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Classification Algorithms for Human and Dog Movement Based on Micro-Doppler Signals

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** Regular Paper*

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***Abstract*:** We propose classification algorithms for human and dog movement. The proposed algorithms use micro-Doppler signals obtained from humans and dogs moving in four different directions. A two-stage classifier based on a support vector machine (SVM) is proposed, which uses a radial-based function (RBF) kernel and 16^{th}-order linear predictive code (LPC) coefficients as feature vectors. With the proposed algorithms, we obtain the best classification results when a first-level SVM classifies the type of movement, and then, a second-level SVM classifies the moving object. We obtain the correct classification probability 95.54% of the time, on average. Next, to deal with the difficult classification problem of human and dog running, we propose a two-layer convolutional neural network (CNN). The proposed CNN is composed of six (6x6) convolution filters at the first and second layers, with (5x5) max pooling for the first layer and (2x2) max pooling for the second layer. The proposed CNN-based classifier adopts an auto regressive spectrogram as the feature image obtained from the 16^{th}-order LPC vectors for a specific time duration. The proposed CNN exhibits 100% classification accuracy and outperforms the SVM-based classifier. These results show that the proposed classifiers can be used for human and dog classification systems and also for classification problems using data obtained from an ultra-wideband (UWB) sensor.

***Keywords*:** Moving object classification, UWB, SVM, CNN, AR spectrogram

1. Introduction

Classification of moving objects via microwave signals can be applied to defense and surveillance and in the private sector [1, 2]. Since Doppler radar can detect a nonstationary target by minimizing the clutter effect, it has been widely used for moving-object detection and classification. The micro-Doppler signatures generated from various motions of a moving body can be a key feature for detection and classification [3]. Research on human detection and tracking problems has been extensively conducted. Since a micro-Doppler signature obtained from the human body is time-varying, the signature can be represented in the time–frequency domain. To classify humans, animals, and vehicles, micro-Doppler signals were analyzed [4]. Many studies have been done into human activity classification, such as walking, running, crawling, etc. In early studies, Fourier spectrum analysis of micro-Doppler signals was used to classify targets without time domain information. The spectrum-based algorithms identified targets by using a distinctive Doppler shift, so they showed improved performance compared with the other methods. The time-varying signatures extracted from spectrograms were later exploited to recognize various human activities [5]. Time-varying features extracted from auto regressive (AR) spectrograms were investigated and proven to be effective and efficient in classification of human and dog movements [6]. Similarly, linear predictive code (LPC) was also suggested for real-time processing so it could dramatically reduce computational costs [7].

Since it is necessary to extract discriminative features from among the obtained features, transformation or reduction of features were applied to recognize target types [8]. Li et al. [9] used the well-known principal component analysis (PCA) and linear discriminant analysis (LDA) to extract feature vectors.

Although the mentioned algorithms achieved good classification performance in human or other movement detection, intrinsically, they had their limits. In other words, they were based on conventional supervised learning, so they required preprocessing of input signals to obtain discriminative features. The drawbacks reduced application of those algorithms to various other classification problems.

To overcome the problems, we propose a support vector machine (SVM)-based classification algorithm for human and dog movement. The proposed SVM classifier is composed of a two-stage SVM to classify movements of humans and dogs running and walking by using an obtained ultra-wideband (UWB) signal.

It is well known that deep-learning techniques have provided a lot of progress in image processing and object detection and classification. Deep learning employs multi-level architectures to extract and obtain high-level features. The essence of deep learning is based on a hierarchical structure that can compute multi-level features of incoming input, which are features obtained from lower-level ones [10]. The deep-learning algorithms have diverse applications in computer vision, speech recognition, image feature coding, robotics, etc.

