Human detection by neural networks using a low-cost short-range Doppler radar sensor

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***Abstract*—In this paper, we propose the human detection technique using Neural Networks to effectively classify the Doppler signals caused by human walking along with the background noise sources. The frequency or phase feature vectors converted from the given input signal are directly used as the input of Neural Networks. In addition, Gaussian noise is added in the input nodes of Neural Network in order to prevent the overfitting problem. We developed the low-cost & short-range K-band Doppler radar for the experiment. The proposed technique was examined with human walking data accompanied with the background noises caused by the fan, rain, snow, and other outdoor environmental factors. The trained Neural Network detection technique can detect human walking with 95.2% of the true positive rate and it has 4.6% of the false positive rate.**

Keywords—Doppler radar; background noise removal; human detection; Neural Network; radar target classification

I. INTRODUCTION

A low-cost and short-range K-band Doppler radar sensor (Doppler radar sensor, Microwave motion sensor) detects Doppler signals generated by moving targets. It provides velocity information of targets within the detected area. This radar sensor has been widely applied for LED controlling and alarm monitoring in indoor environments. Conventional detection methods with the use of Doppler radar sensors have been processed by comparing the received signal power (or phase) and the threshold level. Such method is very simple in the aspect of computational complexity, and thus has been widely applied for indoor commercial products.

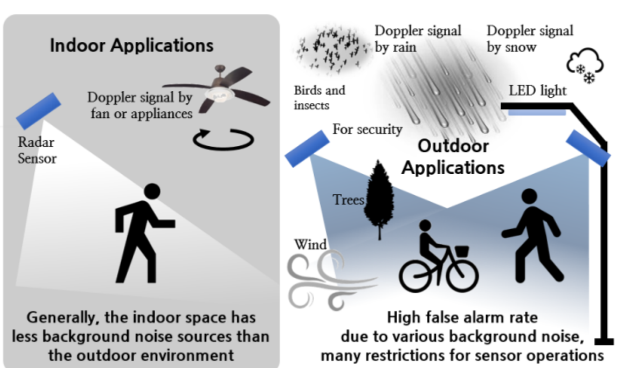


Fig. 1. Radar sensor applications and various background noise sources

However, these conventional detection methods have limitations to remove unwanted Doppler signals that are caused by various background noise sources present in indoor and outdoor situations. For example, unwanted Doppler signals caused by the fan continuously cause false alarms, and Doppler signals caused by the rain and the snow increase the false alarm rate. Because the performance of detection and false alarm is highly susceptible to the background environment, the methods have many restrictions on many applications and installations despite of the outstanding sensitivity of Doppler radar sensor. These restrictions are shown in Figure 1.

Recently, many researches related to Doppler radar human detection methods using the pattern recognition methods have been reported [1][2][3]. Many of them require mathematical investigations to look for meaningful feature vectors which directly affect the estimation accuracy performance of the classifiers [4][5]. However, these approaches of selecting meaningful feature vectors are done with lots of heuristic trials [1][2][6]. Also, in order to extract feature vectors from the micro-Doppler spectrum, they demand a relatively long time, compared with the conventional detection methods [1][2][6].

In this paper, we propose the detection techniques using Neural Network to distinguish human walking micro-Doppler signals from Doppler signals that include background noises. In addition, unlike the previous approaches that require heuristic ways to select meaningful feature vectors from micro-Doppler spectrum, in this paper, the frequency or phase feature vectors converted from the given input signal are directly used without any additional feature selection processing or dimension reduction method. Moreover, Gaussian noise is added in the input nodes of Neural Network in order to prevent the overfitting problem. The addition of Gaussian noise to the input data of Neural Network during training leads to significant improvements in generalization performance [7], like L2 regularization.

II. HARDWARE AND SIGNAL PROCESSING

A. Hardware of K-band Doppler radar sensor

In order to be widely used as a sensor for commercial purposes, the price of a radar sensor should be low. To reduce the price of the sensor, two parts were reflected in the hardware design. First, the phase locked loop was not applied. Second, an inexpensive micro-controller including ADC and FPU was used. Of course, recent advances in the semiconductor technology can provide improved development environments for making cost-effective products. The designed radar hardware configuration to reduce cost is shown in Figure 2.

