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CNN based distance and velocity estimation of target for OFDM radar systems

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Abstract.
Background/Objectives: The objective of this paper is to propose a new target distance and velocity estimation technique for orthogonal frequency division multiplexing (OFDM) radar systems.
Methods/Statistical analysis: First, the 2D periodogram (range-Doppler) is collected from the reflected signal via fast Fourier transform (FFT) of received OFDM symbols. The largest value of a 2D periodogram often represents the target so that its position indicates the distance and velocity. The constant false alarm rate (CFAR) is one of the famous conventional techniques to find the peak in the 2D periodogram. In this paper, a convolutional neural network (CNN) based estimator is proposed. The proposed CNN directly finds the distance and velocity from the 2D periodogram.
Findings: The proposed method requires only 2D periodogram to estimate the target's distance and velocity. On the other hand, the conventional methods need noise variance as well as the periodogram. The performance is examined through computer simulation. In the simulation, the mean absolute errors (MAEs) are compared between the conventional and proposed methods. According to the results, the MAEs of the proposed method are lower approximately 8 m in distance and 7 km/h in speed to the conventional method.
Improvements/Applications: The proposed OFDM radar technique can be applied to 6G mobile communications to identify the moving targets without additional frequency resource allocation for the radar system. In other words, by using the proposed technique, the convergence of the communication and radar can be possible.

Keywords: Target detection, OFDM radar, CNN, CFAR, Distance estimation, Velocity estimation.

1. INTRODUCTION

Recently, mobile wireless terminals such as smartphones and tablet PCs have been increasing rapidly. The resulting surge in data traffic is deepening the overcrowding of the frequency spectrum [1]. Due to the demands on the spectrum for wideband communications, it is difficult to allocate additional frequency resources for the radar use since the radar system often requires wide spectrum bands. As one of the solutions to this problem, frequency sharing technique for coexistence of the radar and communication systems are receiving much attention [2-4]. The convergence technique of the radar and communication uses the communication signals as the radar waveform.

The orthogonal frequency division multiplexing (OFDM) systems are well known to be suitable for high speed wireless communications [5]. In multipath environments, OFDM waveform provides frequency diversity to improve the communication performance and is very robust against multipath fading [6, 7]. The wideband OFDM waveform also satisfies the requirements of the radar signals for range and Doppler estimation. Because of those advantages, interest in OFDM radar systems is increasing and being used in various radar applications such as commercial, industrial and military, especially in automotive fields [6]. The target detection techniques in OFDM radar systems have been researched in many literatures [8-10]. Among them, to the best of the authors' knowledge, convolutional neural network (CNN) based distance and velocity estimators have not been released.

Deep learning has been spotlighted in various fields [11, 12]. Especially, many researches have been conducted to solve the radar problem by applying deep learning. However, to the best of the author's knowledge, no method has been proposed to estimate the distance and velocity of targets based on CNN for OFDM radar systems.

In this paper, we propose CNN based distance and velocity estimation technique for the target in OFDM radar systems. The overall process for signal generation is as follow: Modulated signal vector is generated first, and then it is converted into a time domain signal via inverse fast Fourier transform (IFFT). After parallel to serial conversion of the time domain signal, cyclic prefix (CP) is added at front of the resulting signal. The final signal is transmitted and the reflected signal is received. The CP of the reflected received signal is removed and the frequency domain signal is obtained via FFT. This signal is divided by the transmitted signal to eliminate modulation effect. The same procedure is repeated for successively received OFDM symbols and the modulation-free received signals are stacked to form 2 dimensional (2D) signal. By taking 2D FFT, the 2D signal is converted into range-Doppler signal. Finally, the absolute of the 2D spectrum or 2D periodogram is used for the target's distance and velocity estimation. Typically, the local maximum of 2D periodogram indicates the target and the peak's x-axis and y-axis represent velocity and distance, respectively. 2D periodogram looks like the monochrome image and it is the input of both the conventional and proposed CNN. In case of the conventional method, the target detection is based on comparison of the 2D periodogram with a threshold, and appropriate threshold is essential to correctly find the peak. To get the optimal threshold, is known that additional information is required, such as noise variance. In contrast, the proposed method requires any other information than the 2D periodogram. CNN is a kind of neural network architectures for deep learning that learns directly from the input data without manual feature extract. Also, CNN is particularly useful when finding patterns for object, face and scene recognition in images [13, 14]. In the proposed technique, the 2D periodogram is entered into the proposed CNN. Here, two types of input are also proposed. One is to input one image and the other is to input two images. In the former, the input periodogram is composed of clutters and a target. In the latter, the first input is the same as the former, and the second input is added, which consists of only clutters. Therefore in the latter, clutter only signal is required. We call the former and the latter cases as single image and double image, respectively. The radar performance is examined through computer simulation. According to the results, the distance estimation mean absolute error (MAE) performances of the conventional, proposed single image input, and proposed double image input are 10 m, 2 m and 0.7 m, respectively. For the velocity estimation, the MAEs of the conventional, proposed single image input, and proposed double image input are 10 km/h, 2 km/h, and 1.1 km/h. It is confirmed that the proposed techniques are much better than the conventional method, and between the two proposed methods, the double image input CNN is better than the single image input CNN.

