Master's Thesis

A Deep Learning Approach to Noise Source Localization on a Piping System

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A Deep Learning Approach to Noise Source Localization on a Piping System

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이 논문을 공학석사 학위논문으로 제출함

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Abstract

The noise on a piping systems become a serious issue in the industries of shipbuilding. This noise originating from various sources such as main machinery can be propagated to many parts of a ship including outer hull, workshops, and accommodation areas. In addition, this noise exerts a negative effect on workers, residents and also underwater radiated noise (URN). Especially in submarines, URN is directly related to survivability and degrades detection performance of sonar (sound navigation and ranging). Conventional source localization methods with time difference of arrival (TDoA) are not applicable in complex systems because it is too noise sensitive. Moreover, these methods are limited to transient noise sources from defects and leak, and a single type of pipe by using more than two sensors. Recent studies on source localization have shown that deep learning application have the potential to solve these problems. Therefore, We propose the deep learning approach to noise source localization on a pipe system with a single accelerometer. Transfer learning and fine tuning are applied for the suggested method for noise source localization on pipes. As pre-trained convolutional neural network (CNN) models, VGG16 for classification and ResNet50 for regression are used. We suggest both the classification method and the regression method combined with classification model for 2D pipe source localization, which is applicable in 3D pipes. This can also be possible solution for unseen data due to complex and narrow piping systems. For training the models, the structure-borne noise dataset is acquired from the experiments according to four typical conditions which are a variety of source types, with and without the presence of water in the pipe, boundary conditions, and configuration of pipes. The collected signals are pre-processed from raw signals to Log-Mel spectrogram images so as to train the deep learning model. The performance of the model are evaluated by 5-folds cross validation. Though this thesis is focused on the pipe noise source localization, the proposed methods

can be employed for source localization methods in other systems as well as in the pipe systems of other industries.

Keyword : Noise source localization, Deep learning, Convolutional neural network, Piping systems
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Chapter 1.

Introduction

1.1. Backgrounds

Ships have various hull shapes and internal structures according to their purpose of use. A ship is composed of several systems, and each of the systems is organic and has a complex structure. In addition, since a ship is a steel structure, it has a characteristic in which noise is easily propagated. Various noises affect not only around the noise source but also in many parts of the hull.

In particular, the types of noise in submarines are as follows: machinery noise, propeller noise, flow induced noise, and pipe noise. The main noise sources are main machinery and propeller noise. These noise affects the overall noise level of the ship. Therefore, it is necessary to figure out the main transmission path of noise through noise and vibration analysis at the design stage of ship, and insulate the sound.

Recently, the need for soundproofing a ship against especially pipe noise has emerged. If sound insulation of various pipes connected to the equipment is poor, the noise affects the entire parts of ships as shown in Figure 1.1. The workers suffer a degradation of ability and a hearing loss because of noise. The noise is also transmitted to the exterior structures through the pipe, which has an effect on the overall underwater radiated noise (URN) in the case of submarines. This leads to degrade performance of sonar and survivability of submarines. In addition, in the case of secondary noise caused by flow and pressure changes inside the pipe, it is very difficult to locate the noise source and to take measures for soundproofing and vibration prevention. In addition, unlike what a ship is designed and is predicted, there are cases in which abnormal noise occurs after shipbuilding.

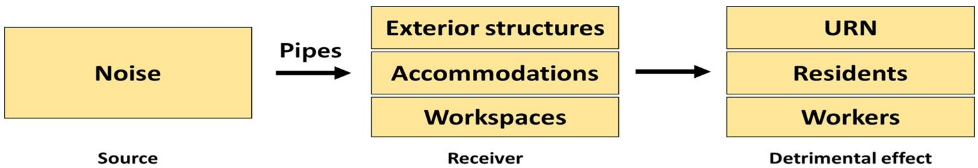

Figure 1.1: Propagation of noise through pipes and negative effects.

1.2. Purpose of research

Piping noise is very difficult to identify the noise source through measurement and analysis when a problem occurs during sea trial, in the case of a submarines, due to the complexity of the piping system and the narrow internal space. The identification can be divided into three aspects, (a) detection, (b) recognition, and (c) localization, but they have their own difficulty.

(a) In the detection stage, when noise occurs, it is difficult to determine whether it is noise from the piping systems or from other systems. (b) There is a problem in that it is hard to find which piping system among various piping systems in terms of recognition. Finally, (c) in terms of localization, it is not easy to find where the noise source occurred on the pipe.

In conclusion, the most fundamental solution to this is to directly locate the noise source in the piping system. Accordingly, shipyards are using various methods as a way to identify the noise source in the piping system. Figure 1.2 shows two representative methods: a frequency−based noise source location estimation method and an on−off test

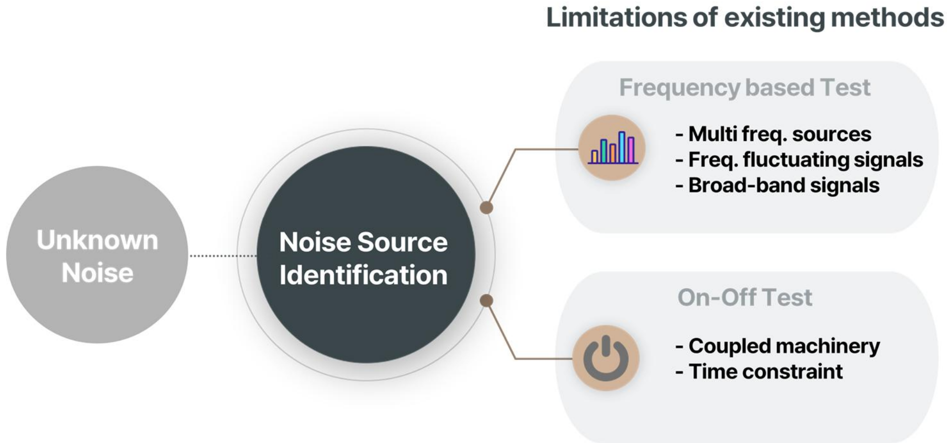

Figure 1.2: The existing noise source identification methods used by shipyards and their limitations.

The first method is to analyze the frequency to find the noise source corresponding to the frequency of interest. However, this methods have limitations that several noise sources have the same frequency component and also broadband frequency component, and the frequency signals can be fluctuated as it passes through the transmission path.

The on−off test is to turn off the internal machinery and turn them on one by one to determine where the noise is coming from. Then, the number of cases of noise sources is reduced compared to the frequency−based method, so that the location can be estimated more efficiently. However, due to the complex structure of the ship, there are some problems that most machinery is coupled with each other and the method is too time consuming.

For such reasons, these existing methods has many limitations to be applied in reality. It is necessary to develop the existing method and introduce a new method.

1.3. Related works

1.3.1 Source localization methods on a piping system

Source localization on a piping system is mainly used for leak detection. Conventional pipe noise source localization methods are mostly based on the time difference of arrival (TDoA) method as shown in Figure 1.3. By TDoA methods, two or more sensors are attached on a pipe system and the noise propagated from a noise source is acquired from the sensors. There is difference in arrival time at each sensor because of the distance from source to sensor position. The position of source can be calculated with the wave speed of the pipe and the time difference.

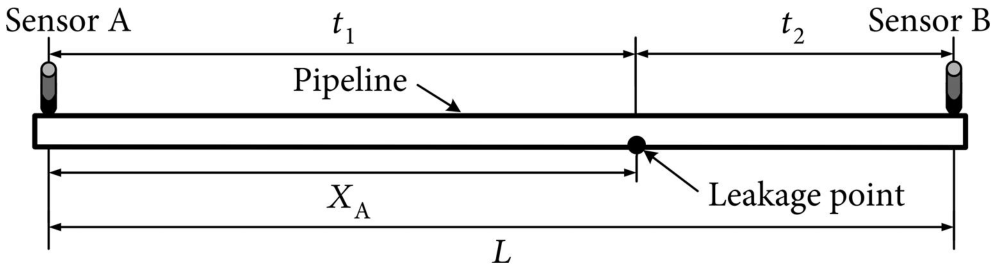

Figure 1.3 Source localization based on TDoA [1]

Pan et al. [2] proposed a source localization method that uses cross−correlation to know the time difference after narrowing the interested area with the attenuation property of the noise signal amplitude. Kousiopolous et al. [3] showed the result of a method using cross−correlation, and suggest improved method. The improved method converts time series data to frequency domain data through FFT, and multiplies the cross spectral density between two sensors by introducing a weighting function, and performs inverse FFT. Shehadeh et al. [4] proposed a localization method which estimates pipe noise source location through sliding window energy technique, cross−correlation of decomposed signals, threshold method, cross−correlation method, and Gabor wavelet transform. First, the sliding window energy technique calculates the energy ratio of a high−frequency band and a low−frequency band at uniform time intervals. The point at which the ratio rapidly decreases was computed with a time delay from two sensors. The second method analyzes cross−correlation after decomposing the signal into wavelets. Third, the threshold was initially set with the threshold method. When a signal of a certain value comes in, it is determined that a wave has arrived and is obtained through a time delay between sensors. The next method is to use cross−correlation, and the last method is to find peaks in time−frequency data by applying Gabor wavelet transform, and estimate the position through the time difference between the peaks. Gao et al. [5] proposed a method similar to Kousiopolous' method [3] without a weighting function. Choi et al. [6] improved cross−correlation results for various types of pipe by introducing a maximum likelihood (ML) pre−filter. Kang et al. [7] estimated by cross−correlation as a graph−based calculation method. In order to estimate an accurate position, a virtual node was determined by a method similar to matched−field process to find a location where the cost function is minimized. Guo et al. [8] used cubic interpolation search (CIS) in a similar way to Kang's method. Liu et al. [9] used the generalized cross correlation−phase transform (GCC−PHAT) to overcome of limitation of the cross−correlation analysis.