Researchers showed that stochastic gradient descent learning via error backpropagation was effective for training convolutional neural networks (CNNs) [11, 12]. Document recognition with CNNs was reported [13]. Since then, new algorithms have been developed for image classification [14, 15]. They showed remarkably high image classification accuracy in the ImageNet Large Scale Visual Recognition Challenge. This success caused researchers to adopt much deeper networks and bigger networks for training, which is possible with the benefit of improved computing power. Since then, deep learning has shown superior performance over existing algorithms, such as the SVM, the hidden Markov model (HMM), etc. [16, 17]. Recently, human detection and activity detection by CNNs and the fast Fourier transform (FFT)-based spectrogram were reported [18], where Kim and Moon used data obtained from a target that is only approaching a Doppler radar. Their algorithm, based on unidirectional data, makes its application to real situations difficult. However, they reported high classification performance by using multiple stationary features of the targets.

To cope with real situations, we propose an algorithm based on data obtained from multiple directions, i.e. forward and backward, left-to-right, and right-to-left. These can represent real situations, but a small fraction of the data is useful for classification, so multiple features of targets cannot be obtained easily. To tackle this problem, we propose a CNN-based algorithm that is designed to classify humans and dogs that are running. Intrinsically, time- frequency representations of the running signals are not easily distinguishable. To cope with this problem, we use image features obtained in a short time frame of the signal. To reduce the computational costs of feature extraction, we propose an image feature based on an AR spectrogram rather than an FFT-based spectrogram. Through experiments, we show that the proposed AR spectrogram–based CNN algorithm can be a feasible solution to real situations.

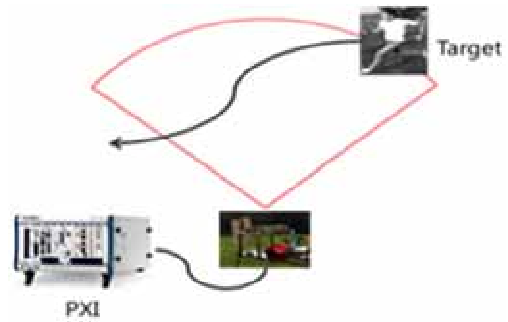


Fig. 1. Measurement setup.

The rest of this paper is organized as follows. The next section describes data measurement in which the database and experiment setup are described in detail. In the proposed scheme section, we propose two algorithms that are based on SVM and CNN. The first algorithm proposed is a two-stage SVM algorithm that is designed to classify the running and walking movements of humans and dogs. The second algorithm, based on CNN, is also presented in this section. The performance evaluation section includes performance evaluations of the proposed algorithms and a discussion of the results. Finally, we conclude this paper in the last section.

2. Data Measurement

We measure signals reflected from humans and dogs. To detect body motion of moving objects, we use a Doppler radar system that captures complex characteristics of the received signal via input I and Q channels. The measurement system with the moving object detection range is depicted in Fig. 1.

The system is designed to detect and classify the object within the detection area shown within the red line in Fig. 1. The maximum detection range is set to 10 m, and the normal detection angle is from –60 to +60 degrees.

The front end of the system is composed of a transmit antenna, a receive antenna, and a radio frequency module made by Samraksh Inc. The center frequency is 5.8 GHz and it uses the Industrial, Scientific and Medical band for data transmission. When an object appears in the detection area, the signal obtained by a UWB antenna sensor is transferred to, and stored in, a LabVIEW PXI system. To build a signal database of moving objects, we consider lone humans and lone dogs as moving objects. Two types of movement, i.e. walking and running, are considered, as shown in Fig. 2. To collect various data sets, we measured data from a total of 10 humans and four dogs.

Next, we consider four different movement paths to obtain various Doppler signals, and we illustrate the paths

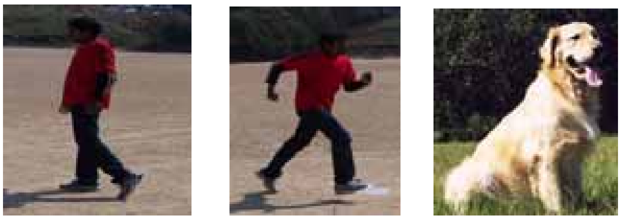


Fig. 2. Human walking and running, and a dog.

