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Research Article

Distance Measurement by Neural Network Learning of Near-Field Microwave Reflection Spectra

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Microwave-based distance measurements are limited depending on the sensing environment, such as the propagation medium and surrounding obstacles, and the complex environment also affects the measurement performance. To tackle this problem, we propose a method for predicting the distance based on the artificial neural network learning of near-field microwave reflection spectra. In principle, the spectral data is expected to contain a signature of the distance of the target object. Based on this, we proposed a two-step neural network to extend the measurable distance range while ensuring prediction performance. The first step is to predict the coarse range of the target by classification, and the next is to predict the precise distance value through multidimensional regression within that coarse range. The method was verified through experiments to predict the position of an object in an underwater environment, which was difficult to measure with conventional methods.

1. Introduction

Distance measurement is a common interest in many fields, including scientific and industrial applications. To date, various techniques have been developed. The techniques are generally divided into contact and noncontact types. The first requires an object to touch the sensor, which usually complicates and slows the measurement process and can damage the inspected object. Moreover, if the measurement target is a soft material such as rubber, textile, or tissue, it cannot be measured at all. On the other hand, the noncontact type, in which the sensor and the object to be measured are separated, has the advantages of low inspection cost and short inspection time. Therefore, it is excellent in usability [1]. The noncontact distance measurement sensor uses ultrasonic waves, radio waves, infrared rays, visible light, and so on [2, 3]. In principle, the distance can be simply computed from the time of flight (ToF) in a straight line from the transmitted source.

Ultrasonic sensors have the advantages of being low cost and compact in size [2]. However, the distance measurement in ultrasonic sensors is based on the speed of sound, which varies depending on the propagation medium, temperature, and relative humidity [4], causing an error in the distance measurement. The infrared sensor offers a lower cost and a faster response than ultrasonic sensors [5], but they have nonlinear characteristics due to the reflectance properties of the object surfaces [6]. Radar sensors using radio waves are not affected by the surrounding weather and have high precision [7], and the computational cost can also be reduced [8]. However, there are disadvantages in that it is difficult to identify small objects and understand the types of objects. Lidar sensors, using a laser pulse, obtain high-resolution long-distance 3D data as well as precise distance measurements and have the advantage of analyzing visibility in space [9]. It can track objects at a range of 200 m or more and a wide field of view [10]. However, there is the disadvantage that it is affected by the environment such as illuminance and weather, and the price is quite expensive.

To overcome the limitations of using each sensor alone, a method of using several types of sensors together has been proposed. For example, there is a method of combining an ultrasonic sensor and an infrared sensor, or a method of combining a radar sensor and a lidar sensor [3, 10]. However, these methods increase the complexity of the measurement system and accordingly increase its size and cost.

Another method to measure the distance is to use a stereo camera that is widely used in areas such as robots and autonomous vehicles and can measure relatively accurately [11]. In addition, distance measurement using a stereo camera is being improved through continuous research and efficient use of algorithms [12–15]. However, outdoor use may cause problems in bad weather with little light, such as fog or rain, because the camera is affected by light.

As such, there are many ways to measure distance. However, when optical visibility is not guaranteed, when refraction modeling is difficult, or when there is strong interference in a measurement signal, it is often difficult to use the above-described conventional method. For this reason, using microwaves may provide a meaningful sensing signal even in the measurement environment. However, until now, it has been difficult to extract meaningful information from the measured signal. Meanwhile, recent remarkable breakthroughs in machine learning have had a profound impact on problems such as regression, classification, and optimization [16–18] and have been widely applied in various fields [19, 20]. In particular, artificial neural networks (ANNs), one of machine learning, are effective modeling methods that can deal with nonlinear and multivariable problems. This is because ANNs can learn and model nonlinear and complex relationships, generalize, and, unlike many other prediction techniques, do not impose restrictions on input variables. Due to these advantages, such ANNs have been applied in many practical applications, such as nonlinear dynamic system control [21], material property prediction [22, 23], and crack detection in concrete structures [24]. Considering the recent situation, ANN is expected to be able to extract meaningful information from complex microwave signals.

To this end, in this paper, we propose a short-range distance measurement method through ANN learning of near-field microwave reflection spectra measured from the surrounding environment. In detail, we first investigate the change in the reflection spectrum as the distance of an object placed in water changes. Then, we present a one-step neural network and a two-step neural network for distance prediction and evaluate their performance.

2. Materials and Methods

2.1. Microwave Reflection Spectrum. The distance of an object is related to the nature of the signal that the transmitted microwave reflects off the object and returns. Here, the nature of the signal can be expressed with the reflection spectrum that describes how much of a wave is reflected by an impedance discontinuity in the transmission medium according to the microwave frequency. The reflection spectrum can be obtained from the scattering coefficient (also called the S-parameter [25]). In general, the parameter is defined as

$$S_{ij} = \frac{V_i^-}{V_j^+}, \tag{1}$$

where V_i^- is the wave signal voltage out from the port i, and V_j^+ is the wave signal voltage into the port j. Here, the reflection coefficient (S_{ii} or S_{jj}) is defined as the ratio of the output voltage to the input voltage at the same port. Therefore, the microwave reflection spectrum, measured by the one-port antenna used in this work, can be obtained from the logarithmic magnitude of reflection coefficient, $20 \log |S_{11}|$.