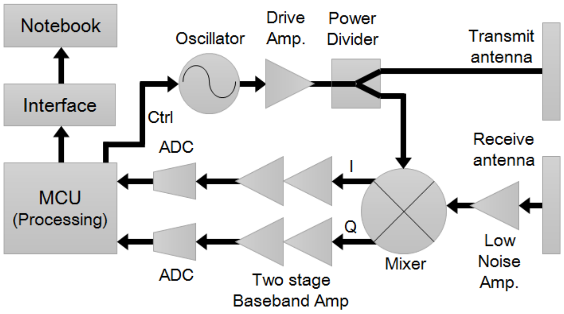


Fig. 2. Configuration of the low-cost & short range K-band Doppler Radar

Doppler radar sensor hardware is composed of circuits for transmitting/receiving and signal processing. The transmit /receive circuit includes the microstrip patch antenna, CW signal generator, low noise amplifier, heterodyne I/Q mixer and two-stage baseband amplifiers. The signal processing circuit includes the integrated microcontroller for AD conversion & data processing and interface ICs for the external link. Figure 3 shows the implemented hardware board. Table 1 describes the development specifications.

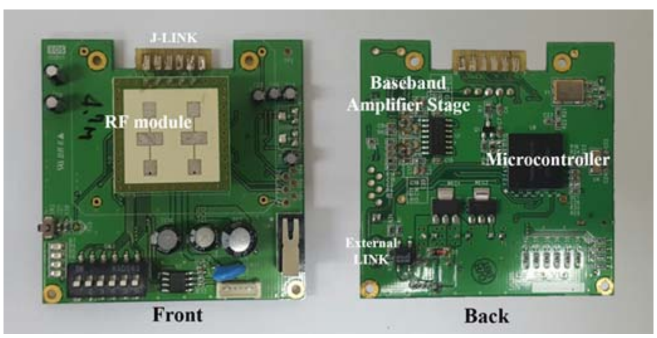


Fig. 3. Implemented Doppler radar sensor board

TABLE I. SPECIFICATIONS OF K-BAND DOPPLER RAAR

items	specifications	Ref.
Operating freqeuncy	24.125GHz	
RF output	16 dBm	
Detection range	Max. 20m, typ. 15m	Human walking
Detection angle	-40 ~ +40	Azimuth
Microcontroller	Freescale kinetis k60	Clock: 100MHz
Size	60mm × 60mm × 15mm	

B. Conventional detetion methods

In the conventional detection methods, the average power p(t) or the unwrapped phase q(t) calculated from the received signal x(t) is compared to the static or dynamic threshold level. These are described in Equation (1), (2) and (3). When p(t) or q(t) exceeds the threshold level, the radar sensor determines the detection of target. Figure 4 shows these conventional methods.

$$p(t) = \frac{1}{M}\sum_{k=1}^{M}\left(x_k(t)\times x_k(t)\right) \tag{1}$$

$$\psi(t) = [\psi_1, \psi_2, \cdots, \psi_M] = unwrap(\ \angle x(t)\ ) \tag{2}$$

$$q(t) = \psi_M \tag{3}$$

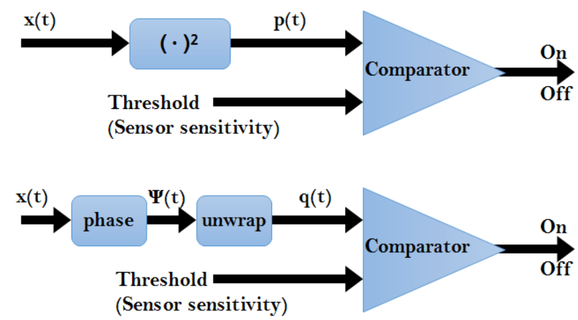


Fig. 4. Doppler signal characteristics caused by human walking and rain

This approach is very simple, but it can cause many false alarms if there exists background noise. Figure 5 shows $x(t)$, $p(t)$ and $q(t)$ of Doppler signals caused by human walking and rain. If we use the conventional methods, $p(t)$ and $q(t)$ of the human walking data can be processed by the appropriate detection reference. In the case of the rain data, $p(t)$ and $q(t)$ have to be removed for reducing false alarms, because these are the background noise. However, if we still use the conventional methods, there are lots of difficulties to effectively remove $p(t)$ and $q(t)$ by the rain data.