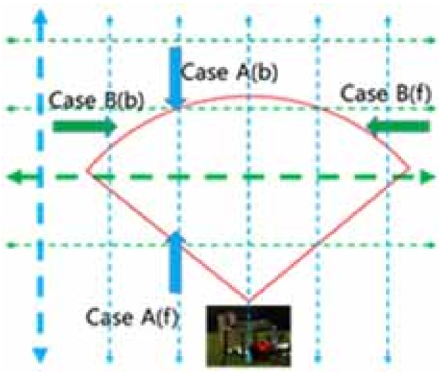


Fig. 3. Four different object movement paths.

Table 1. Signal database.

Case	Motion	Dog	Human
A	Run	40	70
	Walk	20	70
B	Run	63	140
	Walk	20	140
	Total	143	420

in Fig. 3. At first, we set movement as horizontal and vertical, which are the green arrow and the blue arrow, respectively. Then, we denote vertical and horizontal movement as Case A and Case B, respectively.

Next, we divide both movements into the backward and forward directions, which specify the direction coming toward the UWB sensor and the direction going away from the sensor. The backward and forward directions are labeled (b) and (f) in Fig. 3. For example, Case A(b) corresponds to vertical movement toward the UWB sensor. Using the movement paths, we collected signals from humans and dogs, which are summarized in Table 1.

3. The Proposed Scheme

3.1 Feature Extraction

We assume that the received micro-Doppler signal x[n] at time n, can be expressed as a linear combination of past signals, x[n-k], where k>0. This assumption is valid, since the signal during a short time range is stationary when the sampling frequency is high enough. Signals such as speech, sonar, and radar can be analyzed by using a stationary assumption. We apply this assumption to the feature

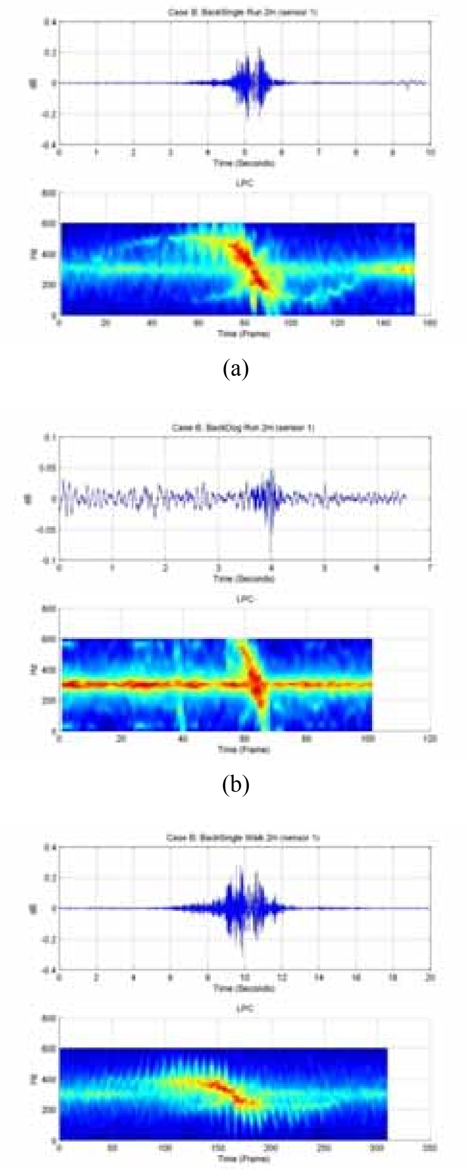


Fig. 4. Measured signals and AR spectrograms of (a) a human running, (b) a dog running, (c) a human walking.

extraction process and use LPC, which is based on an all-pole system that models micro-Doppler signal x[n] as the linear combination of the previous p samples. Then, we can write the predicted signal as follows:

$$x[n] \cong \sum_{k=1}^{p} a_k x[n-k] + \varepsilon \tag{1}$$

where a_k denotes the LPC coefficients, ε is the residual modeling error, and p is the order of the LPC. Here, we use the 16th order of the LPC coefficients as a feature vector. In Fig. 4, we demonstrate AR spectrograms for three different movements. For data processing, we use a sampling frequency of 2000 Hz, a frame length of 256 samples (with half overlapping), extract the 16th order of LPC coefficients, and obtain an AR spectrogram from each frame. We can observe different Doppler reflections according to fast and slow movement of objects.

