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Advancing Loose Part Monitoring System with Deep Learning Techniques

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ABSTRACT

Loose part monitoring systems (LPMS) monitor loose parts in the primary system of nuclear power plants. Loose parts can damage the pipelines and vessels of the reactor system. It is important to estimate the impact location within a proper time limit for maintenance decision making. The paper proposes a deep-learning-based method that estimates the impact location hit by loose parts. First, the time difference of arrival (TDOA) of the impact signal is estimated using the anomaly detection method. Then, domain-knowledge guided neural networks are designed to estimate wave velocity. Finally, the impact locations are determined using the triangulation method. The proposed method is verified using experimental data from the simple steel plate. The experimental results show the effectiveness of the proposed method.

INTRODUCTION

Inside the primary system of the nuclear power plant, the generation of metal fragments may arise from various factors, including the degradation of internal structural integrity, corrosion, wear, or the inflow of foreign substances in maintenance period. These metal fragments collide with the internal surface of the steam generator along the rapid and high-pressure coolant flow, it has the potential to inflict substantial damage upon the primary system of the nuclear power plant. Loose part monitoring systems (LPMS) are employed for assessment of damage caused by metal fragments within the primary system.

LPMS employs acceleration signals obtained from the sensors positioned within the reactor and steam generator to estimate the impact location and mass of the metal fragment. Despite the established procedures within the existing method for LPMS, there exists a significant degree of uncertainty in determining the impact position and mass. Consequently, a domain expert intervenes to provide the final calculation for these parameters. The exigency of this process demands swift execution within predefined temporal constraints, and the outcome is reliant on the subjective judgment of the domain expert. Thus, there is a need for an efficacious implementation methodology for LPMS.

Several studies have been conducted on impact localization. Choi et al. (2011) presented a methodology for estimating the time difference of arrival (TDOA) through the envelope phase delay of impact signals, subsequently employing triangulation method for the estimation of impact location. Gorgin et al. (2021) presented a probability-based approach for impact localization. The methodology entails identifying the arrival time of the impact signal by determining when the root mean square value of the impact signal amplitude surpasses a threshold that expert determined. Subsequently, the impact position is probabilistically estimated through the calculation of the error index parameter, which is based on TDOA of the impact signal. Kalimullha et al. (2023) presented a method for estimating impact positions on anisotropic plates utilizing a multi-fidelity physics-informed neural network. The determination of TDOA for the impact signal involves the envelope method, followed by experimental determination of the wave velocity. Subsequent steps encompass physics-informed neural network learning, utilizing triangulation method as a loss function with low fidelity data which is simulation data, and transfer learning through fine-tuning the neural network. These methods require expert experience for each impact signal during TDOA estimation, which affects the accuracy of the determined impact location. Therefore, impact localization process needs to be automated to address the need to reduce expert fatigue.

To address this issue, this paper proposes a method for a deep learning-based approach to estimate the impact location of foreign substances. The accuracy of the proposed method was assessed through the experimental data to impact position estimation on a steel plate. Furthermore, Gaussian noise was added to the experimental data to evaluate the robustness of the proposed method in the noise.

METHODOLOGY

This study employs a deep learning based method for the estimation TDOA of impact signals and wave velocity, crucial variables for impact location determination, and subsequently proposes a methodology for impact location estimation. Figure 1 illustrates the comprehensive process of the proposed method. Initially, the arrival time of the impact wave at each sensor is estimated, using anomaly detection, a method of self-supervised learning and calculate TDOA. Subsequently, the wave velocity is determined utilizing domain-knowledge guided neural networks. The impact coordinates are then estimated by applying the calculated TDOA and wave velocity values into triangulation method.

