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Communications Network Security Based on Radio Frequency Fingerprinting and Variational Mode Decomposition

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Abstract: A technique that shows promise for physical layer security in wireless networks is radio frequency fingerprinting (RFF). RFF is a security solution for communication networks that relies on identifying the distinct characteristics of radio frequency transient signals. In this work, we assessed the RFF technique's performance using variational mode decomposition (VMD). The foundation of radio frequency fingerprinting (RFF) is the recognition of distinctive characteristics of RF transient signals that Bluetooth (BT) devices emit. BT devices' RF transient signals are non-stationary, nonlinear time series with brief durations. In order to do this, Bluetooth (BT) transient signals are broken down into a number of band-limited modes using VMD. The transient signal is then rebuilt from the modes. From the complicated form, higher order statistical (HOS) characteristics are retrieved of VMD-reconstructed transients. The BT devices are then identified using a classifier called the Linear Support Vector Machine (LVM). Experimental testing of the method has been conducted using BT devices from various mobile brand and model names. The classification performance for the same dataset shows that the (RFF with VMD) approach outperforms the (RFF without VMD) strategy by about 2.3%. Ultimately, it has been demonstrated that variational mode decomposition (VMD) provides an effective means of enhancing classification security and accuracy when utilized to extract features from Bluetooth (BT) transient signals.

Keywords: Bluetooth signals, Classification, Feature extraction, Specific emitter identification, VMD.

Introduction

One approach to wireless device authentication that shows promise is radio frequency fingerprint identification (RFF). Oscillator, mixer, modulator, and other hardware components make up the analog front-end of wireless devices [1]. There are several hardware impairments in these components, and their specification parameters differ from what they should be. Due to differences in the manufacturing process, each circuits in analog circuitry may have different hardware. These flaws can serve as the device's own fingerprint because they are ubiquitous, recognizable, and permanent. These fingerprints, which are derived from the electromagnetic waves produced during device communication, appear as RFFs. Since the impairments are specific to each device, they may be used as characteristics to distinguish emitting gadgets, much like fingerprints from people. There are two categories of RFF methods: modulation-based and transient-based RFF. From transient signals that occur at the start of the transmissions, features are extracted using a transient-based approach. Otherwise, transceiver modulator flaws are the focus of modulation-based approaches [2]. Numerous methods in the wavelet and spectrum domains have been employed over time. The significance of security for communication networks led us to investigate the development and enhancement of RFF as a means of securing wireless networks. It is challenging to discern between the various wireless emitters of these signals when the signals that wireless devices

Function through straightforward calculation and is not linked to mode mixing issues. A novel modal decomposition technique called VMD has been presented as a denoising technique in recent years. In addition to having excellent resistance against the impact of background noise on signal decomposition accuracy, VMD modes are band-limited functions that alleviate mixing problems. In this study, VMD is utilized to improve identification performance and boost network security accuracy in the RF fingerprint application of BT device categorization.

Variational Mode Decomposition (VMD)

A decomposition method is called variational mode decomposition (VMD) [3]. Dividing the input signal into distinct discrete modes (where K is the number of decomposed modes) is the aim of VMD. Every discrete mode in the frequency domain, where all modes are expected to condense around a central frequency, has a finite bandwidth. The total of the breakdown modes represents the reconstructed signal. High operating efficiency, resilience against noise, and a solid underlying mathematical theory are all features of VMD. Compared to other decomposition techniques like wavelet and empirical mode decomposition, VMD does not experience mode mixing, which makes it an excellent choice for handling non-stationary data. This is how the bandwidth of the input signal is calculated:

1) The Hilbert transform is used to compute the associated analytic signal (complex) for each mode, resulting in a one-side frequency spectrum; 2) An exponential tuned to the corresponding estimated center frequency is mixed to shift the frequency spectrum of each mode to baseband; 3) The bandwidth $\Delta\omega$k of each mode can be found by calculating the integral of the square of the time derivative of the frequency-translated function component [4-5].

$$i.e. \Delta w_k = \int \left|\partial_t\left(u_k^D\right)\right|^2 dt \ = \left\|\partial_t\left(u_k^D\right)\right\|^2 \qquad (1)$$