3.2 Classification Algorithms

For classification of moving objects, we use the support vector machine developed by Vapnik et al. The support vectors lie on planes y_i defined by the equation $y_i(\mathbf{x}_i \cdot \mathbf{w} + b) = 1$, where **w** is weight vector, b is bias, $\mathbf{x}_i$ is an input vector, and $[\cdot]$ represents the dot product. Then the "hard" margin is equal to 2/||**w**||. It is well known that an SVM provides the optimal separating hyper-plane by maximizing the margin. In the case of separable classes, the hard margin is maximized by minimizing ||**w**||. For non-separable classes, the concept of a "soft" margin can be introduced for classification. The soft margin is created by adding non-negative slack variables. The slack variables represent the shortest distance between an incorrectly classified training vector and its correct classification region.

Slack variables help the SVM to minimize training errors. Maximizing the soft margin requires minimizing the objective function:

$$E = \frac{1}{2}\|\mathbf{w}\|^2 + C\sum_{i=1}^{l} \varsigma_i \tag{2}$$

where C represents a trade-off parameter, and ζ_i is non-negative slack variables. For linear SVM, we have the following relationships:

$$\mathbf{x}_i \cdot \mathbf{w} + b \geq 1 - \varsigma_i \qquad for \quad y_i = 1 \tag{3}$$

$$\mathbf{x}_i \cdot \mathbf{w} + b \geq \varsigma_i - 1 \qquad for \quad y_i = -1 \tag{4}$$

$$\varsigma_i \geq 0 \qquad \forall i \tag{5}$$

For a non-separable training vector set, we can use a non-linear SVM that uses a kernel function mapping the input data space into a higher dimensional feature space. The most common kernel functions are polynomial, radial-based function (RBF), sigmoid function, etc. In this paper, we use an RBF function for SVM training with the movements.

For better classification of complicated input, we employ a CNN, which is one of the most successful deep learning algorithms. The CNN is a supervised learning algorithm that attempts to learn mapping between input data and the corresponding labels provided beforehand. The hierarchical structure of the CNN is shown in Fig. 5. The CNN is inspired by the human visual cortex and was proven effective for image recognition problems. The CNN aims to use spatial information between the pixels of an image, so they are based on a two-dimensional convolution.

The CNN comprises three main components. The first is a two-dimensional mask, often called a convolution filter. The convolution filter is applied to small local fields of input data in a sliding-window manner. Often, multiple convolution filters are used in parallel at each layer so that an individual filter can work as a specific feature detector.

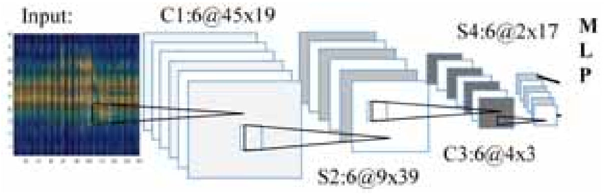
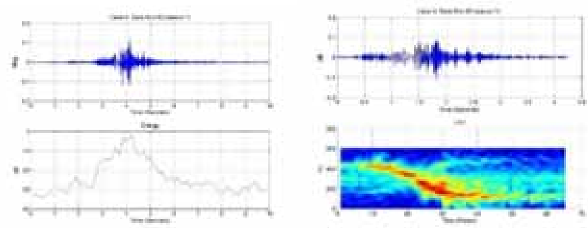


Fig. 5. Structure of the CNN.



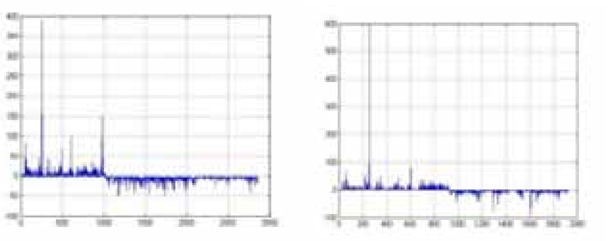
(a) (b)

Fig. 6. (a) Human running signal waveform (top) and its energy (bottom), (b) the segmented signal (top) and its AR spectrogram (bottom).

