Adaptive RF Fingerprint Decomposition in Micro UAV Detection based on Machine Learning

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***Abstract*—Radio frequency (RF) signal classification has significantly been used for detecting and identifying the features of unknown unmanned aerial vehicles (UAVs). This paper proposes a method using empirical mode decomposition (EMD) and ensemble empirical mode decomposition (EEMD) on extracting the communication channel characteristics of intruding UAVs. The decomposed intrinsic mode functions (IMFs) except noise components are selected for RF signal pattern recognition based on machine learning (ML). The classification results show that the denoising effects introduced by EMD and EEMD could both fit in improving the detection accuracy with different features of RF communication channel, especially on identifying time-varying RF signal sources.Whilte**

***Index Terms*—Micro UAS Detection, EMD, EEMD, RF Fingerprint, Machine Learning, time-varying RF signal**

I. Introduction

In recent years, the advancing in control and material technology has made the micro unmanned aerial system (UAS) more reliable. With the price dropping on armature UAS, the market of micro UAS has been expanding for a while. However, the imminent threat brought by it leads to the less secured airspace for those sensitive facilities, such as airports, nuclear power plants, electrical transformers [1] [2] [3] [4].

Doppler radar has been investigated for a few years in detecting the presence of micro UAS [5] [6] [7]. Micro-Doppler signature generated by the blade flashing has been effectively applied in the unknown UAV detection [8] [9] [10]. In [11] [12], the authors show that the Short Time Fourier Transform (STFT) and Fast Fourier Transform (FFT) could be well applied in estimating the blade flashing characteristic of micro UAS, rotation rate, physical parameters of the rotor blade with a long period of signal sampling time. However, the limited surveillance airfield of active radar could cause the low spectrum resolution to realize long range detection.

RF fingerprint is also used as the main resource for detecting micro UAVs. In [13] [14] [15] [20], the author applied conventional STFT and ML algorithm to find the time-frequency-energy spectrum pattern when UAVs present. In [16], a static RF source detection has been discussed for identifying the numbers of intruding UAVs in the indoor experiment. Due to the features of scattering transmission and reception in RF communication, a short period of signal sampling should not appear to be the problem in RF based long range detection. On the other hands, the low signal noise ratio (SNR) and increasingly complex wireless signal environment are the main issues.

Compared with conventional Fourier transform, the empirical mode decomposition (EMD) shows more benefits in mitigating the noise generated by UAS body vibrating, environment effects [11]. In [9], six popular entropy features from the micro Doppler signature (m-DS) is introduced by selected intrinsic mode function (IMF). The results show that the combination of features could be well applied in recognizing the UAVs' presence. [8] discussed the possibilities in applying EMD in reconstructing the blade flashing signal for distinguishing the m-DS of micro UAS.

Inspired by the two methods on denoising the received signal, we propose the long range UAVs detection method by applying EMD and EEMD on extracting features of RF finger print from intruding UAVs. The decomposed intrinsic mode functions (IMFs) except noise components are selected for RF signal pattern recognition based on machine learning (ML). In the end, various machine learning classifiers (i.e., CNN, MLP, Decision Tree, SVM) training results would compare the denoising performance of EMD and EEMD on the received signal data.

The rest of the paper is organized as follows. In section II, the comparison and background between two primary adaptive signal decomposition methods, EMD and EEMD, is presented. In section III, a detailed description of the experiment setting and data acquisition would be given. The classification results from different classifiers are discussed in section IV. Finally, in section V, we conclude our paper.

II. Methodologies

Fig. 1 shows the overview of the proposed method for obtaining the pattern of time varying RF signal of UAS. Two types of IMFs (CS-IMFs and VS-IMFs) are obtained based on the transformation of received complex signal. The non-noise and featured IMFs are selected to form the time- frequency-energy spectrum by STFT. Finally, we use the ML classifiers in identifying the intruding UAVs based on the received RF signal patterns.

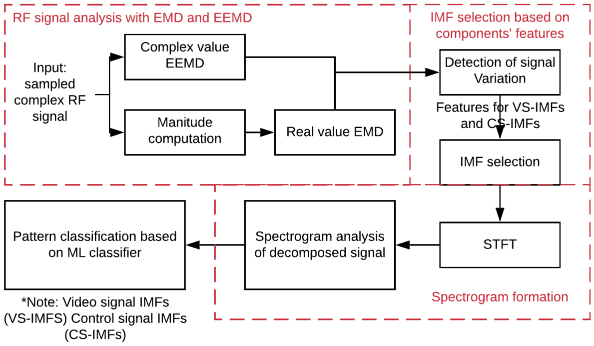

Fig. 1: An overview of the proposed RF finger print recognition method

A. EMD and EEMD

EMD algorithm is firstly introduced by Huang et.al [17], which is a data driven method for analyzing the non linear and and non stationary signal. EMD is an adaptive method to decompose time sequential data into a set of intrinsic mode function (IMF) components, which becomes the basis of representing the data. The obtained basis mostly own a physically meaningful representation of the underlying processes and there is no need for harmonics [18]. It could be formulated as follows.

