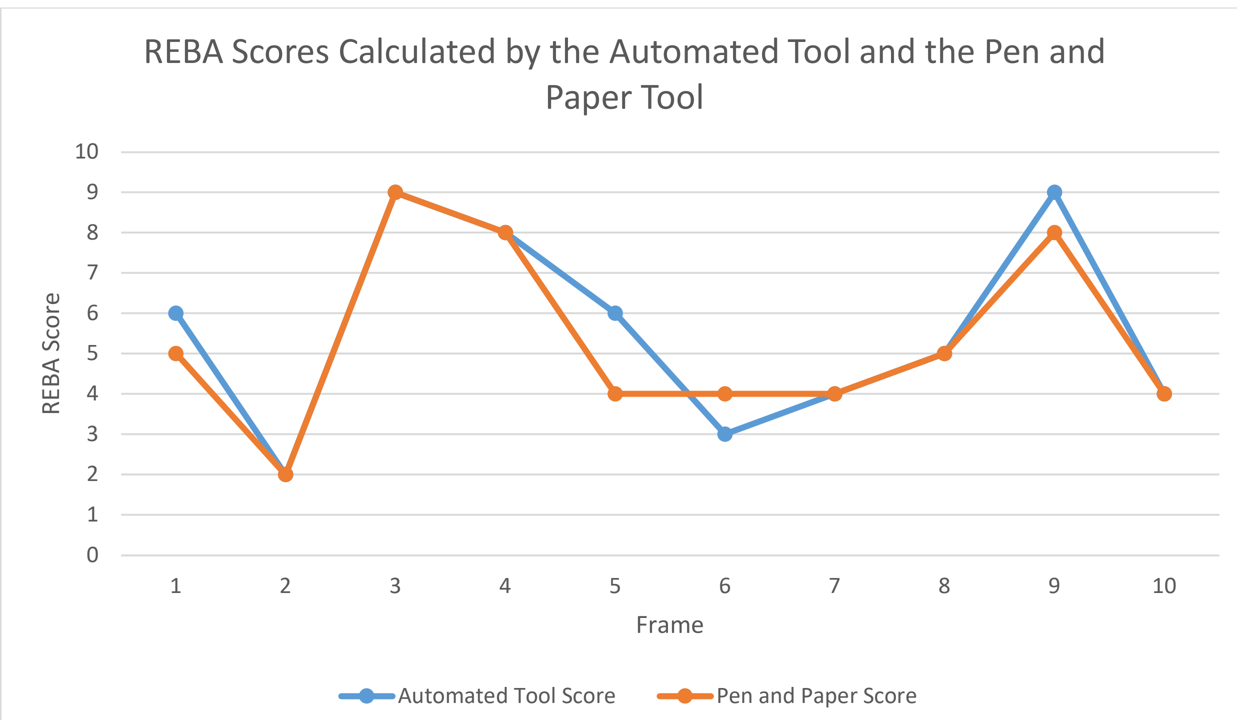


Figure 4. Filled out REBA worksheet for the 10th selected frame of the validation test trial (left) and the synchronized video from the Xsens software of the same frame (right).

2.3 Collaborative Robot System

This section will detail the technology used in the cobot system, the development methods used for programming the robot, and how the automated REBA scoring tool was integrated with the robot.

2.3.1 Technology

The Rethink Robotics Sawyer cobot was used for this research. Sawyer is a 7 degrees of freedom one arm robot designed to be inherently safe and to collaborate with humans. It was connected with a PC running Linux Ubuntu 16.04 and was programmed using Python and the Robot Operating System (ROS) middleware framework.

Figure 5. Rethink Robotics Sawyer Robot. (rethinkrobotics.com)

2.3.2 Feedback System

The Sawyer cobot can be programmed to move to specific positions in order to complete tasks and interact with human workers. In this research, a robot motion control method was developed that aimed to minimize ergonomic posture risk for human workers during a collaborative manual assembly task.

Robot motion planning was done by using an inverse kinematics client in ROS and Python for Cartesian trajectory planning. The function took XYZ position and XYZW orientation (quaternion) of the robot end effector as inputs and calculated the joint angles necessary to move the end effector to that position as well as the trajectory needed to get it there. This made it possible to work in the Cartesian space of the robot arm's end point which was the part of the robot interacting with the human subject. Source code can be found in Appendices J – L.

Feedback for minimizing the ergonomic risk score was done by recording body motion with the Xsens inertial sensor system and using the automated REBA scoring tool discussed in section 2.1. The end goal was to create a system that reduced ergonomic risk by manipulating the location in space where the human worker makes contact with the robot during simultaneous manipulations. For example, if the robot were to hand something off to the human, it would not be ergonomically optimal for it to hold the item 3 meters in the air because that would force the human worker to reach overhead to grab it and result in a high (risky) REBA score.

The first step was to figure out how to get the human and the robot in the same frame of reference so that data regarding body position could be translated to the position of the robot. The solution for this research application was to have the human workers perform all interactions with the robot at a set location. This approach restricted the movement of the human worker but was necessary because there was a limited ability to send data from the Xsens systems to the Sawyer robot in real time. The advantage of this method, however, was that it facilitated the creation of a safety zone – this set location doubled as a zone that was just outside of the reach of the robot arm, protecting the participant from being struck in the head or torso. This setup is illustrated in Figure 6.

Figure 6. Robot setup showing the safety zone lines for the robot and the participant in light blue masking tape on the ground.

The next step was to develop a method for identifying the safest ergonomic postures and translating them to information that the robot could use. Functionality was added to identify the frame within a motion recording that had the lowest REBA score. The XSENS sensor suit was used to record body posture for each participant during a practice run after calibration. This recording was then analyzed further in a Matlab script (Appenix I). The script extracted the position of the dominant hand and foot for each frame. The hand position was extracted because it was the point of contact with the robot arm during simultaneous manipulation tasks. The foot position was extracted because it was a relatively stationary point on the ground within the set location discussed in the previous paragraph. Then, the automated REBA assessment tool was used to identify the frame within the recording with the lowest REBA score. The dominant foot and hand positions were indexed from this frame and the vertical distance (h) and the horizontal distance (d) between the foot and the hand were calculated. The vertical distance (h) was defined as the distance between the dominant hand IMU and the dominant foot IMU along the craniocaudal axis. The horizontal distance (d) was defined as the distance between the dominant hand IMU and the dominant foot IMU along the anteroposterior axis. A visual representation of these variables is shown in the Figure 7. The result was position information for the dominant hand in the frame with the lowest REBA score for the practice trial. This position was considered the optimal ergonomic position.

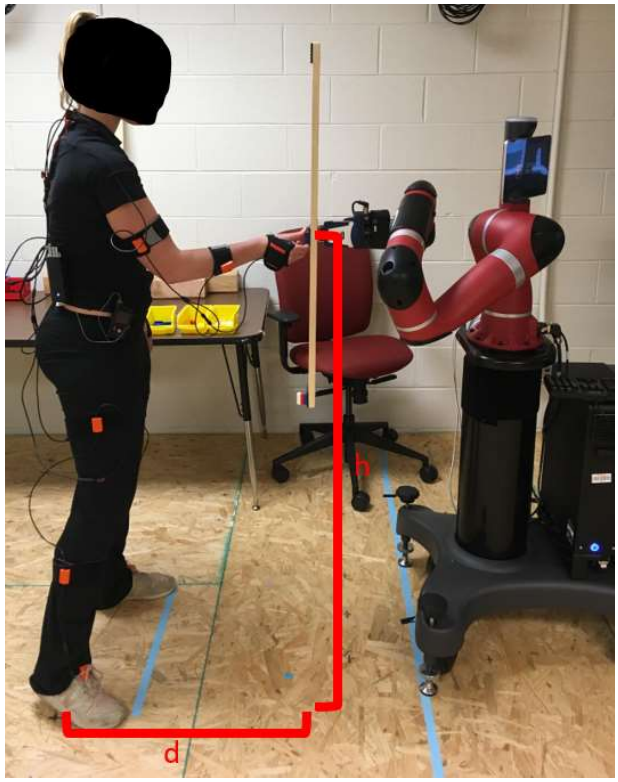


Figure 7. Diagram of the variables h (vertical distance between hand and feet) and d (horizontal distance between hand and feet).

The final step was to incorporate the h and d variables into the motion planning for the robot. The Python script used to move the robot arm took h and d as inputs when called. The script used this information to move the end effector of the robot arm to the location described by h and d. As described above, this location corresponded with the lowest REBA score for the human worker during the analyzed practice task sequence and for the purpose of this project was deemed the ergonomically optimal position. Using this method, the robot was programmed to move task objects to the ergonomically optimal position at specific times and theoretically reduce the ergonomic risk of the task. A user study was implemented to test whether this method was successful.

2.4 User Study

This section will describe the methods used for the user study that was conducted to test the aforementioned system. The experiment took place in the Biomechanics Laboratory in the Edward P. Fitts Department of Industrial and Systems engineering at North Carolina State University.

2.4.1 Participants

Ten participants ages 18-51 (Mean = 24.8, Median = 23.5, SD = 9.58) were recruited for this study. There were 6 males and 4 females. The sample was generally a younger population because most participants were recruited online or by flyers posted on the campus of North Carolina State University. Many were students either graduate or undergraduate. None of the participants reported any physical disabilities that would prevent them from lifting and moving light objects and every participant indicated that they would be capable and willing to lift and move light objects. Each participant was compensated at a rate of $10.00 per hour for an experiment that lasted approximately 2 hours.

2.4.2 Independent Variables

The independent variable for this experiment was the type of human-robot collaboration task. The three types were non-collaborative (type 1), semi-collaborative (type 2), and collaborative (type 3). The non-collaborative task configuration had no robot involvement, the semi-collaborative configuration had partial robot involvement, and the collaborative configuration utilized the full collaborative system. Each participant was asked to perform each of the three types twice throughout the course of the experiment. The order in which they did the types was random.

2.4.2.1 Task Description

The task for the user study was a simple puzzle piece assembly task utilizing Legos. Legos were chosen due to their ease of use, configurability, and accessibility. The aim was to simulate the snap fit pieces that are commonly found in manufacturing settings. This idea originates from the popular engineering methodology, Design for Manufacture and Assembly (DFMA), which calls for the use of snap fit pieces in place of screws or other fasteners in order to make manufacturing and assembly processes more efficient (Boothroyd et. al., 1994).

Three Lego baseplates were attached to a 50 cm task board spaced evenly apart along the length so that participants would have to reach or bend to complete the entire task. At each baseplate, the participant was required to place three Lego bricks stacked on top of each other. The participants were instructed to place the three Legos in a specific color order (blue, red, white). The task board was positioned vertically, and the participant was instructed to start by placing three Legos on the bottom baseplate, then the middle baseplate, and finally the top baseplate. Figure 8. is a photo of the task board after each of the Legos has been correctly placed.

Figure 8. Photo of the task board fixed to the robot arm with the Legos in the correct, completed positions.

The basic task of securing the Legos remained constant throughout the three treatments, the change in trial type was how much the robot was involved. In the non-collaborative (type 1) trial type the task board was placed on a table propped vertically against a wall. Figure 9 shows a photo of this setup. In the semi-collaborative (type 2) trial type the task board was fixed to the robot arm and the robot did not move while the participant fixed Legos to it. The position of the task board in the type 1 and type 2 trials were the same. Type 2 was included to see if just the introduction of the robot, without unique motion planning, would result in changes in performance or user preference. In the collaborative (type 3) trial type the task board was fixed to the robot arm and the robot arm would move during Lego placement to position each of the three Lego baseplates at an ergonomically optimal position. This third trial type was representative of the fully functioning methodology described in section 2.3. These procedures are described and illustrated in further detail in section 2.4.6.

Figure 9. Photo of the task board in the non-collaborative (trial type 1) configuration.

Several factors were controlled across each of the three trial types. The participants completed the task from top to bottom in each instance. The position of the task board relative to the participant was held constant. The orientation of the task board was also controlled. In addition, the Legos that had not yet been placed were kept in plastic bins in the same position and orientation relative to the participant.

2.4.3 Dependent Variables

2.4.3.1 Average REBA Score

Average REBA score was the average score of every frame during the task actions of each trial (6 total per participant). Task action refers to reaching for the Lego pieces, moving them to the task board, and placing them in the correct location in the configurations described in section 2.4.2.1. This distinction is made because during each trial the subject would have to stand and wait for short periods of time during which the Xsens system would continue to collect data. During pilots testing it was found that the variable standing periods between and within subjects caused skewed REBA score because standing still is a low ergonomic risk posture. Therefore, the standing time periods were removed from the recording during data processing leaving only the movements and postures directly related to the task for analysis.

2.4.3.2 Perceived Workload

Perceived workload was measured using the NASA Total Load Index (TLX). An online tool was used to administer the survey during the experiment (Sharek et. al., 2011). This survey provides a score for overall workload as well as subscales for workload demands of physical, mental, effort, performance, frustration and temporal measures. This research looked at the overall score as well as the impact of each individual subscales. Detailed information on survey structure and definitions of each of the workload demand types can be found in Appendix B.

2.4.3.3 Task Performance

Task performance was measured by tallying the number of errors that occurred within a trial. An error was tallied when the participant chose the wrong color Lego, put a Lego in the wrong color order, or dropped a Lego. Errors were not tallied for minor fumbling events. These errors were tallied manually by the experimenter based on observations.

2.4.3.4 Likert Scale Rating

A Likert scale survey was used to assess usability and acceptability of the robot system. The statements were designed to measure user preference between trial types and previous research in human robot interactions were used as a reference for their design (Busch et. al., 2018). The participant was asked to rate each question on a scale from 1 to 5 where 1 was "strongly disagree" and 5 was "strongly agree". A full copy of the survey can be found in Appendix C.

2.4.4 Experimental Design

The experiment followed a within-subject design so that all subjects were exposed to all three trial types. There were three treatments of human-robot interaction: non-collaborative (type 1), semi-collaborative (type 2), and collaborative (type 3). Each participant completed each trial type twice for a total of six trials and the order that they were presented the treatments was randomized. A table of the randomization can be found in Appendix D. The objective of this design was to reduce errors associated with individual differences. The randomization was performed in order to minimize carryover effects.