The second component is an activation function that is applied to output of the convolution filter. The activation function usually adopts a nonlinear function, which transforms data to a new domain, and thus, it makes discrimination among classes easier. The conventional choice for the activation function is the sigmoid function and restricted linear units (ReLU), which was proven to achieve better empirical results. The third component is pooling, which reduces the dimension of the convolution output. Through the pooling process, classification performance can become stable, and robust to variations in input images, such as translation, rotation, etc.

In order to use the input signal, we use an AR spectrogram of the signal as training input for the CNN. By treating the AR spectrogram as an image, we convert the classification problem into an image recognition problem. Since we are not sure when the moving object appears, we set 20 seconds for the recording time, and measure the incoming micro-Doppler signals. After obtaining an input signal, we decimate the data by 2, and segment the data by setting an appropriate threshold. By changing threshold levels from 0dB to 50dB at 5dB increments, we obtain an optimum threshold of 30dB. Then, we apply this threshold to the input signal to segment the signal and obtain the 16^{th}-order AR spectrogram, which can be obtained from a frame length of 256 samples with half of them overlapping. We demonstrate these procedures in Fig. 6. The input signal obtained of the human running and its energy are shown in Fig. 6(a). The segmented signal and its AR spectrogram are shown in Fig. 6(b). We see that the chosen threshold is appropriate, so we can obtain a well-segmented signal and its AR spectrogram, which can be used as CNN input.

Next, we resize the AR spectrogram image so it is a 50x200 normalized image. Since the number of training data is not large enough for a big CNN model, we adopted a relatively small CNN model. The adopted CNN model for training, is composed of two convolution layers, where



(a) (b)

Fig. 7. SVM training results (a) running (+1) and walking (-1), (b) dog (+1) and human (-1).

each layer has six convolution filters at 6x6. For pooling, we used (5x5) max pooling for the first layer and (2x2) max pooling for the second layer. We use a sigmoid function as an activation function. We assume that the CNN has fully connected layers that directly connect the output of the second pooling and the target classes, and we used MATLAB software for training and testing.

4. Performance Evaluation

4.1 Activity Classification

In order to evaluate performance by the proposed scheme, we used a data set described in Section 2. To train the data, we used six files from each class, and used an SVM classifier. The SVM training parameters are as follows: (1) C=10000, and (2) the kernel function is an RBF. To verify the training procedure, we present an example of the training results in Fig. 7. We denote running as (+1) and walking as (–1) in Fig. 7(a), and denote a dog as (+1) and a human as (–1) in Fig. 7(b). We can see that the given data set is well trained.

To compare classification performance of single-stage SVMs and two-stage SVMs, we use two different-stage SVM configurations. The configurations of the two-stage SVMs are shown in Fig. 8. The classification results are summarized in Table 2. In terms of overall human and dog classification performance, configuration II is the best. However, configuration I (which determines vertical and horizontal movement directions at first, and then classifies moving objects) exhibits rather poor performance for dog motion but good performance for human motion. This implies that the first-level SVM determining moving direction is not appropriate, especially for classifying dog movement. From these results, we conclude that training of all directions at the same level provides better classification performance.

4.2 Running Object Classification

In order to deal with rather difficult classification problems, we adopt a CNN. We considered humans and dogs running, for which typical AR spectrograms are shown in Figs. 4(a) and (b). In this experiment, we used a data set labeled Case A in Table 1. We used a total of 80 data sets obtained from 40 data sets with dogs and 40 data sets with humans. Of them, 20 data sets with dogs and 20 data sets with humans were used for training. The rest of the 40 data sets were used for testing. To verify the performance of the proposed CNN, we used an SVM classifier. For SVM training parameters, we used an RBF kernel. To train the CNN, we set the number of epochs to 400, and used the CNN structure depicted in Fig. 5. The CNN model has two convolution layers, in which each layer has six convolution filters at 6x6, with (5x5) max pooling for the first layer and (2x2) max pooling for the second layer. The obtained mean square error (MSE) according to epoch is shown in Fig. 9. In the figure, we can see that the given data set is well trained with 400 epochs.