In another expression, the reflection coefficient Γ [25] at the load is also given as

$$\Gamma = \frac{Z_L - Z_0}{Z_L + Z_0}, \tag{2}$$

where Z_L and Z_0 are the load impedance and the reference impedance (50Ω), respectively. The reflection coefficient can be measured using a vector network analyzer (VNA). The load impedance depends on the position of the object placed in the measurement environment and varies with the microwave frequency. As a result, the resonant frequency changes according to the distance between the antenna and the object. In [26], a study on distance measurement was conducted using the phenomenon. However, the method has a disadvantage in that the available change in the resonance frequency according to the distance is limited, and thus, the measurement range is limited. If there are several obstacles in the vicinity other than the object of interest, the mutual interference of microwaves will cause inaccurate measurements.

In another aspect, the reflection spectrum contains the signature signal of the object of interest despite its complex environment. Owing to this fact, we can expect that it will be possible to use neural networks with excellent learning ability on complex and nonlinear data. That is, the measured spectral data becomes the input to the ANN, and the output of the ANN becomes a prediction for the distance of the object to be measured.

2.2. One-Step Neural Network Approach. ANN is a machine learning technique created by mimicking the structure of neurons in living things. It is similar to the process by which a neuron receives a signal and is activated when that signal crosses a threshold. In this work, the measured microwave reflection spectrum becomes the input to the ANN, and the output of the ANN becomes the predicted distance of the object.

To predict the distance of the object, we first consider a simple one-step ANN as shown in Figure 1, which uses a neural network for regression with one input layer, one hidden layer, and one output layer. The input data of the input layer is spectral data with N points in the range of frequencies f_1 to f_N. The output is the distance of the object.

As the ANN training algorithm, the Levenberg-Marquardt backpropagation (LMBP) algorithm is applied. This combines the Gaussian Newton method and the gradient descent

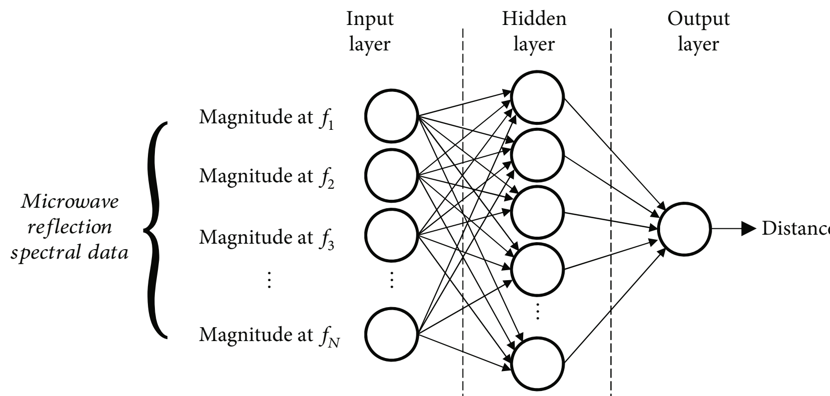


Figure 1: One-step neural network for distance prediction.

method, which is the most widely used method for nonlinear function optimization problems [27]. Next, a data set should be prepared to train the neural network. To this end, the spectral data of the microwave reflection signal are sufficiently acquired in advance according to the location of the target for which the distance is to be measured. And training is done using the dataset.

2.3. Two-Step Neural Network Approach. To predict a wide range of distances, it is expected that a large amount of training data and a large amount of training time will be required accordingly in the standard one-step ANN. To improve this problem, we propose a two-step neural network as shown in Figure 2. It consists of a single ANN for classification and multiple ANNs for regression. The first ANN predicts a coarse range of an object, and the second ANN predicts a fine range (precise distance of the object).

The detailed flow of the two-step ANN is as follows. When the spectral data of an object placed at a certain distance are measured using the VNA, the data is input to the first neural network, an appropriate segment corresponding to the coarse range is selected, and the precise distance is predicted through the regression neural network selected.

In this work, the scaled conjugate gradient backpropagation (SCGBP) algorithm is applied for the classification training algorithm. The scaled conjugated gradient algorithm, which combines the trust region method with the general conjugate gradient, can provide fast supervised learning [28]. On the other hand, the training of each neural network to predict the final precise distance is trained with the minimum data set required by each neural network.

2.4. Experimental Setup. To verify the proposed method, we established an experimental testbed for measuring the microwave reflection spectrum of the surrounding environment where the object is placed, as shown in Figure 3. Here, a thin monopole antenna was used to detect the reflection spectrum. To accurately set the desired distance of the object, the antenna sensor is moved using an XY table driven by a stepping motor. The microwave reflection spectrum is obtained as the magnitude of the reflection coefficient measured by the VNA (Keysight E5063A). For the study, the measurement frequency band was set to 300 kHz to 1.5 GHz. The personal computer controls the XY table and VNA that also collects measurement data.