2. OFDM RADAR SYSTEMS AND SIGNAL MODEL

OFDM radar system considered in this paper is shown in Figure 1. For the OFDM transmission, modulated symbols are generated. The m-th transmitted vector signal is denoted as $\boldsymbol{s}_m = [s_{0,m}, s_{1,m}, \cdots s_{N-1,m}]^T$ where N is the FFT size. $s_{n,m}$ is a modulated complex number. The vector signal, $\boldsymbol{s}_m$, is converted into the time domain signal via IFFT. Then, guard interval CP is inserted in front of IFFT signal and transmitted. The CP prevents that channel would not leak energy from one OFDM symbol into the next, or the CP changes linear convolution (between the transmitted signal and the channel impulse response) into circular convolution. Next, the reflected signal from the targets is received and the CP is removed. By FFT of the CP removed signal, frequency domain signal is obtained. The output of FFT is denoted as $\boldsymbol{f}_m = [f_{0,m}, f_{1,m}, \cdots f_{N-1,m}]^T$. The same process is repeated on consecutive received OFDM symbols. Due to the Doppler frequency of the reflected signal and time delay due to propagation delay between transmitted and reflected waveforms, $\boldsymbol{s}_m$ and $\boldsymbol{f}_m$ are not same. The target's distance and speed can be identified by comparing $\boldsymbol{s}_m$ and $\boldsymbol{f}_m$.

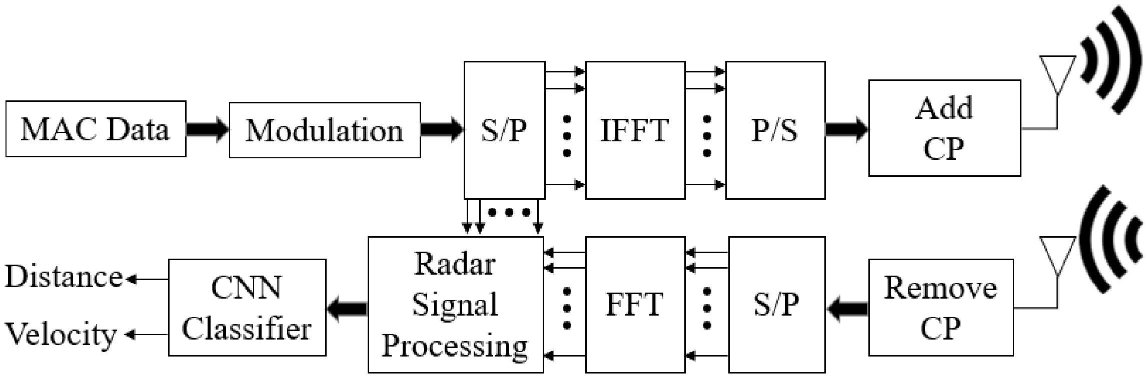

Figure 1. OFDM Radar System Model

A transmitted OFDM symbols are represented by a matrix. If total M OFDM symbols are transmitted, the transmitted and received signals are represented as (1) and (2), respectively.

$$\boldsymbol{S} = \begin{pmatrix} s_{0,0} & s_{0,1} & \cdots & s_{0,M-1} \\ s_{1,0} & s_{1,1} & \cdots & s_{1,M-1} \\ \vdots & \vdots & \ddots & \vdots \\ s_{N-1,0} & s_{N-1,1} & \cdots & s_{N-1,M-1} \end{pmatrix} \quad (1)$$

$$\boldsymbol{F_r} = \begin{pmatrix} f_{0,0} & f_{0,1} & \cdots & f_{0,M-1} \\ f_{1,0} & f_{1,1} & \cdots & f_{1,M-1} \\ \vdots & \vdots & \ddots & \vdots \\ f_{N-1,0} & f_{N-1,1} & \cdots & f_{N-1,M-1} \end{pmatrix} \quad (2$$

In the matrices, each row represents one subcarrier and each column correspond to one OFDM symbol. For example, $s_{2,1}$ indicates the data of third subcarrier in second OFDM symbol. The subcarrier space is Δf, therefore the OFDM symbol duration is $T = 1/\Delta f$. The duration of the CP is T_G. The sampling rate after the IFFT is f_S and $\Delta f = f_S/N$. The carrier frequency is f_C.