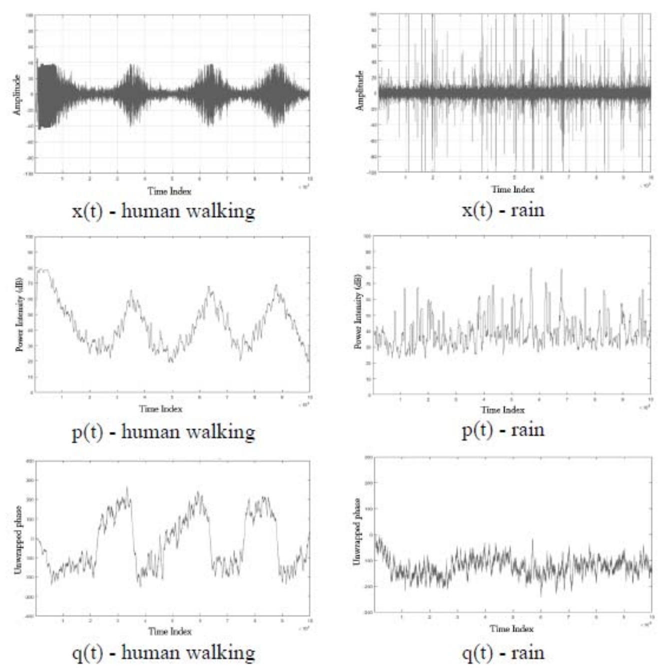


Fig. 5. Doppler signal characteristics caused by human walking and rain

The rain data x(t) has the form of an impulse waveform. And the rain data p(t) can have relatively high values for high rainfall intensity. If p(t) is used for the parameter of detection processing, radar performance will be reduced remarkably due to lots of false alarms. If the boresight direction of the radar is pointing to the ground, the rain data q(t) tends to have negative value because of the directionality of rain falling. Considering this directionality phenomenon, the false alarm rate can be reduced under the given conditions. However, when the rain is combined with wind, this assumption about the directionality of rain falling has to be modified because the error increases. Especially, this wind combining phenomenon is easily observed during snow falling. Therefore, using p(t) and q(t) for the detection is hardly a right approach to distinguish targets from background noise. Doppler signals by the fan causes lots of false alarm with similar reasons as well. Therefore, the new approach of pattern recognition is required to solve these problems.

C. Human detection technique using pattern recognition

In the previous research, heuristic ways have been applied to select meaningful feature vectors from a micro-Doppler spectrum [1][2][6]. For example, the fundamental frequency, micro-Doppler bandwidth, the user defined offset bandwidth and so on were extracted from micro-Doppler spectrogram accordingly [1][2]. Effective feature extraction is the key point to improve classification performance. However, Extracting meaningful features from input signal requires many experiments and experiences. Also, pre-processing for feature extraction can increase the total computation complexity, because pre-processing can require complex formulas [8][9]. This conventional pattern recognition approach is shown in Figure 6. Meanwhile, Principal Component Analysis algorithm was used for dimension reduction of feature vectors [10]. However, this approach increase processing time and calculation complexity.

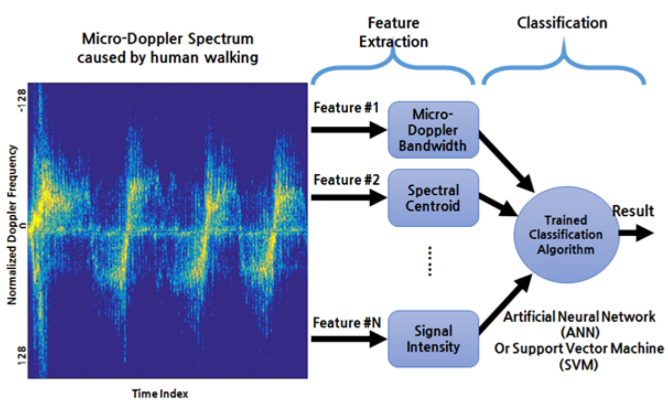


Fig. 6. Conventional pattern recognition approach for classification

In order to overcome these problems, we propose the Doppler radar detection processing using Neural Networks. Neural Network is the well-known pattern recognition algorithm. Feed-forward Neural Network (FNN), called Multi-Layer Perceptron (MLP), has been widely used. Recently, Deep Neural Network (DNN) using five or more layers has been researched for classification [11]. DNN requires high-performance MCUs due to high-level computational complexity. In this study, we use FNN for making cost-effective product, because it is expected that FNN can provide effective classification performance. Simplified architecture of FNN is shown in Figure 7.