Source localization on a piping system is based on not only TDoA method but also other methods as follows: Wang et al. [10−11] used a matched−field processing method which determines source position by comparing among the candidate source positions acquired from simulation and the actual position and finding the best position minimizing difference. Lang et al. [12] developed a new position estimation method based on the relationship between the position of the source and the speed of the wave heading to both ends of the pipe. Wang et al. [13] used a beamforming method, which is a method of finding where an array comes from like a radar by inserting several arrays.

1.3.2 Source localization methods using deep learning

Artificial intelligence (AI) has emerged as a solutions to localize the source. AI based source localizatiton methods are widely used in field of room acoustics and speech and prove a good performance in these fields. The research trends of existing AI-based noise source localization methods are as follows: Heng et al. [14] utilize short-time Fourier transform (STFT) spectrogram images. The signals were collected from two sensors located at both ends of the straight pipe. Each of two signals was converted into the two spectrogram images by STFT. These two spectrogram were combined, which made a cross-correlation map. CNN model was trained by this cross-correlation map. Ebrahimkhanlou et al. [15] excited each node in a riveted metallic panel to obtain a signal through a sensor, and proceeded with CNN classification. Yiwere et al. [16] presented a method for identifying the location and direction for the distance and orientation from the noise source based on deep learning. Park et al. [17] used two microphones to find the source position by predicting the horizontal angle. Yalta et al. [18] adjusted the SNR to a room with white noise and evaluated whether it showed good performance even in a noisy environment. The signal was collected from a microphone array, and the direction was estimated by learning it with STFT image data. Vera-Diaz et al. [19] measured noise with a microphone for a noise source moving in 3D space. Moing et al. [20] locate a source on a two-dimensional plane for multiple noise sources. Choi et al. [21] acquired noise signals according to various types of noise sources and location of noise sources for inter-floor noise in a building using a smartphone recorder, and found the location through CNN classification. Kita et al. [22] proposed the 3D source localization method of structural transmission noise using a vibration sensor

1.4. Approach

AI has actively applied in structural health monitoring of piping structures. Ahn et al. [23] suggested a leak detection method using support vector machine. Jung [24] and Shin [25] proposed the AI methods for fault detection used accelerometer which is non-invasive and relatively economical sensor. In deep learning, convolutional neural network (CNN) is popularly employed in pattern recognition of an image [26]. Currently, CNN models are also used for source localization [27-28] and are trained by spectrogram images [27, 29].

The conventional in-person method used in the shipbuilding company is too sensitive to noise and is time-consuming tasks and the piping systems is too complex and narrow to find a source in person especially in submarines. Previous researches using TDoA source localization methods studied with one type of pipes and impulse source including leak and faults. In this research, we considered four representative conditions such as various types of pipes and source types a piping system. In addition, TDoA has low accuracy because it is noise sensitive and it is difficult to know the accurate time difference and wave speed. Moreover, it is hard to do modeling the piping system. Therefore, we proposed a deep learning approach to localize the noise source on a piping system. We used CNN model for classification and regression to find a position of noise source with an spectrogram image. For this, a structure-borne noise is measured from a single accelerometer which is non-invasively installed on a pipe.

Thus, Figure 1.4 shows the overall flow of this study. The dataset is needed for training a CNN model. At first, the data are acquired from an vibrational sensor. Then the data are pre-processed from vibration signal to spectrogram, especially Log-Mel spectrogram. This spectrogram is an input of CNN model. With this input, the CNN model's parameters are learned for classification and regression. In order to do source localization, this model produces outputs as a distance from a sensors to source position.

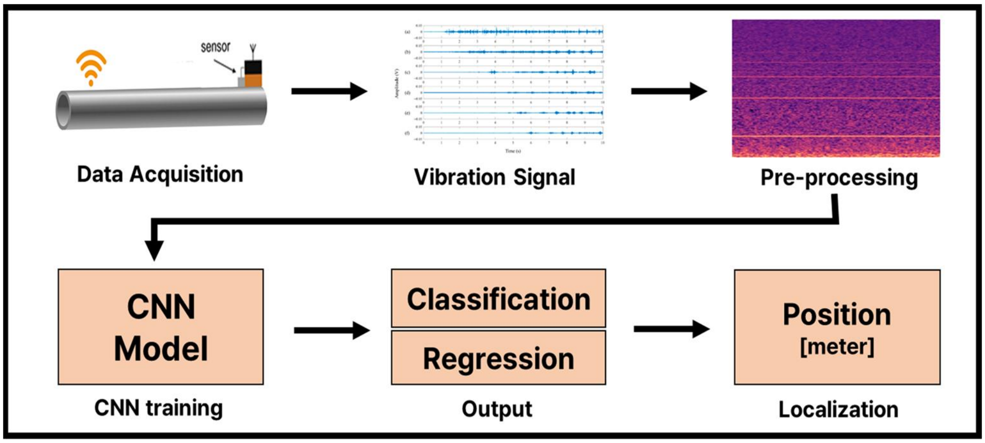

Figure 1.4: Overall flow of this research

1.5. Organization of the thesis

This chapter consists of four parts which are the Backgrounds, the purpose of research, the related works and the approach. The remainder of this thesis is organized as follows. In chapter 2, experiment and data processing method are described. To be specific, features of source of a piping noise, purpose of experiment, configuration of experiment and data processing are demonstrated. In chapter 3, source localization on a piping system is presented. This chapter is composed convolutional neural network (CNN), CNN classification and regression for source localization on a piping system, CNN training and source localization results. Chapter 4 concludes this thesis with summary, application, and future work

Chapter 2.

Experiment and data processing

2.1. Experiment

2.1.1 Features of noise on a piping system

The characteristics of the noise source can be considered in terms of noise source, transmission path, and receiver.

First, main machinery can be noise source. Ships have become large−sized, high−speed, and high−output. As a result, the excitation force has increased, which has become a factor in increasing vibration and noise. The operation of propulsion engines, generators, and pumps is also the cause of the unpleasant sound. Moreover, there is secondary noise due to the pressure difference. It occurs when the kinetic energy of the compressed fluid at the orifice is converted into noise and vibration. A control valve is also one of factors making pressure difference by controlling the flow rate or reducing pressure. In addition, flow noise may be generated from discontinuity including piping components and supports. To be specific, noise is made as the flow changes while passing through flanges, dampers, etc. and is caused by defects in these parts. Finally, there are various types of piping in ships and submarines, and noise is generated because of the configurations of the piping such as an elbow and a branch pipe by making vortex.

Second, the transmission path of pipe noise can be divided into two types. When a noise is generated, there are airborne noise transmitted through the air and structure-borne noise transmitted via a structure including pipe. Through this, the noise propagates throughout the inside and outside of the ship.

Finally, the noise source depends on the receiver. As discussed in the transmission pathways, noise is transmitted from the noise source through pipes to the hull structure, decks, walls and ceilings. Then, it has negative effect on workers in workspace, residents in accommodations, and underwater radiation noise.

2.1.2 Purpose of experiment

The experiment was conducted under four representative conditions in a piping system as follows: (1) various types of noise source, (2) the presence and absence of water in the pipe, (3) different boundary conditions, and (4) the configurations of pipes. The pipes are fully filled with water except for the case of absence of water in the pipe of condition (3), and also are without any flow of water.

Condition (1): The purpose of the experiment is that various noise sources exist in each piping system of ships and submarines. There will also be impulse signals caused by defects, water hammering, and so on. In particular, signal of noise from main machinery is continuous and has a periodicity. Since the most noise sources are complex and tend to have a broad-band and modulated frequency. The data were obtained for verifying the location estimation capability for each noise source.

Condition (2): The experiment based on the presence or absence of water in the pipe was carried out. Each Pipe has the different water level for its purpose. Therefore, as representative cases, the case where water is present and the case where water is not are considered.

Condition (3): There are many types of boundary conditions making up a pipe system including U−bolt for support. The boundary conditions have an influence on the noise when the wave passes through. For this experiments, steel U−bolt and rubber U−bolt are used.