Therefore, the required minimization problem is

$$\min_{\{u_k\},\{\omega_k\}} \left\{\sum_k \left\|\partial_t\left(u_k^D\right)\right\|^2\right\} \ , \quad s.t. \quad \sum_k u = f \qquad (2)$$

$$\min_{\{u_k\},\{\omega_k\}} \left\{\sum_k \left\|\partial_t \left[\left(\delta(t) + \frac{j}{\pi t}\right) * u_k(t)\right] e^{-j\omega_k t}\right\|_2^2\right\}, \qquad (3)$$

The production of the Lagrangian multiplier λ and the balancing factor α transforms the minimization problem into a non-constrained problem.

$$(\{u_k\},\{\omega_k\},\lambda) = \alpha \sum_k \left\|\partial_t \left[\left(\delta(t) + \frac{j}{\pi t}\right) * u_k(t)\right] e^{-j\omega_k t}\right\|_2^2 + \left\|f(t) - \sum_i u_i(t) + \frac{\lambda(t)}{2}\right\|_2^2 - \left\|\frac{\lambda(t)^2}{4}\right\|_2^2 \qquad (4)$$

In order to minimize the non-constrained issue with regard to, the following formulation of the minimization equation is used:

$$u_k^{n+1} = \arg\min_{u_k \in X} \left\{\alpha \sum_k \left\|\partial_t \left[\left(\delta(t) + \frac{j}{\pi t}\right) * u_k(t)\right] e^{-j\omega_k t}\right\|_2^2 + \left\|f(t) - \sum_i u_i(t) + \frac{\lambda(t)}{2}\right\|_2^2\right\} \qquad (5)$$

This problem can be solved in spectral domain:

$$\hat{u}_k^{n+1} = \arg\min_{\hat{u}_k, u_k \in X} \left\{\alpha \left\|j\omega \left[(1 + sgn(\omega + \omega_k))\hat{u}_k(\omega + \omega_k)\right]\right\|_2^2 + \left\|\hat{f}(\omega) - \sum_i \hat{u}_i(\omega) + \frac{\hat{\lambda}(\omega)}{2}\right\|_2^2\right\} \qquad (6)$$

Change of variables $\omega \to \omega - \omega_k$ in the first term:

$$\hat{u}_k^{n+1} = \underset{\hat{u}_k, u_k \in X}{\arg\min}\left\{\alpha \left\| j(\omega-\omega_k)\left[(1+sgn(\omega))\hat{u}_k(\omega)\right]\right\|_2^2 + \left\| \hat{f}(\omega) - \sum_i \hat{u}_i(\omega) + \frac{\hat{\lambda}(\omega)}{2}\right\|_2^2\right\} \quad (7)$$

Written as a space integral on the positive side frequencies are the two expressions:

$$\hat{u}_k^{n+1} = \underset{\hat{u}_k, u_k \in X}{\arg\min}\left\{\int_0^\infty 4\alpha(\omega-\omega_k)^2 \left|\hat{u}_k(\omega)\right|^2 + 2\left|\hat{f}(\omega) - \sum_i \hat{u}_i(\omega) + \frac{\hat{\lambda}(\omega)}{2}\right|^2 d\omega\right\} \quad (8)$$

This quadratic optimization problem has the following solution:

$$\hat{u}_k^{n+1}(\omega) = \frac{\hat{f}(\omega) - \sum_{i\neq k} \hat{u}_i(\omega) + \frac{\hat{\lambda}(\omega)}{2}}{1+2\alpha(\omega-\omega_k)^2}, \quad (9)$$

The following formula may be used to determine each mode's update center frequency:

$$\omega_k^{n+1} = \frac{\int_0^\infty \omega \left|\hat{u}_k(\omega)\right|^2 d\omega}{\int_0^\infty \left|\hat{u}_k(\omega)\right|^2 d\omega}, \quad (10)$$

RFF implementation

The fundamental steps of the VMD-based RFF approach include signal capture for data collection, transient detection, transient breakdown using VMD, HOS feature extraction, and classification phases. An overall process diagram is shown in Fig. 1. Each step is explained in the context of this study in the sections that follow [6-7].

1) Signal capture (data collection): this process collects the radio frequency signals that the emitting devices (Bluetooth devices) create.
2) Transient detection: a crucial step in the fingerprinting process, it comprises certain characteristics of the emitting devices. Signal filtering is required prior to transient detection in order to minimize undesired frequency components, such as noise.
3) Signal decomposition: variations that might taint signals and interfere with signal identification are removed by applying VMD to transient signals in order to produce band-limited modes.
4) Features extraction: unique properties of emitting devices are included in the transient of the RF signals in Fig. 2 that are being processed. At this point, these traits may be retrieved.
5) Classification: This section of the system identifies the specific traits and creates a connection between the transmission equipment that produced the RF signals and the signals that were received. Ultimately, conclusions were drawn by comparing the real-world outcomes with one another.