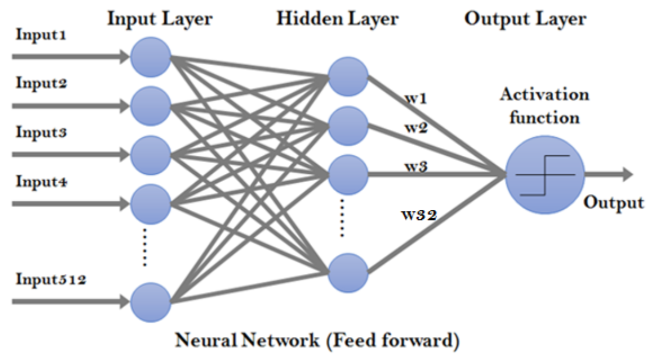


Fig. 7. Diagram of an neural network (Multi-layer perceptron)

By using FNN, we propose a new approach of using neural networks for human motion detection processing. This detection process is shown in Figure 8. The architecture of the proposed detection processing is similar with CFAR (Constant False Alarm Rate).

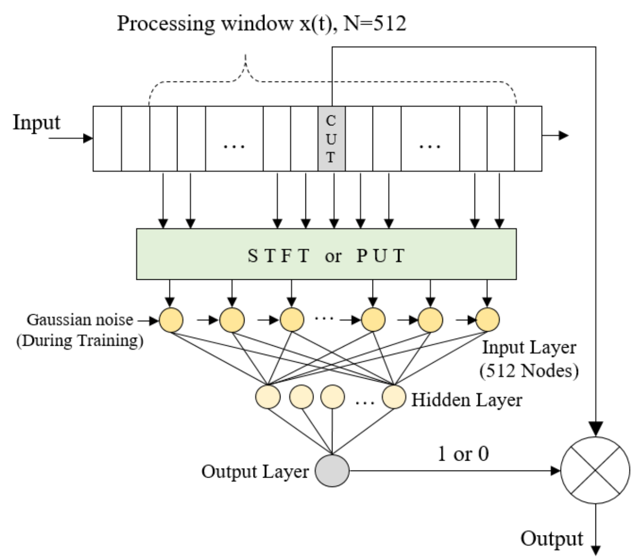


Fig. 8. Doppler radar detection processing architecture using ANN

Unlike these previous researches, the frequency domain data or the angle domain data is directly used as the input vector of Neural Network in the proposed technique. The frequency domain data is calculated by the Short-Time Fourier Transform (STFT) and the angle domain data is calculated by Phase Unwrapping Technique (PUT). We do not use an additional processing for selecting meaningful features and for reducing the dimension of feature vector. That is, heuristic methods are no longer used for feature extraction. Thus, the proposed method reduces trial and error related to looking for meaningful features. The STFT and PUT processing window size is N = 512. The dimension of the feature vectors is 512. The input layer consists of 512 nodes and the hidden layer has 32 nodes. The addition of Gaussian noise of the input nodes of the neural network during training is the effective method to reduce generalization error [7], like L2 regularization. Mixing Gaussian noise with training data is known to be an effective way to prevent overfitting given data [7].

In the proposed detection method, a sequential output combining '0' and '1' is generated according to the input data. '0' means background noise, and '1' means human motion detection. The combination of successive detection alarms improves the detection accuracy. For example, detection accuracy is improved if detection is determined when there are several '1' s in the detection confirmation time, such as '11110111'.