2.4.5 Procedures

After responding to recruitment inquires via email the participant was sent an email with a link to a screening survey for eligibility via password protected NCSU Qualtrics account. The survey questions can be seen in Appendix E. Upon confirmation of eligibility, the participant scheduled a time at their convenience to come to the Biomechanics Laboratory housed in the Fitts Department of Industrial and Systems Engineering. When the participant arrived at the lab, the experimenter provided a brief introduction of the study including an overview of what it would entail. The participant was then presented with the informed consent document (Appendix F) and asked to sign and date after reading it in full. The participant was then be asked to complete a demographic questionnaire which can be found in Appendix G. Body measurements such as height, arm span and leg length were collected by the experimenter using a tape measure to be used for calibration of the inertial measurement unit (IMU) system (Xsens, the Netherlands). The experimenter then assisted the participant in securing the Xsens IMU system to their body.

Before beginning the experiment, the participant was shown how to safely complete each of the three trial types and was given a chance to practice each one. The experiment performed calibration for the Xsens system. The Xsens data from the final calibration and testing run through was used to calculate the vertical and horizontal distance between the dominant hand and foot,*h* and *d, respectively.* These are discussed further in section 2.3.2. Each participant performed each of the three trial types two times for a total of six trials and the order was randomized. Each of the three trial types had the subject complete the task with a slightly different procedure:

- *Non-Collaborative (Trial Type 1):* The subject stood at the simulated assembly station shown in Figure 6. They then completed the task by inserting the snap fit puzzle pieces in the correct position and in color order on the assembly task part. After completing the task as described in section 2.4.5, the subject waited for the experimenter to reset the task. This procedure was completed 5 times successively. The participant was instructed to complete the task quickly, but to prioritize accuracy and correctness.

- *Semi-Collaborative(Trial Type 2):* The subject stood at the simulated assembly station at a position marked by masking tape (this was the set location discussed in section 2.3.2). The robot was holding the assembly task part in front of the participant. The participant completed the task by inserting the snap fit puzzle pieces in the correct position and in color order on the assembly task part. In this configuration the robot did not move during completion of the task. When the task was completed, the robot simulated placing the assembly task part to the left. (In order to simplify the process, the robot did not actually let go of the part, just moved it back to starting position where the experimenter could reset the task). This procedure will be completed 5 times successively.
- *Collaborative (Trial Type 3):* The subject stood at the simulated assembly station at a position marked by masking tape (this was the set location discussed in section 2.3.2). The robot was holding the assembly task part in front of the participant in a position determined by the variables *h* and *d* calculated earlier using Xsens body posture data. The participant then completed the task by inserting the snap fit puzzle pieces in the correct position and in color order on the assembly task part. During this trial, the robot moved the assembly task part so that each snap fit action occurs at the same calculated location. When the task was completed, the robot simulated placing the assembly task part to the left. In order to simplify the process, the robot will not actually let go of the part, just move it back to starting position. This procedure was completed 5 times successively. Figure 10. shows a series of photos of a participant interacting with the robot in this trial type.

Figure 10. Series of three photos of a participant using the robot in the collaborative trial type (type 3) where the robot is moving to accommodate each of the three baseplates. The participant places a Lego on the bottom task location (left), middle task location (middle), and top task location (right).

Prior to each of the six trials a short calibration procedure for the Xsens system was performed that required the participant to stand still for approximately five seconds. After the completion of each trial the participant completed the NASA TLX Load Index Survey. After the completion of all of the trials, the participant completed the End of Study Likert Scale Survey found in Appendix C. Lastly, the participant filled out a payment form and departed the lab. The entire length of the study took approximately 2 hours.

2.4.6 Hypotheses

Based on the information discussed in the above sections, the following hypotheses were formulated:

H1: Trial type 3 (collaborative) is expected to result in lower ergonomic risk than trial type 2 (semi-collaborative) and trial type 1 (non-collaborative), indicated by a lower average REBA Score.

H2: Trial type 3 (collaborative) is expected to result in lower overall perceived workload and lower perceived physical demand than trial type 1 (non-collaborative) and trial type 2 (semi-collaborative). Indicated by a lower NASA TLX score.

H3: Trial type 3 (collaborative) and trial type 2 (semi-collaborative) are expected to result in higher perceived temporal demand than trial type 1 (non-collaborative). Indicated by higher NASA TLX scores for temporal demand.

H4: Trial type 3 (collaborative) is expected to result in better task performance than trial type 2 (semi-collaborative) and trial type 1 (non-collaborative). Indicated by less errors committed.

H5: Participants are expected to prefer to work with the robot than without it. Indicated by Likert scale ratings.

2.4.7 Statistical Data Analysis

Data collected from all 10 subjects were available for data analysis. Diagnostics were conducted on all of the response measures to ensure that the data met analysis of variance (ANOVA) assumptions. Shapiro-Wilk's test was used to assess the residual normality assumption and Bartlett's test was used to assess homoscedasticity. When these assumptions were violated, the Wilcoxon non-parametric test method was applied.

A one-way ANOVA model was developed to test the effect of trial type on average REBA score with a significance level of $\alpha = 0.05$. A statistical model was developed based on the experimental design to assess the effects of trial type on average REBA score. The model was structured as follows:

$$Y_{ij} = \mu + \tau_i + \sigma_j + \varepsilon_{ij} \qquad \text{(Equation 2)}$$

Where μ = grand mean; τ_i = trial type effect (i = 1,2,3); σ_j = subject effect (1, …, 10); ε_{ij} = error.

Wilcoxon rank sum non-parametric test was applied to the NASA TLX Scores because the data did not meet the ANOVA assumption of normality.

3. RESULTS

This section details the results from the experiment described in section 2.4 including descriptive statistics, figures for visual interpretation, and a report of the results from statistical tests.

3.1 REBA Score

Figure 11 provides a visual representation of the average REBA score data. A one-way analysis of variance (ANOVA) approach was used to test the effect of trial type on average REBA Scores. The results found the difference between REBA scores for trial types to be highly significant (F-ratio = 46.3878, $p < 0.0001$). An interaction term for handedness was also included in this model because it was suspected that the task design would result in left-handed participants have lower REBA scores. REBA scores between right-handed and left-handed participants were found to be significantly different (F-ratio = 34.0040, $p < 0.0001$) but the interaction effect between trial type and handedness was not statistically significant (F-ratio = 0.7794, $p = 0.4638$).

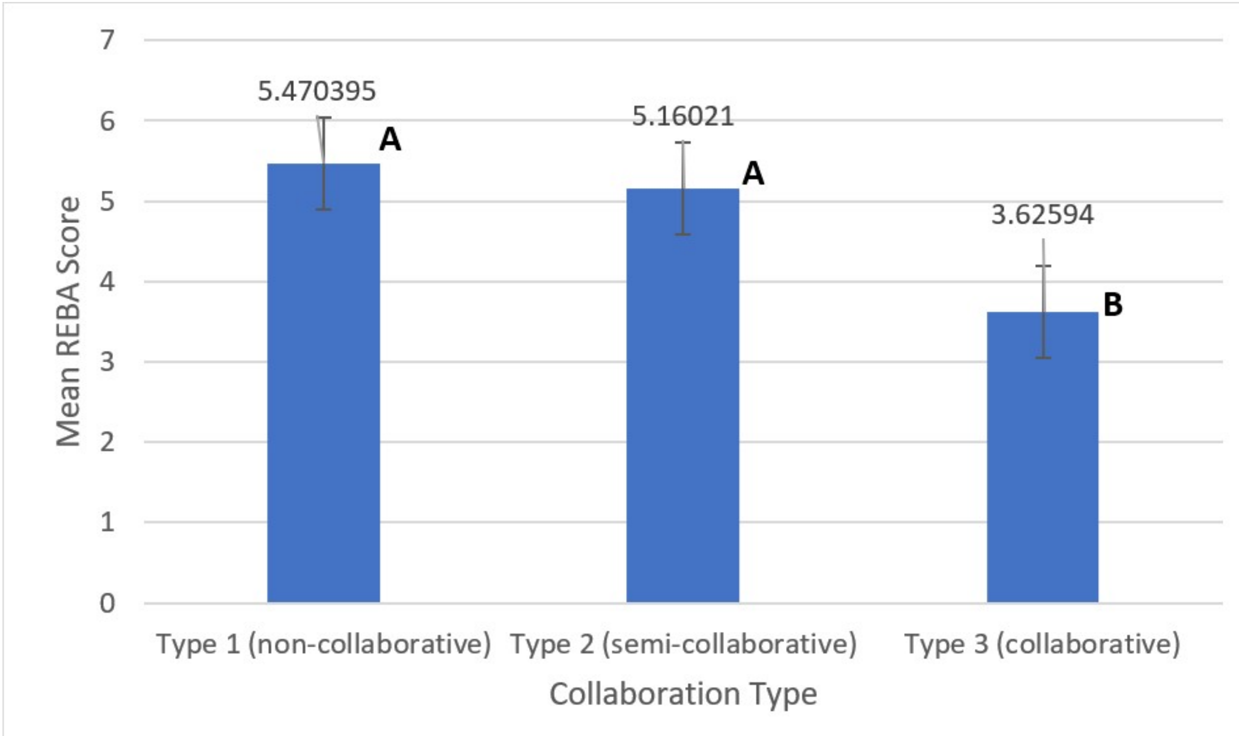


Figure 11. Mean REBA Score values for each trial type with +/- SE bars and connecting letter report from a Tukey-Kramer HSD test.

A post-hoc Tukey-Kramer HSD test found significant differences in means between the non-collaborative and collaborative trial types ($p < 0.001$) and the means between the semi-collaborative and collaborative trial types ($p < 0.001$) but not between the non-collaborative and semi-collaborative trial types. Table 2 shows the connecting letter report for all pairs.

Participant height was also tested as a covariate of REBA scores. The height effect measures were not found to have a significant effect on REBA scores.

3.2 Performance

Descriptive statistics for the number of errors for each trial type is shown in Figure 12. Errors were attributed to the trial that they occurred in and tallied when the participant chose the wrong color Lego, put Legos on in the wrong order, or dropped a Lego. A Wilcoxon test found that there was not a statistically significant difference in the number of errors by trial type (p =

0.2702). A post-hoc power analysis showed, however, that there was inadequate statistical power (0.3182), likely due to an error rate too low to gather an appropriate sample size. The sample size for this experiment was 60 trials. Assuming that the error rate remains the same, there would need to be approximately 188 trials to achieve a statistical power of 0.800, a commonly accepted minimum for this metric.

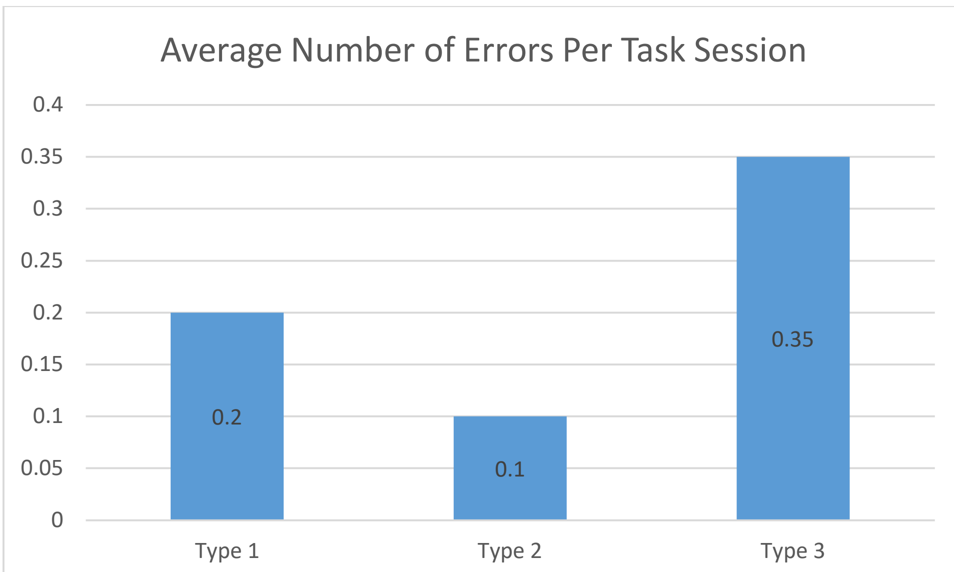


Figure 12. Descriptive statistics of error per trial type.

3.3 NASA TLX

Figure 13 shows the descriptive statistics for the NASA TLX matched pair comparison between the values of each workload factor after each of the 3 trial types. The data did not meet normality assumptions so a Wilcoxon signed rank test was performed on the overall TLX score and each of the workload demand types against the trial type conditions. There was no significant difference in overall TLX score between the 3 trial types ($p = 0.3325$). Of the individual workload demand types, the following were found to have a significant difference between trial types: physical workload ($p = 0.0073$); temporal workload ($p = 0.0007$).

Nonparametric comparisons for each pair using the Wilcoxon method were applied to these measures. For physical workload: type 3 was significantly different from type 1 (p = 0.0093) and type 3 was significantly different from type 2 (p = 0.0052). For temporal workload: type 2 was significantly different from type 1 (p = 0.0002) and type 3 was significantly different from type 1 (p = 0.0094).