On the other hand, the object to predict the distance is embodied in the water. In such an environment, it is practically difficult to utilize the existing distance measurement method. The size of the water tank is $600 \times 600 \times 400\,\mathrm{mm}^3$. The object is a metal plate with a size of $150 \times 250\,\mathrm{mm}^2$. The main resonance frequency of the antenna sensor is about 950 MHz (see Figure 4).

In the experimental setup, we prepare data for training, validation, and testing of the proposed ANN model. After positioning the monopole antenna 10 mm in front of the measurement target, the microwave reflection spectrum is measured and stored. These measurements are taken in 1 mm intervals up to 250 mm, 30 times in each position. As a result, a total of 7,230 data were prepared. For model training and model evaluation, we used 4,338 (60%) of the data in the training set, 1,446 (20%) in the validation set, and 1,446 (20%) in the test set.

As shown in Figures 1 and 2, the ANN is a multilayer network consisting of connected neurons in input, hidden, and output layers. In this study, we use microwave reflection spectral data as the input to the network and consider the distance of the target object as the output of the network. Therefore, the input neurons are 201 which is the number of data points at a frequency sampled equally spaced between 300 kHz and 1.5 GHz. The output neuron is 1 in the case of one-step NN (see Figure 1). In the two-step NN (see Figure 2), the output neurons of the NN in the first step are 4 (the number of segments of the measurement distance) and that of the NN in the second step is 1 (the output is a predicted distance). The number of neurons in the hidden layer is mainly dependent on the accuracy requirement of the practical problem to be tackled [21]. In general, the trial-and-error approach is used to determine the optimal neuron number of the hidden layer. In this work, by increasing the number of hidden layers to 100, the optimal number of hidden neurons was determined, with a small number and without overfitting. As a result, 10 hidden neurons were

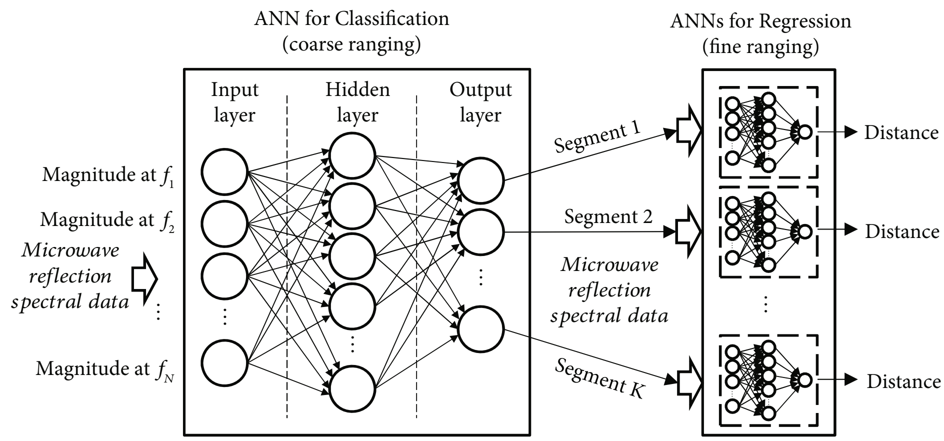


Figure 2: Two-step neural network for distance prediction.

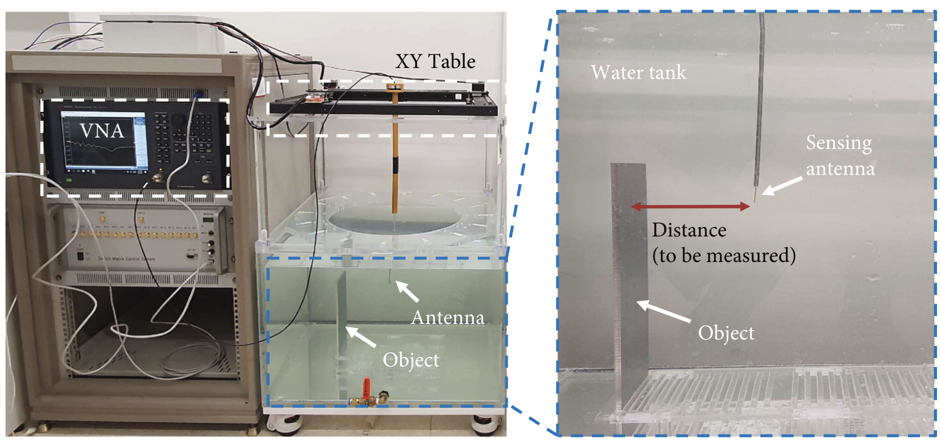


Figure 3: Experimental testbed.

selected. The training is performed with a backpropagation algorithm to optimize the connecting weights in the ANN model.

3. Results and Discussion

3.1. Results of the Microwave Reflection Spectrum. To investigate the effect according to the distance of the object (metal plate), we measured the reflection spectrum in the prepared experimental environment. Here, the spectral data were collected by moving the metal plate by 10 mm in the range of 10 to 250 mm. The microwave frequency range used was up to 1.5 GHz.