In general, the radar systems analyze the received signal to determine the range and velocity of the target. Therefore, transmitter and receiver must be synchronized and there should be no frequency or time offset. The received signal can be written as

$$(\boldsymbol{F}_r)_{n,m} = \sum_{\hbar=0}^{H_t-1} b_\hbar (\boldsymbol{S})_{n,m} e^{j2\pi T f_{D,\hbar} l} e^{-j2\pi\tau_\hbar \Delta f k} e^{j\phi_\hbar} + \sum_{i=0}^{H_c-1} b_i (\boldsymbol{S})_{n,m} e^{-j2\pi\tau_i \Delta f k} e^{j\phi_i} + (\widetilde{\boldsymbol{Z}})_{n,m} \quad (3)$$

where H_t is the number of reflecting targets, $f_{D,h}$ ($= 2 \times v_{rel,h}/c_0$) is a Doppler shift of the signal caused by relative velocity (v_{rel}), c_0 is the speed of light, and ϕ_h is an unknown phase offset. b_h is attenuation magnitude of the reflected signal. The attenuation b_h can be written as

$$b_\hbar = \sqrt{\frac{c_0 \sigma_{RCS,\hbar}}{(4\pi)^3 d_\hbar^4 f_C^2}} \quad (4)$$

where d_h is $(h+1)$-th target distance which can be calculated by time delay τ_h ($= 2 \times d_h/c_0$), and σ_{RCS} is the radar cross section. The second summation at the right-hand side of (3) represents the clutter components and the number of components is H_c. Clutter components are unwanted back-scattered signals or echoes by in the natural environments or between Tx and Rx antennas or circuits. Thus, the time delays or equivalent distances of clutter components are close to zero. In this paper, the clutter components are generated by the Weibull probability density function (PDF).

$$f(d_c; \eta, \beta) = \frac{\beta}{\eta}\left(\frac{d_c}{\eta}\right)^{\beta-1} e^{-(d_c/\eta)^\beta} \quad (5)$$

where η and β are scale and shape parameters, respectively. The clutter components have zero Doppler frequency. The matrix $\widetilde{\boldsymbol{Z}} \in C^{N\times M}$ is white Gaussian noise. To remove the modulation effect in $\boldsymbol{F}_r$, element-wise division is performed to yield.

$$(\boldsymbol{F})_{n,m} \triangleq \frac{(\boldsymbol{F}_r)_{n,m}}{(\boldsymbol{S})_{n,m}}$$

$$= \sum_{\hbar=0}^{H_t-1} b_\hbar e^{j2\pi T_O f_{D,\hbar} l} e^{-j2\pi\tau_\hbar \Delta f k} e^{j\phi_\hbar} + \sum_{i=0}^{H_c-1} b_i e^{-j2\pi\tau_i \Delta f k} e^{j\phi_i} + (\boldsymbol{Z})_{n,m} \quad (6)$$

where $(\boldsymbol{Z})_{n,m} = (\widetilde{\boldsymbol{Z}})_{n,m}/(\boldsymbol{C})_{n,m}$. The radar problem is to detect and identify two sinusoids. The first exponential inside the summation in (6) contains the Doppler frequency and the second exponential has the time delay or distance. The radar cross section can be found from the magnitude. To separate and estimate the sinusoids for the target, 2D periodogram (magnitude square of discrete Fourier transform (DFT)) is used:

$$(\boldsymbol{R})_{n,m} = \frac{1}{NM}\left|\sum_{k=0}^{N-1}\sum_{l=0}^{M-1} (\boldsymbol{F})_{k,l} (\boldsymbol{W})_{k.l} e^{-j2\pi\left(\frac{kn}{N_{FFT}} + \frac{lm}{M_{FFT}}\right)}\right|^2 \quad (7)$$

