Variational Mode Decomposition-Based Radio Frequency Fingerprinting of Bluetooth Devices

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ABSTRACT Radio frequency fingerprinting (RFF) is based on identification of unique features of RF transient signals emitted by radio devices. RF transient signals of radio devices are short in duration, non-stationary and nonlinear time series. This paper evaluates the performance of RF fingerprinting method based on variational mode decomposition (VMD). For this purpose, VMD is used to decompose Bluetooth (BT) transient signals into a series of band-limited modes, and then, the transient signal is reconstructed from the modes. Higher order statistical (HOS) features are extracted from the complex form of reconstructed transients. Then, Linear Support Vector Machine (LVM) classifier is used to identify BT devices. The method has been tested experimentally with BT devices of different brands, models and series. The classification performance shows that VMD based RF fingerprinting method achieves better performance (at least 8% higher) than time-frequency-energy (TFED) distribution based methods such as Hilbert-Huang Transform. This is demonstrated with the same dataset but with smaller number of features (nine features) and slightly lower (2-3 dB) SNR levels.

INDEX TERMS Variational mode decomposition, Bluetooth signals, specific emitter identification, feature extraction, signal classification.

I. INTRODUCTION

Radio frequency fingerprinting (RFF) is promising method for physical layer security in wireless networks. RFF is based on the use of hardware originated imperfections (so-called “RF fingerprints”) of the transmitting devices. RF fingerprints can be extracted either from the transient or the steady state regions of the transmitted signal. Transient signal based RF fingerprinting method consists of transient detection, feature extraction and classification stages. Distinctive features, as RF fingerprints, are extracted from the transient signal characteristics. Typical transient signal characteristics are instantaneous amplitude, frequency and phase. For example, features are extracted from instantaneous amplitude of the transients of Wi-Fi signals in [1]–[3]. On the other hand, some recent works have proposed transform techniques in RFF implementation. Wavelet transform [4], discrete Gabor transform (DGT) [5], energy spectrum [6], and Hilbert-Huang Transform (HHT) [7] have been employed successfully for different types of wireless devices.

Transform techniques allow us to extract some robust features of the transient signals. Characteristics of the transient signals play a critical role in extracting robust features. Transient signals emitted by wireless devices are very short in time, typically non-stationary and in the form of nonlinear time series. Then, robust and subtle features must be extracted such that devices with the same model and manufacturer can be distinguished accurately. Among the most accurate techniques, HHT allows decomposition of transients signals both in time and frequency domain so that many subtle features can be extracted [8]. However, empirical mode decomposition (EMD) employed in HHT suffers mode-mixing problem and has higher computational cost along with lack of mathematical theory. An improved decomposition technique, known as Variational Mode Decomposition (VMD), has been proposed recently [9]. VMD utilizes simultaneous decomposition of all the modes non-recursively both in temporal and spectral domain. VMD has been demonstrated to outperform EMD in several applications including wind turbine condition monitoring [10], single hop radio relaying stations [11] and fluctuation analysis [12]. A novel method based on VMD has been demonstrated successfully for extracting of pulse radar
fingertips using unintentional modulations on pulses [13].
To the knowledge of the authors, there has been no published
work regarding the performance of VMD with the transient
signals of low power Internet of Things (IoT) devices such as
Bluetooth (BT). This paper presents performance of VMD in
RFF of Bluetooth devices, and reports comparison with HHT
using the same dataset in [7].

II. VARIATIONAL MODE DECOMPOSITION (VMD)

Variational mode decomposition (VMD) is based on the
concepts of Wiener filtering, analytic signal and frequency
mixing or heterodyning [9]. Briefly, any real valued input
signal $s$ is decomposed into a number of discrete modes $s_z$ ($z = 1, ..., Z$) that have specific properties to reproduce
the input signal. Each discrete mode has limited bandwidth,
and is assumed to be compacting around a center frequency
$\omega_z$ ($z = 1, ..., Z$) to be determined along with the decomposition.
Basically, there are two steps for creating each mode: i) compute the associated analytic signal of the mode (Hilbert transform) ii) shift the frequency spectrum of the mode to
“baseband” (heterodyning) iii) estimate the bandwidth of the
mode by smoothing the demodulated signal (Wiener filtering).
The following [9] describes the decomposition process for the signal $s(t)$.

