UAV Detection Using the Cepstral Feature with Logistic Regression

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Abstract**—** The unmanned aerial vehicle system has been employed in various aspects, but the need for anti-unmanned aerial vehicle system technology is emerging due to privacy violation and bypass of a security system. In this paper, we propose a detection algorithm for an unmanned aerial vehicle system using acoustic sensors. The learned detection model is employed for the acoustic signal of the unmanned aerial vehicle system to obtain higher recognition performance. The cepstrum of the acoustic signal sampled during operation of the unmanned aerial vehicle system is applied to the feature vector and the logistic regression model is developed for the detection model. The learned model is verified through ten arbitrary cross-validations. The detection error for verification data is about 17.48%.

Keywords—unmanned aerial vehicle system, logistic regression, passive sensor, acoustic feature, cepstrum

I. INTRODUCTION

The unmanned aerial vehicle (UAV) industry, which was biased toward military use in the past, is leapfrogging forward in various fields such as broadcasting, hobby, and sports [1]. In proportion to this phenomenon, abuse such as privacy invasion or terror using UAV is increasing. For this reason, it is important to develop a valid UAV surveillance system even in the environments such as homes or public institutions, where various interferences exist. In particular, UAV is highly valued in the military aspect. Thus, it is more important because it can result in national security threat when it is abused. Many researchers are aware of the importance of research on the anti-UAV technology for this reason, and many studies are underway in this field.

Anti-UAV technology means detecting or disabling a UAV operation with malicious purposes. This identifies objects in a specific area and neutralizes threats by disabling unexpected UAVs, which can be divided into detection, identification, and disabling. Among them, detection is the most important and difficult area. Recently, commercially available UAVs are small and have low reflectivity, which makes detection and identification difficult [2]. Detection is largely divided into active and passive methods. Research on radar, which is a kind of active methods, is very popular. Radar has the shadowing problem that the radar system cannot detect a target due to the shadowing effect. In recent studies, it is the most important issue to distinguish whether a detected object is a UAV or the other.

This research was supported by Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education (2017R1D1A1B03032101).

The UAV's frame and configuration are diverse, but include basically waterproof motor frames, flight and motor controllers, motors, transceivers, propellers, and batteries or other energy sources. Therefore, radar, radio frequency (RF) sensor, vision sensor and acoustic sensor are mainly used for UAV detection. However, there are constraints on each sensor. The radar sensor and the vision sensor, are affected by the interference environment such as weather and surrounding buildings. When the size of the object is small, especially, it cannot be detected. For the RF sensor, it is easy to detect UAV by monitoring specific radio frequency band, but unexpected false detection is likely to occur due to the various frequency band operation of wireless devices used in the urban environment. Similarly, the acoustic sensor is highly effective in a quiet environment, but it is observed that its detection performance depends on the magnitude of the background noise in an urban environment.

The advantage of the acoustic sensors is that they are inexpensive, have good coverage and require a small amount of prior information compared to other sensors. It is also easy to acquire acoustic data that are expected to have similar characteristics. Using these features, previous studies are carried out to detect a UAV using harmonic components and propeller blade rate (PBR) such as harmonic characteristics of brushless direct current motor [3,4]. However, these methods have difficulty in the UAV detection because the maximum detection range is unclear depending on UAV types, a noise condition, and directionality, and are sensitive to the environment. To overcome this problem, we propose a logistic regression model with a cepstral feature vector.

The datasets used in this study are acoustic signal samples of the commercially available UAV's, various background noises, and sound samples of a scooter and a motorcycle that can be mistaken for a UAV in a quiet environment. In this study, the proposed algorithm is developed by modifying the existing techniques [3], which are sensitive to background noise, exploiting the UAV propeller noise characteristics as the notable feature. The feature robust to the background noise is extracted from the acoustic data through the preprocessing process. After that, we improve the detection accuracy by learning a model that can identify UAV through machine learning.