where $\boldsymbol{R} \in C^{N_{FFT}\times M_{FFT}}$ is 2D periodogram of $\boldsymbol{F}$ and DFT size is $N_{FFT} \times M_{FFT}$. Usually, N_{FFT} and M_{FFT} are chosen as integer multiples of N and M to improve estimation resolution. $\boldsymbol{W}$ is a window matrix generated by

$$\boldsymbol{W} = \boldsymbol{w}_N \boldsymbol{w}_M^T, \boldsymbol{w}_N \in R^{N\times 1}, \boldsymbol{w}_M \in R^{M\times 1} \quad (8)$$

where $\boldsymbol{w}_N$ and $\boldsymbol{w}_M$ are one-dimensional window vectors and we use the Hanning window. If the target's range and Doppler frequency are limited within certain ranges, only a cropped region of periodogram $\boldsymbol{R}$ is useful for target detection. Detecting and identifying targets corresponds to the detection of peaks in the periodogram. If a peak is found at indices $(\hat{n}, \widehat{m})$, the target distance can be calculated as

$$\hat{d} = \frac{c_0 \hat{n}}{2\Delta f N_{FFT}} \quad (9)$$

and the relative velocity is given by

$$\hat{v} = \frac{c_0 \widehat{m}}{2 f_C T M_{FFT}} \quad (10)$$

Due to the subcarrier spacing Δf and the OFDM symbol duration T, there are maximum unambiguous ranges and relative velocities as follows:

$$|d_{max}| = \left|\frac{c_0}{2\Delta f}\right| \quad (11)$$

$$|v_{max}| = \left|\frac{c_0}{2 f_C T}\right| \quad (12)$$

If the subcarrier spacing and the OFDM symbol duration are designed to be small enough, the maximum unambiguous values can cover the target's available distance and speed.

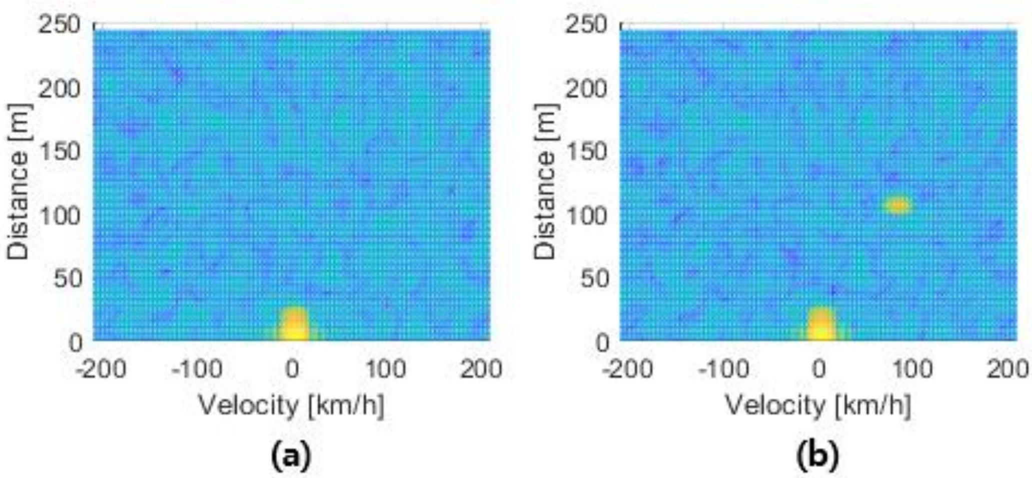

Figure 2. Example of 2D periodogram, R, (a) Clutter Image (b) Clutter Plus Target Image

Figure 2 shows an example of ***R***, (a) is clutter only exist image, and (b) is clutter plus target image. Clutter components such as stationary target are observed at speed 0, and one strong peak indicate the target in figure 2 (b). Positive and negative velocity implies approaching and moving away target, respectively. In this paper, figure 2 (a) is called 'C', and (b) is called 'C+T'.

3.1. CONVENTIONAL METHOD

An important task of radar system is to accurately detect targets. To detect the target, appropriate thresholds must be found and compared to signals. In general, the threshold is a function of probability of detection and probability of false alarm rate. The formula of the threshold is given by

$$TH = \alpha P_n \tag{13}$$

Where α is a threshold factor and P_n is the estimated noise power. One of the conventional methods for target detection is constant false alarm rate (CFAR). Among various CFAR techniques, cell averaging CFAR (CA-CFAR) is most popular. In CFAR technique, a single cell to be tested is referred to as the Cell under Test (CUT) and guard cells (G_i) are defined to be next to the CUT. Training cells are established on the outside of G_i. P_n is estimated from the training cells and can be calculated as

$$P_n = \frac{1}{N_t} \sum_{i=1}^{N_t} T_i \tag{14}$$

Where T_i is the values of periodogram and N_t is the number of training cells.