Firstly, the bandwidth of the modes $\omega_z$ ($z = 1, ..., Z$) is calculated
by the following optimization

$$\Delta \omega_z = \int |\partial_t (s_z(t))|^2 dt = \|\partial_t (s_z(t))\|^2 $$

$$\min_{\{|s_z|, \{\omega_z\}, \lambda\}} \left\{ \sum_z \|\partial_t (s_z(t))\|^2 \right\}, \quad s.t. \quad \sum_z s = f $$

$$\min_{\{|s_z|, \{\omega_z\}\}} \left\{ \sum_z \|\partial_t \left[ \left( \delta(t) + \frac{j}{\pi t} \right) * s_z(t) \right] e^{-j\omega_z t} \|^2 \right\},$$

$$s.t. \quad \sum_z s = f $$

To transform the optimization problem into an unconstrained
form, the quadratic penalty function and Lagrange multiplier
are introduced as follows

$$L (\{|s_z|, \{\omega_z\}, \lambda\}) = \alpha \sum_z \left[ \|\partial_t \left[ \left( \delta(t) + s_z(t) \frac{j}{\pi t} \right) \right] e^{-j\omega_z t} \|^2 \right]$$

$$+ \left\{ f(t) - \sum_i s_i(t) + \frac{\lambda(t)}{2} \right\}^2 - \frac{\lambda^2(t)}{4} \right\|^2 $$

$$\lambda$$ is the Lagrangian multiplier and $\alpha$ is the bal-
ancing parameter. Alternate Direction Method of Multipli-
ers (ADMM) algorithm is employed to the unconstrained
problem form. As a minimization with respect to $s_z$, the sub-
problem is rewritten as

$$s_z^{n+1} = \arg\min_{s_z} \left\{ \alpha \sum_z \left| \partial_t \left[ \left( \delta(t) + \frac{j}{\pi t} \right) \right] \right|^2 $$

$$\left( f(t) - \sum_i s_i(t) + \frac{\lambda(t)}{2} \right)^2 - \frac{\lambda^2(t)}{4} \right\|^2 $$

This problem can be solved in spectral domain as

$$\hat{s}_z^{n+1} = \arg\min_{\omega_z} \left\{ \alpha \|f(\omega) \right\|^2$$

$$+ \|\hat{f}(\omega) - \sum_i \hat{s}_i(\omega) + \frac{\hat{\lambda}(\omega)}{2} \|^2 $$

By changing of variables ($\omega \rightarrow \omega - \omega_z$) in the first term

$$\hat{s}_z^{n+1} = \arg\min_{\omega_z} \left\{ \alpha \|f(\omega - \omega_z) \right\|^2$$

$$+ \|\hat{f}(\omega) - \sum_i \hat{s}_i(\omega) + \frac{\hat{\lambda}(\omega)}{2} \|^2 $$

Then, both terms are written as half-space integrals over the
non-negative frequencies as

$$\hat{s}_z^{n+1} = \arg\min_{\omega_z} \left\{ \int_0^\infty 4\alpha (\omega - \omega_z)^2 |\hat{s}_z(\omega)|^2 + 2|\hat{f}(\omega)$$

$$- \sum_i \hat{s}_i(\omega) + \frac{\hat{\lambda}(\omega)}{2} |^2 d\omega \right\}$$

The solution of this quadratic optimization problem can be
written as

$$\hat{s}_z^{n+1}(\omega) = \frac{\hat{f}(\omega) - \sum_i \hat{s}_i(\omega) + \frac{\hat{\lambda}(\omega)}{2}}{1 + 2\alpha (\omega - \omega_z)^2} $$

The center frequencies $\omega_z$ appear only in the first term. This
quadratic problem is then solved as

$$\omega_z^{n+1} = \frac{\int_0^\infty \omega |\hat{s}_z(\omega)|^2 d\omega}{\int_0^\infty |\hat{s}_z(\omega)|^2 d\omega}$$