$$f(n) = \sum_{k=1}^{K} IMFs_k(c_k) + r(n) \tag{1}$$

where the $IMFs_k(n)$ denotes the kth intrinsic mode function (IMF) with the certain frequency components at c_k and $r(n)$ is the residual between the local extremals and final divided IMF signal. $K = 10$ is picked here.

The linear combination of $IMFs$ and residual function forms the signal decomposed. The following equation explains the process of getting IMFs.

$$h_i(n) = f(n) - m_i(n) \tag{2}$$

where $m_i(n)$ is the average value of the upper envelope and lower envelope, $h_i(n)$ is the potential intrinsic mode function which obeys the following sifting rule.

$$Std_i = \sum_{n=0}^{N} \frac{h_i - 1(n) - h_i(n)^2}{h_i^2 - 1(n)} \tag{3}$$

in which, Std_i denotes the standard deviation of sum on difference rate of the $h_i^2 - 1$, the IMF could be defined when Std_i shows a smaller value than the given threshold value.

However, with the influence of extremal point unevenly distributed on the signal, EMD counters the IMF decomposition mistakes of mode mixing. EEMD [19] solves the mode mixing problem. EEMD defines the true IMF components as the mean of an ensemble of trials. In each trial white noise of finite amplitude is added into the signal and then EMD is applied to the signal and then EMD applied to this signal. It could be explained as following procedures:

1. Add white noise series w(n) to the targeted time sequence data $f(n)$ and decompose the $IMFs_k(n)$ into IMFs.

2. Repeat step 1 for multiple times with different white noise series and ensemble of corresponding IMFs of the decomposition gives the final IMF.

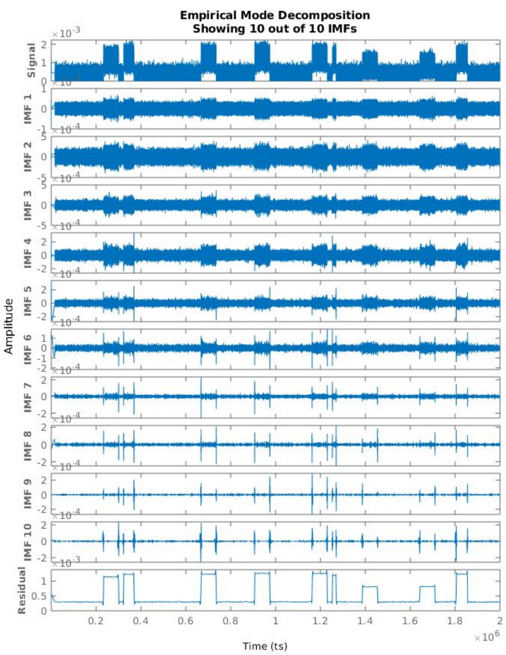

Fig. 2: 10 EMD IMFs of 2.4G Control Signal

Fig. 2 shows the EMD decomposition on the 2.4G uplink of micro UAS. The $10th$ IMF still keep the same trigger edge comparing with original signal. It suggests EMD could not fully extract the packet transmission feature signal by a limited number of IMF, which implies the mode mixing while decomposing the original signal as multiple sub-factors.

EEMD is applied here to generated 10 IMFs graphs of 2.4G uplink signal between micro UAS and remote controller. Notably, we see that the Fig. 3 decomposition process stops at the $5th$ IMFs. The IMF6 to IMF10 reveals the features closed to white noise.Considering the IMFs after IMF5 is mainly dominated by the noise component as there is no package transmitting in the UAS communication link. Therefore, we choose IMF1-IMF5 as for the subsequent pattern formation by STFT.