Condition (4): The experiment according to the configuration of the pipes. Ships and submarines have not only straight pipes, but also various types of pipes. This pipe tests with different configuration with straight, elbow, and branch pipes are for verifying the effectiveness and performance of the noise source localization method of the CNN algorithm.

2.1.3 Configuration of experiment

The experimental equipment was made for pipe noise data acquisition. Figure 2.1 shows the support of pipe which was fabricated and installed because of deflection of pipes.

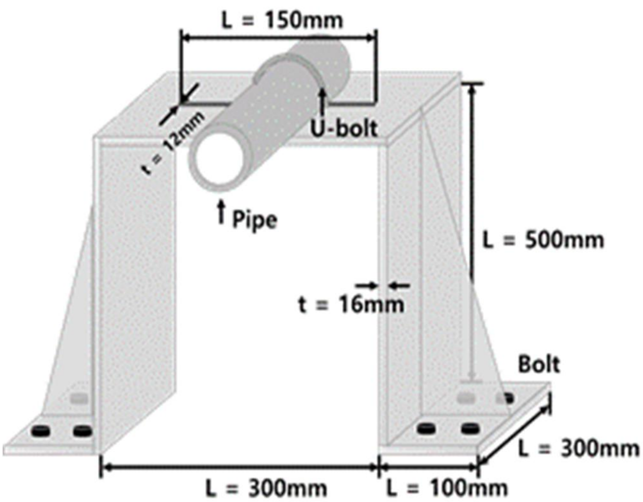

Figure 2.1: Support of pipes

Figure 2.2 shows the overall setup of experiment. The blue dot means the support for pipes and the red dot is an accelerometer as a sensor which are placed on the pipes. The sensors were used to measure the structure−borne type of vibration transmitted from the noise source through the pipe.

For the straight pipe, two 6 meter straight pipe made of CuNi, which is most commonly used in actual submarines, were connected with flange. Since there are not only straight pipes in the ship, elbows and branch pipes were used in consideration of this. These two pipes are made of steel generally used for water pipes, and the length in the vertical direction on the figure was determined to be 2m each in consideration of the laboratory space.

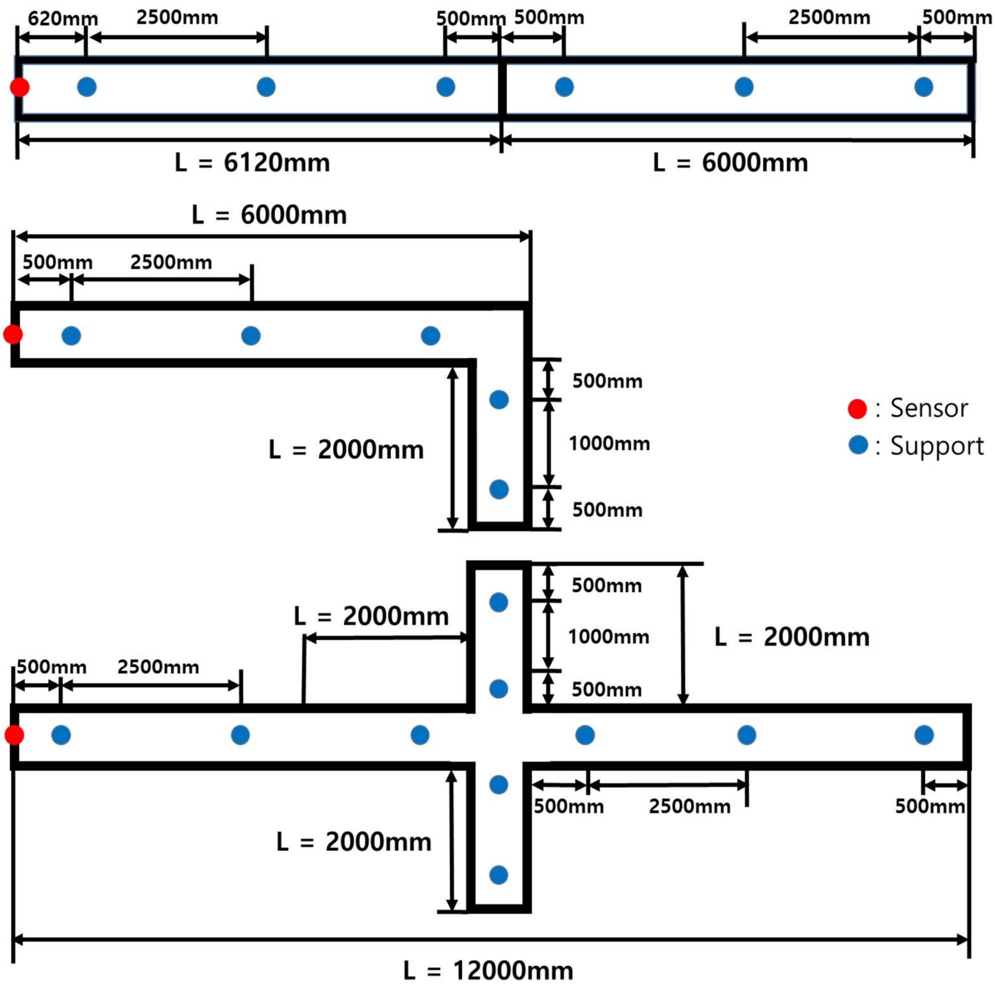

Figure 2.2: Setup of experiment - straight, elbow, and branch

2.1.4 Data acquisition

For data acquisition, B&K's Lan−XI was used as a data acquisition system with Pulse and BKconnect program. Commonly, the sampling frequency was set to 32,768 Hz (B&K standard 12,800 Hz). Time−acceleration data was recorded with 5 seconds duration. One accelerometer (PCB's 352A60) was placed on the left end of each pipe. Another accelerometer was installed at the excitation point to compare coherence for validation of the experiments.

The pipes were vibrated by an impact hammer and shaker. The impact hammer was used for making an impulse source, and the exciter (B&K's V406) for periodic and broad−band source. Periodic and broadband signals were made by the exciter with a function generator (Agilent 33250A) and an audio amplifier (Behringer's NX4−6000). The pipes were excited with distance of 0.5 m starting from the left end. In the case of a straight pipe, since the pipe is 12 meter, the total excitation points is 25 points as shown in Figure 2.3. Elbows and branches are 17 and 33 points, respectively. For every excitation point, 100 data with each frequency were acquired for continuous signals and 50 data for impulse signals.

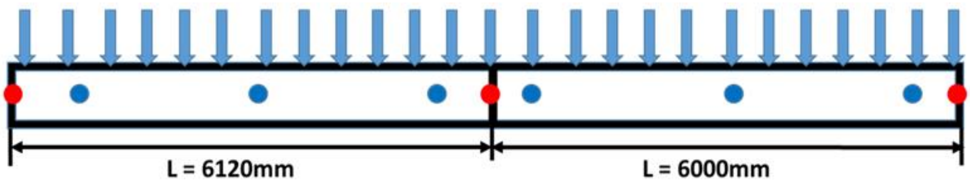

Figure 2.3: Excitation points for a straight pipe

Condition (1): Three types of source are considered. The types of source on the straight pipe are impulse, continuous, and modulated respectively and the interest frequency is below 1 kHz. The impulse signals were collected by comparing the coherence through the impact hammer. The continuous signals had each frequency of 100 Hz, 200 Hz, and 500 Hz with a sine waveform. The modulated signal was set between 100 Hz to 1000 Hz frequency bands. The total data number of impulse, of continuous, and of modulated is 750, 7500, and 2500, respectively.

Condition (2): The straight pipe fully filled with water and the straight pipe without water are used. Since the data from the pipe fully filled water was already collected in condition (1), the data from the pipe without water was conducted on a sine wave of 100 Hz. The total data number from test with rubber U−bolts is 2500.

Condition (3): Boundary conditions are compared between two different types of U−bolts. The straight pipe is fastened to steel U−bolts or rubber U−bolts. The pipes with different U−bolts are vibrated with continuous wave having each frequency of 100 Hz, 200 Hz, and 500 Hz with 25 points of excitation. Each of data number of the pipe with steel U−bolts and rubber U−bolts is 2500 and 7500.

Condition (4): In terms of configuration of pipes, the data are acquired by using straight, elbows, and branch pipes. These three types of pipes were excited with a continuous sine waveform of 100 Hz, 200Hz,and 500Hz frequency. The number of data is 7500, 5100, 9900 each from straight, elbow, and branch structure.