The experimental result is in Figure 4 that shows that the resonant frequency and magnitude are affected by the distance of the metal plate apart from the sensing antenna. In particular, the changes in resonance frequency and magnitude were plotted in Figure 5. It is noteworthy that the change oscillates and decreases rapidly as the distance increases. In this case, it is difficult to apply the method reported in [26] because it is impossible to determine the unique distance of the metal plate with only the reflection magnitude at the resonant frequency. Therefore, the overall pattern around the resonance point is an important clue in predicting the distance of the object.

3.2. Results of the One-Step Neural Network Approach. As mentioned earlier, we need to prepare a dataset of the microwave reflection spectrum for training the neural network. For this, the training distance interval was determined based on the wavelength of the microwave used. The wavelength λ can be obtained from

$$\lambda = \frac{c}{f\sqrt{\varepsilon_r}}, \tag{3}$$

where c is the speed of light (3×10^8 m/s), f is the operating frequency, and ε_r is the relative permittivity of the propagation medium. Considering our experimental environment operating in the water, the wavelength is 36 mm, computed with a microwave frequency of 945 MHz (a typical resonance frequency as shown in Figure 4) and a relative permittivity of 78 (water).

Therefore, in this study, we considered four cases with distance intervals of 18 mm ($\lambda/2$), 9 mm ($\lambda/4$), 6 mm ($\lambda/6$), and 3 mm ($\lambda/12$). Using each acquired dataset, a standard one-step ANN (see Figure 1) was trained. The corresponding test results are shown in Figure 6. This is the error of the distance predicted by a trained neural network while moving the metal plate by 1 mm. According to the results,

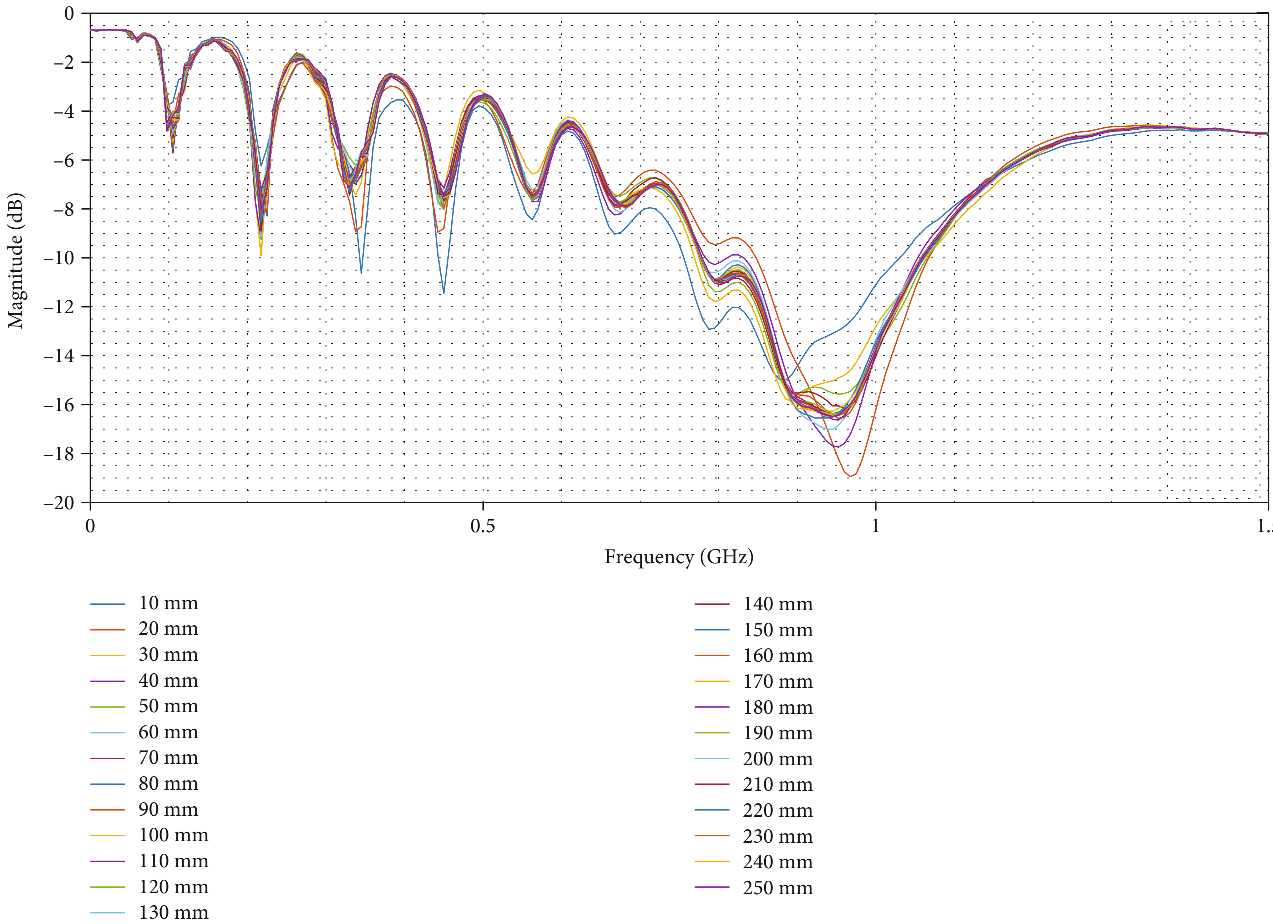
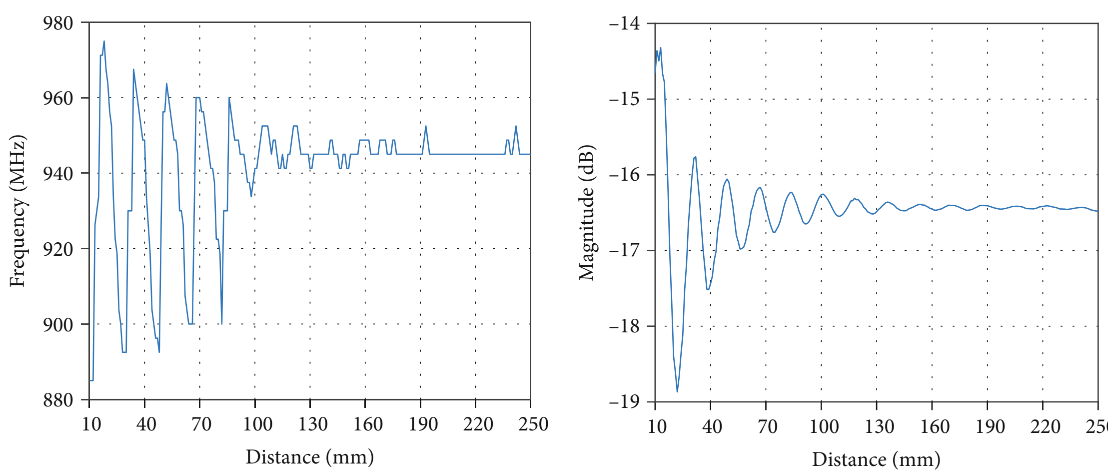


