Radar-based Hand Gesture Recognition Using I–Q Echo Plot and Convolutional Neural Network

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***Abstract*—The present paper proposes a technique for the automatic recognition of hand gestures using a 2.4-GHz continuous radar and a convolutional neural network. The proposed technique applies the neural network to the time-domain I–Q plot of radar echoes. The accurate recognition capability of the technique was established with a set of radar data for three types of hand gesture performed by a participant. The radar echo trajectories were converted to low-resolution images to achieve fast signal processing, and the neural network was trained using the images. Another set of I–Q plot images were used for the evaluation of the recognition accuracy. The results indicate that the proposed technique is able to recognize hand gestures with accuracy exceeding 90%.**

***Index Terms*—radar, hand gesture, classification, convolutional neural network**

I. INTRODUCTION

Man–machine interfaces based on gesture recognition are among the most active fields of research. For gesture recognition, numerous wearable devices [1]-[4] have been proposed and developed. Although wearable devices allow for accurate and reliable measurement of human posture and motion, wearing such devices is inconvenient and can interfere with daily life. To avoid this inconvenience, noncontact gesture recognition is considered an important technology realizing a convenient and user-friendly interface with computers or machines. Noncontact gesture recognition using computer vision and depth-of-field cameras [5]-[8] have also been intensively studied, although there are privacy concerns surrounding the recording of users.

Radar is another approach for noncontact gesture recognition that is considered to be less invasive than computer vision, in terms of privacy. For example, Google Soli [9] realizes hand gesture recognition using a 60-GHz ultra-wideband radar with a 2×4 multiple-input multiple-output array, although such a radar system is not one of the most low-cost systems. Fan et al. [10] developed a low-cost continuous wave (CW) radar system for measuring target position and motion for gesture recognition. Molchanov et al. [11] proposed a technique for combining a depth-of-field camera and frequency-modulated CW radar data of gestures. Y. Kim et al. applied a convolutional neural network (CNN) to time–frequency distribution images containing gesture micro-Doppler information [12]. Similar techniques using machine learning with spectrogram images have been used for various radar target classification applications [13], [14].

In practice, time–frequency analysis is computationally expensive and simple time-domain approaches are preferable. S. Y. Kim et al. applied the CNN to the time-domain signals of an impulse-radio radar for recognizing gestures [15]. Gao et al. proposed the use of barcode-like patterns generated from time-domain signals for gesture recognition [16]. This paper proposes a time-domain gesture recognition technique using a low-cost 2.4-GHz CW radar and CNN. The proposed method applies CNN to in-phase (I)-quadrature (Q) trajectory images of radar echoes for gesture recognition. The performance of the proposed method is evaluated using measurement radar data.

II. SYSTEM MODEL

A. Radar System

We use a single-antenna mono-static CW radar system with frequency of 2.4 GHz and transmitting power of 10.0 dBm. The antenna has a gain of 8.0 dBi, vertical polarization, and E- and H-plane beamwidths of 60.0 and 80.0 degrees, respectively. The received signal is mixed with I and Q signals and low-pass filtered, and analogue-to-digital (A/D) converted to obtain I and Q signals, where the sampling frequency is 1.0 kHz. The A/D converter is connected to the signal cable through AC coupling, and the A/D converted data thus do not contain DC components. A block diagram of the measurement setup is shown in Fig. 1.

B. Measurement of Hand Gestures

We measured radar echoes from a healthy adult participant. The received signals contained mainly echoes from the arm

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TABLE I
GESTURE TYPES

Gestures	Arm Motion	Hand Shape/Motion
1	Back and forth	Palm
2	None	Palm rotating left and right
3	None	Making fist and palm

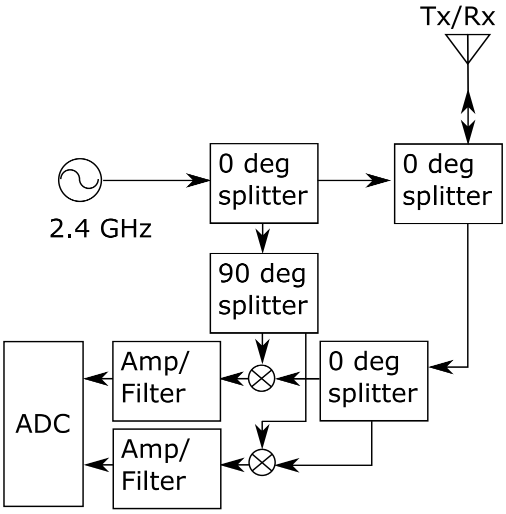

Fig. 1. Block diagram of the measurement setup.