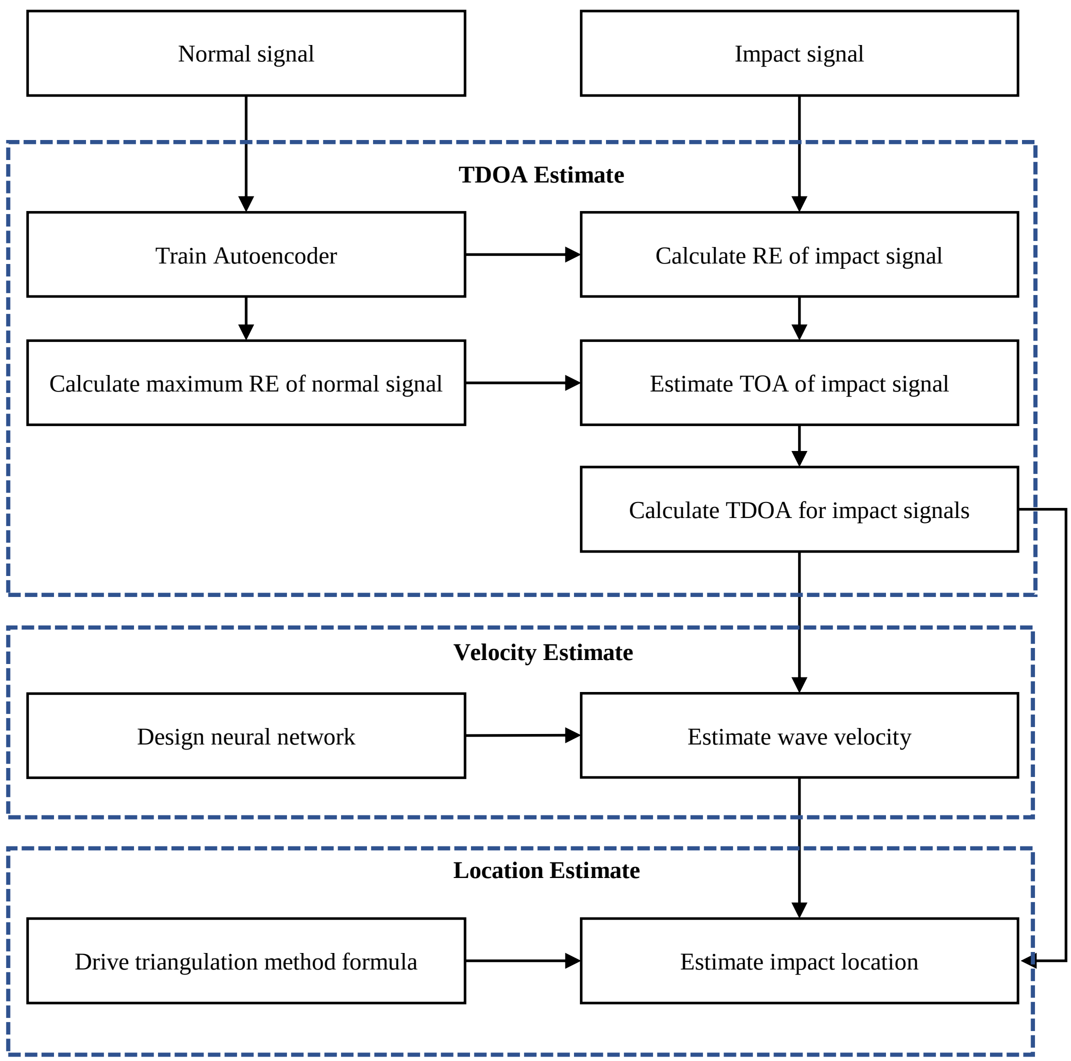
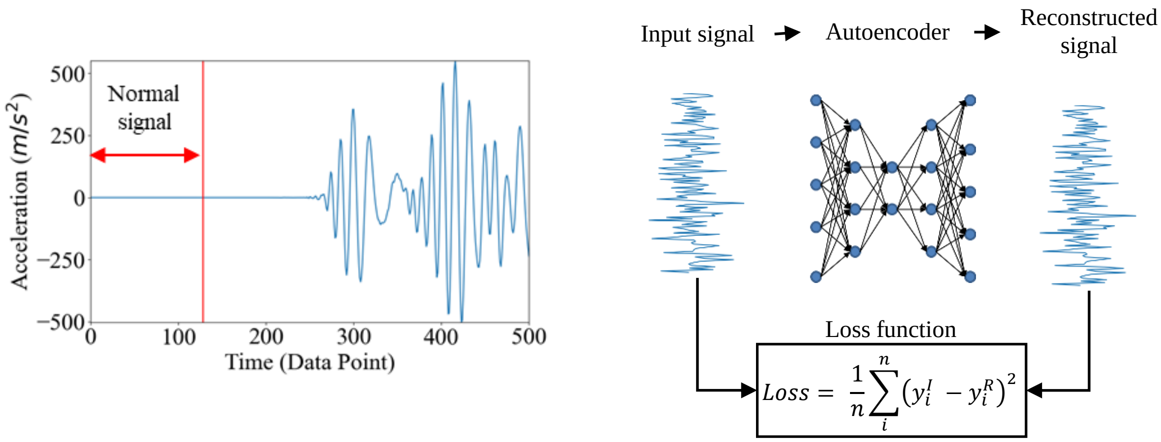