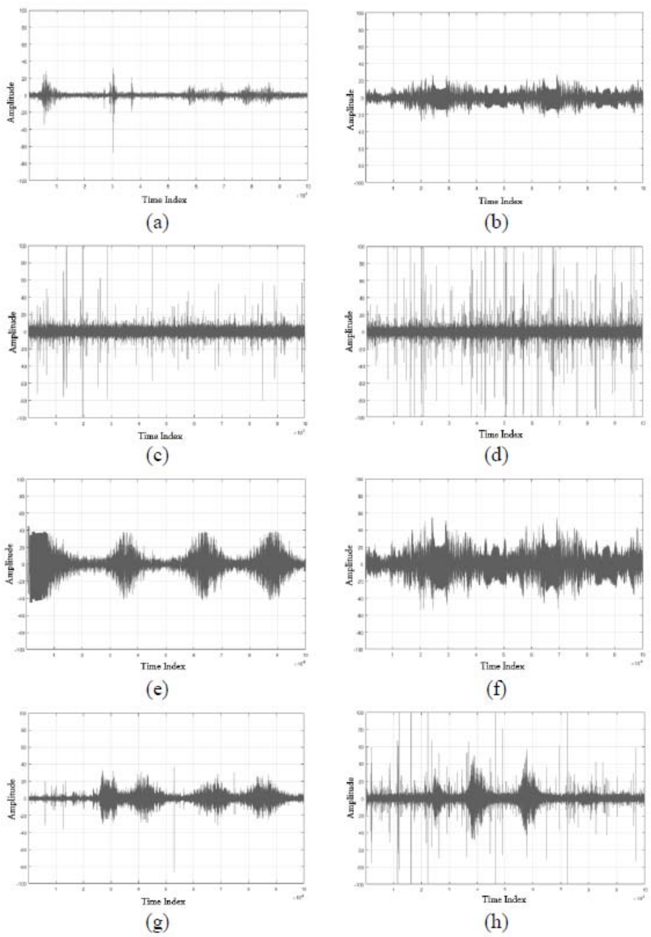


Fig. 9. Doppler signals x(t) of eight cases

III. DATA GATHERING OF DOPPLER SIGNAL

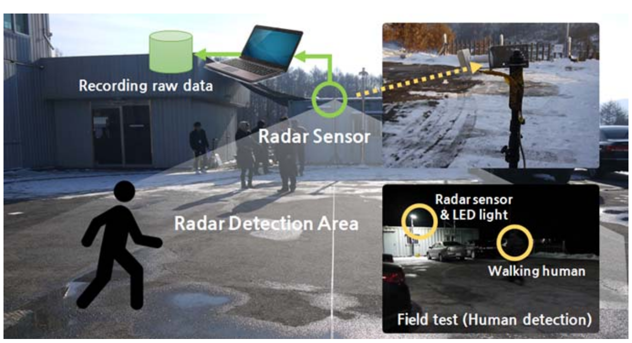


Fig. 10. Signal gathering of Doppler radar sensor

Radar was installed in selected test sites and raw data was collected for a long time. In order to measure the signals by human motion, the experimenter moved only within the radar detection area. For light control purposes, human motion includes walking and fast walking. Strange human movements such as crawling and irregular movements were excluded. In order to collect Doppler signals caused by background noise, a limited test environment was applied so that the various noise sources do not mix with each other. The test site where the radar is installed is shown in Fig 10.

