Target Detection using U-Net for a DTV-based Passive Bistatic Radar System

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Abstract—Digital Television (DTV) has a wider bandwidth than a radio signal, and the signal power is stronger than Wi-Fi or LTE, so it is advantageous in exploiting a Passive Bistatic Radar (PBR) signal for drone detection. Most of the PBR systems detect a target using a Constant False Alarm Rate (CFAR) detector. However, CFAR detection suffers from multi-clutters, noise, and sidelobes. To overcome the limitation of CFAR, we propose a target detector exploiting semantic segmentation. The proposed detector is based on U-Net, a model for semantic segmentation. Training datasets for the proposed detector are generated by synthesized DTV signals. The performances of the CFAR and the proposed detector were compared using actual drone measurement data. The proposed detector detects drones better than the CFAR one while reducing the number of false alarms.

Keywords—DTV, passive bistatic radar, drone, target detector, semantic segmentation

I. Introduction

For the past few years, different types of drones have been commonly used in many ways because of their excellent accessibility and low cost. However, despite using their advantages, there are many problems such as invasion of privacy and attacks on national facilities, and these cases can weaken the security of society and the national defense [1]. Therefore, it is essential to build a system for detecting and tracking drones.

Recently, many drone detection technologies using a Passive Bistatic Radar (PBR) have been presented. PBR has a structure in which a transmitter and a receiver are separated from each other, and illuminators of opportunity for PBR are broadcasting signals such as Frequency Modulation (FM), Digital Television (DTV), Wi-Fi, and so on [2]-[4]. Because of the structure, the detection area is more expansive than monostatic, and by using a high-power illuminator like DTV, it is easier to detect small objects [5]. Besides, since it is not necessary to set a transmitter separately, the cost of installation is reduced.

PBR receives a line of sight signal and target reflection signal to calculate the Cross Ambiguity Function (CAF) and estimates the target's bistatic distance and Doppler frequency from CAF. However, in the received signal, not only the target signal but also multi-clutters and noise can appear [3]. Moreover, sidelobes may exist in CAF due to signal characteristics [6]. Since these factors cause false alarm in target detection, it is essential to determine whether the target is within the Range Doppler (RD) map, which is the 2D matrix with bistatic range axis and Doppler frequency axis. Usually, PBR determines targets by applying the Constant False Alarm Rate (CFAR) detector to the CAF [7].

However, the CFAR detector needs to apply a separate algorithm that calculates the threshold value for a particular environment, and performance depends on the structure and parameters. In this paper, a new strategy for target detection is proposed by exploiting semantic segmentation. The proposed target detector detects a target by imaging and learning various synthetic data of CAF for drone detection. Unlike the CFAR detector, which calculates a threshold according to a noise figure within a specific range, the proposed method can use the more broad values of CAF to detect a target. Learning the synthetic data has the advantage of reducing false alarms and the accuracy of target detection.

II. Fundamentals

A. Passive Bistatic Radar

Fig. 1 is a simplified structure of PBR. In the signal reception, there are two channels, the reference channel and surveillance channel, and they receive a reference signal and target signal, respectively. Commonly, a reference antenna is used to obtain a direct path signal from a transmitter. A surveillance antenna is used to receive target or multi-clutter signals which are delayed signals of the reference signal.

In this process, mitigating the multi-clutter signals is essential because the target signal usually has lower power than the other signals. Typically, we can use the Extensive Cancellation Algorithm (ECA) to remove the clutters in the surveillance signal, making the target results more evident in the RD map [8].