Figure 1. Overall procedure for location estimation

TDOA Estimate Process Using Anomaly Detection

Pang et al. (2021) introduced that anomaly detection is a type of data driving method for identifying abnormal patterns in a dataset. It is a technique that distinguishes a specific signal through outliers by learning the pattern of a normal signal. In this study, the Anomaly detection method is used to estimate the impact wave arrival time of the signal measured from the acceleration sensor

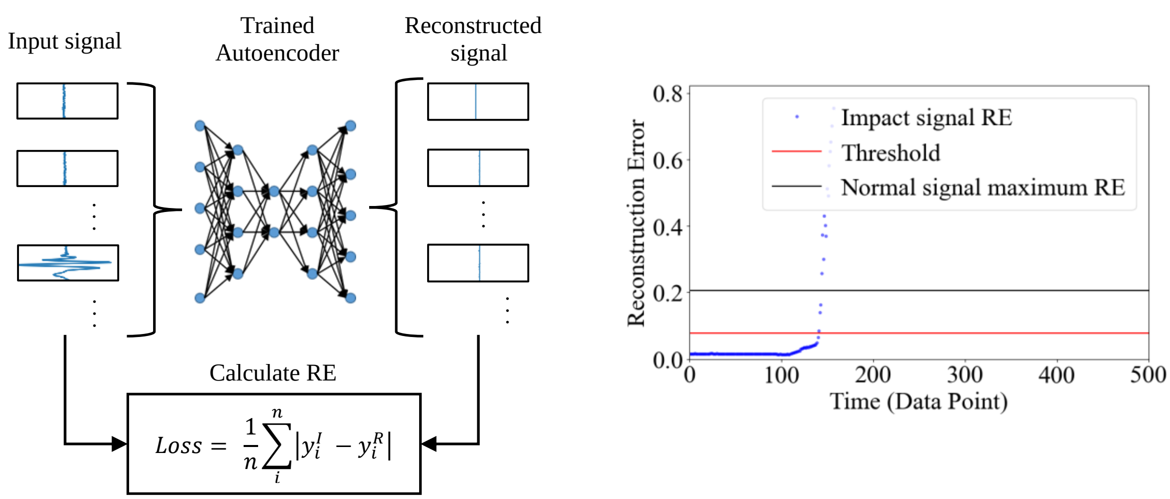
First, as shown in Figure 2(a), the signal preceding the arrival of the impact wave is defined as the normal signal, and this normal signal is extracted from all training data. The gathered normal signal serves as the training dataset for the neural network structured as an autoencoder. An autoencoder, a neural network designed to compress input data and restore it to its original dimensions, and is used to reduce the dimension of input data or generate data. In This study, the autoencoder neural network is constructed using fully-connected layers, with the network trained to accept normal signal data as input and accurately reconstruct the normal signal, as illustrated in Figure 2(b).



(a) Normal signal definition

(b) Autoencoder training about normal signal

Figure 2. Normal signal training for TDOA estimation



(a) Reconstruct error calculation for time of arrival estimation

(b) Impact signal reconstructed error

Figure 3. Time of arrival estimation for impact signal

Subsequently, as shown in Figure 3(a), the impact signal is segmented into uniform intervals, and the reconstruction error is assessed after introducing it to the pre-trained autoencoder neural network. Nelson et al. (1984) proposed a method for finding outliers using statistical techniques. As shown Figure 3(b), the Nelson 1st law is applied to the reconstruction error of the impact signal, positioned below the reconstruction error of the normal signal. This is executed to ascertain the threshold value by adding three times the standard deviation to the mean of the reconstruction error. The temporal point surpassing the determined threshold value is identified as the impact wave arrival time. This process is iterated across the remaining acceleration sensors' impact signals. Consequently, TDOA is computed concerning the arrival time of the reference sensor.