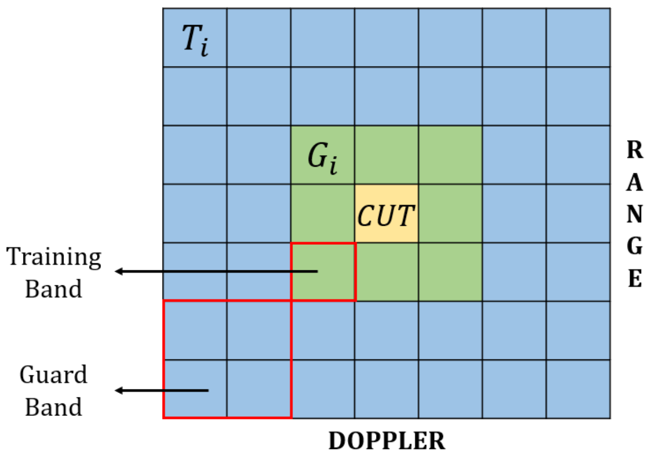

Figure 3. Example of CFAR detector

Figure 3 shows an example of 2D CFAR detector when the training band (TB) size is 2×2 and the guard band (GB) size is 1×1. Commonly, the number of cells on both sides is the same based on the CUT. The purpose of G_i is to avoid signal components from leaking into T_i. The scaling factor α is calculated as

$$\alpha = N_t(P_{fa}^{-1/N_t} - 1) \tag{15}$$

Where P_{fa} is the false alarm rate.

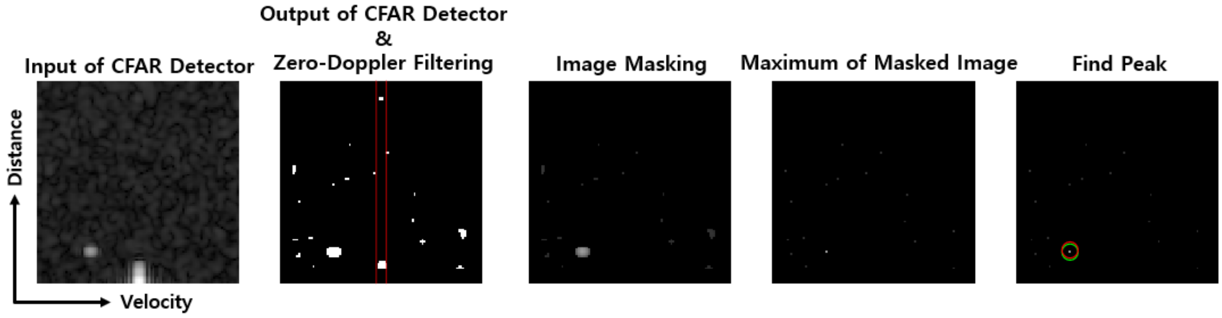

Figure 4. Procedure of CA-CFAR Detector

Figure 4 shows procedure of CA-CFAR detector. First, a 2D periodogram is inputted into the detector. The CFAR detects the target. The CFAR result becomes different by the specified TB, GB and P_{fa}. In CFAR process, noise power is estimated from T_i and the CUT exceeding TH becomes one and otherwise, the CUT becomes zero. Next, clutters are removed by zero Doppler filtering in the CFAR output. The CFAR output is element-wise multiplied by the **R.** Finally, find the maximum value from the result 2D signal. The maximum is considered as the target. In Figure 4, the circle indicated the found target. In zero-Doppler filtering procedure, the target with relative velocity close to zero can be discarded. This cause detection error and may be a potential problem of CFAR.