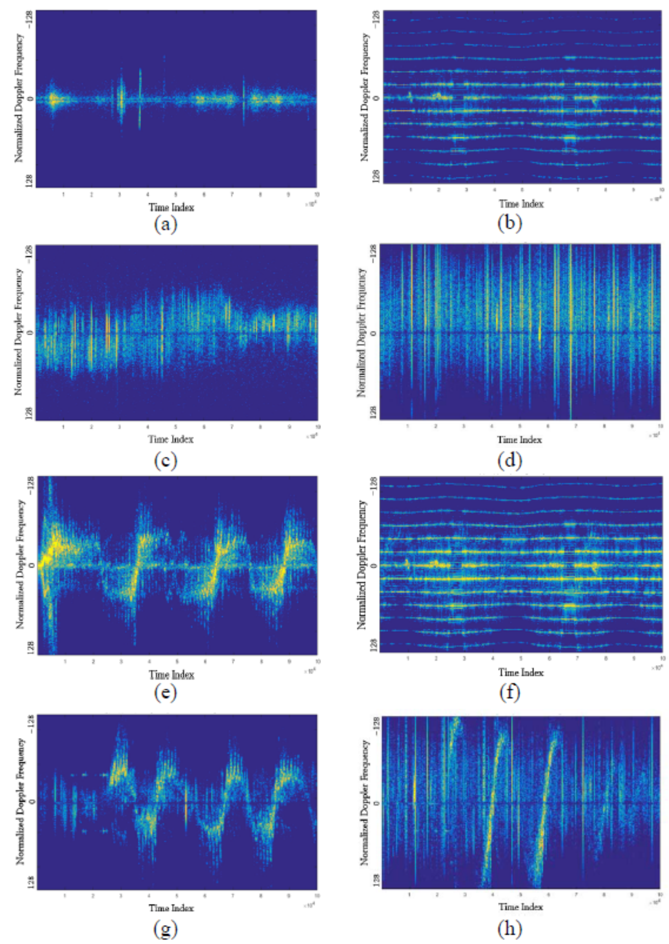


Fig. 11. Doppler Sectrogram procced by STFT

Doppler signals were collected by the following eight cases. The eight cases are (a) outdoor environment (LOS), (b) fan, (c) snow, (d) rain, (e) human walking, (f) human walking with fan, (g) human walking with snow (h) human walking with rain. And these signals were collected three times in the three different places. Figure 9 shows a Doppler signal x(t). Figure 11 shows the processed result of STFT of x(t).

As shown in Figure 9 and 11, micro-Doppler signals of rain and snow have instantaneous wide-bandwidth characteristics. They have characteristics of an impulse signal. Snow with wind causes low-frequency modulation at the center of the micro-Doppler signal. In the case of rain, we can observe that the center of the micro-Doppler spectrum is in the negative region due to the directionality of the rain. The micro-Doppler signals of the fan consists of the constant fundamental frequency and its harmonic frequencies. The micro-Doppler spectrogram of human walking motion has a periodic form because the data was achieved from a person walking back and forth in the given radar-detectable area.

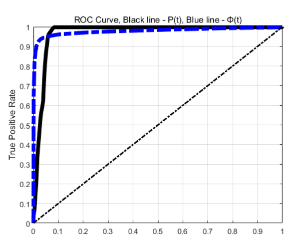
The Micro-Doppler spectral results in Figure 11 can give us the idea that we can easily classify them. In the previous chapter, however, conventional pattern classification methods have to extract meaningful features from these spectral imaging results, which is difficult and may require complex formulas. Recent studies have applied image processing techniques to process this spectral image [12]. However, at least two seconds are required to obtain an image size that contains meaningful spectral information [12]. This approach not only increases the amount of computation but also reduces the response speed of the sensor. For example, in the case of a light control, this slow reaction causes that the LED turns on slowly. To overcome this problem, we explained the new detection method using FNN in the previous chapter. This proposed method has the advantage of fast operation with small amount of computation.

IV. EXPERIMENTAL AND ANALYSIS

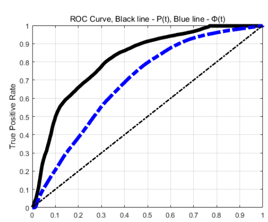
A total of 1.6 million origin data are generated from the raw Doppler signals. Among them, 160,000 were randomly selected. The 160,000 data consists of 80,000 background noise class and 80,000 human walking class. The background noise class includes 20,000 outdoor environment data, 20,000 fan data, 20,000 snow data and 20,000 rain data. Also, the human walking class includes 20,000 human walking data, 20,000 human walking data with fan, and 20,000 human walking data with snow, 20,000 human walking data with rain.

A. Detection performance of the conventional method

ROC (Receiver operating characteristic) curve is used to measure the detection performance. It is obtained by calculating the overlapped area (AUC, Area under the ROC) between the two class probability distributions. Figure 8 shows the ROC curve of the conventional detection processing method. In Figure 12-(i), only (a) an outdoor environment data and only (e) human walking data were used to analyze the detection performance. AUC by p(t) and q(t) is measured to be about 0.47 and 0.48 respectively. Meanwhile, in Figure 12-(ii), the total 160,000 data were used for analyzing ROC. AUC by p(t) and q(t) is measured to be about 0.31 and 0.19 respectively.



(i) Outdoor environment data vs Human walking data



(ii) Background noise class vs Human walking class

Black line : ROC of $p(t)$, Blue dash line : ROC of $q(t)$

Fig. 12. ROC curve of the convetional detection processing method

The detection accuracy performance was reduced remarkably because of the external noises (fan, snow and rain). This result shows that applying the conventional detection processing method under these conditions causes a severe performance degradation. In Figure 12-(ii), when the false positive rate (false alarm rate) of p(t) is 5% or 10%, the true positive rate (detection sensitivity) is about 30% or 50%. If the detection sensitivity of p(t) has 90%, the false alarm rate will be approximately 50% that is an unacceptable performance. These results show that it is not possible to apply conventional detection methods for outdoor purposes.