The procedure of the VMD may be summarized as follows

- Initialize modes $\hat{s}_z^1, \omega_z^1$ and $\hat{\lambda}_z^1$, set $n$ to $0$.
- Update the modes $\hat{s}_z^{n+1}(\omega)$

$$\hat{s}_z^{n+1}(\omega) = \frac{\hat{f}(\omega) - \sum_i \hat{s}_i^{n+1}(\omega) + \frac{\hat{\lambda}(\omega)}{2}}{1 + 2\alpha (\omega - \omega_z^n)^2} $$

- Update the centre frequencies $\omega_z^{n+1}$

$$\omega_z^{n+1} = \frac{\int_0^\infty \omega |\hat{s}_z^{n+1}(\omega)|^2 d\omega}{\int_0^\infty |\hat{s}_z^{n+1}(\omega)|^2 d\omega}$$

- Update Lagrangian multiplier $\hat{\lambda}_z^{n+1}(\omega)$ until the convergence

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\[ \hat{\lambda}^{n+1}(\omega) \leftarrow \hat{\lambda}^n(\omega) + \tau \left( \hat{f}(\omega) - \sum_{\zeta} \hat{z}_{\zeta}^{n+1}(\omega) \right) \]

\[ \sum_{\zeta} \left\| \hat{z}_{\zeta}^{n+1} - \hat{z}_{\zeta}^n \right\|_2^2 / \left\| \hat{z}_{\zeta}^n \right\|_2^2 < \epsilon \]

The values of the parameters in running the procedure have been obtained after examining related works [9]–[12], and experimental analysis as suggested in [9], [11]. These are balancing parameter (\( \alpha = 200 \)), the number of modes (\( Z = 3 \)), the tolerance of convergence (\( \epsilon = 10^{-7} \)), the initialization of center frequencies (\( \omega_0 = 0 \)).

III. PROPOSED RF FINGERPRINTING (RFF) METHOD

Proposed RF fingerprinting method involves the following stages: data collection (signal capturing) and transient detection, reconstruction of transient signals using VMD, extraction of statistical features and classification.

A. DATA COLLECTION AND TRANSIENT DETECTION

Bluetooth (BT) signals were collected from different mobile phones of different brands, models and serial numbers. The list of devices presented in Table 1 of [7] is considered in this study. Briefly, ten different models of five popular brands (Huawei, IPhone, LG, Samsung, and Sony) were acquired for the experiments. Two different serial numbers of each model (indicated as A and B in Table 1 of [7]) were acquired. BT signals emitted by cell phones were captured in the laboratory by using high sampling rate oscilloscope (20 GSPS). Approximately exactly, 150 BT signals were captured for each device. Then, there was a total of 3000 records, each of which consists of noisy part (channel noise), transient signal part and steady state part. The captured BT signals were band-pass filtered (BPF) for removing undesired signals of adjacent channels. Detection of transient signals’ start and end points is critical for the performance of RFF system. For transient signal detection, performance of various techniques based on signal phase, amplitude and energy has been studied well in the literature. An improved technique proposed in [14] was employed for transient detection. Next, in order to evaluate the performance of the RFF method under realistic noise conditions, different levels of captured channel noise were added randomly to the recorded transients that were captured initially at high Signal to Noise Ratio (SNR). For this purpose, three different datasets with varying SNR levels were created. The SNR ranges of the datasets are determined as i) low SNR (5-10 dB), ii) moderate SNR (10-15 dB) and ii) high SNR (15-25 dB). Distribution of SNR values of each dataset (and each device) follows approximately Gaussian distribution in order to prove that the performance is evaluated with varying SNR values within the range. As an example, the distribution of SNR values (each value is rounded to the nearest integer) of the records for high SNR range (created from a total of 3000 transients) is plotted in Figure 1.