The paper is organized as follows. In Section 2, the features of the UAV signal used in this study are analyzed,

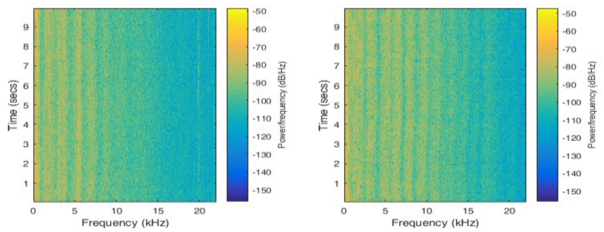

Fig. 1. Spectrograms of the two types of UAV's hovering signals for full band.

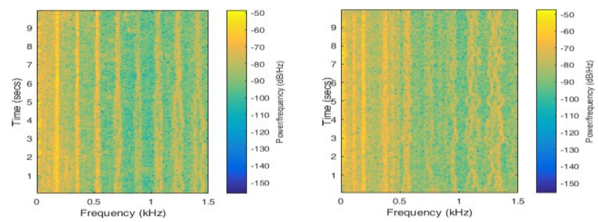

Fig. 2. Spectrograms of the two types of UAV's hovering signals for limited band (100 ~ 1500 Hz).

and the feature extraction method is described, focusing on the UAV detection algorithm using the acoustic sensor. Section 3 describes the process of learning the logistic regression model with the extracted features. In Section 4, the performance of the learned model is verified and the experimental results are discussed. Finally, Section 5 concludes the paper and describes future research plans.

II. Feature Extraction

A. Acoustic Property of UAV Signal

The platform noise of a UAV consists of wind noise, propeller noise, and platform vibration. The propeller noise is analyzed in terms of the acoustic characteristics. The propeller noise is generated by the motor and is dependent on the motion and/or the speed of a UAV. The change in revolutions per minute (RPM) has a continuous characteristic.

Due to this nature, the acoustic UAV detection can cause confusion for other objects, which use a motor, such as a motorcycle or a scooter with similar characteristics. However, the UAV requires higher RPM than that of a general motor equipment in order to maintain a certain altitude in the air or to move and operate, which can distinguish the UAV from other objects. According to [5], the noise of a UAV is sharper and more disturbing than the sound of a car or a motorcycle. It is observed that the acoustic characteristics of the UAV include higher frequency components than other objects so that one can distinguish them.

Figure 1 displays two spectrograms of the ten-second signals of two different UAV's that are hovering. Since the experiment was conducted in a relatively wide and quiet outside environment, it can be assumed that the component that has a major influence on the characteristics of the signal is propeller noise. The analysis is performed for a band from 100 Hz to 1000 Hz, where the fundamental frequency and its harmonic components can be observed.

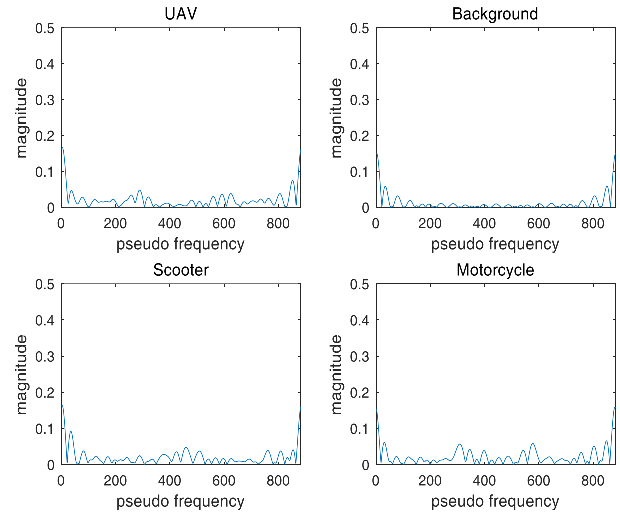

Fig. 3. Complex cepstrum magnitude.

