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Radar Application of Deep Neural Networks for Recognizing Micro-Doppler Radar Signals by Human Walking and Background Noise

Jihoon Kwon[1], Seoungeui Lee[1], and Nojun Kwak[2]
[1]Radar R&D Center, Hanwha Systems and Seoul National University, Seoul, Republic of Korea
[2]Graduate School of Convergence Science and Technology, Seoul National University, Seoul, Republic of Korea

Abstract - **The purpose of this paper is to show the radar application of the deep neural networks for recognizing the micro-Doppler radar signals generated by human walking and background noises. We collected various signals considering the actual human walking motion and background noise characteristics. In this paper, unlike the previous researches that required complicated feature extractions, we directly use the FFT results of the input signal as the feature vectors. This technique helps not to use heuristic approaches to get meaningful feature vectors. We designed and analyzed MLP (Multilayer perceptron) and DNN for multiclass classifiers. According to the experimental result, the classification accuracy of MLP was measured as 89.8% for the test dataset. The classification accuracy of DNN was analyzed as 97.2% for the test dataset.**

Index Terms **—Doppler Radar, Deep Neural Network, Micro-Doppler, Radar Pattern Recognition, Radar Machine Learning**

1. Introduction

Doppler signals of a radar are used to filter moving objects from complicated background noises. In the case of air surveillance radar, the Doppler filtering process can be relatively not complicated because the speed of targets is fast than background noises. However, in the case of radars for detecting human motion on the ground, the problem to separate Doppler signals caused by human walking from various background noises is considerably difficult, because the speed of human walking is quite slow. That's because the bandwidth of Doppler signals by human motion overlap the bandwidth of Doppler signals by background noises. In this situation, traditional methods can lead to frequent false alarms.

Radar pattern recognition (or radar machine learning) that recognize patterns of received signals has been researched as a good alternative to overcome these limitations [1-4]. According to the reported studies, many researchers have described or proposed mathematical equations or approaches to find meaningful feature vectors that affect the classifier's estimation accuracy [1-3][5-7]. However, approaches to select meaningful feature vectors are based on heuristic methods that require a lot of effort and time.

On the other hand, in previous studies, received signals during a window processing time are converted into the micro-Doppler spectrum (time-frequency domain) data. Meaningful features should be searched and defined statistically from this 2D micro-Doppler spectrum data. Also, pre-processing time to extract feature vectors is related to a window processing time of radar. Since the frequency bandwidth of the micro-Doppler by human walking and background noises is quite low, extracting features related to frequency deviation can requires a relative long window processing time. Problem is that increasement of a window processing time makes a response speed of a radar slow. This response speed is generally considered to be an important performance of commercial radars.

In this paper, we propose the deep neural networks (DNN) that classify human micro-Doppler signals and background noises. And this approach does not require a heuristic method and pre-processing that extract meaningful features for the classifier. This DNN is designed as a multiclass classifier to simultaneously recognizes the micro-Doppler signals by human walking as well as the micro-Doppler signals by background noises. The DNN has several hidden layers, and ReLUs and SoftMax are used as an activation function for a multiclass classifier.

2. Micro-Doppler Signals

The eight cases of the micro-Doppler signals were collected. These signals were collected three times in the three different places. Fig. 1 shows the STFT (Short Time Fourier Transform) result of the micro-Doppler signals that we collected.

3. Deep Neural Networks

The lower layer of the DNN receives information from the upper layer, and meaningful features are combined and formed gradually through the process of passing several hidden layers. This can be understood as the key advantage of DNN. In other words, this means that we can naturally design an optimal feature extraction model for complicated micro-Doppler signals by using DNN that have many layers and nodes. The designed multi-class classifiers are shown in Fig. 1 and Fig. 2. In this paper, DNN compares to MLP that is conventional neural networks.