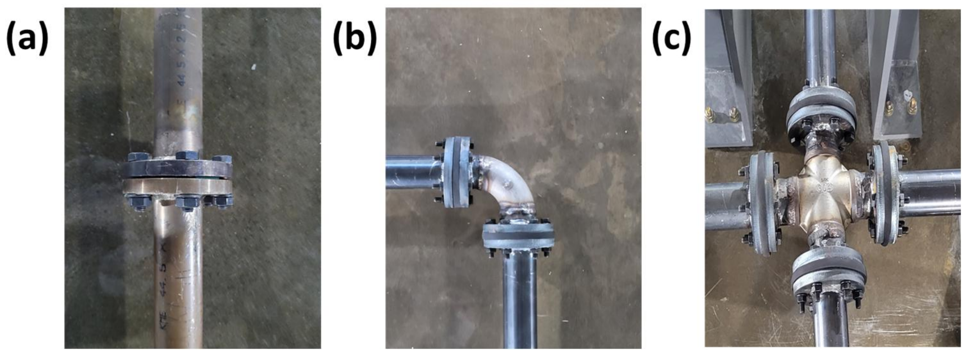

Figure 2.4 The connection of (a) straight pipe (b) elbow pipe (c) branch pipe

2.2. Data processing

The collected data are time and acceleration data. Figure 2.5 shows the raw signal and FFT results of impulse source. Firstly, the noise was filtered from the raw data to remove the frequency components that are beyond the range of frequency which a sensor can measure .The filtered data could be used as one−dimensional data, but it is more effective to convert the this data into two−dimensional data. Due to the characteristics of CNN, when CNN extracts the features of an two−dimensional data, it could take the absolute value of each data. Furthermore, it is possible to recognize the relationship about each pixel and its neighbor pixels. In two dimensional image, the data could be pixels of the image. Therefore, when one−dimensional data such as time series data is input of CNN, the data can find a relationship of only one direction. Therefore, using two dimensions is more suitable for CNN.

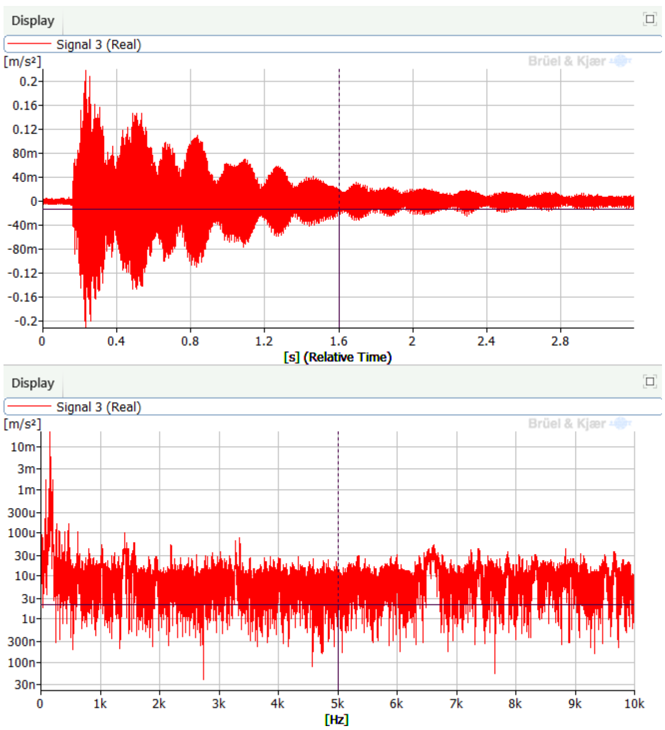

Figure 2.5: One raw signal and FFT results of impulse source

For vibrational data, one of the two-dimension data is a spectrogram which has information on both time and frequency data. Therefore, a short-time Fourier transform (STFT) image could be used as the input of the CNN. The flow of calculating STFT is shown in Figure 2.6. STFT divides time data into several time frames of uniform size, and then each time frame is changed into frequency data. Next, these frequency data per time frame are arranged in accordance with order of time, which means that x-axis is time axis and y-axis is frequency axis. Therefore, STFT data represent the change in frequency value according to the time interval. This spectrogram can be visualized in two-dimensional space and displayed like an image.

Through spectrogram image, CNN extracts both time and frequency characteristics and reflect the information more comprehensively than time data and frequency data separately. In addition, if a CNN model takes just acceleration data in a time domain, it is not robust against offset or noise. However, it does not matter for STFT. Also, The number of samples of time-domain signal sampled at a frequency of 32,768 Hz during 5 seconds is 163,840, but the size of the image for input of CNN including ResNet and VGG is reduced to 50,176 which has 224 x 224 input image. Therefore, the computational cost can be reduced.

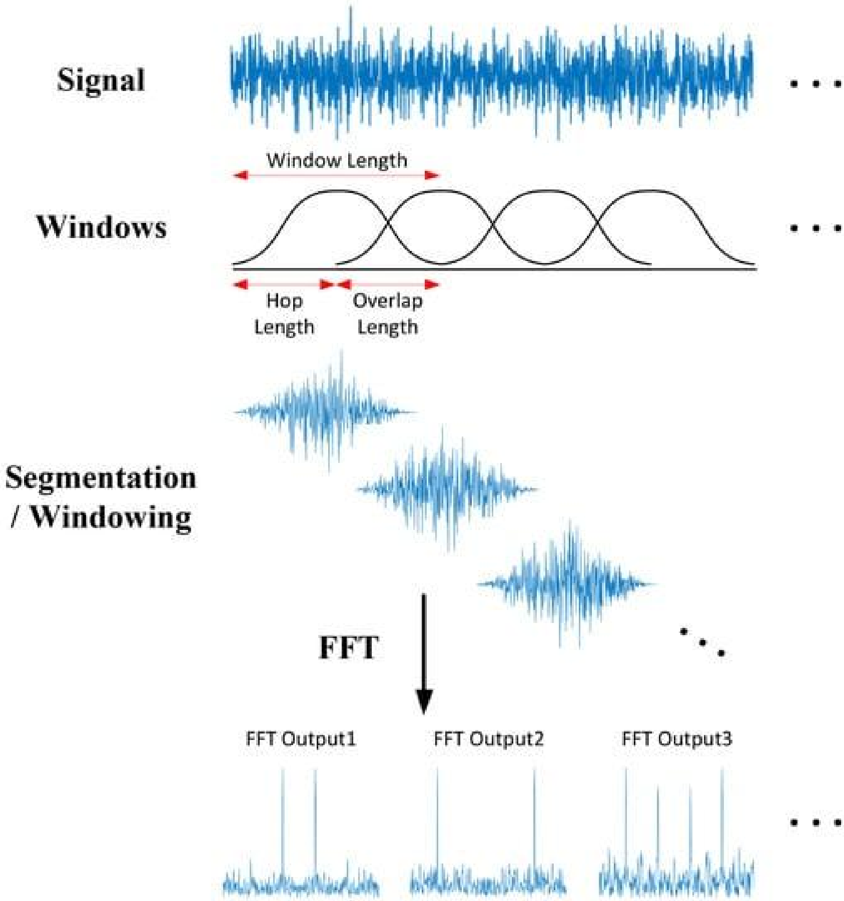

Figure 2.6: Overview of short-time Fourier transform (STFT) [30]

For STFT, there is a trade–off between resolution of time and frequency. when a window size is narrow, a time resolution is better, and vice versa. So choosing a window size is important and the number of Fast Fourier Transform (FFT) number determines frequency range. In terms of making a spectrogram image, The hop size is controlled to match the horizontal length of 224.The window function is Hanning window.

STFT was converted into Mel–spectrogram which emphasizes the low frequency band, because the frequency range of interest is below 1000 Hz, A concept of the Mel scale is from human ear which perceives lower frequencies more precisely than higher frequencies. Human detects frequencies on Mel scale not linear scale. Figure 2.7 shows an example of Mel filter bank. Power spectrum from FFT results were applied to Mel filter bank in order to create Mel−spectrogram. In this research, maximum frequency of mel scale was set to 10,000 Hz. The mel scale is defined as

$$m = 2595 \log_{10} \left(1 + \frac{f}{700} \right), \tag{2.1}$$

where f is frequency.

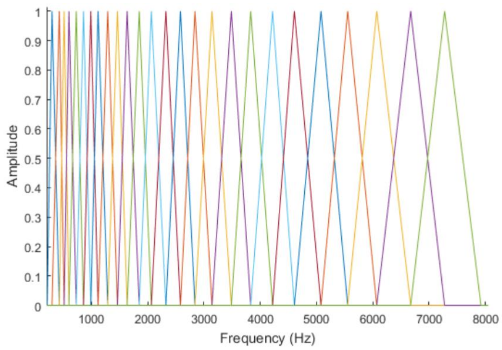

Figure 2.7: An example of filter bank on Mel-scale [31]

But the Mel−spectrogram was made but was poorly visualized. It is hard to distinguish the feature of Mel−spectrogram. Thus, log−scale is used for feature extraction. This is called a Log−Mel Spectrogram. Figure 2.8 shows an example of Mel−spectrogram. Additionally, normalization of an image is performed to improve CNN learning performance. To be specific, normalization makes distribution of the data even, so the process of updating the gradient in the CNN model works well, which has an advantage in speed of calculation.