Figure 2 shows two spectrograms of 0 to 1,500 Hz for the same signals. It can be observed that the acoustic signals collected from the two types of UAV's have similar harmonic characteristics. The feature vector extraction is carried out by exploiting the acoustic characteristics of the UAV in the corresponding band.

B. Cepstrum

Cepstrum [6] is a type of feature extraction method widely used in speech processing. It is more robust against noise than other feature extraction methods because it weakens the influence of speaker variation. This approach is mainly applied to speaker recognition, speech recognition, and noise reduction [7,8,9]. Since cepstrum is semantically identical to the spectrum of a spectrum, the fundamental frequency and its harmonic series of the analytical signal are collapsed to one component. Because of these characteristics, it is suitable for analyzing signals with harmonic characteristics such as UAV.

In this study, the magnitude of the cepstrum of the acoustic signal is used as a feature vector in order to train the logistic regression model. The magnitude of the cepstrum is as follows:

$$\hat{x}[n] = \left|\frac{1}{2\pi}\int_{-\pi}^{\pi} \log X(e^{j\omega})\, e^{j\omega n}\, d\omega\right|, \tag{1}$$

where $X(e^{j\omega})$ is the DTFT result of $x[n]$ and $\hat{x}[n]$ is the inverse DTFT of the spectrum's logarithmic $\log X(e^{j\omega})$.

In order to make the feature vector from the acoustic signal, 20ms signal samples are used. Figure 3 shows the cepstrum magnitude for hovering UAV, background sound, scooter, and motorcycle. It can be observed that each signal in the pseudo frequency domain has different characteristics. Because all of them have motors, the cepstra of UAV, motorcycle, and scooter look similar.

Note that the motorcycle's cepstrum is more similar to that of UAV than the scooter's cepstrum. This is because the harmonic characteristic of the motorcycle is similar to the UAV than the scooter. Based on this observation, the logistic

TABLE I. NUMBERS OF EXPERIMENTAL DATASET

Category	Number of feature vectors
UAV	18,000
Background	15,000
Scooter	1,500
Motorcyclce	2,000

regression model is learned by using the cepstral feature vectors.

III. LOGISTIC REGRESSION MODEL

In this study, the logistic regression is employed to develop a detection model [10,11]. Logistic regression is a regression analysis model that predicts the likelihood of occurrence by learning the relationship between dependent and independent variables. Unlike general regression models, dependent variables are represented by categorical data rather than numerical type by the logistic function. Therefore, the logistic regression method is exceptionally defined as the classification and has high performance in the binary classification method. For the binary logistic model considered here, the probability $p(y=1|x)$ is given by

$$p(y=1|x) = \frac{e^{\omega \cdot x + b}}{1+e^{\omega \cdot x + b}} \tag{2}$$

where $p(y=1|x)$ represents the probability that the output y belongs to the category of 1 given the feature vector x, and ω is the weight vector with a scalar shaped bias b. The notation "·" denotes inner product.

Logistic regression is divided into the training mode and the verification mode. The feature vector x is a $d \times 1$ vector. The label y is 0 or 1. The learning parameters ω and b is obtained in the direction that the probability of label y with respect to a specific feature vector x increases. In this case, ω is a weight of each component of the feature vector and has the same dimension as the feature vector. In the verification mode, the feature vector x is applied to the model established in the learning mode and the predicted label $\hat{y}$ is output. The label 1 represents the case with a UAV while the label 0 does the case without a UAV.

IV. EXPERIMENT AND RESULTS

A. Experimental Setup

To train the logistic regression model, the acoustic signals are collected for four kinds of signals: background sound, UAV, scooter, and motorcycle. The sampling rate is 44100 Hz and the samples are collected for 10 seconds at a time, which can provide 500 feature vectors. Each feature vector consists of 882 components, which is equivalent to 20 ms. The acoustic signals used in the experiment were collected under the following environment.

- **UAV:** Acoustic collection of two mid-sized UAV's in an outdoors with few interference elements. They are in hovering mode at 5 m and 10 m among from the sensor, respectively.