Figure 4: Changes in the microwave reflection spectrum with distance.



(a) (b)

Figure 5: Changes in (a) resonance frequency and (b) reflection magnitude with distance.

the larger the distance interval used for training, the larger the distance prediction error. In particular, when the target object is at a close distance (below about 50 mm), the prediction error is much larger. It can be seen in Figures 1(a) and 1(b). Moreover, at the distance used for training, the prediction error is close to zero. That is, as shown in Figure 1(a), the prediction error is close to zero for every 18 mm interval: 18 mm, 36 mm, 54 mm, ⋯, 180 mm, 198 mm, etc., which are the distances of the training dataset. On the other hand, the result of training with a dataset measured at every 3 mm

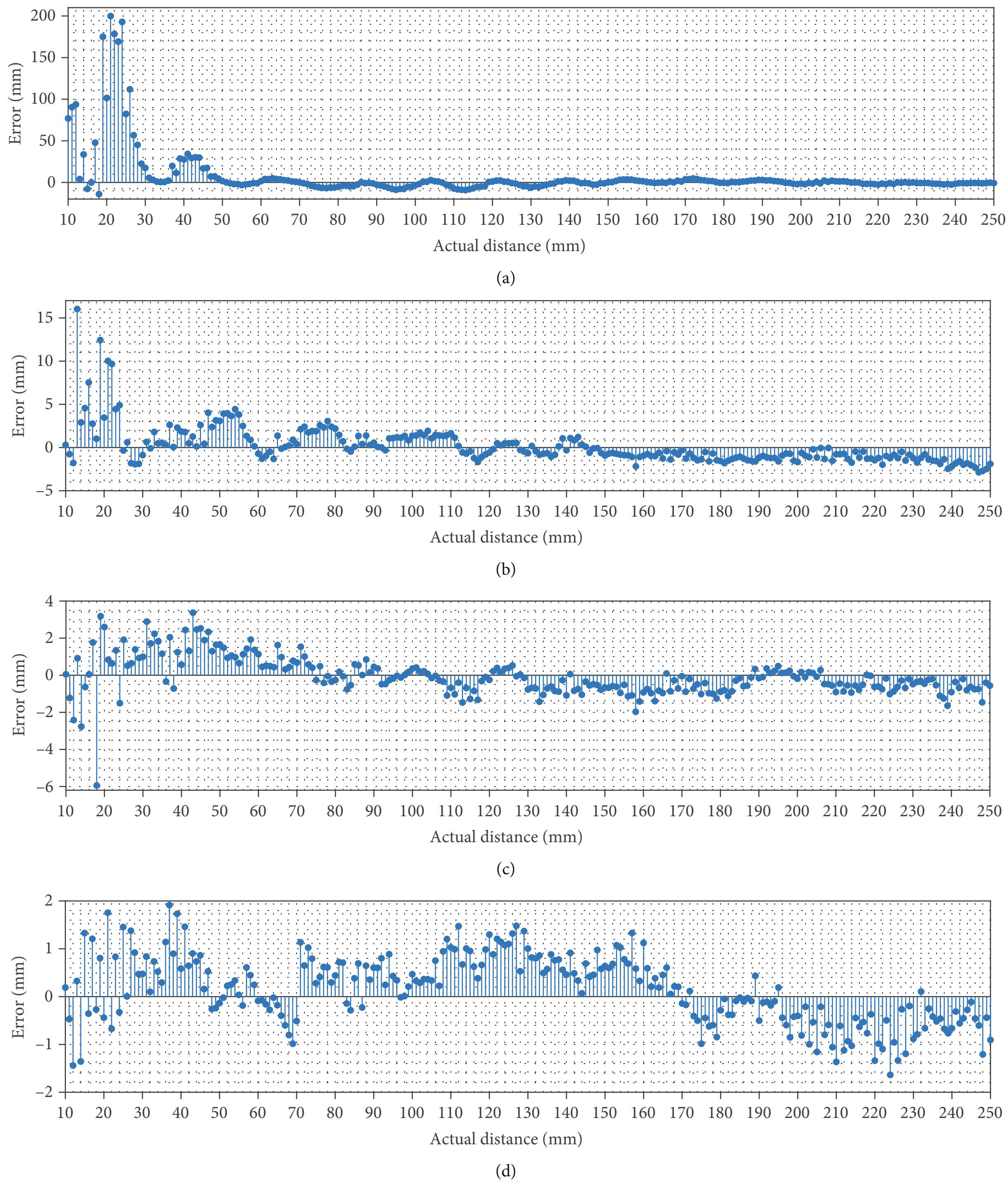


Figure 6: Distance prediction errors using a one-step neural network trained with a dataset measured at (a) 18 mm, (b) 9 mm, (c) 6 mm, and (d) 3 mm intervals.

interval (Figure 1(d)) shows that the best prediction error over all ranges is within 2 mm.