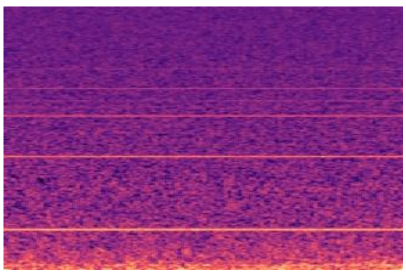

Figure 2.8: An example of Log-Mel spectrogram

Chapter 3.

Source localization on a piping system

3.1. Convolutional neural network (CNN)

Convolutional neural network (CNN) is one of the deep learning algorithms. It was developed to compensate for the disadvantages of general Deep neural network (DNN).

General neural networks are trained with one-dimensional data. Even if data is two-dimensional, the data should be changed to one-dimensional data as an input as shown in Figure 3.1. When this happens, data which have two dimensions can easily lose their important features. These data including images and videos have important information about the relationship among its surrounding pixels as well as absolute value of one pixel. Therefore, CNN recognizes 2D pattern of 2D data whereas general DNN finds 1D pattern. In the view of signal processing, CNN is fit for images and videos data, while DNN is suitable for time-series data.

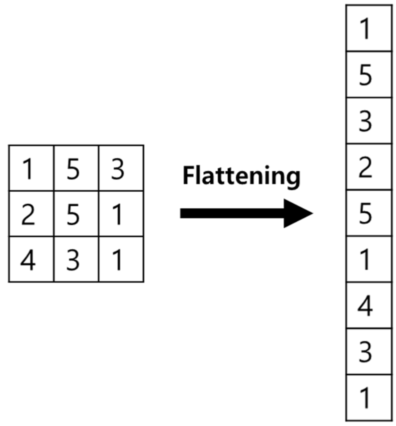

Figure 3.1 Flattening 2D data for input of general DNN

CNN uses a convolutional kernel to extract the feature from an image. Figure 3.2 shows that the convolution operation in convolutional layer compute a dot product of image (I) and kernel or filter (K) to get a feature (I∗K). And move one pixel to the right and repeat same thing. The number of cell to move is called stride (S), which decides the size of feature. Padding (P) also affects the dimension of feature by adding zeros surrounding the image. The feature size is expressed as

$$\left[\frac{I-K+2P}{S}\right] + 1 \qquad (3.1)$$

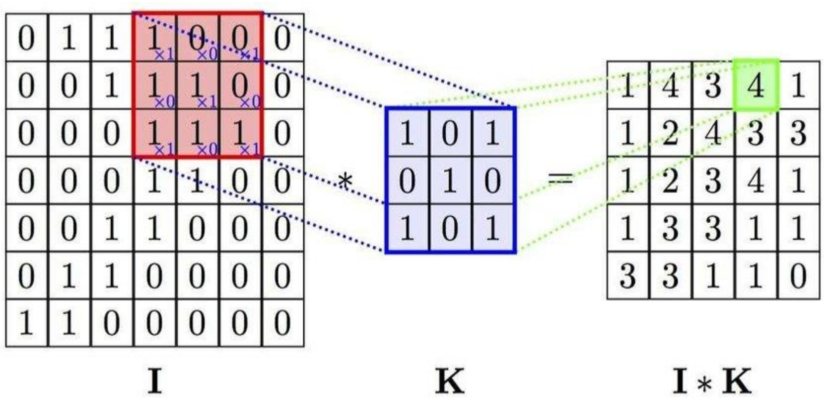

Figure 3.2: An example of convolution operation [32]

Figure 3.3 shows an example of CNN architecture. CNN architecture is divided into two major parts; the feature extraction and classification or regression.

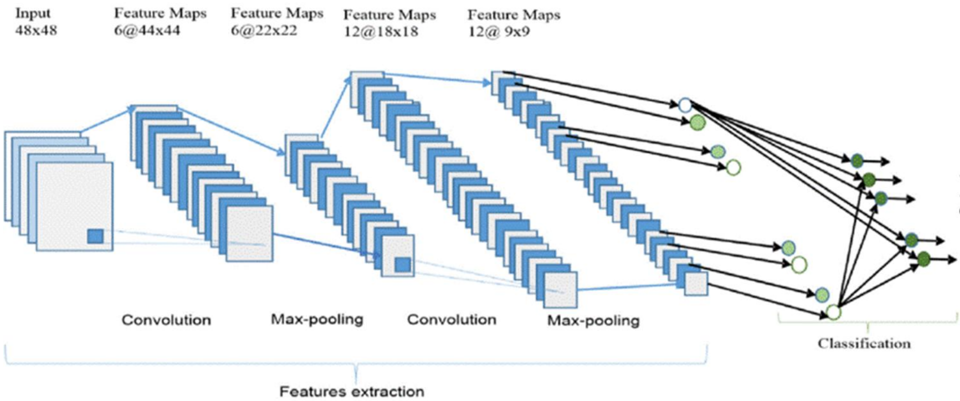

Figure 3.3 An example of CNN architecture [33]

There are two types of layer which are convolutional layer and pooling layer in feature extraction part. When an input image is fed into the CNN model, A convolution layer extracts a feature from the input by convolution operation between the input and kernel. The output of convolution layer is called feature map. A pooling layer follow a convolutional layer and reduce the feature map size. There are many kinds of pooling layer. A max pooling is mostly used and takes the maximum element from feature map. All this process is repeated as to get a good feature.

After feature extraction, a fully connected layer (FC layer) is used in second part. The FC layer flatten the feature map from last convolutional layer and reduce the feature map size. There is an activation function in the last layer of CNN. Classification model has softmax activation function so as to estimate the value with probability for each label. The label with the highest probability (argmax) is output whereas regression model does not have. Softmax function is defined as

$$\text{softmax}(z)_i = \frac{e_i^z}{\sum_{j=1}^{N} e_j^z} \quad , i = 1, 2, \ldots, N \qquad (3.2)$$

where z is the vector of outputs of the network and N is number of classes. So, Figure 3.4 shows the difference of regression and classification. Output of classification which classify the data into different categories is only one discrete number or label. Because regression model predicts a value from input, a real number is output.

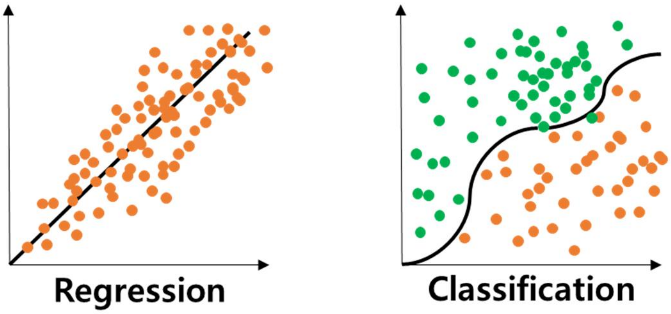

Figure 3.4: Regression and classification

Classification and regression have different loss function. Cross-entropy loss function is used for classification and mean squared error loss (MSE loss) function is used for regression to optimize the parameters of CNN. CNN Training is minimizing the loss between target value and predicted value.

The introduction of CNN improve a performance in image recognition. Currently, CNN is the most widely used neural network.

3.2. CNN classification and regression for source localization on a piping system

The preprocessed image data is labeled for each excitation position starting from the left end where a sensor is placed as shown in Figure 3.5. For example, each 0 m, 0.5 m, ..., 12 m is 0, 1, ..., 25. This input fed into the CNN model. Then, CNN model performs feature extraction from each label through training. As explained in the CNN theory, each loss function produces the output of optimized classification and regression model.

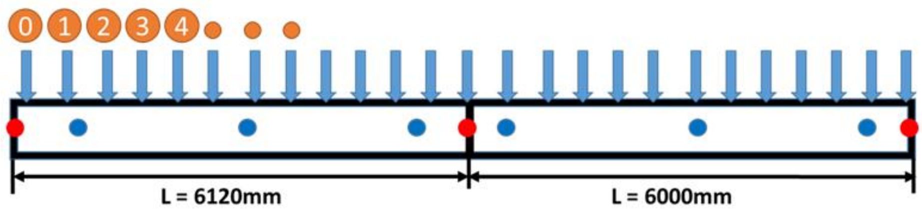

Figure 3.5: The method of labeling on a straight pipe

A discrete label value with the highest probability among labels is output of classification model through softmax function. In this research, the position is label and the position can be classified by CNN classification model.

For regression, a continuous real number value like 1.5014 is output of CNN model. Estimation of distance from the sensor is possible.

In the case of 2D pipes, the classification approach is able to applied in similar method as shown in Figure 3.6. However, the regression approach needs to be improved. The regression model can estimate the distance not the position of source. So I suggest the 2D regression source localization method as shown in Figure 3.7 and 3.8. The method utilize classification and regression at the same time. To be specific, the CNN model classify the branch of pipes. Then, regress the distance. This method can be explainable to 3D piping system problem.