To verify whether the convolution filters in the CNN represent the input image properly, we show the filter

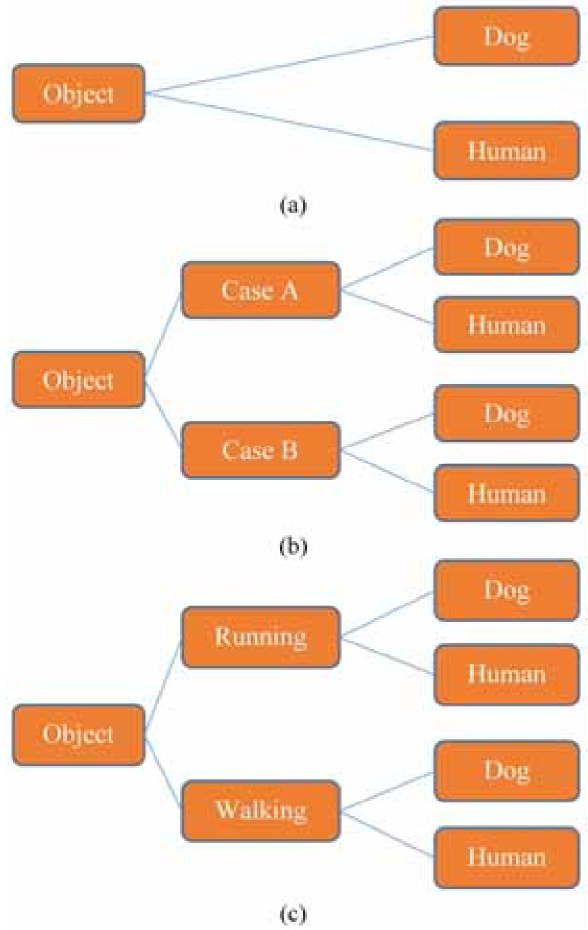


Fig. 8. (a) Single-stage SVM, (b) two-stage SVM-I, classifying cases at the first stage, (c) two-stage SVM-II, classifying movement at the first stage.

Table 2. Classification results using SVMs.

	Single SVM		SVM-I		SVM-II	
Case	Dog	Human	Dog	Human	Dog	Human
A	37/40	80/80	29/40	80/80	36/40	80/80
B	46/50	92/100	39/50	98/100	48/50	96/100
Accuracy (%)	92.22	95.56	75.5	98.89	93.3	97.78