B. Detection performnace of the proposed technique

The proposed Neural Network detection techniques overcome this performance degradation. The frequency domain features processed by STFT or the angle domain feature processed by PUT are directly used as the feature vectors for these Neural Network detection techniques. PUT has lower computational complexity than STFT.

Training, validation, test data set was composed to analyze the classification accuracy as following: 75% of the total data set (160,000) for the training set, 15% for the validation data set, and 15% for the test set. The training set trains Neural Network classifier while the validation data set is used in order to avoid overfitting and to adjust classifier's parameter.

Test set is used for classification performance evaluation of the classifier determined by training and validation. The test error is measured by the test data set. The test error results are shown in Table 2 and Table 3. The result of the ANN detection processing using STFT yields in 95.3% = (95.4% +95.2%) ÷2 for the classification accuracy. The false positive rate of this classifier is 4.6% and the true positive rate is 95.2%. The result of Neural Network detection processing using PUT yields in 90.65% of the classification accuracy. The false positive rate of this classifier is 8.8% and the true positive rate is 90.1%.

TABLE II. ERROR RESULT – ANN DETECTION PROCESSING(STFT)

Confusion Matrix		**Actual Class**	
		Background Noise	**Human**
Estimated Class	***Background Noise***	11468 (95.4%)	573 (4.8%)
	Human	551 (4.6%)	11408 (95.2%)

TABLE III. TEST ERROR RESULT – ANN DETECTION PROCESSING(PUT)

Confusion Matrix		**Actual Class**	
		Background Noise	**Human**
Estimated Class	***Background Noise***	10923 (91.2%)	1195 (9.9%)
	Human	1053 (8.8%)	10829 (90.1%)

For the final detection decision, successive '0' and '1' outputs are combined during the detection confirmation time.

And, when the number of '1' is more than N during this time, the final detection is confirmed. Regarding the appropriate detection confirmation time and N of threshold level, the classification accuracy for the test set was improved to be about 97%. In particular, this detection confirmation method is an effective approach for the purpose of reducing false alarm rate.

V. Conclusion & Discussion

The conventional detection processing methods of the Doppler radar sensor use the static or dynamic threshold level to detect a moving target. Generally, the average power p(t) or the unwrapped phase q(t) is compared to the threshold level. However, these conventional methods can cause high false alarm rate because of the unwanted background noise. So, there are limitations that hinder further installations and applications.

In order to overcome such limitations, in this paper, we proposed the Neural Network detection processing techniques using the pattern recognition algorithm. This proposed detection processing techniques require neither complex & heuristic feature selection approaches nor feature dimension reduction methods. Without any additional pre-processing for feature extraction, the frequency domain feature vectors processed by STFT or the angle domain feature vectors processed by PUT are directly used as the input of the neural network. In this study, heuristic methods for looking for meaningful features are not required. Also, this proposed methods have the advantage of fast operation with small amount of computation.

To analyze the classification accuracy, we construct training set, validation set and test set. After training and validation, the classification accuracy of Neural Network human detection technique using STFT was measured as 95.3%. In the case of PUT, the classification accuracy was analyzed as 90.65%. Neural Network using STFT has better performance. In Figure 12-(ii) of the conventional methods, if the true positive rate is 90%, the false positive rate is measured as 50% while having 70% of classification accuracy. Therefore, under this experiment, Neural Network human detection techniques have better performance than the conventional detection methods.

However, lots of Doppler signals associated with more places and environments are required for the algorithm generalization. In this paper, we dealt with normal human walking motions. The radar detection performance can be changed according to the definition of various human motions (ex. walking, running, clawing and so on). As mentioned, this paper showed that the human detection techniques using Neural Network have the enhanced classification performance compared to the conventional methods. Even if more noises and more types of human motion are added, the tendency of performance results would likely be maintained. Also, an improvement in the classification accuracy performance is expected if RNN (Recurrent Neural Network) are applied as a classifier to reflect the dynamics of the signal. In addition, it is expected that DNN can be effectively applied for problems related to classification of multiple classes.

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