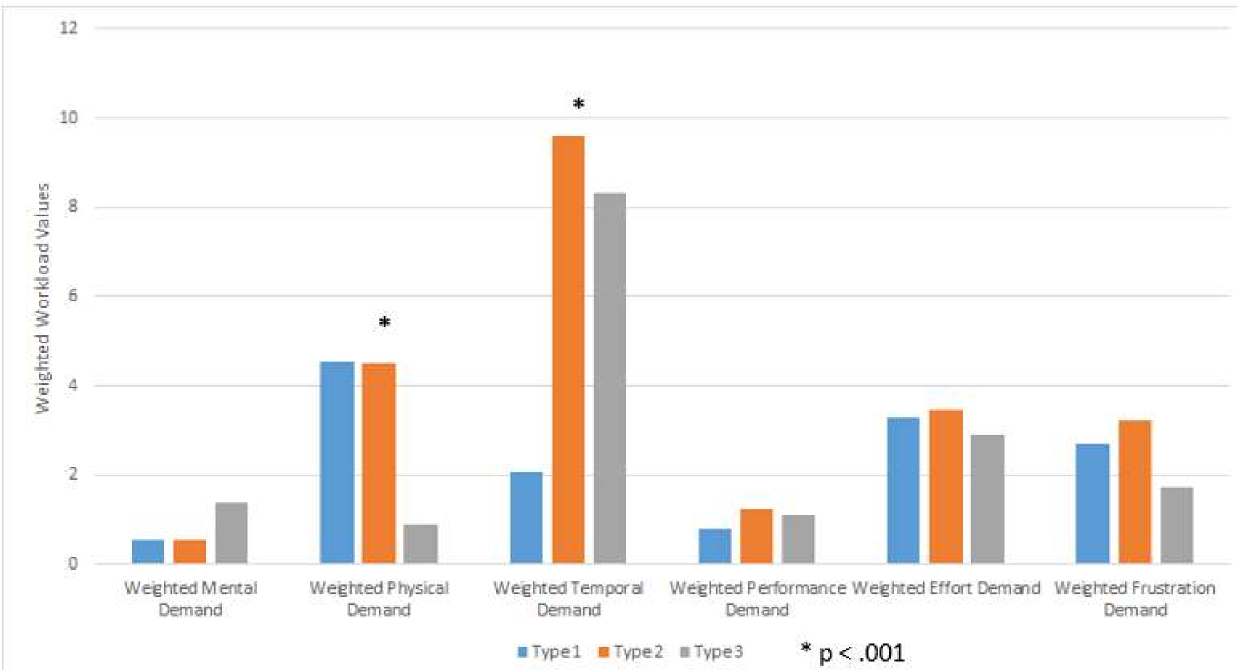


Figure 13. Mean value (after weighting is applied) that each participant placed on each demand type for each workload factor by trial type.

3.4 Likert Scale Survey

On average, when asked to rate statements from 1 to 5 where 1 is “strongly disagree” and 5 is “strongly agree”, participants indicated that they preferred working in the cobot trial type. Figure 14. shows each of the statements presented and the mean value given to them. Positive statements are graphed in blue and negative statements are graphed in red. The statements graphed in green were categorized differently because they were asking the participant to extrapolate their experience to a longer working time period as opposed to asking them to reflect on the actual experiment. They do, however, also indicate a preference for working with the robot.

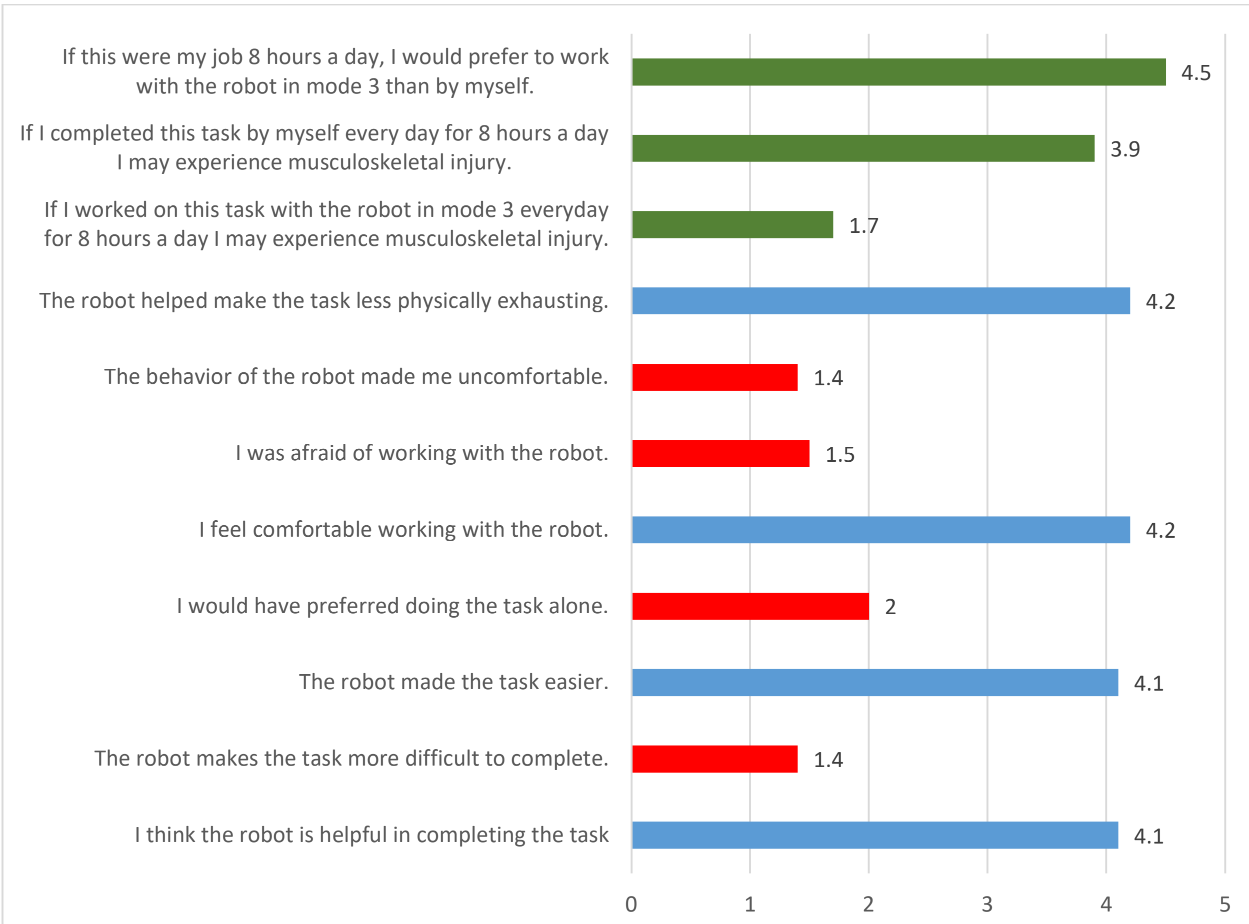


Figure 14. Mean values for Likert survey statements where 1 is "strongly disagree" and 5 is "strongly agree".

4. DISCUSSION

There is a readily apparent need for investigating ways to reduce ergonomic risk in manufacturing assembly tasks, in particular when paired with new technology such as cobots. This need is recognized in the literature as well as by the National Institute for Occupational Safety and Health in their Strategic Plan for 2019-2023 (NIOSH, 2019). This project proposed a method for automatically assessing ergonomic risk and tested its effectiveness in a cobot scheme for manufacturing assembly. This was accomplished by setting up a user study wherein participants completed a task in three different treatments with varying levels of robot collaboration and measuring ergonomic risk, task performance, perceived workload, and user preference.

It was hypothesized that trial type three would result in lower ergonomic risk than trial type two, as indicated by a lower average REBA score (H1) and that trial type three would result in lower ergonomic risk than trial type one (H1.) These hypotheses were supported by the data from the user study with statistically significance. Trial type three was designed so that the robot manipulated the position of the assembly task part to keep the point of contact between the participant and the robot at a position that encouraged good ergonomic posture. As a result, in trial type three, the participants were not required to reach high above their heads or bend down in order to complete the task. Furthermore, several participants made positive comments about their physical posture during this trial type. One participant even stated “this feels better on my back” when completing trial type three and another commented on how mild workout-related soreness was aggravated by the bending required in trial type one. There was also no statistically significant difference in ergonomic risk between trial type two and trial type one. This is because even though trial type two did utilize the robot, it did not factor in body posture data from the

IMU-based REBA tool. These findings suggest that incorporating individual body posture data as feedback for robot motion in cobot tasks could reduce ergonomic risk for the human coworkers.

Perceived workload was measured using the NASA Total Load Index (TLX). It was hypothesized that trial type three would result in lower overall perceived workload than trial type one and trial type two, indicated by a lower NASA TLX score (H2). The results of the experiment did not support this hypothesis. There was not a significant difference in overall perceived workload between the trial types. A further analysis of this result shows that this was likely because there was a split in the specific types of demand that each trial type required. Trial type three resulted in lower perceived physical demand than trial type one and two (H2) but trial type one resulted in lower perceived temporal demand than trial types two and three (H3).

The lower physical demand in trial type three is likely because trial type three did not require the participant to bend down or reach up high in order to complete the task. This was not the case in trial type one and two. In trial types one and two, some shorter participants had to stand on the tips of their toes and some taller participants had to bend almost 90 degrees at the knees. Participants likely counted these actions as physical work and completed the TLX accordingly. These results suggest that using ergonomic feedback in cobot schemes can be effective at reducing physical workload.

The discrepancy in temporal demand can likely be attributed to participants feeling rushed when working with the robot. The robot was programmed to move at set time intervals that were designed to give participants adequate time to complete the task but nonetheless were still restrictive. In trial type one the participants could complete the task on their own without any time constraints from a robot partner. In future studies, it may be important to either program the robot to move only when a participant is ready for it to move or to control for the amount of time allotted to complete the task across all trial types. In a real-world manufacturing environment, workers may feel temporal pressure regardless of the presence of a robot due to the demands of production quotas. If this is taken into consideration then it is possible that the perceived temporal demand would be the same in a real-world environment and that the cobot scheme in trial type three would result in lower overall perceived workload, as expected in H2.

It was also hypothesized that trial type three would results in better task performance than the other two trial types as indicated by less errors committed (H4). The reason for this hypothesis was that there may be a correlation between good ergonomics and the quality of the performance (Falck et al., 2010). The results of this part of the study were inconclusive. Statistical tests of the number of errors for each treatment found that there was not a significant difference in performance, but a post hoc-power analysis revealed low power, likely due to an inadequate sample size. This could be remedied in future studies by either using more participants or increasing the complexity of the task. The participants in this study did not make mistakes at a high enough rate for an adequate sample.

The last research question in this project was whether the participants preferred to work with the robot or without it. This was measured by collected Likert Scale ratings, a common method in usability studies. Three groups of statements were rated by participants and can be seen in figure 14: positive statements about the robot (blue), negative statements about the robot (red), and predictive statements (green). High ratings indicate agreeance with the statements and low ratings indicate that the participant disagreed with the statement.

Each of the positive statements about the robot had an average rating of 4.1 out of 5 or above. Participants indicated that they felt the robot made the task easier, less physically exhausting, and that they felt comfortable working with the robot. Each of the negative statements about the robot had an average rating of 2 out of 5 or below indicating that they disagreed with the negative statements about the robot. These results suggest that the participants had a clear preference for working the robot. This is consistent with what was expected in H5 and illustrates the potential for incorporating cobots into manufacturing assembly tasks.

The predictive statements coded in green were excluded from the positive and negative groups because they were not asking the participant about the system they used in the experiment but instead were asking them to extrapolate their experience to a hypothetical full work day scenario. Participants predicted that they would prefer to use the robot configuration from trial type three if they had to do the task eight hours a day. Participants also predicted that working with the robot over an eight-hour period would reduce their risk of musculoskeletal injury when compared to not working with the robot for this task. These ratings support the hypothesis that participants would prefer working with the robot but it should be noted that none of the participants had any prior experience on a manufacturing floor so their ability to extrapolate the experience to a full-time scenario was limited.

5. CONCLUSION

Prior research in human robot collaborations has shown that using measures of ergonomic risk as feedback for controlling robot motion can reduce the risk of physical injury (Busch, 2018; Marin et al., 2018), but there has been limited research in using inertial measurement units to accomplish this. There has also been limited research in applying these technologies to specific occupational tasks. The goal of this project was to develop a prototype IMU tool for assessing full body ergonomics in human robot collaborations and to test its effectiveness for a manufacturing assembly task using a cobot.

A tool was developed and tested in a within subjects experiment with 10 participants. Each participant completed a simulated manufacturing assembly task with three treatment conditions of varying levels of robot involvement. The findings of this research suggest that incorporating individual ergonomic assessment into the design of cobot tasks can reduce ergonomic risk and physical workload. These findings also support the use ergonomic optimization in cobots for manufacturing assembly tasks and shows that participants prefer to work with a robot than without one.

5.1 Limitations

Several limitations of this study must be addressed. The task chosen for the user study experiment was a simplified simulation of a task that might occur in an actual occupational environment. While the actions had many similarities to real world manufacturing assembly, the task intensity may not have been as strenuous as a real task. A more strenuous or complicated task might have resulted in different results for perceived workload and Likert Scale preferences than were found in this research. Furthermore, a more complicated task would likely have resulted in the participants making more errors and would have produced more meaningful task performance results. It is difficult to choose a task that is representative of all manufacturing assembly tasks so going forward it is recommended that many tasks be tested in different settings.

The transfer of body information data from the Xsens system to the robot was not in real-time. For the purposes of this work, a real-time configuration was not required but it is expected that adding this could result in interesting findings. This limitation will be discussed further in the future work section.

Inertial Measurement Unit systems, such as the Xsens, employ algorithms to estimate the orientation of the sensors within a global coordinate system and rely upon measurements from magnetometers to calibrate these estimations. Therefore, there is the potential for inaccuracies in measurements in the presence of magnetic disturbances, such as those induced by ferromagnetic materials. Some efforts have been made by Xsens to combat this issue (Xsens, 2019) but this limitation should be kept in mind particularly considering that in this research the IMU system was used in close proximity to a robot arm.

Another limitation is that none of the participants had any experience working on a manufacturing floor. They were within the right demographic categories but had not actually done any assembly work before. This was likely because recruitment was done on a university campus. Actual manufacturing workers may have been able to offer more accurate results, in particular for the Likert Scale ratings.

6.2 Future Work

Future research work in this area may focus on improved methods for determining body motion and posture that are feasible for use in real world. As discussion in section 1.3, researchers have used various methods for determining body posture for feedback in human robot collaborations but each one has its limitations. For example, video camera-based methods may face issues of object occlusion in a real environment while on-body inertial measurement unit methods can be intrusive. Improving these methods and then applying them to similar human-robot interaction schemes could be a great opportunity for innovation.

In this research, the communication of body position information to the robot was not in real-time. In future work, in may be beneficial to test using a real-time configuration that continually updates the robot with IMU information regarding the human's actions. In addition, it could be useful to investigate systems where multiple human workers interact with the same robot sequentially and the robot adapts to postural information from each of the workers. This may be more representative of operations within a real-world manufacturing facility.