Wave Velocity Estimate Process Using Domain-Knowledge Guided Neural Networks

Domain-knowledge guided neural network is a learning approach that integrates physical understanding into artificial neural networks. Dash et al. (2022) presented the integration of domain knowledge into artificial neural networks. This involves the utilization of domain knowledge for handling input data, the construction of a loss function through the application of physical formulas, and the transformation of the architecture of a neural network model by infusing it with physical insights.
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In this study, domain-knowledge guided neural network focuses on learning to estimate wave velocity suitable for triangulation method, elucidating the impact location effectively, as shown in Figure 4. Employing triangulation method as a loss function, a neural network comprising fully-connected layers is constructed.

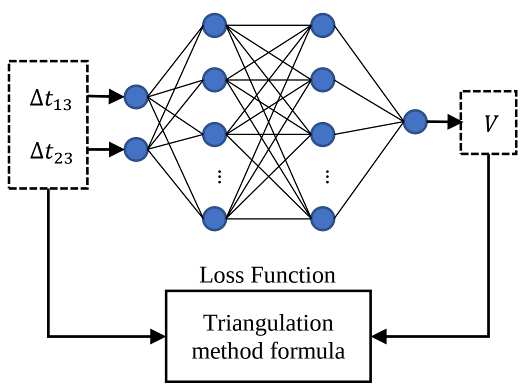


Figure 4. Domain-knowledge-based neural network for estimating wave velocity

This network takes the previously estimated TDOA as input and yields an output for the wave velocity. The resultant wave velocity, along with TDOA used as input, is integrated into the loss function, and the weights and biases within the neural network are iteratively adjusted to minimize the loss function. The loss function is defined by the equation provided below.

$$Loss\ \ function = \frac{1}{N}\sum_{i=0}^{N}\left(\sqrt{(x_i - x_a)^2 + (y_i - y_a)^2} - \sqrt{(x_i - x_b)^2 + (y_i - y_b)^2}\right) - V(\Delta t_{ab}) \tag{1}$$

where x_i and y_i represent the coordinates of the impact point, respectively, and x_a, y_a, x_b, and y_b represent the coordinates of each sensors. V represents the wave velocity of the impact wave estimated by the neural network, and Δt_{ab} represents TDOA of each sensor. The neural network is trained to find a wave velocity V that minimizes the loss function.

Impact Location Estimation Using Triangulation Method

The coordinates of the impact location are calculated by substituting the previously estimated TDOA and wave velocity into triangulation method. Equation (2) represents the triangulation method.

$$\begin{bmatrix} \sqrt{(x_i - x_a)^2 + (y_i - y_a)^2} - \sqrt{(x_i - x_b)^2 + (y_i - y_b)^2} \\ \sqrt{(x_i - x_c)^2 + (y_i - y_c)^2} - \sqrt{(x_i - x_b)^2 + (y_i - y_b)^2} \end{bmatrix} - V \begin{bmatrix} \Delta t_{ab} \\ \Delta t_{cb} \end{bmatrix} \tag{2}$$

where x_i and y_i represent the coordinates of the impact point, respectively, and x_a, y_a, x_b, y_b, x_c and y_c represent the coordinates of each sensor. V represents the wave velocity of the impact wave estimated by the neural network, Δt_{ab} and Δt_{cb} represents TDOA of each sensor. Through equations (2), if TDOA, the wave velocity, and the coordinates of each sensor are known, the coordinates of the impact point can be calculated analytically.

CASE STUDY

The efficacy of the proposed methodology was validated through an impact experiment involving a flat plate with a side length of 2 m. As illustrated in Figure 5, the plate, impact point positions, and accelerometer locations used in the experiment are depicted.