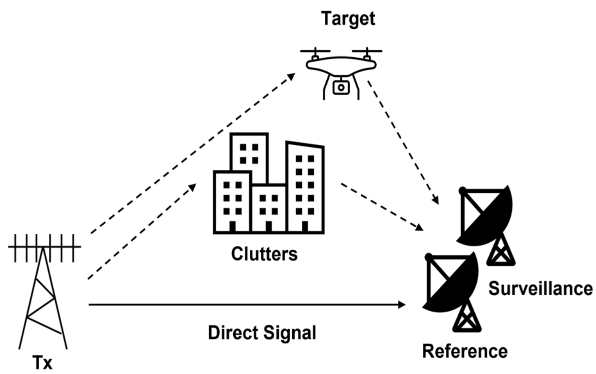

Fig 1. Sketch of passive bistatic radar

CAF can be calculated by cross-correlation with a reference signal and surveillance signal. Bistatic range and Doppler frequency of target can be estimated to find a peak of

CAF. Target signal has delay and Doppler frequency shift, so when the RD map is drawn, information of target's bistatic range and velocity can be extracted. The CAF equation can be derived from time delay τ and Doppler frequency f_d. The equation is represented by

$$C(\tau, f_d) = \int_{-\infty}^{\infty} x(t) s_{rf}^{*}(t-\tau) e^{-j2\pi f_d t} dt \tag{1}$$

where $x(t)$ is result of ECA, and $s_{rf}(t)$ is reference signal.

B. Constant False Alarm Rate Detector

The structure of the CFAR detector is shown in Fig 2. The CFAR detector consists of a test cell, guard cell, and reference cell. It estimates the average power of noise to get the threshold value from the surrounding reference cells and compares the value with the test cell to determine the presence of a target [7]. At this time, the area around the target peak has relatively high power, so setting a guard cell can exclude them when calculating the average power. The threshold is adaptively determined according to the noise measurement environment to keep the false alarm probability of the test cell constant. Therefore, the type of calculating algorithm can affect the performance of detection. In this paper, under the assumption of a uniform noise figure, 1-D Cell-Average (CA) CFAR detector along the Doppler axis was used in drone detection. Equation (2) is the threshold calculated with average noise power n_{CA}, number of the reference cell N, and false alarm probability P_{FA}.

$$T_{CA} = n_{CA}(P_{FA}^{-1/N} - 1) \tag{2}$$

C. Proposed U-Net-based detector

Semantic segmentation is a pixelwise classification method that predicts and labels whether an image has a specific class for each pixel to sort the objects in the image from one another [9]. In this paper, we exploited semantic segmentation method to target detection since the RD map displayed with single image as a result of CAF. Therefore, the most representative U-Net model in semantic segmentation was used [10]. The structure of U-Net has an encoding part for extracting the features of the input image and a decoding part for creating the desired result by using the convolutional neural network. The development of the input data coming out through the decoder shows probabilities of the classes for each pixel, and it is called a score map. Finally, U-Net classify the target by setting a threshold on the score map.

III. Experiment and Result

In this chapter, we will compare the results of applying the U-Net-based target detector and CFAR Detector to the actual data of the drone detection. About CFAR Detector, there were 8 guard cells, 16 reference cells. We has tests to find suitable false alarm probability in practical drone detection data and

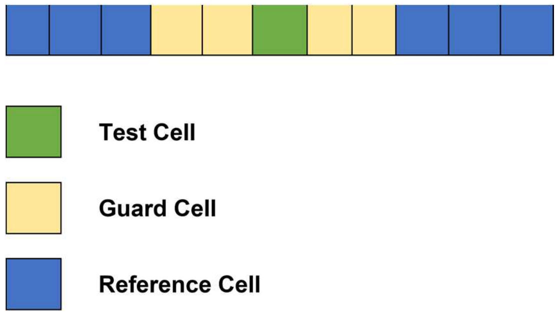

Fig 2. Simplified structure of 1-D CFAR detector

selected as 10^{-4} for superior performance. Less than 10^{-4}, the number of false alarm had increased, and in opposite case, the CFAR detector couldn't find the target.

When it comes to the U-Net-based target detector, we collected DTV signals and added a random target signal to the collected data to make synthetic training data. A total of 12,000 pieces of training data were generated through simulation with 10 signal-to-noise ratio (SNR) ranging uniformly from -44 to -35 dB, and the target positions were randomly placed on the RD map. In addition, the number of targets was set to be uniformly selected in range of 1 to 3 for each training data. We set the maximum value of target peaks on the RD map to label of training data. Fig 3. is an example pair of training and label data. In the Label, only the peak point is the target class, and others are noise. We exploited training optimizer of the U-Net-based target detector as Adam algorithm, and the first learning rate was 10^{-4}, which reduced by 2% every 2 epochs [11]. The batch size was 32, and when the 50 epochs were completed, training was finished.