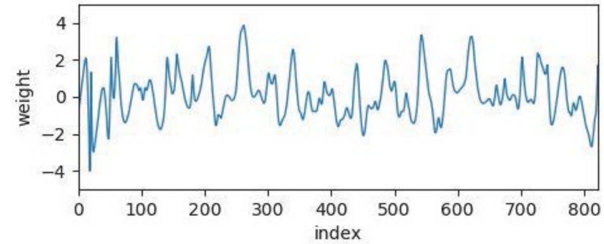

Fig. 4. The weight ω of the learned model.

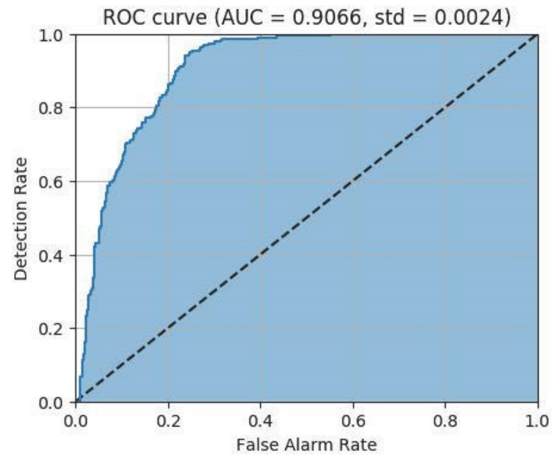

Fig. 5. One of the ROC curves of the trained models.

- **Background sound:** Background sound collection in a small outdoor environment with little interference elements such as a playground and a narrow outdoor environment such as a parking lot.
- **Scooter:** Acoustic collection of a four-wheeled scooter in an outdoors with a start-up condition.
- **Motorcycle:** Acoustic collection of a two-wheel motorcycle in an outdoors with a start-up condition.

To improve the reliability of the collected data, the samples that experienced artificial anomalies in the recording process are manually excluded. The length of each data is 20ms and the numbers of vectors used in the experiment are listed in Table I.

The logistic regression model for the proposed UAV detection uses the cepstral magnitude as the feature vector. "Liblinear" is used to optimize the learning parameters of the model [12].

B. Result

The learned model is evaluated in terms of the area under ROC curve (AUC) [13]. The evaluation method is the 10 times shuffle-split cross-validation. The minimum number of the training data set is limited to 18,000, and the ratio of the training data to the verification data is 1 in this experiment.

Figure 4 shows the weights of the trained model. It is observed that the relatively high pseudo-frequency components have small weight value.

TABLE II. CONFUSION MATRIX OF EXPERIMENT

		Predicted Label $\hat{y}$		
		No UAV	*UAV*	*Total*
True Label y	*No UAV*	73,854	18,808	92,662
	UAV	13,091	76,747	89,838
	Total	86,945	95,555	182,500

Figure 5 shows one of the ROC curves of the model evaluated by 10 times shuffle-split cross-validations. The average of the AUC's obtained from 10 assays is 0.9066 and the standard deviation is 0.0024. In general, an AUC of 0.9 or better is evaluated as an excellent model [11]. The confusion matrix is shown in Table II. The detection error in the 10 times shuffle-split cross-validations is 17.48%, and the proposed model demonstrates fairly good detection performance.

V. CONCLUSION

In this paper, we implemented and evaluated a UAV detection model using the cepstrum as a feature vector for frequency characteristics of 100 to 1000 Hz region. Despite of the motorcycle and the scooter, which can make false alarm because of having similar harmonics to the UAV, the high detection performance implies that the feature of the cepstrum magnitude is effective. As a result, it is possible to narrow down the category of the objects that make a false alarm by using the logistic regression model compared with the conventional method using only the harmonic characteristic. Note that the proposed algorithm is evaluated using the signals with high SNR. Therefore, it is necessary to verify the model using the signals containing complicated characteristics in the urban environment. In addition, since a single acoustic sensor system is utilized in this study, it is necessary to extend to sensor array systems.

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