3.2. PROPOSED METHOD

The proposed method predicts the distance and velocity of the target directly from the periodogram by a CNN classifier. CNN is one of the deep learning techniques, specialized in image classification. Finding peak in 2D periodogram can be considered as an image detection problem. Therefore, it is suitable for solving radar problems using CNN. The proposed CNN structure for estimating target distance and velocity is shown in Figure 5. The input layer, convolutional layers and the fully connected layer are linked, and at the end, the value corresponding to the distance or velocity is outputted. As mentioned earlier, there are two cases of input. The input signal is a cropped periodogram and that size is $S \times S \times 1$ for single image input (only input 'C+T') and $S \times S \times 2$ for dual image input (input 'C+T' and 'C'). The convolutional layer extracts features, and the fully connected layer classifies of the image. The proposed CNN consists of 5 convolutional layers and 1 fully connected layer. The filter size of the all convolutional layers is 5×5, and the numbers of filters of convolutional layers are doubled from 16 to 256. Every convolutional layer has batch normalization layer, rectified linear unit (ReLU) layer and max pooling layer of stride 2. The number of the fully connected layer output is also S. Finally, one value which is a class of distance or velocity is output through the softmax layer and classification layer. If the network is for distance, the output is the class corresponding to the target's distance. The input or output size of CNN are varied by number of OFDM symbols, 2D FFT size and available target detection range.

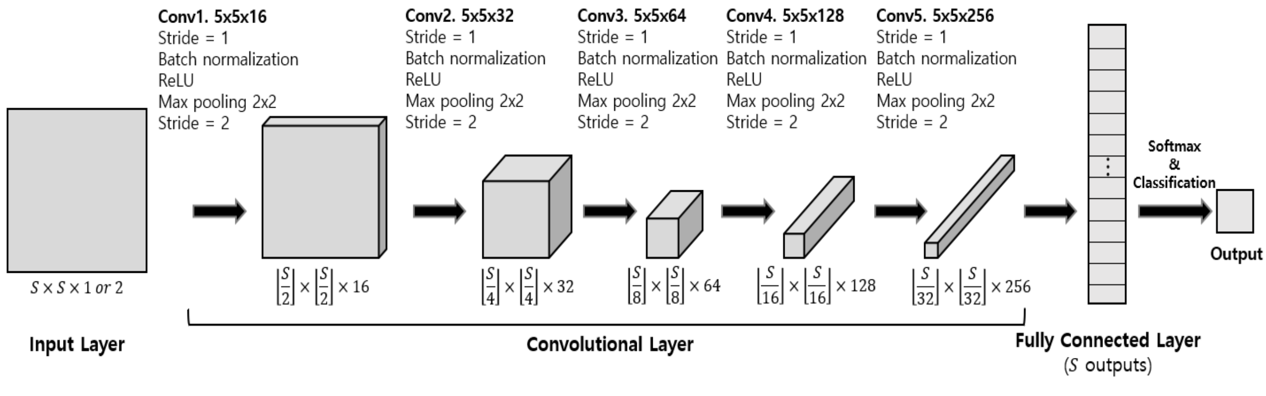

Figure 5. CNN Structure of Proposed Estimation Method

If the clutter only periodogram can be obtained, dual input can be possible. By using two inputs, the performance of estimating distance and velocity may be improved. The signal that has only clutter can be obtained through the antenna when targets are not moving around, such as dawn. The acquired signal is the background of the place and is added into the CNN input along with the signal when the target is in motion. Unlike the conventional method, the proposed CNN classifier does not require any additional information such as noise power estimate and noise variance.

4. SIMULATION RESULTS

4.1. SIMULATION ENVIRONMENT

The performance of the proposed CNN was verified through computer simulation using MATLAB. In the simulation, $f_S = 122.88MHz$, $N = 4096$, $M = 16, 32, 64$, $N_{FFT} = 2048$ and $M_{FFT} = 128$. The length of CP is 296. Thus, the symbol duration is $T = 35.74\mu s$. The subcarrier spacing is $\Delta f = 30kHz$. Among the total 4,096 subcarriers, only 1,284 subcarriers are used, and the resulting signal bandwidth is about 40 MHz. The carrier frequency is $f_C = 28GHz$. The reflected signals on a target are randomly generated between SNR = -20 to +30 dB. We crop the periodogram by 200 x 200 or S = 100. Due to the cropped 2D periodogram, the detectable range of distance and velocity is from 0 m to 244 m and from -211 km/h and 211 km/h, respectively. The clutter components are randomly generated using Weibull distribution and the associated parameters are $\eta = 1$ and $\beta = 1$. In the conventional method, the parameters TB and GB sizes are 5×5 and 1×1, respectively. Also, P_{fa} for 16, 32 and 64 symbols are 0.24, 0.21 and 0.21, respectively. Figure 6 shows the spectrum of generated OFDM signals.