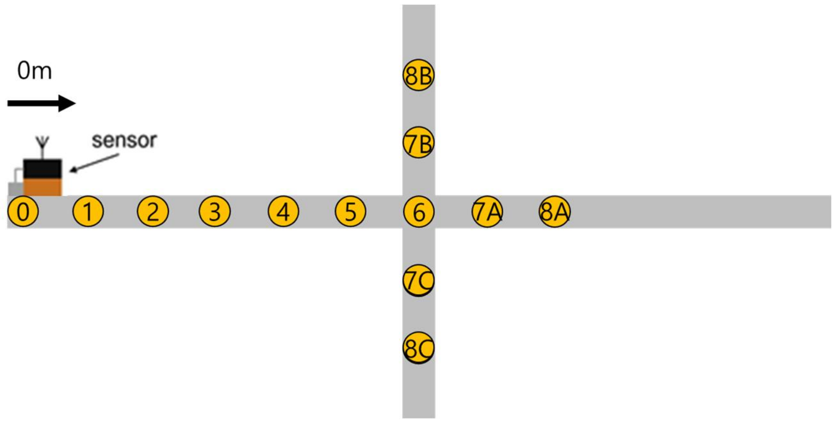

Figure 3.6: The method of labeling on 2D pipe

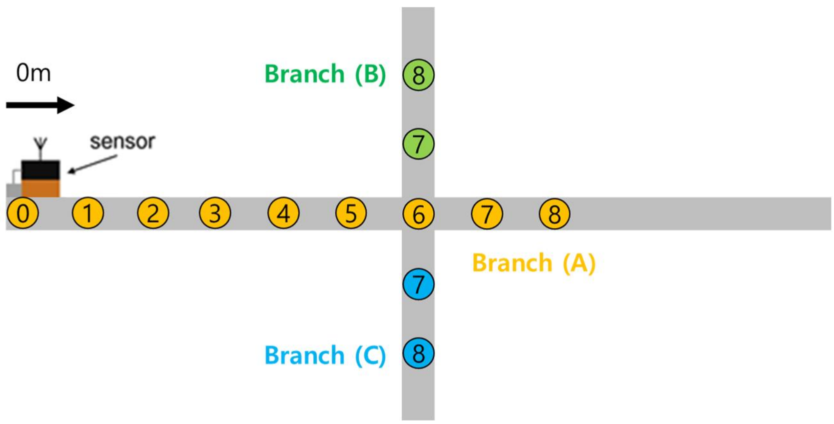

Figure 3.7: The source localization method on 2D pipes for regression

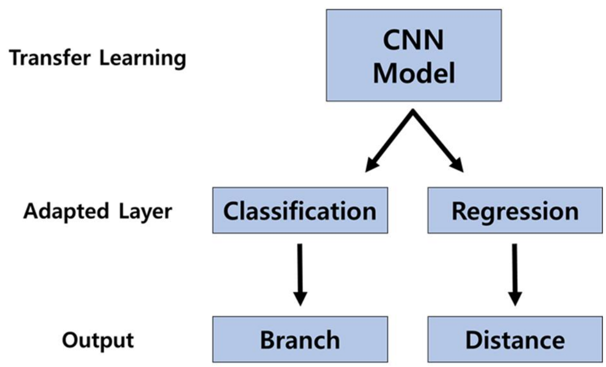

Figure 3.8: The source localization strategies on 2D pipes for regression

3.3. CNN model training

The more complex the problem, the deeper the CNN model. However, training such a deep CNN model requires an enormous amount of data. In this research, the data is not enough to train a the deep CNN model and obtaining more data has limitations of time. In terms of time and finance, it takes a long time to train the model, and it is difficult to build a model structure. Therefore, transfer learning was used for this study. Transfer learning is a method of utilizing an existing model that has already been trained through a large amount of image data and has shown good performance in image recognition problem. In a new problem, even if the data is insufficient, it shows good results of performance and save the time for learning parameters. Also a fine-tuning should be used to apply to the new task. Fine-tuning is adjusting parameters in the transfer-learned model to suit the purpose of new problem.

In this study, a CNN architecture optimized for image classification among existing CNN models was selected. For classification, VGG16 model was used as shown in Figure 3.9. But, for regression, ResNet50 model was used as shown in Figure 3.10. This is because ResNet50 model gave better performance for the data of this study. For fine-tuning, adaptation layers which consists of fully connected layer, pooling layer, and activation functions was added. Output size was adjusted to match with output size of classification and regression. As an activation function, classification model was optimized with cross-entropy loss, and regression model with MSE loss.

Cross-entropy loss is defined as

$$\mathrm{CE} = -\sum_{i}^{C} t_i \log(f(s_i)), \qquad i = 1,2,\ldots,n, \qquad (3.3)$$

where f(s) is output of neural network and t is target value. And MSE loss is defined as

$$\frac{1}{N}\sum_{i=1}^{N}(y_i - t_i)^2, \qquad i = 1,2,\ldots,n, \qquad (3.4)$$

where y is output of neural network and t is target value.

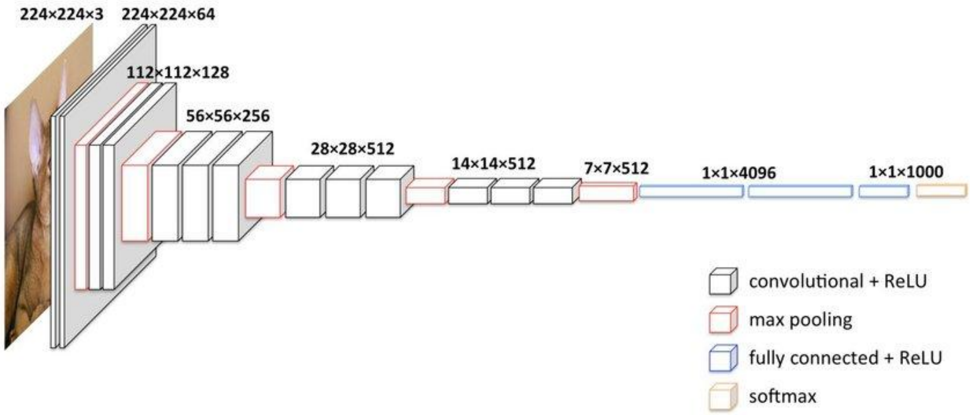

Figure 3.9: Architecture of VGG-16 model [34]

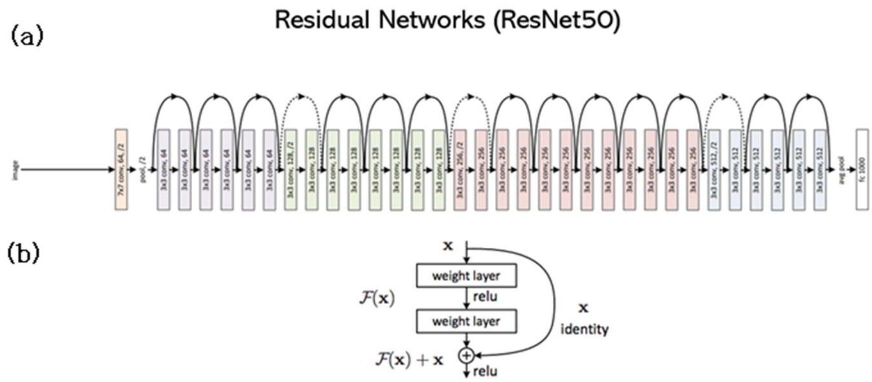

Figure 3.10: (a) Architecture of residual networks (b) residual learning [35]

For the rest of the hyper-parameters, the total number of epochs was set to 100 and the batch size was set to 32. To prevent over-fitting, an early-stopping method was applied in which learning was stopped if the minimum validation loss did not update the minimum loss value for 10 epochs during learning. The learning rate and regularization values used values around 0.0001 through random search.

k-fold cross validation evaluate the performance of this model. Figure 3.11 shows the 5-fold cross-validation. All dataset is divided into the k number of folds. Then, one of folds is used as test set and the remainder of the dataset becomes the training dataset. The performance of model trained with the training dataset is evaluated with the test set. This step is repeated by using each fold as a test set.

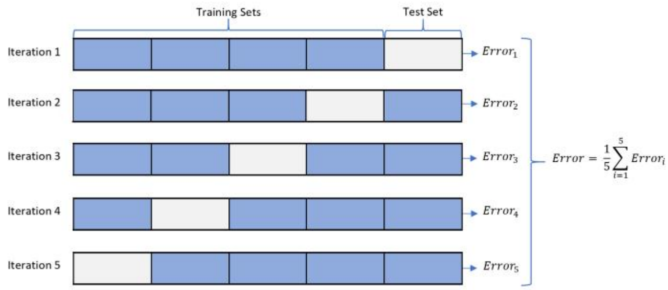

Figure 3.11 5-fold cross-validation [36]

3.4. Source localization results

For classification, the validation loss is cross−entropy loss and mean accuracy is average accuracy of 5−fold cross validation. For regression, the validation loss is MSE loss.