From the experimental results, it was confirmed that distance prediction is possible using a one-step ANN trained with the spectral reflection data, but more densely spaced training data are needed to more accurately predict the distance close to the antenna.

3.3. Results of the Two-Step Neural Network Approach. From the distance prediction results obtained through a one-step ANN, we know that the prediction error is related to the amount of training data. That is, the wider the range to predict, the greater the amount of training data required. In particular, a more densely spaced training data set is needed near the sensing antenna. Meanwhile, it would be more

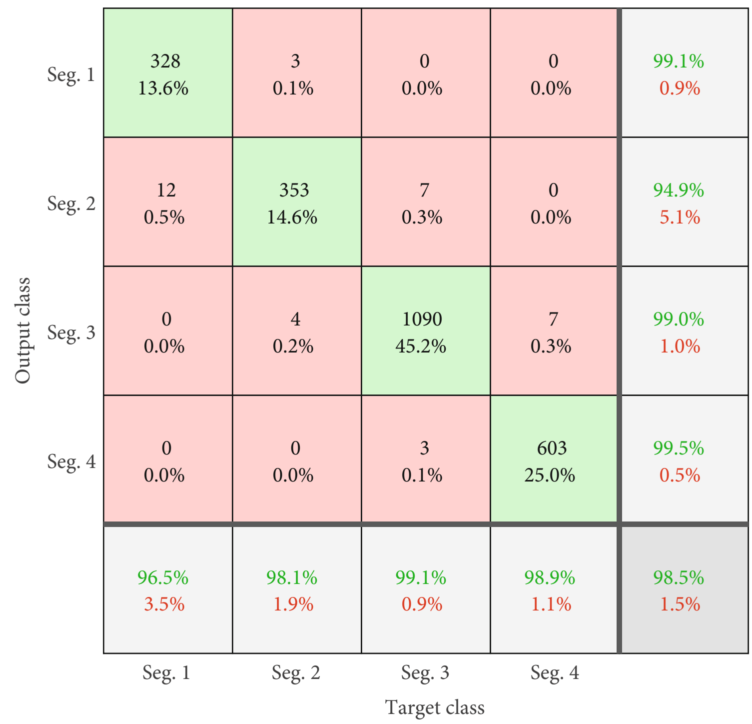


Figure 7: Confusion matrix of classification in a two-step neural network.

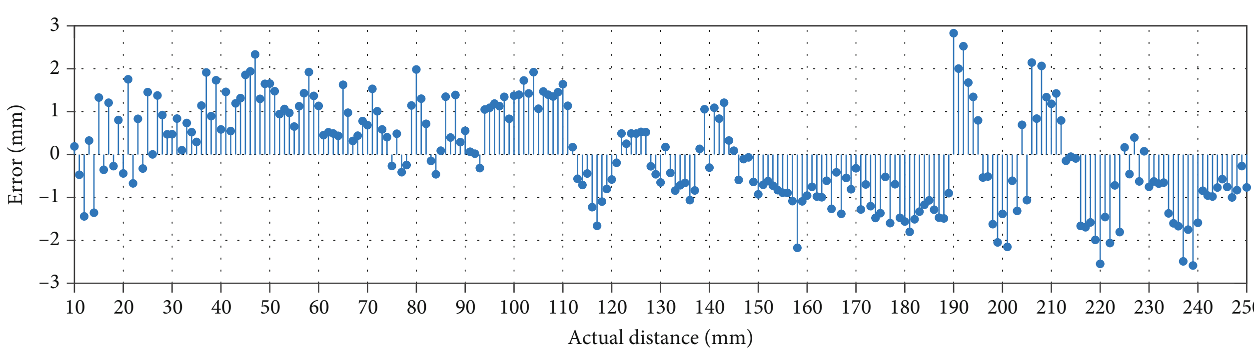


Figure 8: Distance prediction errors in a two-step neural network.

efficient if the prediction performance could be improved with as little training data as possible. Based on this idea, we proposed a two-step ANN (see Section 2.3) that satisfies the desired performance with fewer training data.