Future work could also explore the use of this technology in other injury-prone tasks. This work primarily investigated postural deficiencies in the context of repeated motions but other tasks such as manual lifting could have interesting results as well.

Further research could explore the manipulation of more parameters of the robot's motion to improve the human co-worker's ergonomics. The robot could be programmed to optimize not only the x, y, and z positions but also the orientations, the speed, and the acceleration of the robot end effector. It would be interesting to find out if there are optimal levels for these parameters for a given task that improve human work ergonomics.

Finally, future work should explore the use of cobots with similar ergonomic optimization capabilities on a variety of tasks. This project explored the implications of using this technology in a manufacturing and assembly task but there are many different types of tasks across industry sectors that could potentially benefit from innovative solutions, each with its own challenges. A collective effort to research and develop safe and effective cobot systems would have a significant positive impact on the general workforce.

REFERENCES

Home - Xsens 3D motion tracking. (n.d.). Retrieved January 6, 2020, from https://www.xsens.com/

Cobots and Collaborative Robotics in Industrial Applications Research Service. (n.d.). Retrieved January 6, 2020, from https://www.abiresearch.com/market-research/service/cobots-and-collaborative-robotics-industrial-applications/

NASA TLX - Online NASA-TLX Workload Measurement Tool. (n.d.). Retrieved January 6, 2020, from http://nasatlx.com/

Industry Injury and Illness Data. (n.d.). Retrieved January 6, 2020, from https://www.bls.gov/iif/oshsum.htm#18Summary_News_Release

Ifr. (n.d.). Industrial Robots: Robot Investment Reaches Record 16.5 billion USD. Retrieved from https://ifr.org/ifr-press-releases/news/robot-investment-reaches-record-16.5-billion-usd

NIOSH Strategic Plan: FYs 2019−2023. (n.d.). Retrieved January 6, 2020, from https://www.cdc.gov/niosh/about/strategicplan/default.html

Acemoglu, D., & Restrepo, P. (2019). Robots and Jobs: Evidence from US Labor Markets. Journal of Political Economy. https://doi.org/10.1086/705716

Ajoudani, A., Zanchettin, A. M., Ivaldi, S., Albu-Schäffer, A., Kosuge, K., & Khatib, O. (2018). Progress and prospects of the human–robot collaboration. Autonomous Robots, 42(5), 957–975. https://doi.org/10.1007/s10514-017-9677-2

Akella, P., Peshkin, M., Colgate, E., Wannasuphoprasit, W., Nagesh, N., Wells, J., … Peacock, B. (1999). Cobots for the automobile assembly line. Proceedings - IEEE International

Conference on Robotics and Automation, 1, 728–733. https://doi.org/10.1109/robot.1999.770061

Alberto, R., Draicchio, F., Varrecchia, T., Silvetti, A., & Iavicoli, S. (2018, September 13). Wearable monitoring devices for biomechanical risk assessment at work: Current status and future challenges—A systematic review. International Journal of Environmental Research and Public Health, Vol. 15. https://doi.org/10.3390/ijerph15092001

Anghel, D.-C., Niţu, E.-L., Rizea, A.-D., Gavriluţă, A., Gavriluţă, A., & Belu, N. (n.d.). Ergonomics study on an assembly line used in the automotive industry; Ergonomics study on an assembly line used in the automotive industry. https://doi.org/10.1051/matecconf/20192

Battini, D., Faccio, M., Persona, A., & Sgarbossa, F. (2011). New methodological framework to improve productivity and ergonomics in assembly system design. International Journal of Industrial Ergonomics, 41(1), 30–42. https://doi.org/10.1016/j.ergon.2010.12.001

Bautista, J., Batalla-García, C., & Alfaro-Pozo, R. (2016). Models for assembly line balancing by temporal, spatial and ergonomic risk attributes. European Journal of Operational Research, 251(3), 814–829. https://doi.org/10.1016/j.ejor.2015.12.042

Bernard, B. P., Putz-Anderson, V., Susan Burt Libby L Cole, M. E., Fairfield-Estill Lawrence Fine, C. J., Katharyn Grant, D. A., Gjessing Lynn Jenkins Joseph Hurrell Jr, C. J., … Tanaka, S. (1997). Musculoskeletal Disorders and Workplace Factors A Critical Review of Epidemiologic Evidence for Work-Related Musculoskeletal Disorders of the Neck, Upper Extremity, and Low Back. Retrieved from http://www.cdc.gov/niosh

Bestick, A. M., Burden, S. A., Willits, G., Naikal, N., Sastry, S. S., & Bajcsy, R. (2015). Personalized kinematics for human-robot collaborative manipulation. IEEE International

Conference on Intelligent Robots and Systems, 2015-December, 1037–1044. https://doi.org/10.1109/IROS.2015.7353498

Bley, H., Reinhart, G., Seliger, G., Bernardi, M., & Korne, T. (2004). Appropriate human involvement in assembly and disassembly. CIRP Annals - Manufacturing Technology, 53(2), 487–509. https://doi.org/10.1016/S0007-8506(07)60026-2

Boothroyd, G. (1994). Product design for manufacture and assembly. Computer-Aided Design, 26(7), 505–520. https://doi.org/10.1016/0010-4485(94)90082-5

Bortolini, M., Faccio, M., Gamberi, M., & Pilati, F. (2017). Multi-objective assembly line balancing considering component picking and ergonomic risk. Computers and Industrial Engineering, 112, 348–367. https://doi.org/10.1016/j.cie.2017.08.029

Busch, B. (2018). Optimization techniques for an ergonomic human-robot interaction. Retrieved from https://tel.archives-ouvertes.fr/tel-01728902v2

Chaffin, D. B., Andersson, G., & Martin, B. J. (2006). Occupational biomechanics. Wiley-Interscience.

Cherubini, A., Passama, R., Crosnier, A., Lasnier, A., & Fraisse, P. (2016). Collaborative manufacturing with physical human-robot interaction. Robotics and Computer-Integrated Manufacturing, 40, 1–13. https://doi.org/10.1016/j.rcim.2015.12.007

Da Costa, B. R., & Ramos Vieira, E. (2010). Risk Factors for Work-Related Musculoskeletal Disorders: A Systematic Review of Recent Longitudinal Studies. AMERICAN JOURNAL OF INDUSTRIAL MEDICINE, 53, 285–323. https://doi.org/10.1002/ajim.20750

Dalle Mura, M., & Dini, G. (2019). Optimizing ergonomics in assembly lines: A multi objective genetic algorithm. CIRP Journal of Manufacturing Science and Technology. https://doi.org/10.1016/j.cirpj.2019.08.004

David, G. C. (2005, May). Ergonomic methods for assessing exposure to risk factors for work-related musculoskeletal disorders. Occupational Medicine, Vol. 55, pp. 190–199. https://doi.org/10.1093/occmed/kqi082

Dianat, I., Molenbroek, J., & Castellucci, H. I. (2018, December 2). A review of the methodology and applications of anthropometry in ergonomics and product design. Ergonomics, Vol. 61, pp. 1696–1720. https://doi.org/10.1080/00140139.2018.1502817

Esmaeilian, B., Behdad, S., & Wang, B. (2016, April 1). The evolution and future of manufacturing: A review. Journal of Manufacturing Systems. Elsevier B.V. https://doi.org/10.1016/j.jmsy.2016.03.001

Falck, A.-C., Örtengren, R., & Högberg, D. (2010). The impact of poor assembly ergonomics on product quality: A cost-benefit analysis in car manufacturing. Human Factors and Ergonomics in Manufacturing & Service Industries, 20(1), 24–41. https://doi.org/10.1002/hfm.20172

Falck, A. C., & Rosenqvist, M. (2014). A model for calculation of the costs of poor assembly ergonomics (part 1). International Journal of Industrial Ergonomics, 44(1), 140–147. https://doi.org/10.1016/j.ergon.2013.11.013

Fang, W., Zheng, L., & Xu, J. (2017). Self-contained optical-inertial motion capturing for assembly planning in digital factory. International Journal of Advanced Manufacturing Technology, 93(1–4), 1243–1256. https://doi.org/10.1007/s00170-017-0526-4

Gonen, D., Oral, A., & Yosunlukaya, M. (2016). Computer-Aided Ergonomic Analysis for Assembly Unit of an Agricultural Device. Human Factors and Ergonomics in Manufacturing & Service Industries, 26(5), 615–626. https://doi.org/10.1002/hfm.20681

Heyer, C. (2010). Human-robot interaction and future industrial robotics applications. IEEE/RSJ 2010 International Conference on Intelligent Robots and Systems, IROS 2010 - Conference Proceedings, 4749–4754. https://doi.org/10.1109/IROS.2010.5651294

Hignett, S., & Ergonomist, L. M. (2000). Rapid Entire Body Assessment (REBA). In Applied Ergonomics (Vol. 31).

Kim, W., Lee, J., Peternel, L., Tsagarakis, N., & Ajoudani, A. (2018). Anticipatory Robot Assistance for the Prevention of Human Static Joint Overloading in Human-Robot Collaboration. IEEE Robotics and Automation Letters, 3(1), 68–75. https://doi.org/10.1109/LRA.2017.2729666

Koskinen, J., Heikkilä, T., & Pulkkinen, T. (2009). Monitoring of co-operative assembly tasks: Functional, safety and quality aspects. 2009 IEEE International Symposium on Assembly and Manufacturing, ISAM 2009, 310–315. https://doi.org/10.1109/ISAM.2009.5376950

Krüger, J., Lien, T. K., & Verl, A. (2009). Cooperation of human and machines in assembly lines. CIRP Annals - Manufacturing Technology, 58(2), 628–646. https://doi.org/10.1016/j.cirp.2009.09.009

Krüger, J., Lien, T. K., & Verl, A. (2009). Cooperation of human and machines in assembly lines. CIRP Annals - Manufacturing Technology, 58(2), 628–646. https://doi.org/10.1016/j.cirp.2009.09.009

Lowe, B. D., Dempsey, P. G., & Jones, E. M. (2019). Ergonomics assessment methods used by ergonomics professionals. Applied Ergonomics, 81. https://doi.org/10.1016/j.apergo.2019.102882

Marin, A. G., Shourijeh, M. S., Galibarov, P. E., Damsgaard, M., Fritzsch, L., & Stulp, F. (2018). Optimizing Contextual Ergonomics Models in Human-Robot Interaction. IEEE International Conference on Intelligent Robots and Systems, 8603–8608. https://doi.org/10.1109/IROS.2018.8594132

Maurice, P., Malaisé, A., Amiot, C., Paris, N., Richard, G.-J., Rochel, O., & Ivaldi, S. (2019). Human movement and ergonomics: An industry-oriented dataset for collaborative robotics. The International Journal of Robotics Research, 38(14), 1529–1537. https://doi.org/10.1177/0278364919882089

Maurice, P., Padois, V., Measson, Y., & Bidaud, P. (2017). Human-oriented design of collaborative robots. International Journal of Industrial Ergonomics, 57, 88–102. https://doi.org/10.1016/j.ergon.2016.11.011

Maurice, P., Padois, V., Measson, Y., & Bidaud, P. (2017). Human-oriented design of collaborative robots. International Journal of Industrial Ergonomics, 57, 88–102. https://doi.org/10.1016/j.ergon.2016.11.011

Naumann, A., & Roetting, M. (2007). Digital Human Modeling for Design and Evaluation of Human-Machine Systems. Retrieved from http://www.ugs.com/Products/tecnomatix/human_performance/jack/

Otto, A., & Scholl, A. (2011). Incorporating ergonomic risks into assembly line balancing. European Journal of Operational Research, 212(2), 277–286. https://doi.org/10.1016/j.ejor.2011.01.056

Pearce, M., Mutlu, B., Shah, J., & Radwin, R. (2018). Optimizing Makespan and Ergonomics in Integrating Collaborative Robots into Manufacturing Processes. IEEE Transactions on Automation Science and Engineering, 15(4), 1772–1784. https://doi.org/10.1109/TASE.2018.2789820

Peppoloni, L., Filippeschi, A., Ruffaldi, E., & Avizzano, C. A. (2014). (WMSDs issue) A novel wearable system for the online assessment of risk for biomechanical load in repetitive efforts. International Journal of Industrial Ergonomics, 52, 1–11. https://doi.org/10.1016/j.ergon.2015.07.002

Pires, J. N., & Azar, A. S. (2018). Advances in robotics for additive/hybrid manufacturing: robot control, speech interface and path planning. Industrial Robot, 45(3), 311–327. https://doi.org/10.1108/IR-01-2018-0017

Ranavolo, A., Varrecchia, T., Rinaldi, M., Silvetti, A., Serrao, M., Conforto, S., & Draicchio, F. (2017). Mechanical lifting energy consumption in work activities designed by means of the “revised NIOSH lifting equation.” Industrial Health, 55(5), 444–454. https://doi.org/10.2486/indhealth.2017-0075