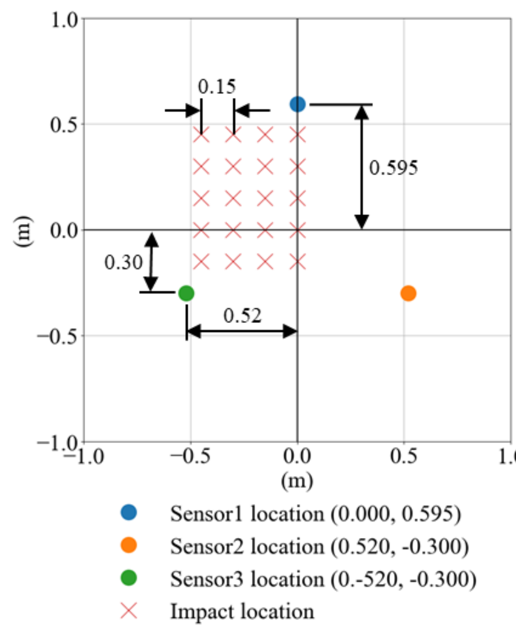


Figure 5. Experimental setup for impact testing on the plate

A comprehensive set of 1000 impact datasets was curated, achieved by conducting 50 impact tests per location for a total of 20 distinct impact locations. The impact location estimation process involved the partitioning of the datasets into 800 for training purposes and 200 for testing purposes.

Case Study 1: Raw signal Condition

The estimation of impact positions was conducted using the raw signals, devoid of any added noise. Figure 6 shows the impact location estimation errors across 20 distinct train and test datasets, revealing an average error of 3.92 cm. Meanwhile, Figure 7 provides a representative illustration of the impact position estimation results on a plate.

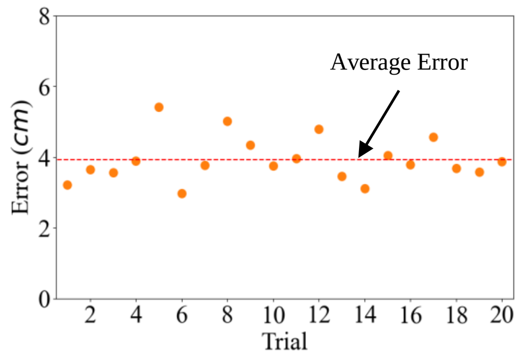


Figure 6. Error in the estimation of impact locations (Average: 3.92 cm)

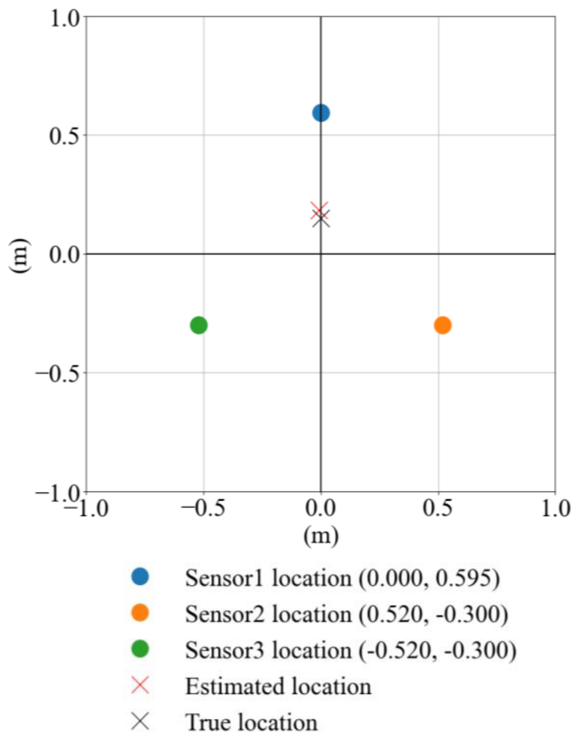
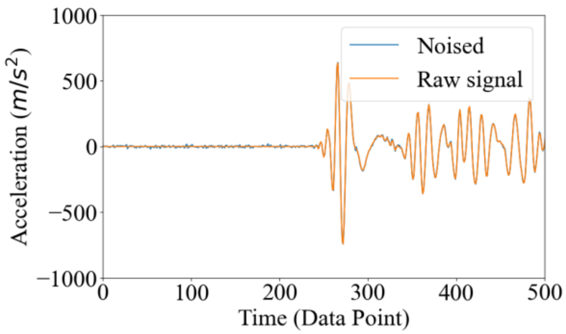