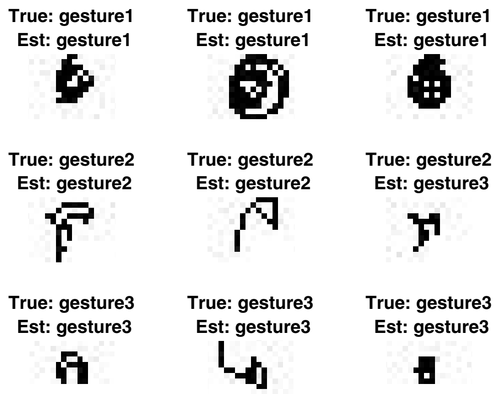

Fig. 3. Radar-echo I–Q plot images and gestures recognized by the proposed method. Out of 27images, 9 are shown. An I–Q plot for gesture 5 is incorrectly classified as gesture 6 (middle right).

and hand of the participant because echoes from stationary body parts were filtered by the AC coupling. The participant was instructed to remain seated and perform each of three hand gestures approximately 120.0 cm from the antennas. Each measurement took 2 s, and each gesture was repeated 29 times. The measurement setup is shown in Fig. 2. Table I shows the types of gesture performed in this study.

III. Gesture Recognition and the CNN

For gesture recognition, our proposed method uses the trajectory image of the I–Q plot of received signals $s_i^P(t)$. These signals are normalized so that $\max_{t,i}|s_i(t)| = 1$. The trajectory images are converted to low-resolution JPEG images with a size of 16×12 pixels. We measured each gesture 29 times, generating 29 images. For each gesture, we used 20 images to train the CNN and the nine remaining images to evaluate the performance. We used 60 images associated with three types of gesture label, and 27 images for performance evaluation of the accuracy.

The input image with a size of 16×12 pixels is convoluted with 10 types of 3×3 filters, generating 10 feature images with a size of 14×10. These feature images are input to a rectified linear unit and max-pooling with non-overlapping 2×2 pixels, which generates $10 \times 7 \times 5$ features. These features are connected to three output neurons with a 350×3 fully connected network, whose weights are optimized using the stochastic gradient descent with momentum optimization algorithm to minimize the difference between the training and output labels.

Fig. 2. Photograph of the measurement setup and a seated participant.

IV. Performance Evaluation

The CNN was trained using 60 images, which optimized the $350 \times 3 = 1050$ weights for synapses connecting neurons in the dense network. The stochastic gradient descent with momentum optimization algorithm was empirically set to 100 iterations. Figure 3 shows 9 out of the 27 images used in the performance evaluation. The figure also shows the actual and estimated labels above each image. In the figure, one of the I–Q plot images for gesture 5 is incorrectly classified as gesture 6 (middle right). The recognition accuracy was $28/29 = 96.6\%$, which suggests the feasibility of gesture recognition using the proposed machine learning approach in the time-domain without computationally expensive time-frequency analysis.

V. Conclusion

We propose a hand-gesture recognition method using a 2.4-GHz CW radar system and a CNN-based machine learning algorithm. The method applies CNN to time-domain I–Q plot trajectory images. The measurement data were analyzed to

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evaluate the accuracy of the proposed method in recognizing three different hand gestures. The proposed technique achieved high accuracy of 96.6%. Although this paper demonstrated the performance of the proposed approach for a single subject located at a fixed distance, it will be an important task to investigate the subject/distance/environment-dependencies of the performance.

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