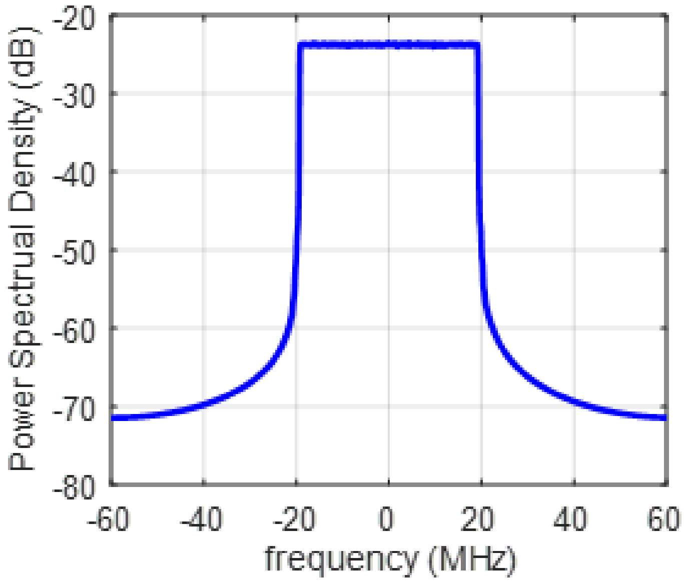

Figure 6. Spectrum of OFDM Signal

4.2. TRAINING CNN

Each proposed CNN has two networks. One is for distance estimation and the other is for velocity estimation. The former learns with distance classes and the latter learns velocity classes. The number of training data used in the training is 110,000. The mini-batch size is 100 and maximum epoch is 20. Therefore, the parameters update 1,100 times in each epoch and total number of parameter updates is 22,000. The optimization algorithm is stochastic gradient descent with momentum (SGDM) with learning rate 0.002 and momentum 0.9. In case of single image input, the number of learnable parameters is 1,499,588. For dual image input, since the input size increases to $S \times S \times 2$, the number of parameters also increase to 1,499,988. The difference between the two parameters is due to the first convolutional layer. The loss function is mean square error (MSE).

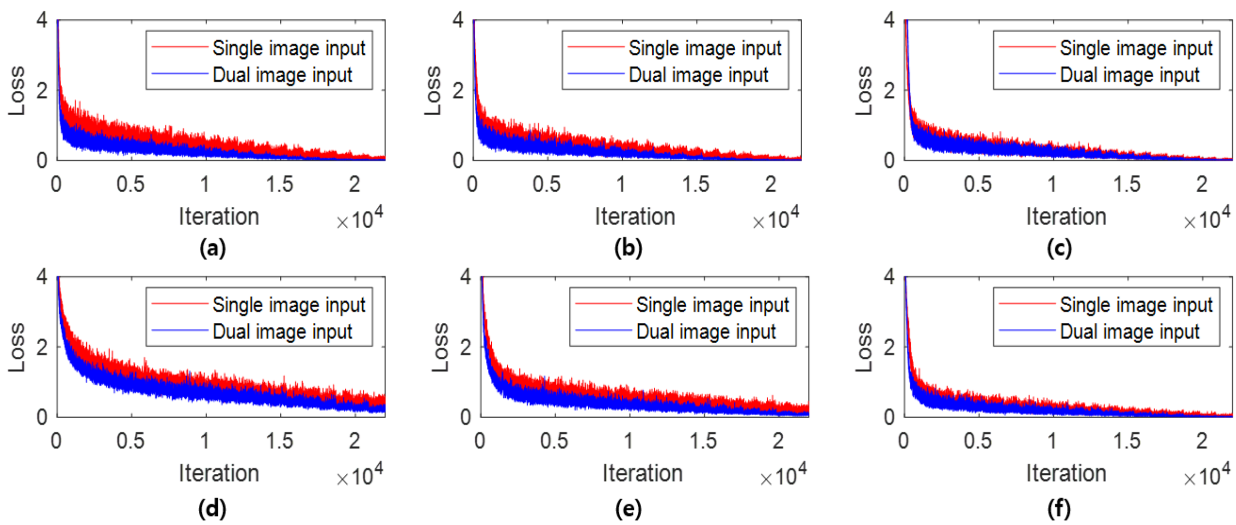

Figure 7. Learning Curves for Distance when (a) $M = 16$ (b) $M = 32$ (c) $M = 64$ and learning curves for Velocity when (d) $M = 16$ (e) $M = 32$ (f) $M = 64$

Figure 7 shows the learning curves of CNNs for distance and velocity when single and dual image input. The numbers of OFDM symbols, M, is 16, 32 and 64. As shown in Figure 7, convergence time becomes shorter for dual image input than single image input. The losses of CNNs after convergence are much closer to zero as the M increases. The reason is that Doppler resolution improves as M increases.