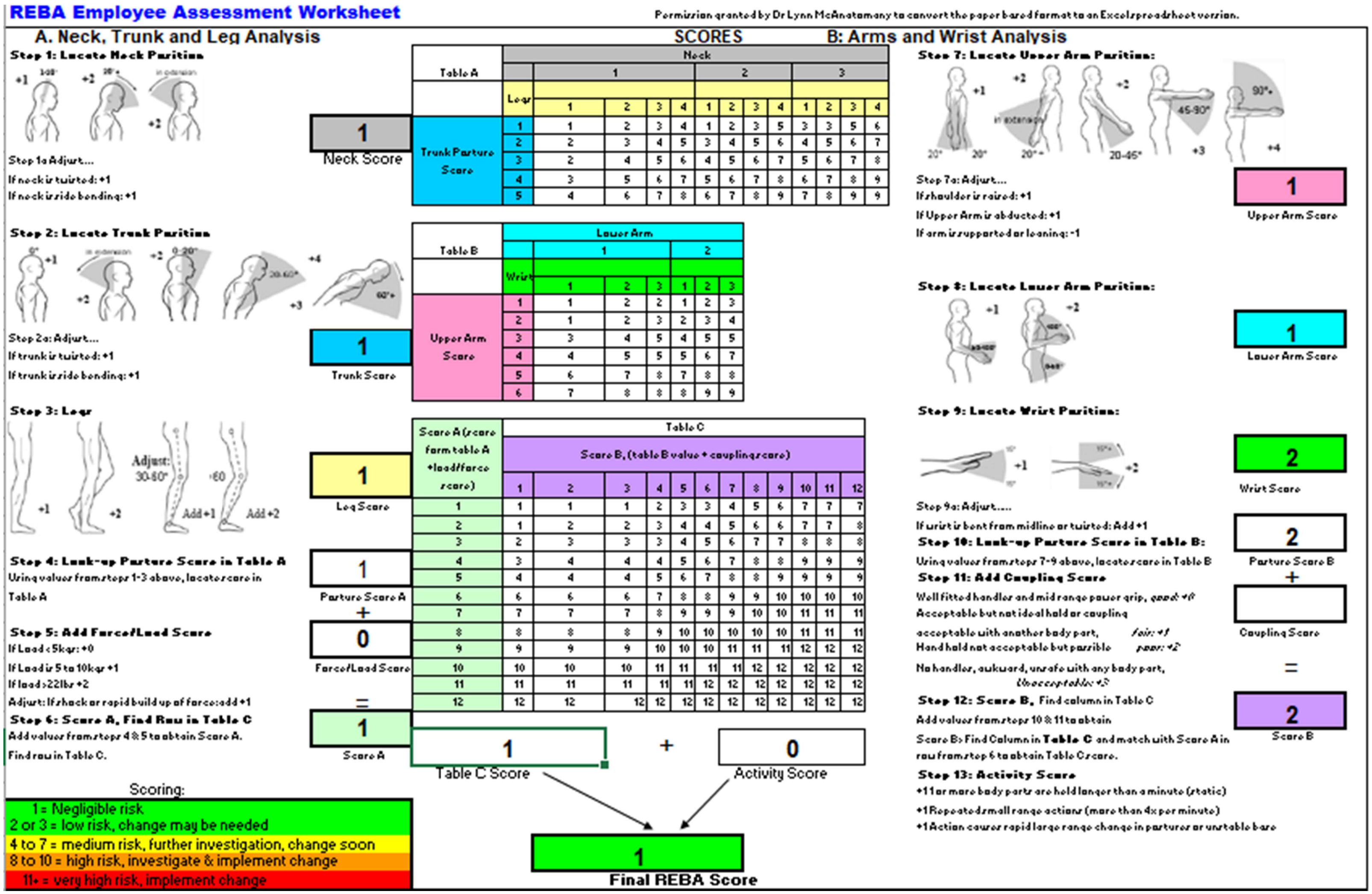
Sina, M., Sc, P. M., Milošˇ, M., Soltanalian, A. M., Patton, J., & Ziebart, B. (2012). Modelling and Control of Object Handover, A Study in Human-Robot Interaction.

Tian, Y., Meng, X., Tao, D., Liu, D., & Feng, C. (2015). Upper limb motion tracking with the integration of IMU and Kinect. Neurocomputing, 159(1), 207–218. https://doi.org/10.1016/j.neucom.2015.01.071

Villani, V., Pini, F., Leali, F., & Secchi, C. (2018). Survey on human–robot collaboration in industrial settings: Safety, intuitive interfaces and applications. Mechatronics, 55, 248–266. https://doi.org/10.1016/j.mechatronics.2018.02.009

APPENDICES

Appendix A: REBA Worksheet



REBA Employee Assessment Worksheet

Permission granted by Dr Lynn McAnatomany to convert the paper based format to an Excel spreadsheet version.

A. Neck, Trunk and Leg Analysis

Step 1: Locate Neck Position

Step 1a Adjust...
If neck is twisted: +1
If neck is side bending: +1

Neck Score: 1

Step 2: Locate Trunk Position

Step 2a: Adjust...
If trunk is twisted: +1
If trunk is side bending: +1

Trunk Score: 1

Step 3: Legs

Adjust: 30-60° Add +1; 60° Add +2

Leg Score: 1

Step 4: Look-up Posture Score in Table A
Using values from steps 1-3 above, locate score in Table A

Posture Score A: 1
+

Step 5: Add Force/Load Score
If Load < 5kgs: +0
If Load is 5 to 10kgs: +1
If load > 22lbs: +2
Adjust: If shock or rapid build up of force: add +1

Force/Load Score: 0
=

Step 6: Score A, Find Row in Table C
Add values from steps 4 & 5 to obtain Score A.
Find row in Table C.

Score A: 1

Scoring:

1 = Negligible risk
2 or 3 = low risk, change may be needed
4 to 7 = medium risk, further investigation, change soon
8 to 10 = high risk, investigate & implement change
11+ = very high risk, implement change

SCORES

Table A

Trunk Posture Score	Neck 1, Legs 1	2	3	4	Neck 2, Legs 1	2	3	4	Neck 3, Legs 1	2	3	4
1	1	2	3	4	1	2	3	5	3	3	5	6
2	2	3	4	5	3	4	5	6	4	5	6	7
3	2	4	5	6	4	5	6	7	5	6	7	8
4	3	5	6	7	5	6	7	8	6	7	8	9
5	4	6	7	8	6	7	8	9	7	8	9	9

Table B

Upper Arm Score	Lower Arm 1, Wrist 1	2	3	Lower Arm 2, Wrist 1	2	3
1	1	2	2	1	2	3
2	1	2	3	2	3	4
3	3	4	5	4	5	5
4	4	5	5	5	6	7
5	6	7	8	7	8	8
6	7	8	8	8	9	9

Table C

Score A (score form table A +load/force score)	Score B, (table B value + coupling score) 1	2	3	4	5	6	7	8	9	10	11	12
1	1	1	1	2	3	3	4	5	6	7	7	7
2	1	2	2	3	4	4	5	6	6	7	7	8
3	2	3	3	3	4	5	6	7	7	8	8	8
4	3	4	4	4	5	6	7	8	8	9	9	9
5	4	4	4	5	6	7	8	8	9	9	9	9
6	6	6	6	7	8	8	9	9	10	10	10	10
7	7	7	7	8	9	9	9	10	10	11	11	11
8	8	8	8	9	10	10	10	10	10	11	11	11
9	9	9	9	10	10	10	11	11	11	12	12	12
10	10	10	10	11	11	11	11	12	12	12	12	12
11	11	11	11	11	11	12	12	12	12	12	12	12
12	12	12	12	12	12	12	12	12	12	12	12	12

Table C Score: 1 + Activity Score: 0

Final REBA Score: 1

B: Arms and Wrist Analysis

Step 7: Locate Upper Arm Position:

Step 7a: Adjust...
If shoulder is raised: +1
If Upper Arm is abducted: +1
If arm is supported or leaning: -1

Upper Arm Score: 1

Step 8: Locate Lower Arm Position:

Lower Arm Score: 1

Step 9: Locate Wrist Position:

Wrist Score: 2

Step 9a: Adjust.....
If wrist is bent from midline or twisted: Add +1

Step 10: Look-up Posture Score in Table B:
Using values from steps 7-9 above, locate score in Table B

Posture Score B: 2
+

Step 11: Add Coupling Score
Well fitted handles and mid range power grip, *good: +0*
Acceptable but not ideal hold or coupling
acceptable with another body part, *fair: +1*
Hand hold not acceptable but possible *poor: +2*
No handles, awkward, unsafe with any body part, *Unacceptable: +3*

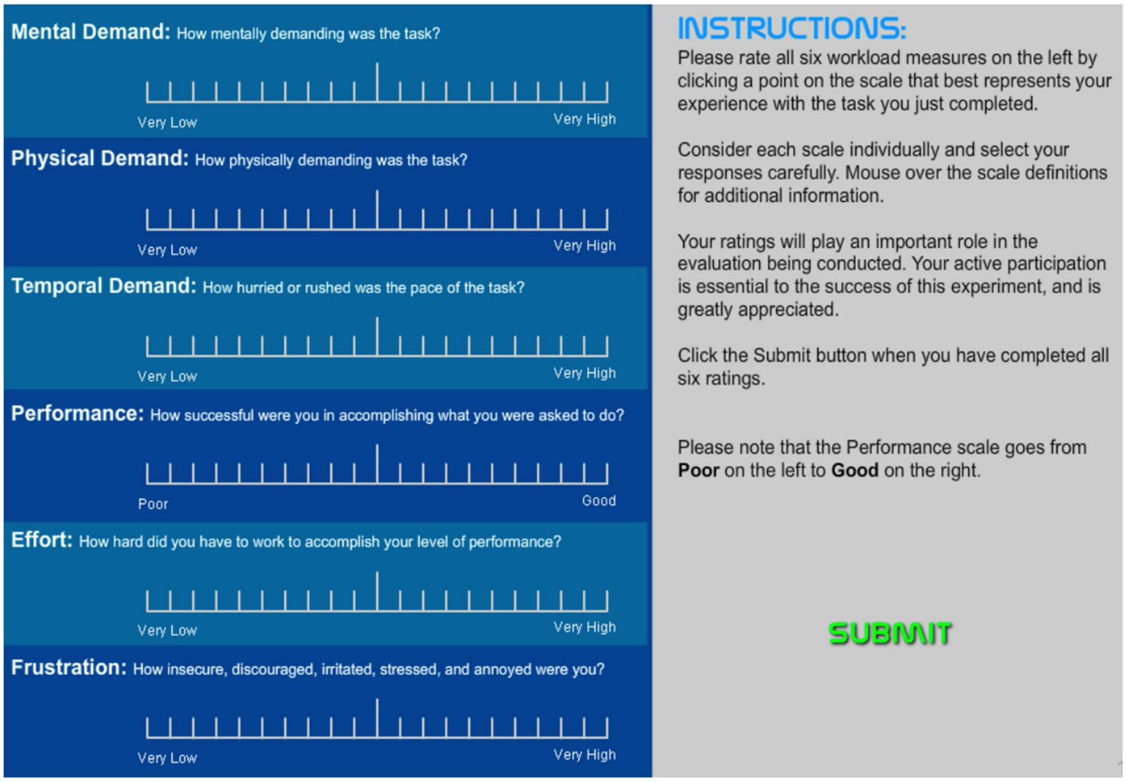
Coupling Score:
=

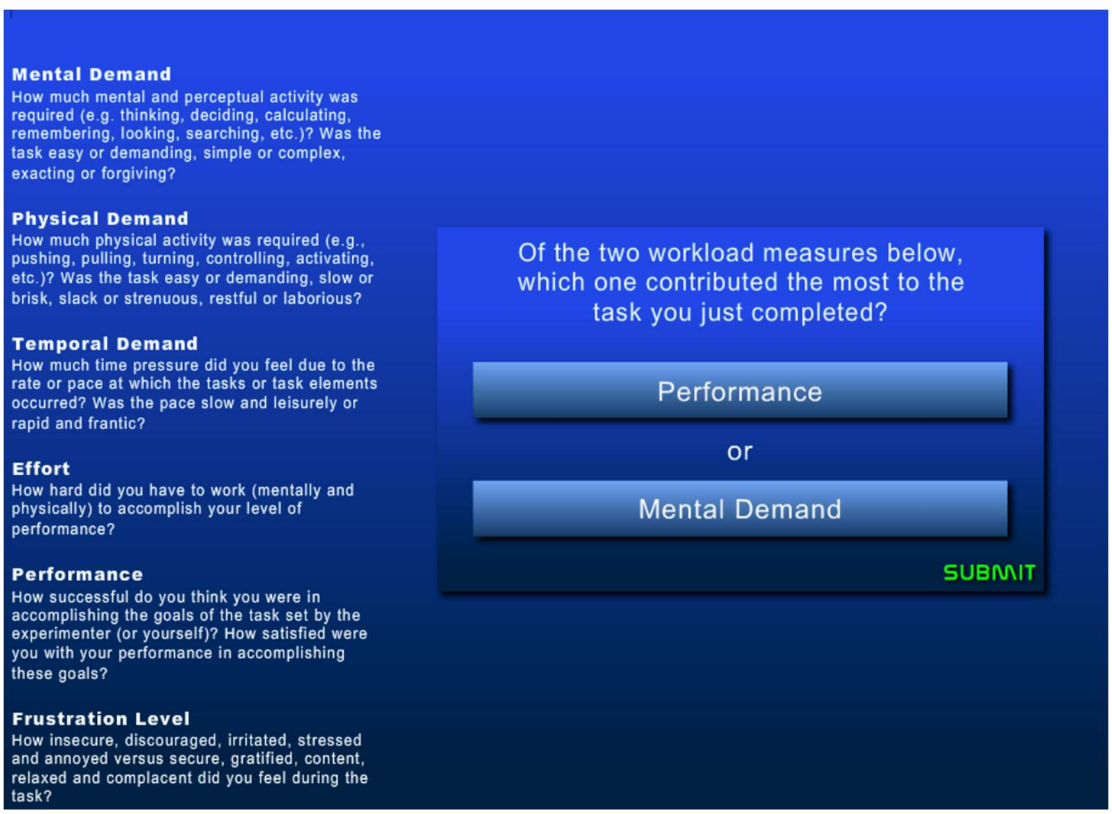
Step 12: Score B, Find column in Table C
Add values from steps 10 & 11 to obtain
Score B. Find Column in **Table C** and match with Score A in row from step 6 to obtain Table C score.

Score B: 2

Step 13: Activity Score
+1 1 or more body parts are held longer than a minute (static)
+1 Repeated small range actions (more than 4x per minute)
+1 Action causes rapid large range changes in postures or unstable base

Appendix B: NASA TLX





Appendix C: Likert Scale Survey

End of Study Survey

Rank agreeance from 1 - 5 where:
1 is “strongly disagree”
5 is “strongly agree”

1. I think that the robot is helpful in completing the task.	
2. The robot makes the task more difficult to complete	
3. The robot made the task easier	
4. I would have preferred doing the task alone	
5. I feel comfortable working with the robot	
6. I was afraid of working with the robot	
7. The behavior of the robot made me uncomfortable	
8. The robot helped make the task less physically exhausting.	
9. If I worked on this task with the robot in mode 3 every day for 8 hours a day I may experience a musculoskeletal injury	
10. If I completed this task by myself every day for 8 hours a day I may experience a musculoskeletal injury.	
11. If this were my job 8 hours a day, I would prefer to work with the robot in mode 3 than by myself.	