B. Short Time Fourier Transform on IMFs

Short time Fourier transform (STFT) obtains the spectrogram of IMFs by calculating the magnitude of signal as follows.

$$STFT(f,t) = \sum_{n=-inf}^{inf} s(t)w(t-m)e^{-j2\pi kn/N} \tag{4}$$

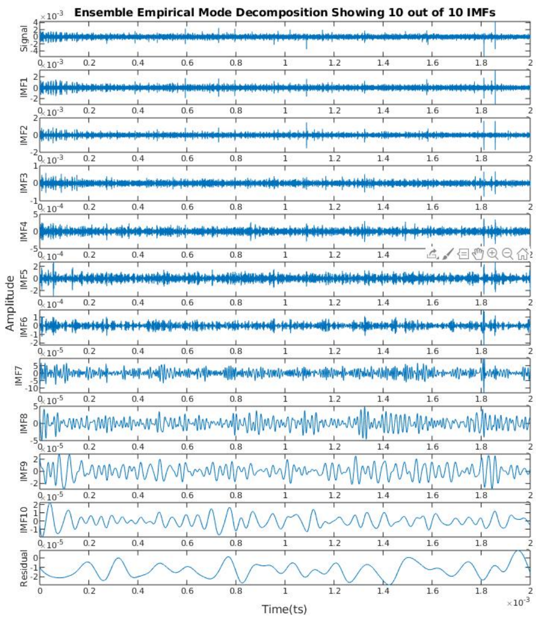

Fig. 3: 10 EEMD IMFs of 2.4G Control Signal

where s(t) indicates the signal on each of IMF $s(t) = IMFs$, $w(t)$ denotes the discreet window function and n represents the sample number and N is the FT analysing window. Index m is the positions of the analysis window, in which $m(i-1) = m(i) + nN$. k indicates the index of frequency components kw_0 where $w_0 = 2\pi f_s/N$.

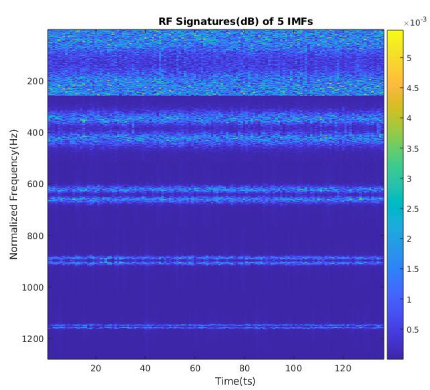

Fig. 4: White noise

To view the different time-frequency spectrum features of different IMF functions, STFT is then applied to each IMF. The time-frequency-energy distributions of the signal are obtained and formed on more prominent features in recognizing the signal. Fig. 4 shows the white noise on the spectrogram after the signal decomposition by EEMD. The main component from IMF1 to IMF5 shows the same signal strength across the time domain.

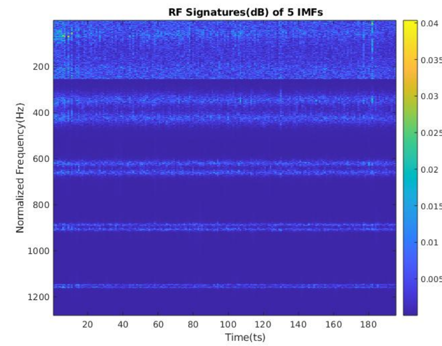

Fig. 5: 1 control signal source

Fig.5 shows a more apparent packet transmission that could be easily distinguished from the "straight-line" features. It could be seen more clearly from the Fig.7 of the downlink signal transmitting. The longer-lasting time of downlink signal emitted from the UAS, it has more potent signal energy on the spectrum. The exciting part from Fig.6 is the signal strength shows a more prominent feature of control packet transmission than any of the previously received signals, and we could see the two packages on the spectrum. It implies the possibilities of EEMD's application in detecting multiple micro UAVs since the package transmission behavior could be easier decomposed by this method.

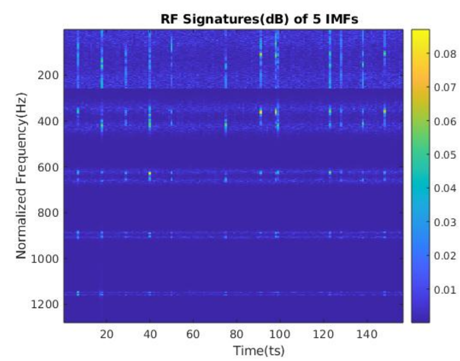

Fig. 6: 2 control signal sources

III. EXPERIMENT

The test micro UAV has two communication channels: 1) downlink at 5.8G transmitting video packet 2) uplink at 2.4G transmitting control packet. To receive the signal with the right center frequency, we adopted GNURadio modules as following parameter setting.

The source library defines the device centering frequency at 2.455G at both receiver 1 and 2 with 31.25MHz sampling frequency. Both signals are connected with the FFT frequency sink of 15MHz bandwidth and file sink to record the complex signal.