Figure 7. Representative example for estimating impact locations (Average: 3.47 cm)

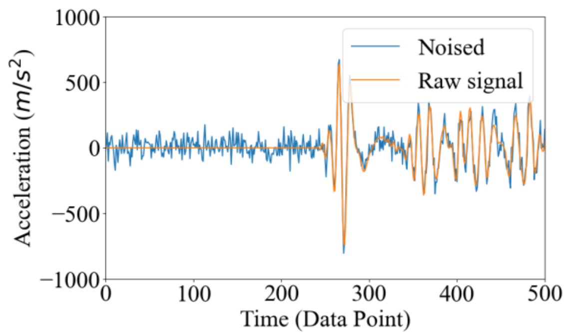
Case Study 2: Noisy Environment

The acceleration signals acquired within an operational nuclear power plant are susceptible to diverse of noise. To ensure precise impact location estimation, the proposed methodology must demonstrate robustness against such noise. In this study, the robustness against noise was examined by adding Gaussian noise to the experimental data from the flat plate experiment. This evaluation aimed to assess the proposed method's capacity to maintain accuracy in impact location estimation in the presence of noise.

Gaussian noise is generated to add noise into the data from the flat impact experiment. Utilizing the normal signal nearest to the average amplitude values of the normal signals, Gaussian noise corresponding to the desired signal-to-noise ratio (SNR) is generated. Subsequently, this noise is incorporated into the existing flat impact experiment data, resulting in datasets at various noise levels. Figure 8 represents the impact signal at each noise level.



(a) SNR: -35 dB,



(b) SNR: -55 dB

Figure 8. Comparison of the raw signal with the noisy signal

Figure 9 is the impact location estimation error in relation to the noise intensity. The findings indicate that the proposed method sustains a consistent degree of error up to a noise level of -55 dB, beyond which the error progressively escalates for lower SNR.

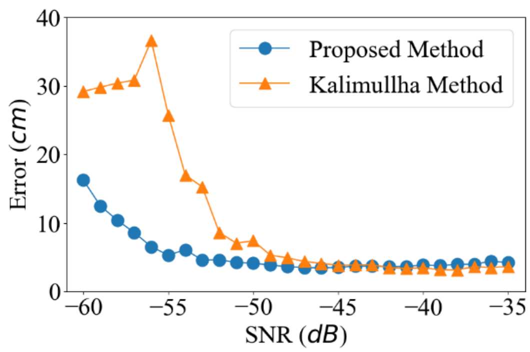


Figure 9. Comparison of the Kalimullha method with the proposed method under noisy environmental setting

On the other hand, in the case of the Kalimullha's method, the error gradually increases from noise at the -50 dB level. The error increases from higher levels of SNR when compared with the proposed method. This is presumed to be due to the fact that the threshold value determined in the Train data to estimate TDOA is not suitable for the test data.

CONCLUSION

This study proposes a deep-learning-based method for estimating impact location coordinates. TDOA and the wave velocity were determined using the anomaly detection model and the domain-knowledge guided neural network model, respectively. The impact location coordinates were estimated using the triangulation method. The performance of the proposed method was assessed using data from flat plate experiments.

Estimating the impact location on the plate using the raw signal without the addition of noise, it was verified that an average error of 3.92 cm. With the impact signal data with an SNR of -50 dB, the Kalimulla's method exhibited an error of 7.41 cm, whereas the proposed method showed an error of 4.12 cm. This showed that the proposed method was robust against external noise. Moreover, the proposed method the proposed method maintained a consistent error level up to -55 dB SNR. The proposed method can help the field experts by providing another tool that can estimate the impact location quickly and work robustly in the noisy environment of nuclear power plants. It is expected to reduce the fatigue of field experts for maintenance decision making.

ACKNOWLEDGMENT

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