Appendix D: Randomization Table

Participant	Trial 1 Type	Trial 2 Type	Trial 3 Type	Trial 4 Type	Trial 5 Type	Trial 6 Type
1	1	3	1	2	3	2
2	2	3	2	1	1	3
3	1	2	1	3	2	3
4	2	3	1	3	1	2
5	2	3	1	3	1	2
6	1	2	3	1	2	3
7	2	1	2	1	3	3
8	2	3	2	1	1	3
9	2	3	1	3	1	2
10	3	1	3	2	1	2

Appendix E: Eligibility Survey

HRI Ergonomics Study Eligibility Criteria

Start of Block: Default Question Block

Q1 Please Enter your name.

____

Q2 Please provide your email address.

____

Q3 Do you have an allergy to Lycra (Spandex)?

- Yes (1)
- No (2)

Q4 Have you ever been diagnosed with any form of color-blindness?

- Yes (1)
- No (2)

Q9 Are you willing to bend, lift, and transfer objects that are approximately 10-20 lbs?

- Yes (1)
- No (2)

End of Block: Default Question Block

Appendix F: Informed Consent

North Carolina State University
INFORMED CONSENT FORM for RESEARCH

Title of Study/Repository: Ergonomic Human Robot Collaborations in Manufacturing Assembly Tasks using Inertial Measurement Sensor Feedback. (eIRB #19086)
Principal Investigator: Bobby Hazel, ryhazel@ncsu.edu, (919) 457-8640

Faculty Point of Contact: Dr. Xu Xu, xxu@ncsu.edu, (919) 513-7205

<u>What are some general things you should know about research studies?</u>
You are being asked to take part in a research study. Your participation in this study is voluntary. You have the right to be a part of this study, to choose not to participate and to stop participating at any time without penalty. The purpose of this research study is to investigate ergonomics in human-robot collaboration tasks.

The study uses Inertial Measurement Unit(IMU) Sensors to track body movement. IMUs are non-invasive sensors that are strapped to the body using velcro straps and a fitted shirt. Each of the sensors are placed on strategic locations of the body. they collect 3D coordinate, orientation and movement data.

You are not guaranteed any personal benefits from being in this study. Research studies also may pose risks to those who participate. You may want to participate in this research because you may gain some insight into how ergonomics research is conducted on biomechanical systems using inertial sensors and motion tracking. You may also be interested in participating to gain insight into collaborative robotic systems. You may not want to participate in this research because this experiment involves bending and light lifting exercises that may cause muscle fatigue.

In this consent form you will find specific details about the research in which you are being asked to participate. If you do not understand something in this form it is your right to ask the researcher for clarification or more information. A copy of this consent form will be provided to you. If at any time you have questions about your participation, do not hesitate to contact the researcher(s) named above or the NC State IRB office (contact information is noted below).

<u>What is the purpose of this study?</u>
The purpose of this research study is to investigate ergonomics in human-robot collaboration tasks. We collect data and make observations while you work with a robot to complete tasks. We have programmed the robot to hold and move items during tasks based on the way that your body is positioned.

<u>Am I eligible to be a participant in this study?</u>
There will be approximately 10-15 participants in this study.

- In order to be a participant in this study you must be between the ages of 18 and 55.
- You cannot participate in this study if you have a physical disability that would prevent you from lifting and handling object of 10-20 lbs.
- You must have full color vision.
- You must not have an allergy to Lycra(Spandex).
- You must be able to fit into a shirt size small to XL

<u>What will happen if you take part in the study?</u>
If you agree to participate in this study, you will be asked to follow this experimental procedure:

1. You will be asked to complete a demographic questionnaire. The information collected using the demographic questionnaire will be self-reported information about age, gender and overall health status. Body measurements such as height, arm span and leg length will be collected by the experimenter using a tape measure.

2. The experimenter will then assist you in securing the XSENS Inertial Measurement Units Sensors to your body. This is a non-invasive sensor system that is secured using a compression shirt for the torso (available in sizes Small to X-Large) and Velcro straps for the legs, arms and feet. The compression shirt can go over your normal shirt, you will not be required to remove any clothing. This setup will take approximately 15-20 minutes.
3. The experimenter will ask for verbal confirmation that the sensor suit is comfortable (Not too tight/loose, no impingement or pinching). You will be reminded that you should immediately notify the experimenter if you feel any discomfort at any time of the study. At no time will you be asked to complete maximum effort.
4. Before beginning the experiment, you will be shown how to complete each of the 3 trials listed in step 5 and you will be given a chance to practice each one. You will also be instructed to press the large, red emergency stop button if at any time you feel uncomfortable with the robot or experiment.
5. The experiment will be broken down into 3 trials that require different activity from you:
    a. Trial 1: You will stand at the simulated assembly line, collect an assembly task part from your left and place it in front of you. You will then complete the task by inserting the snap fit puzzle pieces into the corresponding colored holes on the assembly task part. You will then lift the assembly task part, walk a few paces to your right, and place it on a shelf to the left. This procedure will be completed X times successively, stacking each assembly task part on top of each other on the shelf. You will be instructed to complete the task quickly, but to prioritize accuracy and correctness.
    b. Trial 2: You will stand at the simulated assembly line at a position marked by masking tape. The robot will be holding the assembly task part in front of you in a position that is a safe distance but within reach. Illustration of this setup can be seen in. You will then complete the task by inserting the snap fit puzzle pieces into the corresponding colored holes on the assembly task part. The robot WILL NOT move towards you and will maintain a safe distance the entire time. When the task is completed, the robot will simulate placing the assembly task part on the shelf to the right. (In order to simplify the process, the robot will not actually let go of the part, just move it back to starting position) This procedure will be completed X times successively.
    c. Trial 3: You will stand at the simulated assembly line at a position marked by masking tape. The robot will be holding the assembly task part in front of you in a position that is a safe distance but within reach. This exact position will be determined based on ergonomic safety calculated using the Inertial Measurement Unit Sensor Suit. You will then complete the task by inserting the snap fit puzzle pieces into the corresponding colored holes on the assembly task part. The robot will move the assembly task part so that each snap fit action occurs at the same XYZ location. The robot will maintain a safe distance the entire time. When the task is completed, the robot will simulate placing the assembly task part on the shelf to the right. (In order to simplify the process, the robot will not actually let go of the part, just move it back to starting position) This procedure will be completed 5 times successively.
6. You will be asked to complete each trial (1, 2 or 3) 2 times. The order in which you complete the trials will be randomized and before each trial you will complete a practice trial.
7. After the completion of each trial (6 total) you will complete the perceived exertion survey.
8. After the completion of all of the trial, you will complete the End of Study Survey
9. Lastly, you will fill out a payment form and depart the lab. You will sign, date and write down the amount being compensated. The experimenter will witness you signing the payment form, and the experimenter will pay you right away. This form will be locked in the Ergonomics Laboratory while the study is in session. Upon completion of the entire study, the student researchers will submit this form to the accounting staff in the Industrial and Systems Engineering Department for record purposes. The entire length of the study will take around 2 hours.

The total amount of time that you will be participating in this study is approximately 2 hours.

Risks and benefits

There is minimal risk associated with this research. You will not be performing any heavy lifting, strenuous activity or other tasks that might lead to injury.

You will be interacting with a robotic arm but will not come into direct contact with it during the course of the experiment. The following safety measures are taken to further prevent risk related to the robotic arm:

- The researcher (Hazel) will instruct you to not make physical contact with the robot.
- You will be made aware of the robot movement path before the beginning of each trial.
- The robot is programmed to follow this path and will not perform erratic movements.
- The Rethink Robotics Sawyer Robot is designed to not generate only small amounts of twisting force to be harmful. It will not move quickly enough or push hard enough to cause harm.
- An area will be marked on the floor using tape to indicate the area that you should stand in. The study layout will be designed such that the robot arm will not enter this area or cross the boundary of the tape indicator.
- The robot being used is designed to be inherently safe and is meant to work in collaboration with humans. These safety features are compliant with the following international standards:
    - 10218-1:2011 “Robots and Robotic Devices -- Safety requirements for industrial robots”.
    - ISO/TS 15066:2016 “Robots and Robotic Devices - Collaborative Robots”
- The robot is equipped with an emergency stop button that will cut all power to the robot if necessary. The researcher and study attendant will have easy access to this button for the duration of the experiment.
- By design, the robot operates at human equivalent speeds that are limited by the power limits. This makes it easier for nearby people to avoid unintended contact with the robot.
- For this experiment, the robot has been programmed to not exceed 30% of the maximum speed to further increase safety.
- The robot has smooth, rounded arms with padding in key areas to minimize the chance of injury in the slim chance that contact occurs.
- The robot utilizes Series Elastic Actuator (SEAs): “flexures at all joints provide passive compliance to minimize the force of any contact or impact.”
- These actuators directly measure torque at every join to detect and respond to contact by pausing motion.
- You will be closely monitored for the duration of the experiment.

The likelihood of any injury or excess pain from this experiment is slim. If you experience any pain, you are told to let an experimenter know so the experiment can be stopped. You will be compensated for your time regardless.

If you are hurt or injured, the experimenter will contact the University’s emergency medical services.

You will be instructed to inform the researcher if you are experiencing physical or mental fatigue to the point where you no longer wish to continue. In this case the researcher will allow rest or end the study as needed. You will be compensated for your time regardless.

The inertial measurement sensors are attached to the body using a Lycra (spandex suit and straps). This may cause some mild skin irritation from rubbing. We have included in our exclusion criteria that you must not have an allergy to this material in order to minimize the risk of moderate to severe skin irritation. If the sensor suit/straps are causing irritation to the point where you do not wish to continue, the researcher will allow rest or end the study as needed. You will be compensated for their time regardless.

You are not guaranteed any personal benefits from being in this study. Research studies also may pose risks to those who participate. You may want to participate in this research because you may gain some insight into how ergonomics research is conducted on biomechanical systems using inertial sensors and motion tracking. You may also be interested in participating to gain insight into collaborative robotic systems. This research is expected to benefit the scientific community interested in collaborative robotics by providing further insights into the reduction of ergonomic risk using collaborative robots.

Right to withdraw your participation

You can stop participating in this study at any time. In order to stop your participation, please let an experimenter know and we will stop the experiment. If you choose to withdraw your consent and stop participating you can expect to be compensated for your time regardless.

Confidentiality

The information in the study records will be kept confidential to the full extent allowed by law. All data are collected using a password-protected desktop computer in a locked laboratory space. No data will be stored on laptops. Data will be stored securely on an NC State managed computer. Raw data will only be accessed by the research team, Xu and Hazel. Aggregate data, without identifying any participant in particular, may be shared in the form of a research paper or thesis. All payment information will be immediately submitted to the accounting staff in the Industrial and Systems Engineering Department for record purposes, and they will be locked in the office of the department accountant.

Compensation

For participating in this study you will receive $10 per hour. If you withdraw from the study prior to its completion, you will be paid at a rate prorated for the amount of time present. For example; if you participate for 1.5 hours, you will receive $15.

Emergency medical treatment

If you are hurt or injured during the study session(s), the researcher will contact the University's emergency medical services at 911 for necessary care. There is no provision for compensation or free medical care for you if you are injured as a result of this study.

What if you are an NCSU student?

Participation in this study is not a course requirement and your participation or lack thereof, will not affect your class standing or grades at NC State.

What if you are an NCSU employee?

Participation in this study is not a requirement of your employment at NCSU, and your participation or lack thereof, will not affect your job.

What if you have questions about this study?

If you have questions at any time about the study itself or the procedures implemented in this study, you may contact the researcher Bobby Hazel at ryhazel@ncsu.edu or (919) 457-8640

What if you have questions about your rights as a research participant?

If you feel you have not been treated according to the descriptions in this form, or your rights as a participant in research have been violated during the course of this project, you may contact the NC State IRB (institutional Review Board) Office via email at irb-director@ncsu.edu or via phone at 1.919.515.8754. You can also find out more information about research, why you would or would not want to be a research participant, questions to ask as a research participant, and more information about your rights by going to this website: http://go.ncsu.edu/research-participant

Consent To Participate

"I have read and understand the above information. I have received a copy of this form. I agree to participate in this study with the understanding that I may choose not to participate or to stop participating at any time without penalty or loss of benefits to which I am otherwise entitled."

Participant’s printed name ____________________________________

Participant's signature _______________________________________ **Date** _________________

Investigator's signature ______________________________________ **Date** _________________

Appendix G: Demographic Questionnaire

Pre Study Demographic Questionnaire

1. Subject ID: ____________________
2. Ethnic background: (circle one)
    a. American Indian or Alaskan Native
    b. Asian
    c. Native Hawaiian or Other Pacific Islander
    d. Black or African American, not of Hispanic origin
    e. Hispanic
    f. White, not of Hispanic origin
    g. Two or More Races
    h. Other
3. Sex/Gender: _______ /_______
4. Age: _________________________years old
5. Height: _______________________in/cm
6. Dominant hand
    a. Right
    b. Left
7. Do you have any experience working with robots?
    a. Yes
    b. No

    If yes, please explain:____
    ____
    ____
    ____
    ______

8. Do you have any experience working on a manufacturing floor?
    a. Yes
    b. No

    If yes, please explain:

9. Have you ever had injuries that would limit your ability to exercise your neck, shoulder, back, arms, or legs?
    a. Yes

b. No

If yes, please explain:____

Is this still a problem now?____

Appendix H: Source Code Information Reference

Source Code Information Reference (README)

REBAScoreAndMin.m

This is a MATLAB file that reads and processes data from the .mvnx files produced by the Xsens motion capture system. This script extracts the required data from the .mvnx tree structure and performs a series of calculations in order to determine REBA scores from the data. It will determine a REBA score value for each frame in the .mvnx file and plot the results. It also finds the minimum REBA score and determines important information for a human robot collaboration application.

Inputs:

- .mvnx file
    - Exported with the 'joint angle' option selected on the Xsens exporter
- Load Weight (User Input)
- Participant Handedness (User Input)
- Coupling Score (User Input)
- Activity Score (User Input)

Outputs:

- REBA Scores
    - One Score for each frame of the .mvnx file
    - Organized in a vector under the variable name 'RebaScore'
- Graph of the RebaScore vector
- h –vertical distance between the dominant hand and the left foot
- d – horizontal distance between the dominant hand and the left foot.