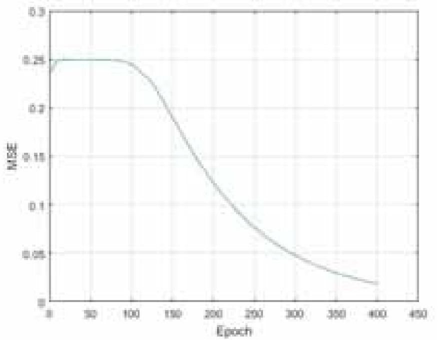
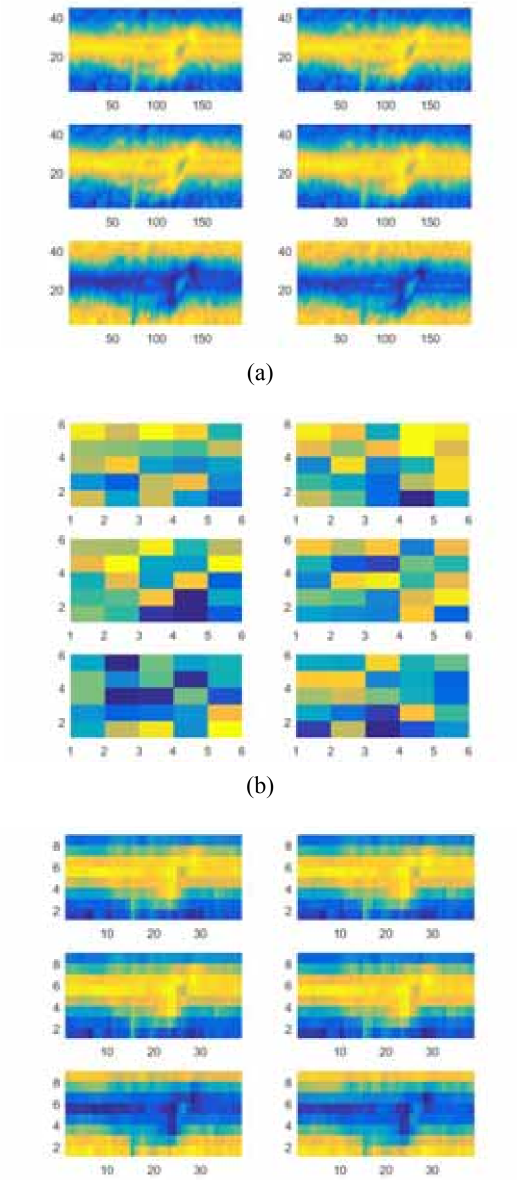


Fig. 9. MSE according to epoch.

Table 3. Classification of CNN and SVM.

	CNN	SVM
Accuracy (%)	100	62.5

output images in Fig. 10. We present the six convolutional filter outputs of the first layer in Fig. 10(a). As seen in Fig. 10(a), the given data set is well trained at the first layer. Next, we present six (6x6) convolution filters in Fig. 10(b), in which a direct explanation is not possible, but the coarse uncorrelated relationship between the six filters can be observed. Finally, the output from six convolution outputs of the first layer, which are six 9x39 images, is in Fig. 10(c). Here, we can see that six output images match well with the input images, even if the size of the images is reduced. The resultant six reduced images are fed into the second layer of the CNN, and then follow the same convolution filtering process. Even though output images from the second convolution filter output are not presented, we can see that the given data set is well trained with the proposed CNN structure within 400 epochs. With the trained CNN structure, we obtain 100% classification accuracy, as shown in Table 3. However, with SVM, we obtain 62.5% accuracy, which is the evaluated ratio of the number of correctly classified files to the total number of files. This low classification with SVM implies that SVM based on individual frame-based training cannot represent overall features of an input image. In contrast to the SVM, the CNN utilizes the whole input image for training, so it can represent overall features of the input image, which results in better classification performance and robustness to small variations between input and test images.



(a)

(b)

(c)

Fig. 10. CNN results from (a) six convolution outputs of the input image, (b) trained convolution filters at 6x6 in the first layer, (c) six convolution outputs of the first layer.

5. Conclusion

In this paper, we propose movement classification algorithms for humans and dogs. The proposed algorithms use micro-Doppler radar signals obtained from four different directions as input signals. For classification of a human running and walking, and for a dog running, we propose a two-stage classifier that is based on SVM. The proposed SVM classifier uses an RBF kernel and uses 16th-order LPC coefficients as feature vectors. With the proposed two-stage SVM, which classifies types of movement and then classifies moving objects, we obtain a correct classification probability of 95.54%, on average. For classification of human and dog running, we suggest a two-layer CNN model that is composed of six (6x6) convolution filters at the first and second layers, with (5x5) max pooling for the first layer and (2x2) max pooling for the second layer. The proposed CNN-based classifier uses an input image of an AR spectrogram generated during a specific time period. We show that the suggested CNN classifier exhibits perfect classification results and outperforms the SVM-based classifier for running object classification. These results show that the proposed classifiers are suitable for human and dog classification and for other classification problems based on a UWB sensor.

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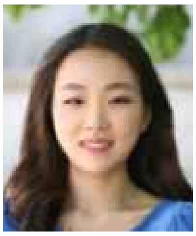

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