4.3. PERFORMANCE COMPARISON

To evaluate performance of distance and speed estimation, new test signals are generated that differ from the train signals. A target was positioned within same range as train data. The SNR is varied with intervals of 3 dB from -20 dB to +22 dB. At each SNR, 10,000 2D periodograms are generated. Mean Absolute Error (MAE) is performance metric for comparing performance of distance and velocity estimation.

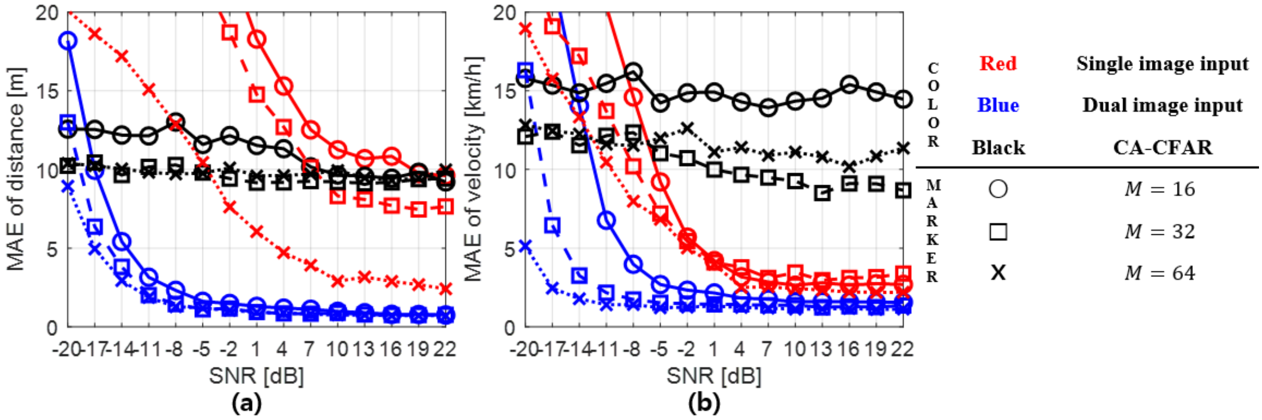

Figure 8. Mean Absolute Error Performance for Conventional and Proposed Method (a) MAE of Distance (b) MAE of velocity

Figure 8 (a) and (b) show the MAEs for the distance and velocity estimates, respectively. In Figure 8, color is used for distinguishing the conventional and proposed methods, and the marker distinguishes the number of OFDM symbols, M. The red and blue lines indicate proposed method's performances for single and dual images, respectively. The black line refers to the conventional CA-CFAR. The MAEs decrease as SNR increases. The best performance is when dual image input and $M = 64$. This means that the proposed method with dual image input is the best and the number of transmitted OFDM symbols has an impact on estimation errors. In the case of CFAR, distance MAE is 9.2 m and velocity MAE is 8.7 km/h at best. For the case of the proposed technique with single image input, the MAEs of distance and velocity are approximately 2.4 m and 2 km/h at best. By comparison, the performance of the proposed dual image input case is much better than the former both cases. For dual image input, the MAEs of distance and velocity are approximately 0.7 m and 1.1 km/h at SNR 22 dB. In addition, the MAEs are lower than CFAR in case of above -14 dB. Those results indicate that much better distance and velocity estimation with periodogram when clutters exist can be expected by using the proposed method. Also, properly increasing the number of the transmission symbols can increase accuracy in estimating distance and velocity.

5. CONCLUSION

In this paper distance and velocity estimation based on CNN for OFDM radar systems has been presented. A novel approach has been proposed that the range-Doppler periodogram as input image of the CNN classifier has been used to estimate the distance and the speed of the target directly. If clutter only periodogram is provided along with normal target plus clutter periodogram, estimation performance can be improved. Through computer simulation, the operability of the proposed concept and its superior performance over conventional method have been proven. The proposed technique can be applied to 5G or 6G mobile communication systems and may enable the convergence of communication and radar with the same waveform. Thus, the proposed one can significantly save frequency resources compared to the method of allocating resources to communication and radar respectively.

6. ACKNOWLEDGMENT

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