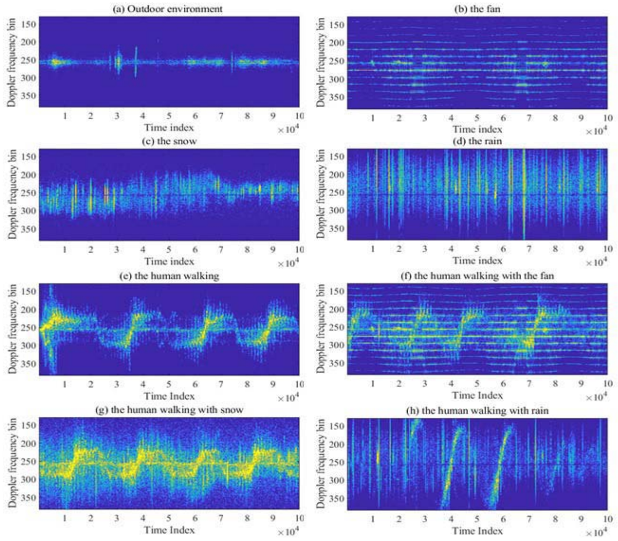

Fig. 1. The micro-Doppler Spectrograms of 8 cases: (a) outdoor environment (LOS), (b) fan, (c) snow, (d) rain, (e) human walking, (f) human walking with fan, (g) human walking with snow and (h) human walking with rain.

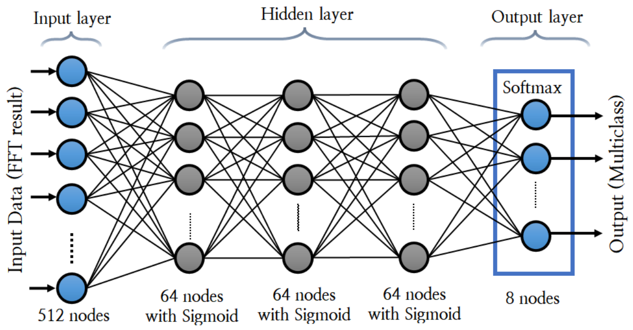

Fig. 2. Multi-class classifier using Multi-layer perceptron

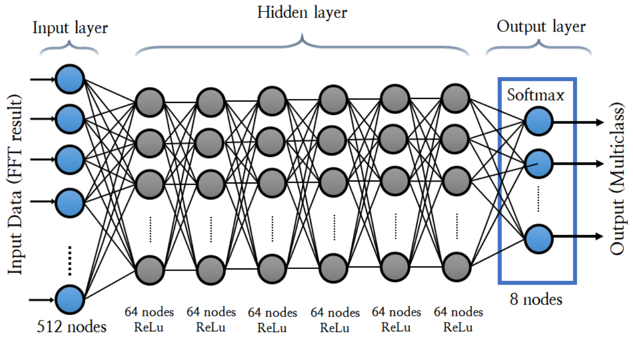

Fig. 3. Multi-class classifier using Deep Neural Network

4. Conclusion

The classification accuracy of MLP was measured as 89.8% for the test set. In the case of the deep neural networks, the classification accuracy for the test set was measured as 97.2%. This result show that the deep neural networks can be applied as an effective approach to improve classification accuracy without requiring complex feature extraction. Even if new datasets are added, we are sure that DNN classifier can be optimized to have high accuracy.

TABLE I: Normalized confusion matrix of Multi-class classifier using Multi-layer Perceptron

Estimated class (unit: %)

Actual class		(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
	(a)	96.4	0.1	0.8	0.1	2.0	0.2	0.1	0.3
	(b)	0.1	95.6	0	0	0.2	4.1	0	0
	(c)	1	0	88.6	0.6	0.6	0.2	8.5	0.5
	(d)	0	0	0.5	86.3	0.5	0.2	1.1	11.4
	(e)	3.1	0.1	1.1	0.8	91	0.3	2.4	1.2
	(f)	0.4	7.1	0.1	0.2	0.2	91.6	0.3	0.1
	(g)	0	0	5.1	0.7	1	0.5	92	0.7
	(h)	0.5	0	0.4	19.2	1.2	0.5	1	77.2

TABLE I: Normalized confusion matrix of Multi-class classifier using Deep Neural Network

Estimated class (unit: %)

Actual class		(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
	(a)	96.4	0.1	0.8	0.1	2.0	0.2	0.1	0.3
	(b)	0.1	95.6	0	0	0.2	4.1	0	0
	(c)	1	0	88.6	0.6	0.6	0.2	8.5	0.5
	(d)	0	0	0.5	86.3	0.5	0.2	1.1	11.4
	(e)	3.1	0.1	1.1	0.8	91	0.3	2.4	1.2
	(f)	0.4	7.1	0.1	0.2	0.2	91.6	0.3	0.1
	(g)	0	0	5.1	0.7	1	0.5	92	0.7
	(h)	0.5	0	0.4	19.2	1.2	0.5	1	77.2

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