3.4.1 Source localization results according to source types

Table 3.1 shows the results of source localization according to source types which are sources with impulse, continuous, modulated signals. The position estimation performance for the experimental data is represented. The total number of classes is 25 which is the number of excitation points because the 12 m straight pipe was excited with 0.5m distance from the left end of pipe. Then, 100 data were collected per frequency through one sensor. (50 in the case of impulse) Therefore, the total number of data is 750, 7500, and 2500, respectively. At that time, the validation classification accuracy came out to be 98.7%, 95.4%, and 95.9%, respectively.

Table 3.1: Classification results of impulse, continuous, and modulated sources in the straight pipe

	Impulse	Continuous	Modulated
Validation loss	0.1415	0.1379	0.1091
Mean accuracy	98.7%	97.4%	96.4%

3.4.2 Source localization results according to existence of water in pipes

Table 3.2 shows the result of verifying the estimated performance according to the presence or absence of water in the pipe. From the experimental data, we trained the CNN using one sensor. The number of classes is the same as in the previous experiment, since it is a straight pipe. We collected 100 data per frequency. Therefore, the total number of data was 2500 and 7500 when water was not present and when water was present, respectively. At that time, the classification accuracy was derived as 98.0% and 95.4%

Table 3.2: Classification results of the straight pipe with and without water in the straight pipe

	With water	Without water
Validation loss	0.1379	0.1940
Mean accuracy	97.4%	98.0%

3.4.3 Source localization results according to boundary conditions

According to the pipe connection structure, it is divided into pipe with steel U−bolt and rubber U−bolt, and Table 3.3 shows the result of checking and verifying the position estimation performance for the experimental data. Table 3.3 shows the result of verifying the estimated performance according to the boundary conditions the pipe. From the experimental data, we trained the CNN using one sensor. The number of classes is the same as in the previous experiment, since it is a straight pipe. We collected 100 data per frequency.

Therefore, the total number of data was 7500 in both cases. At that time, the classification accuracy was derived as 97.4% and 98.0%, respectively, as a validation mean accuracy

Table 3.3: Classification results of the straight pipe with Steel U-bolt and with Rubber U-bolt

	Steel U-bolt	Rubber U-bolt
Validation loss	0.1379	0.1379
Mean accuracy	97.4%	98.0%

3.4.4 Source localization results according to configuration of pipes

According to the pipe connection structure, it is divided into straight, elbow, and branch pipe, and Table 3.3 is the result for verifying the position estimation performance for the experimental data. For the training data used in CNN, one sensor was used from all experimental data. The number of classes to be classified is straight (total 12 m), elbow (total 8 m), and branch (total width 12 m, vertical 4 m), so 25, 17, and 33 at 0.5m intervals. We collected 100 data per frequency. Data were acquired for all three frequencies of 100, 200, and 500 Hz. Therefore, the total number of data was 7500, 5100, and 9900 respectively according to the pipe connection structure. At that time, the classification accuracy was 95.4%, 95.1%, and 98.3%.

Table 3.4: Classification and regression results of the straight, elbow, and branch pipe in the straight pipe

		Straight	Elbow	Branch
Classification	Validation loss	0.1379	0.1369	0.0480
	Mean accuracy	97.4%	95.1%	98.3%
Regression	Validation loss	0.1415	0.0910	0.0480

In the case of regression, the validation loss came out as 0.3646, 0.0910, and 0.0480. A scatter plot is made as shown in Figure 3.12–14 for visibility.

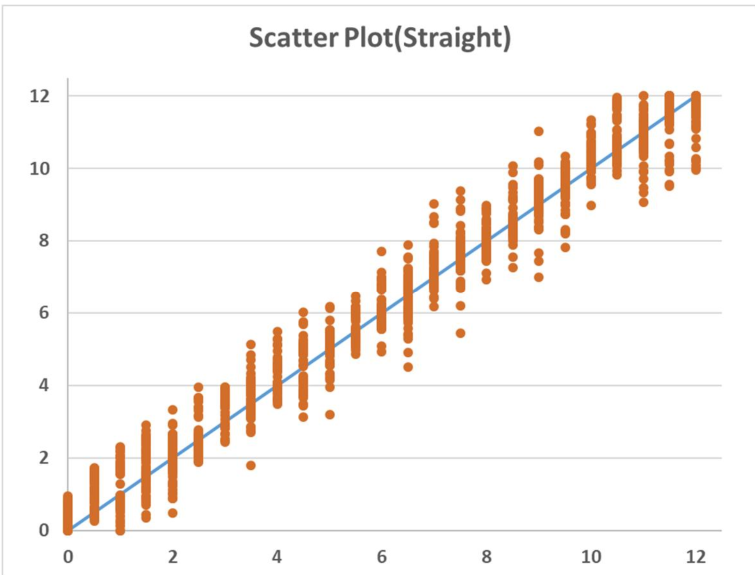

Figure 3.10: The scatter plot of regression on a straight pipe (x-axis : traget value, y-axis: predicted value)

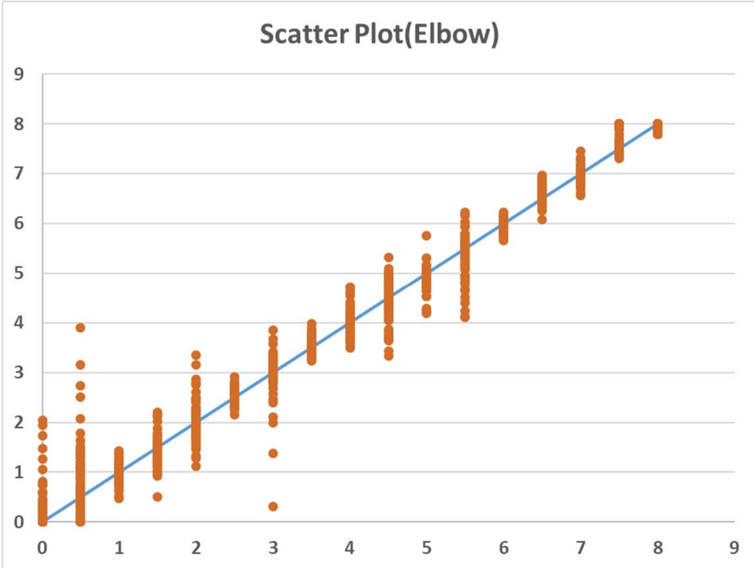

Figure 3.11: The scatter plot of regression on a elbow pipe (x-axis : traget value, y-axis: predicted value)

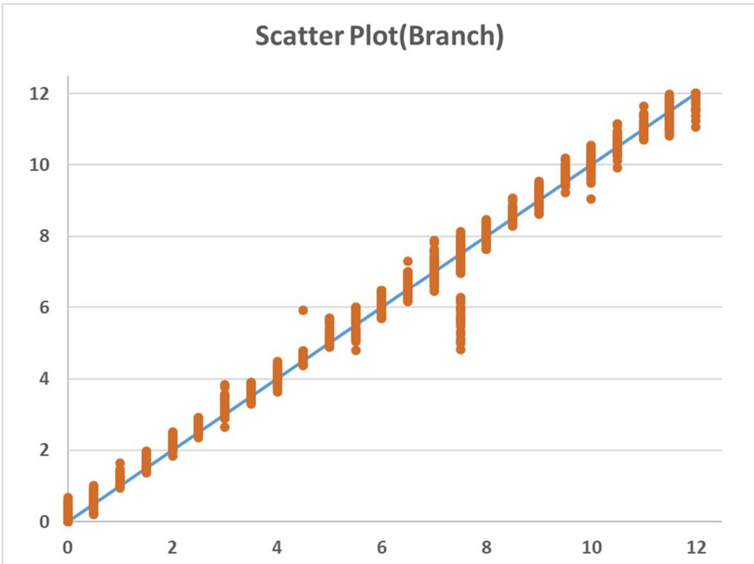

Figure 3.12: The scatter plot of regression on a branch pipe (x-axis : traget value, y-axis: predicted value)

Chapter 4

Conclusions

4.1. Summary

We suggest deep learning based noise source localization method with a single accelerometer. For obtaining the dataset, We considered four representative conditions in a piping system. In condition 1 (source types), This shows that noise source localization on a pipe regardless of source types which is possible to exist in piping systems. In condition 2 (with and without the existence of water in the pipe), most industrial pipes are filled with gas or water, which means that this localization method can be applicable in pipes with water or gas. In condition 3 (boundary conditions), source localization on a piping system with various boundary conditions This shows this method enables to localize the source in pipes having many types of boundary conditions. In condition 4 (configuration of pipes), although there are many configurations of pipes in piping systems, this method can be applied to even unseen data.