Additional Notes:

- Variables are created to hold the .mvnx data for each individual body part and are named using the side of the body (L/R), the body part, and the information it holds (flexion/twisting/abduction/etc.)
- Some lines that were used for testing and visualizing the program and different steps has been commented out and can be ignored if this code is reused.

tfuncs.py

This is a Python file that has several functions that were used to facilitate robot motion. It uses the Robot Operating System (ROS) framework and the Rethink Robotics Intera Motion Interface. It provides functions to setup an inverse kinematics service client and two other functions used to move the robot arm.

Functions:

ik_service_client()

- This function communicates with the robot to translate Cartesian end effector coordinates into desired poses via inverse kinematics from the base of the robot to the hand. It then solves the IK problem, checks that the solution is valid, and the returns joint angles for the solution.

go_to_angles()

- This functions takes inputs of joint angle, speed, acceleration, and a timeout goal and uses that information to move the robot arm to the specified joint angles. It utilizes the robot's built in motion controller interface to create a series of waypoints and trajectory.

move_arm()

- This function takes inputs of Cartesian xyz position and xyzw orientation. It starts an inverse kinematics service client by calling ik_service_client() and passes the joint angle results through go_to_angles().

task2.py

This is a Python file that moves the robot arm through a series of set motions. It initializes a ROS node (executable), defines some Cartesian end effector positions, and loops through sending those positions to the robot via the move_arm() function.

task3.py

This is a Python file that moves the robot arm through a series of motions. It initializes a ROS node (executable), defines some Cartesian end effector positions, and loops through sending those positions to the robot via the move_arm() function. In this case, the scripted is called with inputs for 'h' and 'd', which are variables determined by the REBAScoreAndMin.m file. These arguments change the Cartesian end effector positions that are sent to the inverse kinematic service client and ultimately, to the robot.

Calling task2.py and task3.py

Assuming that the ROS workspace has been properly configured according to instructions, task2.py and task3.py can be called as follows whiles in the directory holding the files:

python task2.py

python task3.py h d

(Where 'h' and 'd' are numerical values)

Appendix I: REBAScoreAndMin.m - Source Code for the Automated REBA Scoring Tool

```
tree = load_mvnx('Test_Bobby-001');
% read some basic data from the file
mvnxVersion = tree;
fileComments = tree.subject.comment;
%read some basic properties of the subject;
frameRate = tree.subject.frameRate;
suitLabel = tree.subject.label;
originalFilename = tree.subject.originalFilename;
recDate = tree.subject.recDate;
segmentCount = tree.subject.segmentCount;
%retrieve sensor labels
%creates a struct with sensor data
% sensorData = tree.subject.sensors.sensor;
%retrieve segment labels
%creates a struct with segment definitions
segmentData = tree.subject.segments.segment;
%%
%extract joint angles from .mvnx file (see main_mvnx.m)
nSamples = length(tree.subject.frames.frame);
start = 3000;
stop = 10000;
%nSamples = length(start:stop);
for i=[4:nSamples]
    joint_angles(i,:)=tree.subject.frames.frame(i).jointAngle;
end

%% calculating h and d
pelvis_p = zeros(nSamples,3);
for i=[1:nSamples]
    pelvis_p(i,:)=tree.subject.frames.frame(i).position(1:3);
end
rfoot_p = zeros(nSamples,3);
for i=[1:nSamples]
    rfoot_p(i,:)=tree.subject.frames.frame(i).position(55:57);
end
rhand_p = zeros(nSamples,3);
for i=[1:nSamples]
    rhand_p(i,:)=tree.subject.frames.frame(i).position(31:33);
end

lfoot_p = zeros(nSamples,3);
for i=[1:nSamples]
    lfoot_p(i,:)=tree.subject.frames.frame(i).position(67:69);
end
lhand_p = zeros(nSamples,3);
for i=[1:nSamples]
    lhand_p(i,:)=tree.subject.frames.frame(i).position(43:45);
end

hr = abs(rhand_p(:,3) - rfoot_p(:,3));
dr = rhand_p(:,2) - pelvis_p(:,2);

hl = abs(lhand_p(:,3) - lfoot_p(:,3));
```

```
dl = lhand_p(:,2) - pelvis_p(:,2);
%%

% indexing important variables
% X = Abduct/Adduct,
% Y = Rotation,
% Z = flex/extend

%C1HeadZ+
NeckFlex= joint_angles(:,18);

%C1HeadY
NeckTwist= joint_angles(:,17);

%C1HeadX
NeckBend = joint_angles(:,16);

%%trunk Angle:
p_Segment1 = zeros(nSamples,3);
for i=[1:nSamples]
    p_Segment1(i,:)=tree.subject.frames.frame(i).position(1:3);
end
p_Segment2 = zeros(nSamples,3);
for i=[1:nSamples]
    p_Segment2(i,:)=tree.subject.frames.frame(i).position(16:18);
end

% trunk vector setup
% we want the angle between the trunk and a vector originating at the
% pelvis and parallel with the y axis. The sagittal plane would not
% accurately represent the angle between the trunk and the lower body.
trunk_vector = p_Segment2 - p_Segment1;
y_axis = [zeros(nSamples,1),zeros(nSamples,1),ones(nSamples,1)];
y_point = p_Segment1 + y_axis;
y_vector = p_Segment1 - y_point;

% %visualize trunk vectors
%  lines = length(p_Segment1);
%  for i=[1:lines]
%      hold on
%
plot3([p_Segment1(i,1),p_Segment2(i,1)],[p_Segment1(i,2),p_Segment2(i,2)],[p_
Segment1(i,3),p_Segment2(i,3)], '-b')
%
plot3([p_Segment1(i,1),y_point(i,1)],[p_Segment1(i,2),y_point(i,2)],[p_Segmen
t1(i,3),y_point(i,3)], '-r')
%  end

% Calculate trunk Angle:
TrunkFlex = zeros(1,nSamples);
for i = 1:nSamples

%TrunkFlex(1,i) =acosd(dot(trunk_vector(i,1:3)
,y_vector(i,1:3))/(dot(norm(trunk_vector(i,1:3)),norm(y_vector(i,1:3)))));
```

```
TrunkFlex(1,i) =
atan2d(norm(cross(trunk_vector(i,:),y_vector(1,:))),dot(trunk_vector(1,:),y_v
ector(1,:)));
end
%correct for trig
TrunkFlex = abs(TrunkFlex - 180);

%L1T12Y -- greater than 2 degrees.
TrunkTwist = joint_angles(:,8);
%L1T12X -- need to calibrate degree amount
TrunkBend = joint_angles(:,7);
%RKneeZ
RKneeFlex = joint_angles(:,48);
%LKneeZ
LKneeFlex = joint_angles(:,60);
%RShoulderZ
RShoulderFlex = joint_angles(:,24);
%RShoulderX
RShoulderAbd = joint_angles(:,22);
%LShoulderZ
LShoulderFlex = joint_angles(:,36);
%LShoulderX
LShoulderAbd = joint_angles(:,34);
%RElbowZ
RElbowFlex = joint_angles(:,27);
%LElbowZ
LElbowFlex = joint_angles(:,39);
%RWristZ -- can use absolute value
RWristFlex = joint_angles(:,30);
%LWristZ
LWristFlex = joint_angles(:,42);
%RWristY
RWristTwist = joint_angles(:,29);
%LWristY
LWristTwist = joint_angles(:,41);
%%
 %REBA calculation
 %% User Inputs
 LoadWeight =input("Please enter the weight of the load in kg:");
 if LoadWeight <= 5
     LoadScore = 0;
 elseif (LoadWeight > 5) && (LoadWeight < 10)
     LoadScore = 1;
 elseif LoadWeight > 10
     LoadScore = 2;
 end

 CouplingScore = input("Please enter a coupling score (Refer to handout):");
 ActivityScore = input("Please enter an activity score(Refer to handout):");
 Hand = input("Enter 1 for right handed and 0 for left handed:");
 %% Neck Score
 NeckScore = zeros(length(NeckFlex),1);
 for i = 1:length(NeckFlex)
     % Neck Flexion and Extension
     if (0 < NeckFlex(i)) && (NeckFlex(i) < 20)
         NeckScore(i) = 1;
```

```
    else
        NeckScore(i) = 2;
    end

    % Neck Twisting
   % if (NeckTwist(i) > 10) || (NeckTwist(i) < -10)
   %      NeckScore(i) = NeckScore(i) + 1;
    %else
 %        NeckScore(i) = NeckScore(i);
   % end

    %Neck Side Bending
    if (NeckBend(i) > 10) || (NeckBend(i) < -10)
        NeckScore(i) = NeckScore(i) + 1;
    else
        NeckScore(i) = NeckScore(i);
    end

end
%% Trunk Score

TrunkScore = zeros(length(TrunkFlex),1);
for i = 1:length(TrunkFlex)
    % Trunk Flexion and Extension
    if TrunkFlex(i)== 0
        TrunkScore(i) = 1;
    elseif (TrunkFlex(i) <= 20) && (TrunkFlex(i) ~= 0)
        TrunkScore(i) = 2;
    elseif (TrunkFlex(i) > 20) && (TrunkFlex(i) <= 60)
        TrunkScore(i) = 3;
    else
        TrunkScore(i) = 4;
    end

    % Trunk Twisting
    if (TrunkTwist(i) > 2) || (TrunkTwist(i) < -2)
        TrunkScore(i) = TrunkScore(i) + 1;
    else
        TrunkScore(i) = TrunkScore(i);
    end

    %Trunk Side Bending
    if (TrunkBend(i) > 3) || (TrunkBend(i) < -3)
        TrunkScore(i) = TrunkScore(i) + 1;
    else
        TrunkScore(i) = TrunkScore(i);
    end

end
%% Leg Score

% Right Side
RLegScore = zeros(length(RKneeFlex),1);
for i = 1:length(RKneeFlex)
    if (RKneeFlex(i) <= 60) && (RKneeFlex(i) >=30)
```

```
        RLegScore(i) = 1;
    elseif RKneeFlex(i) < 30
        RLegScore(i) = 0;
    else
        RLegScore(i) = 2;
    end
 end
 % Left Side

 LLegScore = zeros(length(LKneeFlex),1);
  for i = 1:length(LKneeFlex)
    if (LKneeFlex(i) <= 60) && (LKneeFlex(i) >=30)
        LLegScore(i) = 1;
    elseif RKneeFlex(i) < 30
        LLegScore(i) = 0;
    else
        LLegScore(i) = 2;
    end
 end
% Total Leg Score
LegScore = zeros(length(RKneeFlex),1);
for i = 1:length(RLegScore)
    if RLegScore(i) == LLegScore(i)
        LegScore(i) = RLegScore(i) + 1;
    else
        if RLegScore(i) > LLegScore(i)
            LegScore(i) = RLegScore(i) + 2;
        elseif RLegScore(i) < LLegScore(i)
            LegScore(i) = LLegScore(i) + 2;
        end
    end
end

%% Table A Score
TableA =
[[1,2,3,4,1,2,3,5,3,3,5,6];[2,3,4,5,3,4,5,6,4,5,6,7];[2,4,5,6,4,5,6,7,5,6,7,8
];[3,5,6,7,5,6,7,8,6,7,8,9];[4,6,7,8,6,7,8,9,7,8,9,9]];
ScoreA = zeros(length(LegScore),1);
TableAScore = zeros(length(LegScore),1);
for i = 1:length(LegScore)
    if NeckScore(i) == 1
        TableAScore(i) = TableA(TrunkScore(i),LegScore(i));
    elseif NeckScore(i) == 2
        TableAScore(i) = TableA(TrunkScore(i),LegScore(i) + 4);
    elseif NeckScore(i) == 3
        TableAScore(i) = TableA(TrunkScore(i),LegScore(i) + 8);
    else
        TableAScore(i) = 0;
    end
ScoreA(i) = TableAScore(i) + LoadScore;
end


%% Upper Arm Score
RUpperArmScore = zeros(length(RShoulderFlex),1);
for i = 1:length(RShoulderFlex)
```

```
    if (RShoulderFlex(i) > -20) && (RShoulderFlex(i) < 20)
        RUpperArmScore(i) = 1;
    elseif (RShoulderFlex(i) < -20) || ((RShoulderFlex(i) >= 20) &&
(RShoulderFlex(i) <= 45))
        RUpperArmScore(i) = 2;
    elseif (RShoulderFlex(i) > 45) && (RShoulderFlex(i) <= 90)
        RUpperArmScore(i) = 3;
    elseif RShoulderFlex(i) > 90
        RUpperArmScore(i) = 4;
    else
        RUpperArmScore(i) = 0;
    end
    if RShoulderAbd(i) >=30
        RUpperArmScore(i) = RUpperArmScore(i) + 1;
    else
        RUpperArmScore(i) = RUpperArmScore(i);
    end
end
LUpperArmScore = zeros(length(LShoulderFlex),1);
for i = 1:length(LShoulderFlex)
    if (LShoulderFlex(i) > -20) && (LShoulderFlex(i) < 20)
        LUpperArmScore(i) = 1;
    elseif (LShoulderFlex(i) < -20) || ((LShoulderFlex(i) >= 20) &&
(LShoulderFlex(i) <= 45))
        LUpperArmScore(i) = 2;
    elseif (LShoulderFlex(i) > 45) && (LShoulderFlex(i) <= 90)
        LUpperArmScore(i) = 3;
    elseif LShoulderFlex(i) > 90
        LUpperArmScore(i) = 4;
    else
        LUpperArmScore(i) = 0;
    end
    if LShoulderAbd(i) >=30
        LUpperArmScore(i) = LUpperArmScore(i) + 1;
    else
        LUpperArmScore(i) = LUpperArmScore(i);
    end
end
%% Lower Arm Score
RLowerArmScore = zeros(length(RElbowFlex),1);
for i = 1:length(RElbowFlex)
    if (RElbowFlex(i) >= 100) || (RElbowFlex(i) <= 60)
        RLowerArmScore(i) = 2;
    else
        RLowerArmScore(i) = 1;
    end
end
LLowerArmScore = zeros(length(LElbowFlex),1);
for i = 1:length(LElbowFlex)
    if (LElbowFlex(i) >= 100) || (LElbowFlex(i) <= 60)
        LLowerArmScore(i) = 2;
    else
       LLowerArmScore(i) = 1;
    end
end
%% Wrist Score
RWristScore = zeros(length(RWristFlex),1);
```

```
for i = 1:length(RWristFlex)
    if (RWristFlex(i) >= 15) || (RWristFlex(i) <= -15)
        RWristScore(i) = 2;
    else
        RWristScore(i) = 1;
    end
    if (RWristTwist(i) >= 30) || (RWristTwist(i) <= -30)
        RWristScore(i) = RWristScore(i) + 1;
    else
        RWristScore(i) = RWristScore(i);
    end
end

LWristScore = zeros(length(LWristFlex),1);
for i = 1:length(LWristFlex)
    if (LWristFlex(i) >= 15) || (LWristFlex(i) <= -15)
        LWristScore(i) = 2;
    else
        LWristScore(i) = 1;
    end
    if (LWristTwist(i) >= 30) || (LWristTwist(i) <= -30)
        LWristScore(i) = LWristScore(i) + 1;
    else
        LWristScore(i) = LWristScore(i);
    end
end

%% Table B
TableB =
[[1,2,2,1,2,3];[1,2,3,2,3,4];[3,4,5,4,5,5];[4,5,5,5,6,7];[6,7,8,7,8,8];[7,8,8
,8,9,9]];
ScoreB = zeros(length(RWristScore),1);
TableBScoreR = zeros(length(RWristScore),1);
for i = 1:length(RWristScore)
    if RLowerArmScore(i) == 1
        TableBScoreR(i) = TableB(RUpperArmScore(i),RWristScore(i));
    elseif RLowerArmScore(i) == 2
        TableBScoreR(i) = TableB(RUpperArmScore(i),RWristScore(i) + 3);
    else
        TableBScoreR(i) = 0;
    end
end
TableBScoreL = zeros(length(LWristScore),1);
for i = 1:length(LWristScore)
    if LLowerArmScore(i) == 1
        TableBScoreL(i) = TableB(LUpperArmScore(i),LWristScore(i));
    elseif LLowerArmScore(i) == 2
        TableBScoreL(i) = TableB(LUpperArmScore(i),LWristScore(i) + 3);
    else
        TableBScoreL(i) = 0;
    end
end

TableBScore = zeros(length(TableBScoreL),1);
for i = 1:length(TableBScoreL)
    if TableBScoreL(i) > TableBScoreR(i)
```

```
        TableBScore(i) = TableBScoreL(i);
    elseif TableBScoreL(i) < TableBScoreR(i)
        TableBScore(i) = TableBScoreR(i);
    else
        TableBScore(i) = TableBScoreR(i);
    end
end
for i = 1:length(RWristScore)
    ScoreB(i) = TableBScore(i) + CouplingScore;
end

%% Table C Score
TableC =
[[1,1,1,2,3,3,4,5,6,7,7,7];[1,2,2,3,4,4,5,6,6,7,7,8];[2,3,3,3,4,5,6,7,7,8,8,8
];

[3,4,4,4,5,6,7,8,8,9,9,9];[4,4,4,5,6,7,8,8,9,9,9,9];[6,6,6,7,8,8,9,9,10,10,10
,10];

[7,7,7,8,9,9,9,10,10,11,11,11];[8,8,8,9,10,10,10,10,10,11,11,11];[9,9,9,10,10
,10,11,11,11,12,12,12];

[10,10,10,11,11,11,11,12,12,12,12,12];[11,11,11,11,11,12,12,12,12,12,12,12];
    [12,12,12,12,12,12,12,12,12,12,12,12]];

TableCScore = zeros(length(ScoreB),1);
for i = 1:length(ScoreB)
    TableCScore(i) = TableC(ScoreA(i),ScoreB(i));
end
%% REBA Score and Plot
RebaScore = TableCScore + ActivityScore;
x = 1:length(RebaScore);
hold on
for i = 1:length(x)
    if RebaScore(i) == 1
        plot(x(i),RebaScore(i),'cs')
    elseif (RebaScore(i) == 3) || (RebaScore(i) == 2)
        plot(x(i),RebaScore(i),'gs')
    elseif (RebaScore(i) >= 4) && (RebaScore(i) <= 7)
        plot(x(i),RebaScore(i),'ys')
    elseif (RebaScore(i) >= 8) && (RebaScore(i) <= 10)
        plot(x(i),RebaScore(i),'rs')
    elseif RebaScore(i) >= 11
        plot(x(i),RebaScore(i),'ms')
    end
end
plot(RebaScore, 'k')
ylabel({'REBA Score'});
xlabel({'Frame'});
title({'REBA Score for Test IMU Trial'});
ylim([0,15]);

csvwrite('RebaScore',RebaScore)

%% Find minimum
%AdjRebaScore = RebaScore(2000:(end-2000),:);
```

```
AdjRebaScore = RebaScore;
[MinScore,MinIndex] = min(AdjRebaScore);

%% Sync minimum and hMin & dMin
if Hand == 1
    %Adjh = hr(2000:(end-2000),:);
    %Adjd = dr(2000:(end-2000),:);
    Adjh = hr;
    Adjd = dr;
else
    %Adjh = hl(2000:(end-2000),:);
    %Adjd = dl(2000:(end-2000
    Adjh = hl;
    Adjd = dl;
end

hMin = Adjh(MinIndex);
dMin = Adjd(MinIndex);

%setting safety bound for the d variable
if dMin < 0.5
    dMin = 0.5;
elseif dMin >0.8
    dMin = 0.8;
else
    dMin;
end

disp(hMin)
disp(dMin)
```