B. FEATURE EXTRACTION

After reconstruction of the transients using VMD, some higher order statistical (HOS) features can be derived from the instantaneous amplitude \( a(n) \), instantaneous frequency \( f(n) \) and instantaneous phase \( \varnothing(n) \) of the reconstructed signal. For the discrete form of the reconstructed signal \( s(n) \), an analytic signal \( s^a(n) \) can be written as

\[ s^a(n) = s^I(n) + j s^Q(n) \]

where in-phase \( (I) \) and quadrature \( (Q) \) components are given by \( s^I(n) = s(n) \cdot \hat{s}^Q(n) \), \( s^Q(n) = H\{s(n)\} \), and here, \( H\{\cdot\} \) denotes Hilbert transform. Then, the instantaneous amplitude, phase and frequency characteristics can be calculated as

\[ a(n) = \sqrt{\left( s^I(n) \right)^2 + \left( s^Q(n) \right)^2} \]

\[ \varnothing(n) = \tan^{-1} \left[ \frac{s^Q(n)}{s^I(n)} \right] \]

\[ f(n) = \frac{1}{2\pi} \frac{\varnothing(n) - \varnothing(n-1)}{\Delta n} \]

Next, receiver-induced linear component of the instantaneous phase is removed, and then all characteristics are normalized in order to remove the biases superimposed by the data collection system [4], [7]. Finally, three higher order statistics (HOS), namely, variance, skewness and kurtosis, are calculated from the instantaneous amplitude, frequency and phase. Then, nine feature vectors are created as RF fingerprint of each transient.

C. CLASSIFICATION

In order to make classification, the feature vectors is divided into training data and test data for each Bluetooth device. The training feature vectors serve to establish a relationship between the feature vectors and the BT device from which they are formed. The test data is used to estimate the performance of the classifier. Each feature vector in the test data is fed to the classifier without a label, and the classifier returns the label of the BT device that is most likely be the owner of the feature vector. Linear support vector machine (LSVM) is
employed for classification as it was shown that it achieves the highest performance for the BT dataset [7].

D. RESULTS
As mentioned before, the BT devices presented in [7] are used. Nine extracted feature vectors represent the RF fingerprints of BT devices each with 150 transients. LSVM is trained with a training data of 40% (60 records per device) of the total data (150 records per device). After the LSVM has been trained, the decision function of LSVM is determined. LSVM classifier is then fed with test data of 60% (90 records per device) of the total data. Figure 2 shows the confusion matrix for 20 BT devices (mobile phones) under low SNR range (5dB-10dB). In the confusion matrix, the green cells represent the number and the percentage of correctly classified transients of the devices while the red cells represent the number and the percentage of the misclassified transients. As can be seen, the classification performance is much better than the HHT method in [7]. The highest misclassified transients are still of class 9 (i-Phone 7A as listed in [7]). Overall comparison of the classification performance of VMD and HHT techniques is also listed in Table 1. Classification accuracy of VMD at low SNR, moderate SNR and high SNR levels are 97.4%, 98.5% and 98.8%, respectively. Although the number of the features (9 features) used in this study is relatively smaller than the number of features (13 features) in HHT techniques [7], the performance of VMD is relatively higher than that of HHT. Moreover, it should be noted that the SNR levels in [7] are 2-3 dB higher than the SNR levels used in the VMD implementation.

On the other hand, when device based performance is studied (inspecting the overall percentage of misclassified transients for any specific device and comparing with that of closest device) for HHT based RFF, it was found that several of IPhone models (see Fig.13 of [7]) would be misclassified (lower overall classification rates of 35% and 44.4% were used).
achieved for those devices) at low SNR range. The lowest classification rate in VDM based RFF was found to be 84.4% for IPhone 7 A (15.6% of the transients misclassified as IPhone 6S Plus) model listed in Table 1 of [7].

IV. CONCLUSION
This paper evaluates the performance of RF fingerprinting method based on variational mode decomposition (VMD) for Bluetooth devices. VMD is used to decompose the BT transient signals into a series of band-limited modes. Higher order statistical (HOS) features including variance, kurtosis and skewness are extracted from the reconstructed transient signals. LSVM classifier is employed to identify BT devices at different SNR levels. The classification performance results show that VMD based RF fingerprinting method achieves better performance (8% higher accuracy) than HHT. This is achieved at slightly lower SNR levels and with smaller number of features. There has been no misclassification in VMD based RFF while several of the devices were misclassified in HTT based RFF [7]. The reason for this higher classification performance is that the band limited modes of decomposed signal (VDM) might contain unique characteristics of devices.

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