The test filed includes a 340ft flying track parallel with the receiver location site in which we conducted two types of Micro UAS flying method, one along with the flying site, the

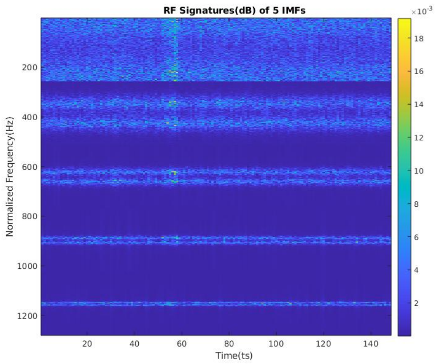

Fig. 7: 1 video signal source

receiver captures varying RF signal strength and the second UAS flying with surrounding the receiver, in which the RF signal keeps the same strength in the recording process.

At the end of the testing phase, we obtained RF signal from micro UAS at 2.4G with one and two uplink signals, 5.8G one downlink signal, white noise from the environment with no major RF signal interference.

IV. RESULT AND DISCUSSION

The machine learning classifier is trained to recognize the spectrogram (i.e., Fig.4-Fig.7) pattern. A 100$\times$ 256 matrix is obtained for representing the 256 frequency points with 100 time samples. By combining the other 5 IMF channels, we obtain a 100$\times$ 1280 matrix for describing 5 IMFs components.

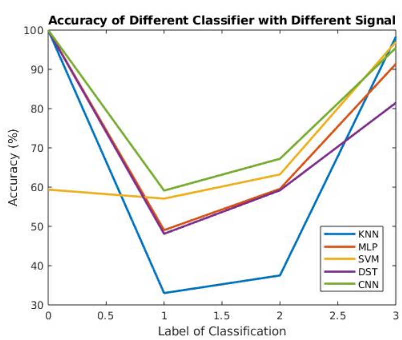

Fig. 8: Accuracy of ML Classification based on EMD

Labels of training classifier are assigned as follows:

1) white noise (label 0)
2) one control signal(label 1)
3) two control signals (label 2)
4) one video signal (label 3)

By comparing Fig. 8 and Fig. 9, EMD generally reaches lower accuracy on label 1 and label 2, which could be explained from Fig. 2 that EMD shows less denoising ability on noncontinuous packet transmission such as control signal on uplink. This leads to the first five IMFs components generated by EMD could not include most channel features and failed to filter the environment noise, resulting in the spectrogram pattern mixing.

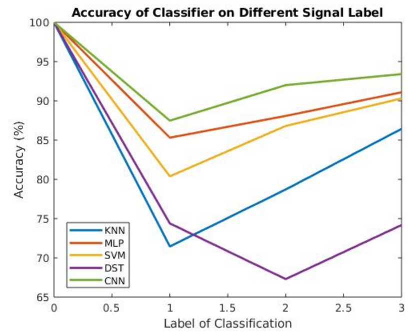

Fig. 9: Accuracy of ML Classification based on EEMD

100% accuracy on label 0 is because the white noise shows lower value on decomposed IMFs compared with packet transmission signal, which implies that both EMD and EEMD denoising method could distinguish the none intruding UAVs situation. This could contribute to more promising UAV presence detection system with lower false-positive rate.

From Fig. 9, Label 3 has the lower accuracy in signal type classification compared with Fig.8, since it has a unique continuous packet transmission pattern, which could be seen from the spectrogram in Fig. 7. Furthermore, continuous packet transmission signals in the downlink channel could be easily mixed up with the noise in EEMD. Due to the fact they share more similar signal distribution in the time domain.

As discussed above, EEMD adds up the white noise in the base of the standard EMD method, which cancels the uneven distribution of extremal points. Therefore, the pattern of two control signals on the label is more obviously represented by the EEMD. However, the less accurate classification result on the downlink channel shows that EMD could effectively detect channel with packet transmission interval. Therefore, it is possible to apply these two adaptive signal denoising methods in identifying the features of unknown UAV RF communication channels.

V. CONCLUSION

This paper has proposed a novel method of applying EMD and EEMD signal decomposition in micro UAS detection. Nearly, the UAS's control and video signal with limited bandwidth was decomposed into a few sets of intrinsic mode functions. Each IMF function represents the different frequency components in the link between the UAV and its remote controller. By classifying the pattern formed by IMFs with different machine learning classifiers, much better detection accuracy shows the advantages of applying two methods on distinguishing different features of UAVs RF communication channels.

ACKNOWLEDGMENT

This research was partially supported through Embry-Riddle Aeronautical University's Faculty Innovative Research in Science and Technology (FIRST) Program and the National Science Foundation under grant No. 1956193.

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