Fig. 4 shows the steering direction of the reference and surveillance channels and the path the drone moves. The reference channel was steered in the direction of Hwangyeongsan, where the DTV transmitting station is

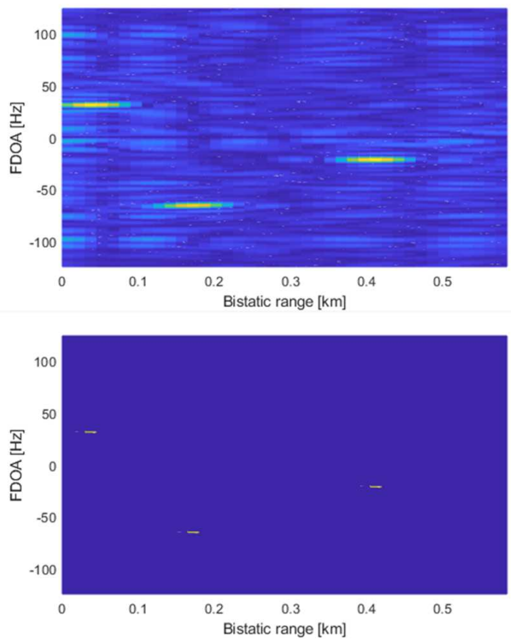

Fig 3. Example of synthetic training data and label

located, and the surveillance channel rotates about 90 degrees from the reference channel. A 701 MHz DTV signal was used to detect the drone, and the receiver was located on the roof of the Pusan National University building. The drone flew in parallel to the directivity of the surveillance channel for 1 minute while passing above the receiver.

In Fig 5. (a) shows a CAF with drone detection that bistatic range is about 90m, and Doppler frequency is about 38Hz, from one of the experiment data. It also can be shown that the noise and sidelobes are displayed on the RD map. Fig 5 (b) and (c) are the results of applying the CFAR detector and the trained U-Net-based target detector to Fig. 5 (a), respectively. Both the CFAR detector and the U-Net-based detector detected the drone well. However, (b) has more false alarms than (c). In addition, U-Net based detector's range resolution for target detection is more sensitive than the CFAR detector's, so it can estimate a more accurate bistatic range.

IV. Conclusion

Since the CFAR detector has problems of false alarm occurrence and inferior target resolution in the range axis, a U-Net-based target detector was proposed in this paper. To learn the statistical characteristics of DTV-based CAF for the proposed detector, synthetic data by adding an arbitrary target to the actual data was exploited. In addition, the performance of the proposed detector was compared and analyzed with the conventional detector using the CFAR algorithm. As a result, we can see that the ability to eliminate the false alarm is better than that of the CFAR detector while the detection performance is not deteriorated. Moreover, the proposed detector has a more precise range resolution than the CFAR detector for target detection. Therefore, it can be regarded as a suitable PBR system target detector in various drone measurement environments.

Fig 4. Geometric environment of drone detection experiment

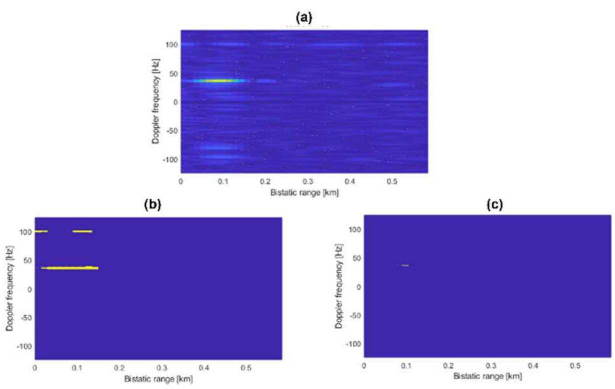

Fig 5. (a) CAF for drone detection, (b) Detection result via CFAR detector, (c) Detection result via proposed detector

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