Appendix J: tfuncs.py - Source Code for Robot Control Functions

```
import rospy
from geometry_msgs.msg import (
    PoseStamped,
    Pose,
    Point,
    Quaternion,
)
from std_msgs.msg import Header
from sensor_msgs.msg import JointState

from intera_core_msgs.srv import (
    SolvePositionIK,
    SolvePositionIKRequest,
)

import argparse
from intera_motion_interface import (
    MotionTrajectory,
    MotionWaypoint,
    MotionWaypointOptions
)
from intera_interface import Limb

# Set up the inverse kinematics service client
def ik_service_client(limb = "right", use_advanced_options = False,
position_xyz=[0,0,0], orientation_xyzw=[0,0,0,0]):

    # return value
    class ret:
   def __init__(self):
      self.result=False
      self.angle=[]
    ret=ret()


    ns = "ExternalTools/" + limb + "/PositionKinematicsNode/IKService"
    iksvc = rospy.ServiceProxy(ns, SolvePositionIK)
    ikreq = SolvePositionIKRequest()
    hdr = Header(stamp=rospy.Time.now(), frame_id='base')
    poses = {
        'right': PoseStamped(
            header=hdr,
            pose=Pose(
                position=Point(
                    x=position_xyz[0],
                    y=position_xyz[1],
                    z=position_xyz[2],
                ),
                orientation=Quaternion(
                    x=orientation_xyzw[0],
                    y=orientation_xyzw[1],
                    z=orientation_xyzw[2],
                    w=orientation_xyzw[3],
                ),
            ),
        ),
    }
    # Add desired pose for inverse kinematics
    ikreq.pose_stamp.append(poses[limb])
    # Request inverse kinematics from base to "right_hand" link
```

```
    ikreq.tip_names.append('right_hand')

    if (use_advanced_options):
        # Optional Advanced IK parameters
        rospy.loginfo("Running Advanced IK Service Client example.")
        # The joint seed is where the IK position solver starts its optimization
        ikreq.seed_mode = ikreq.SEED_USER
        seed = JointState()
        seed.name = ['right_j0', 'right_j1', 'right_j2', 'right_j3',
                     'right_j4', 'right_j5', 'right_j6']
        seed.position = [0.7, 0.4, -1.7, 1.4, -1.1, -1.6, -0.4]
        ikreq.seed_angles.append(seed)

        # Once the primary IK task is solved, the solver will then try to bias the
        # the joint angles toward the goal joint configuration. The null space is
        # the extra degrees of freedom the joints can move without affecting the
        # primary IK task.
        ikreq.use_nullspace_goal.append(True)
        # The nullspace goal can either be the full set or subset of joint angles
        goal = JointState()
        goal.name = ['right_j1', 'right_j2', 'right_j3']
        goal.position = [1, -1, 2]
        ikreq.nullspace_goal.append(goal)
        # The gain used to bias toward the nullspace goal. Must be [0.0, 1.0]
        # If empty, the default gain of 0.4 will be used
        ikreq.nullspace_gain.append(0.4)
    else:
        rospy.loginfo("Running Simple IK Service Client example.")

    try:
        rospy.wait_for_service(ns, 5.0)
        resp = iksvc(ikreq)
    except (rospy.ServiceException, rospy.ROSException), e:
        rospy.logerr("Service call failed: %s" % (e,))
        return ret

    # Check if result valid, and type of seed ultimately used to get solution
    if (resp.result_type[0] > 0):
        seed_str = {
                    ikreq.SEED_USER: 'User Provided Seed',
                    ikreq.SEED_CURRENT: 'Current Joint Angles',
                    ikreq.SEED_NS_MAP: 'Nullspace Setpoints',
                   }.get(resp.result_type[0], 'None')
        rospy.loginfo("SUCCESS - Valid Joint Solution Found from Seed Type: %s" %
              (seed_str,))
        # Format solution into Limb API-compatible dictionary
        limb_joints = dict(zip(resp.joints[0].name, resp.joints[0].position))
        rospy.loginfo("\nIK Joint Solution:\n%s", limb_joints)
        rospy.loginfo("------------------")
        rospy.loginfo("Response Message:\n%s", resp)
   ret.angle=list(resp.joints[0].position)
        ret.result=True
    else:
        rospy.logerr("INVALID POSE - No Valid Joint Solution Found.")
        rospy.logerr("Result Error %d", resp.result_type[0])
        return ret

    return ret


# joint angle motion control for convenient positioning
def go_to_angles(joint_angles_goal, speed_ratio_goal, accel_ratio_goal, timeout_goal):
    try:
```

```
        #rospy.init_node('go_to_joint_angles_py')
        limb = Limb()
        traj = MotionTrajectory(limb = limb)

        wpt_opts = MotionWaypointOptions(max_joint_speed_ratio=speed_ratio_goal,
                                         max_joint_accel=accel_ratio_goal)
        waypoint = MotionWaypoint(options = wpt_opts.to_msg(), limb = limb)

        joint_angles = limb.joint_ordered_angles()

        waypoint.set_joint_angles(joint_angles = joint_angles)
        traj.append_waypoint(waypoint.to_msg())

        if len(joint_angles_goal) != len(joint_angles):
            rospy.logerr('The number of joint_angles must be %d', len(joint_angles))
            return None

        waypoint.set_joint_angles(joint_angles = joint_angles_goal)
        traj.append_waypoint(waypoint.to_msg())

        result = traj.send_trajectory(timeout=timeout_goal)
        if result is None:
            rospy.logerr('Trajectory FAILED to send')
            return

        if result.result:
            rospy.loginfo('Motion controller successfully finished the trajectory!')
        else:
            rospy.logerr('Motion controller failed to complete the trajectory with
error %s',
                         result.errorId)
    except rospy.ROSInterruptException:
        rospy.logerr('Keyboard interrupt detected from the user. Exiting before
trajectory completion.')


# function that calls the ik_service_client and calculates for a set of xyz cartesian
positions and xyzw orientations
def move_arm(xyz, xyzw):
    IK_result=ik_service_client(use_advanced_options=True, position_xyz=xyz,
orientation_xyzw=xyzw)
    if IK_result.result:
        rospy.loginfo("Advanced IK call passed!")
        print("joint angle:", IK_result.angle)
        go_to_angles(IK_result.angle, 0.1, 0.1, 1) # go to the solved joint angle
    else:
        rospy.logerr("Advanced IK call FAILED")
```

Appendix K: task2.py - Source Code for Trial Type 2 Robot Control

```
from tfuncs import *

# initialize the service (only once)
rospy.init_node("rsdk_ik_service_client")

# input parameter for solving IK

# defining cartesian positions for the arm
pos_1 = [0.4,-0.0,0.3011]
orient_1=[1.0,0.0,1.0,0.0]

pos_2 = [0.198,-0.419,0.275]
orient_2=[0.484,-0.476,0.5088,0.528]

# looping through positions by calling the move_arm IK function from tfuncs.py
for i in range(5):
   move_arm(pos_1,orient_1)
   rospy.sleep(45.0)
   move_arm(pos_2,orient_2)
   rospy.sleep(22.0)
```

Appendix L: task2.py - Source Code for Trial Type 2 Robot Control

```
from tfuncs import *
import sys

# prompt user inputs for h and d
h = float(sys.argv[1])
d = float(sys.argv[2])

# initialize the service (only once)
rospy.init_node("rsdk_ik_service_client")
# input parameter for solving IK
z_bot = (h- 0.92) + 0.475
z_cen = h - 0.92
z_top = (h-0.92) - 0.475

x = 1.2 - d

# safety lock for the x axis to keep the arm within a safe distance from the subject
if x > .85:
   x = 0.85
else:
   x = x

# defining cartesian positions for the arm
# bottom
pos_1 = [x,-0.0,z_bot]
orient_1=[1.0,0.0,1.0,0.0]
# center
pos_2 = [x,-0.0,z_cen]
orient_2=[1.0,0.0,1.0,0.0]
# top
pos_3 = [x,-0.0,z_top]
orient_3=[1.0,0.0,1.0,0.0]
# exchange
pos_4 = [0.198,-0.419,0.275]
orient_4=[0.484,-0.476,0.5088,0.528]

# looping through positions by calling the move_arm IK function from tfuncs.py
for i in range(5):
   move_arm(pos_1,orient_1)
   rospy.sleep(22.0)
   move_arm(pos_2,orient_2)
   rospy.sleep(18.0)
   move_arm(pos_3,orient_3)
   rospy.sleep(16.0)
   move_arm(pos_4,orient_4)
   rospy.sleep(20.0)
```