Consider again the experimental testbed to perform distance prediction of the metal plate within the range of 10 to 250 mm. And let us aim to implement a neural network that satisfies the prediction error within 3 mm in the entire range. However, in the case of training with 18 mm interval data, the prediction error was satisfied when the actual distance is greater than about 190 mm (see Figure 6(a)). And, when the training distance intervals were 9 mm and 6 mm, they were satisfied after 80 mm and 45 mm, respectively (see Figures 6(b) and 6(c), respectively). Based on the results, we have divided the overall range of 10–250 mm into four segments: 10–45 mm, 45–80 mm, 80–190 mm, and 190–250 mm.

Therefore, the input of the first neural network is spectral data (201 points), and its output is the selection of the appropriate segment out of four. To evaluate the performance of the classifier, we measured the confusion matrix in the test as shown in Figure 7. This provides better insight into which classification models are getting more accurate and what types of errors are being generated. The result shows that the classification accuracy is 98.5%, and the remaining 1.5% are classified into immediately adjacent segments. Based on these classification results, an appropriate regression network was selected, and the final precision distance was predicted. The result is shown in Figure 8. The prediction error is less than 3 mm in the entire range, unlike the one-step ANN. On the other hand, 1.5% of the input data were misclassified into the immediately adjacent segment. However, this degree of error did not affect the final distance prediction.

4. Conclusions

In this paper, we presented a method for predicting the distance of an object from the acquired microwave reflection spectrum. It was experimentally shown that the spectral data change into a nonlinear complex pattern according to the distance. Therefore, we used an artificial neural network with a strong learning ability for these nonlinear pattern changes. On the other hand, the prediction performance is affected by the distance interval of the training data. In particular, the closer the location of the object to the antenna, the worse the prediction performance. A simple solution to this problem is to use a much denser training dataset. In this case, another problem arises the training data increases proportionally. Therefore, in this paper, we proposed a two-step ANN that combines classification and regression. To verify the method, an experiment was conducted to predict the distance of a wide range of an object placed in water. As a result, the prediction error was within 3 mm in the range of 10–250 mm. Through this study, we confirmed that the distance of the target object can be predicted by learning the microwave reflection spectrum. Therefore, this distance measurement method can also be used in complex environments where unwanted microwave reflections can occur. In future research, we intend to present a practical study of predicting the distance of industrial parts placed in these complex environments and to conduct comparative studies with other machine learning techniques in addition to neural networks.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there is no conflicts of interest regarding the publication of this paper.

Acknowledgments

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References

[1] A. M. Kassim, H. I. Jaafar, M. A. Azam, N. Abas, and T. Yasuno, "Performances study of distance measurement sensor with different object materials and properties," in *Proceedings of 3rd IEEE International Conference on System Engineering and Technology (ICSET)*, pp. 281–284, Shah Alam, Malaysia, 2013.

[2] A. K. Sahoo and S. K. Udgata, "A novel ANN-based adaptive ultrasonic measurement system for accurate water level monitoring," *IEEE Transactions on Instrumentation and Measurement*, vol. 69, no. 6, pp. 3359–3369, 2020.

[3] G. Farias, E. Fabregas, E. Peralta et al., "A neural network approach for building an obstacle detection model by fusion of proximity sensors data," *Sensors*, vol. 18, no. 3, p. 683, 2018.

[4] D. Bohn, "Environmental effects on the speed of sound," *Journal of the Audio Engineering Society*, vol. 36, no. 4, pp. 223–231, 1988.

[5] G. Benet, F. Blanes, J. E. Simó, and P. Pérez, "Using infrared sensors for distance measurement in mobile robots," *Robotics and Autonomous Systems, Elsevier*, vol. 40, no. 4, pp. 255–266, 2002.

[6] B. Mustapha, A. Zayegh, and R. Begg, "Ultrasonic and infrared sensors performance in a wireless obstacle detection system," in *Proceedings of the 1st International Conference on Artificial Intelligence, Modelling and Simulation (AIMS)*, pp. 487–492, Kota Kinabalu, Malaysia, December 2013.

[7] M. Engelhardt, F. Pfeiffer, and E. Biebl, "A high bandwidth radar target simulator for automotive radar sensors," in *Proceedings of the European Radar Conference (EuRAD)*, pp. 245–248, London, UK, October 2016.