There are also clear limitations which is generalization of model. This source localization method should be verified in pipes with flow and real world problems. However, the data are limited.

4.2 Applications

This research can offer possible solutions to the problems to identify the noise source in ships and submarines with a single accelerometer. Most ships and submarines are built based on the series vessels.

Therefore, the piping systems of series vessels are mostly same. By using this fact, firstly, make a model of the pipe network facilities of the reference ship. (2) Test the equipment at the main noise source location or test the exciter at a frequency and frequency band similar to the equipment. Then, (3) the vibration is transmitted and the frequency response is anlayzed through the data collection device in the main region of interest. Compare with the frequency from the noise source in (2), and if a matching frequency is found, set that place as the measurement point. (4) A training dataset is obtained from the measurement point and saved along with location information. (5) Train the model using the developed CNN model and check the validation performance. (6) If abnormal noise occurs after construction or during operation, vibration data for each excitation point is obtained and regression is performed to estimate the location of the noise source in the ship piping system.

Here, it is possible to directly measure a training dataset for CNN training in a piping system of an actual ship, such as a merchant ship and surface ship, using a vibration sensor. In the case of a submarine, in the case of an accessible piping system, a training data set is acquired from the piping system inside the actual submarine. Otherwise, construct the pipe network facilities as in the method in the paragraph above. Also. There is one thing to consider in a submarine. The structure inside the submarine is so sealed and complex that it is difficult to measure it directly. In addition, it is difficult to measure directly in the case of a submarine due to security issues. Therefore, cooperation with national organizations is necessary to solve this problem.

4.3 Future study

Learning with two-dimensional deck and three-dimensional hull

A goal of the this future study is developing from source localization method on a piping system into source localization method on deck and hull. With expansion of dimension, this future study estimates the location of abnormal noise sources in the ship deck and hull. Noise sound directly affects on underwater radiated noise as well as accommodations and workspaces. There are some considerations for studying this future study, as follows: (1) To identify the location of the noise source based on the neural network through the measurement with multiple vibration sensors and noise sensors. To develop the source localization methods for plate structures with (2) various boundary conditions, and (3) noise sources types.

(1) Transmission characteristic of noise in a 2D deck and a 3D hull is need. Noise generated from machinery in a real ship will be transmitted to the deck and hull along the transmission path. Airborne noise as well as structure-borne noise are considered, therefore, both vibration and noise sensors are used. In this way, by using multiple sensors, each sensor is attached to a place of interest to measure the signal. Estimating a azimuth angle or a position using a microphone array, which is a noise sensor.

(2) There are many boundary conditions in the structure of ships and submarines. For 2D, to conduct basic research, nodes on a metal plate are created as in the thesis []. Noise at the node is made, and the location is estimated using the AI method. Various boundary conditions are applied to the plate to conduct experiments to verify classification performance with CNN model. For 3D, it is possible to suggest a method of estimating the location of the internal noise source based on AI methods by implementing a small 3D room with steel plates and creating various structures inside. Alternatively, in

order to diversify the boundary conditions, there may be a method of confirming the performance of the CNN by placing sound sources at various locations within the actual ship and performing location estimation accordingly.

Finally, (3) a variety of source types such as impulse, continuous, modulated signals should be considered

Appendix

TDoA based source localization results

Wave speed for fluids in pipes (v) is expressed as,

$$v = \sqrt{\frac{1}{\rho(\frac{1}{K} + \frac{D\psi}{Ee}}} , \quad \text{(A.1)}$$

where ρ is a fluid's density, ψ is pipe support factor, E is bulk modulus of pipe, K is bulk modulus of fluid, D is internal diameter of pipe. A straight pipe made of Cu-Ni pipe was used, therefore, e is 0.004 m, ρ is 1000 kg/m^3, D is 0.4191, E is 115 GPa, K is 140 GPa, and ψ is 0.8775. Therefore, the wave speed for fluids in pipes is 1183 m/s.

Figure A.1 shows the scatter plot of results of the time difference of arrival (TDoA) based source localization method. Generalized cross-correlation is employed for calculating the time difference of arrival. The MSE loss is 26.3468 which is far higher than the MSE loss from regression model. So our suggested model has better results than conventional TDoA method.

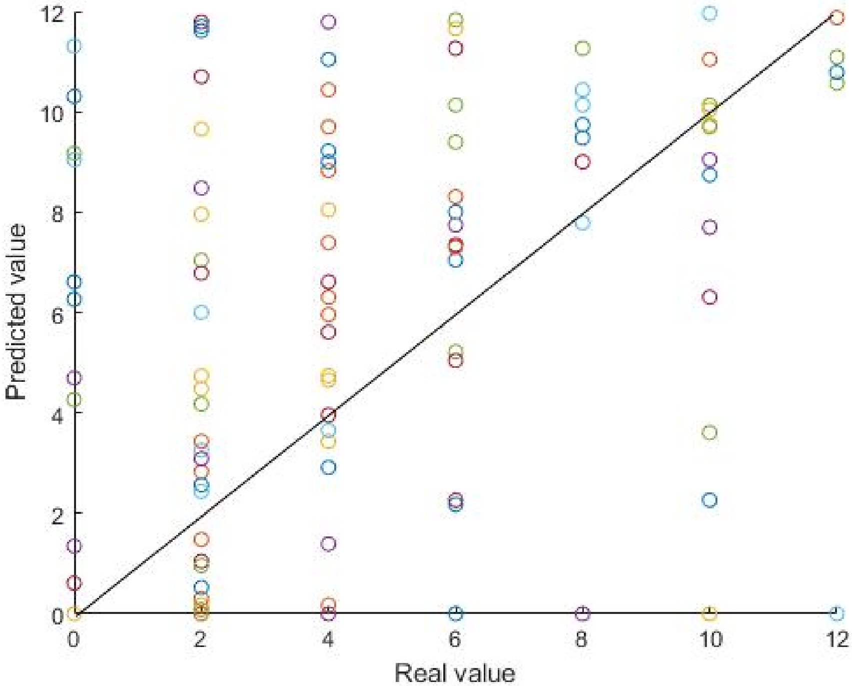

Figure A.1: The scatter plot of estimated value by TDoA method.

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Abstract

파이프 시스템 내 소음원 위치 추정에 관한 딥러닝 접근법

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조선산업에서 선박과 잠수함의 소음원을 규명은 중요한 문제로 대두되고 있다. 주 장비와 같은 다양한 소음원으로부터 발생하는 소음은 선체 외부, 작업장, 그리고 거주구역을 비롯한 선체 대부분에 전파될 수 있다. 게다가, 이러한 노이즈는 작업자들과 거주자들, 그리고 수중 방사 소음에도 여향을 미친다. 특히 잠수함의 경우, 수중 방사 소음은 생존성과 직접적으로 관련되며 소나의 탐지 성능을 저해시키는 원인이다. 도착시간 차이에 의한 기존 소음원 위치 추정방법은 노이즈에 너무 민감하기 때문에 복잡한 시스템에 적용하기는 어렵다. 게다가 이러한 방법들은 두 개 이상의 센서를 사용해서, 파이프 결함이나 누수에 의한 일시적인 소음원이거나 한 가지 파이프 종류에 대해서 한정된 방법이다. 최근 소음원 위치추정에 대한 연구들은 딥러닝 적용이 이러한 문제들을 해결 가능하다는 것을 보여주고있다. 따라서, 우리는 한 개의 센서를 이용해 파이프 시스템에서 소음원의 위치를 추정하는 방법을 제시했다. 전이학습과 미세조정이 제안된 파이프 소음원 위치 추정 방법에 적용되었다. 사전 학습된 컨볼루셔널 신경망으로서, 분류를 위한 VGG 16과 회귀를 위한 ResNet 50이 사용되었다. 우리는 2차원 파이프 위치 추정을 위해 분류를 이용한 방법과 분류 모델이 결합된 회귀를 위한 방법을 제시하였고, 이것은 3차원 파이프에서도 적용이 가능하다. 이것은 또한 복잡하고 좁

은 파이프 시스템으로 인해 볼 수 없는 데이터에 대한 해결책도 될것이다. 모델들을 학습시키기 위해, 구조 전달 소음 데이터셋이 4가지 전형적인 조건들에 따라 실험을 통해 얻어졌고, 그 4가지 조건은 다양한 소음원 유형, 파이프 내에 물이 존재하는지 여부, 경계조건, 그리고 파이프의 형상에 대해 다뤘다. 이렇게 모아진 신호들은 딥러닝 모델을 학습시키기 위해 원신호에서 로그-멜 스펙트로그램 이미지로 전처리 되었다. 모델의 성능은 5-겹 교차검증으로 평가되었다. 비록 이 논문은 파이프 소음원 위치 추정에 초점을 맞춰져있지만, 이 제안된 방법들은 다른 산업에서의 파이프 시스템뿐만 아니라 다른 시스템에서의 소음원 위치 추정에도 이용될 수 있다.