[8] L. Piotrowsky, T. Jaeschke, S. Kueppers, J. Siska, and N. Pohl, "Enabling high accuracy distance measurements with FMCW radar sensors," *IEEE Transactions on Microwave Theory and Techniques*, vol. 67, no. 12, pp. 5360–5371, 2019.

[9] J. Jung, M. J. Olsen, D. S. Hurwitz, A. G. Kashani, and K. Buker, "3D virtual intersection sight distance analysis using lidar data," *Transportation Research Part C: Emerging Technologies*, vol. 86, pp. 563–579, 2018.

[10] D. Göhring, M. Wang, M. Schnürmacher, and T. Ganjineh, "Radar/lidar sensor fusion for car-following on highways," in *Proceedings of the 2011 5th International Conference on Automation, Robotics and Applications (ICARA)*, pp. 407–412, Wellington, New Zealand, December 2011.

[11] K. Adi and C. E. Widodo, "Distance measurement with a stereo camera," *International Journal of Innovative Research in Advanced Engineering (IJIRAE)*, vol. 11, no. 11, pp. 24–27, 2017.

[12] Y. D. Salman, K. R. Ku-Mahamud, and E. Kamioka, "Distance measurement for self-driving cars using stereo camera," in *Proceedings of the International Conference on Computing and Informatics*, vol. 105, pp. 235–242, Kuala Lumpur, Malaysia, 2017.

[13] N. Q. Ann, D. Pebrianti, L. Bayuaji et al., "SKF-based image template matching for distance measurement by using stereo vision," *Intelligent Manufacturing and Mechatronics*, pp. 439–447, 2018.

[14] J. Mrovlje and D. Vrancic, "Distance measuring based on stereoscopic pictures," in *Proceedings of the 9th International PhD Workshop on Systems and Control*, Simonov Zaliv, Slovenia, October 2008.

[15] A. Zaarane, I. Slimani, W. Okaishi, I. Atouf, and A. Hamdoun, "Distance measurement system for autonomous vehicles using stereo camera," *Array*, vol. 5, article 100016, 2020.

[16] S. Ray, "A quick review of machine learning algorithms," in *Proceedings of 2019 International Conference on Machine Learning, Big Data, Cloud and Parallel Computing (COMIT-Con)*, pp. 35–39, Faridabad, India, 2019.

[17] A. E. Maxwell, T. A. Warner, and F. Fang, "Implementation of machine-learning classification in remote sensing: an applied review," *International Journal of Remote Sensing*, vol. 39, no. 9, pp. 2784–2817, 2018.

[18] S. Sun, Z. Cao, H. Zhu, and J. Zhao, “A survey of optimization methods from a machine learning perspective,” *IEEE Transactions on Cybernetics*, vol. 50, no. 8, pp. 3668–3681, 2020.

[19] G. Carleo, I. Cirac, K. Cranmer et al., “Machine learning and the physical sciences,” *Reviews of Modern Physics*, vol. 91, no. 4, 2019.

[20] M. I. Jordan and T. M. Mitchell, “Machine Learning: Trends, Perspectives, and Prospects,” *Science*, vol. 349, no. 6245, pp. 255–260, 2015.

[21] Y. Yang, Y. Li, and J. Li, “Nonparametric modelling of magnetorheological elastomer base isolater based on artificial neural network optimized by ant colony algorithm,” *Journal of Intelligent Material Systems and Structure*, vol. 26, no. 14, pp. 1789–1798, 2015.

[22] Z. Lyu, Y. Yu, B. Samali et al., “Back-propagation neural network optimized by K-fold cross-validation for prediction of torsional strength of reinforced concrete beam,” *Materials*, vol. 15, no. 4, p. 1477, 2022.

[23] T. N. Nguyen, Y. Yu, J. Li, N. Gowripalan, and V. Sirivivatnanon, “Elastic modulus of ASR-affected concrete: an evaluation using artificial neural network,” *Computers and Concrete*, vol. 24, 2019.

[24] Y. Yu, M. Rashidi, B. Samali, M. Mohammadi, T. N. Nguyen, and X. Zhou, “Crack detection of concrete structures using deep convolutional neural networks optimized by enhanced chicken swarm algorithm,” *Structural Health Monitoring*, vol. 21, no. 5, pp. 2244–2263, 2022.

[25] C. A. Balanis, *Antenna Theory Analysis and Design*, John Wiley & Sons, New York, NY, USA, 2nd edition edition, 1997.

[26] A. Zamani, S. A. Rezaeieh, K. S. Bialkowski, and A. M. Abbosh, “Boundary estimation of imaged object in microwave medical imaging using antenna resonant frequency shift,” *IEEE Transactions on Antennas and Propagation*, vol. 66, no. 2, pp. 927–936, 2018.

[27] D. W. Marquardt, “An algorithm for least-squares estimation of nonlinear parameters,” *Journal of the Society for Industrial and Applied Mathematics*, vol. 11, no. 2, pp. 431–441, 1963.

[28] M. F. Møller, “A scaled conjugate gradient algorithm for fast supervised learning,” *Neural Networks*, vol. 6, no. 4, pp. 525–533, 1993.