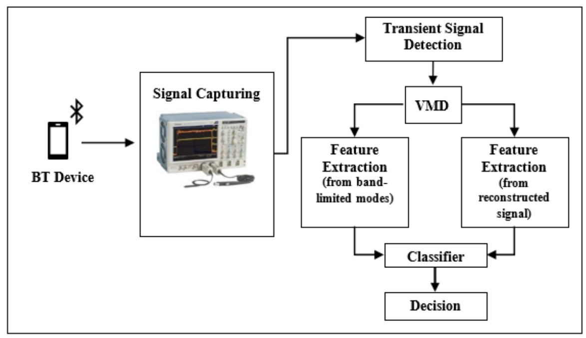

Fig. 1: VMD based RF fingerprinting system

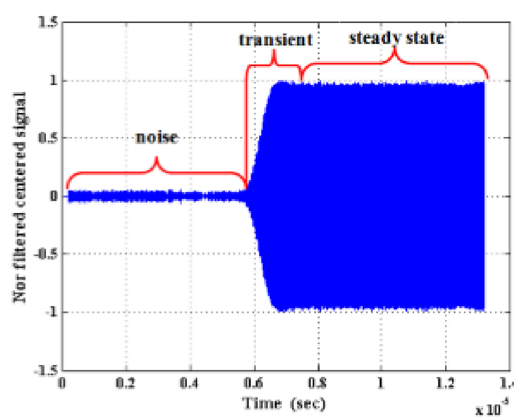

Fig. 2: Transient Signal of Bluetooth signal

Features extraction

The popular box plot is applied to the kurtosis (KURT) and variance (VAR) of transient signals for the ten newly added classes. Fig. 3 is an illustration of it. The box plot provides a clear image of the feature that shows interference between classes. Additionally, the proportion of the data variance concentration may be identified using the box plot. As Fig. 3 illustrates, certain statistics of the various classes show statistically significant variations, while some data are almost identical. The feature can be completely separated if the box values for a particular device's whiskers are separated from the box values of the other devices taken into consideration; if just the whiskers are not separated, then the device being considered will be almost separable feature. One of the most reliable characteristics is the (VAR) of the transient signal instantaneous phase, which is caused by the separation property. The instantaneous properties of the reconstructed transient signal are used to build this feature. As an illustration of the robust properties, the VAR of the instantaneous phases of the reconstructed transient signals of the ten introduced classes with 100 records is presented. A traditional two-dimensional Matlab plot of the reconstructed transient signals' (VAR and KURT) is displayed in Fig. 4.

Fig. 4 suggests that certain groups are entirely divided. For example, classes 5, 7, 8, and 9 are only loosely separated from classes 1 through 10, whereas classes 3 are totally isolated. Some classes in Fig. 4b, such class_1 and class_2, are hardly distinguished from one another. The benefit of using a traditional two-dimensional Matlab plot is that it allows us to determine the quantity of records that have been tampered with as well as the quantity of records for each class.

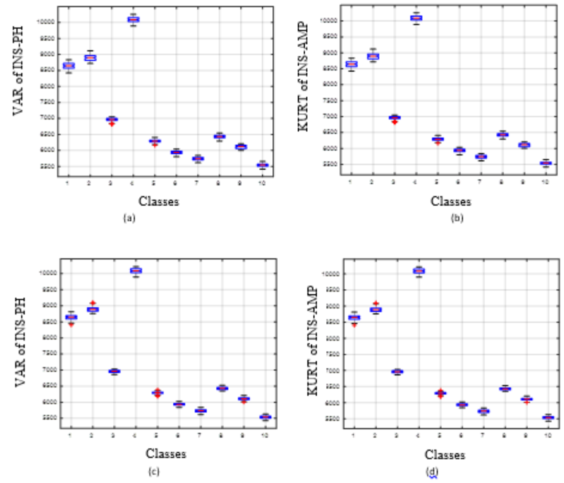

Fig. 3 Box plot of transient features.
(a) and (b) features before applying VMD, (c) and (d) features after applying VMD.

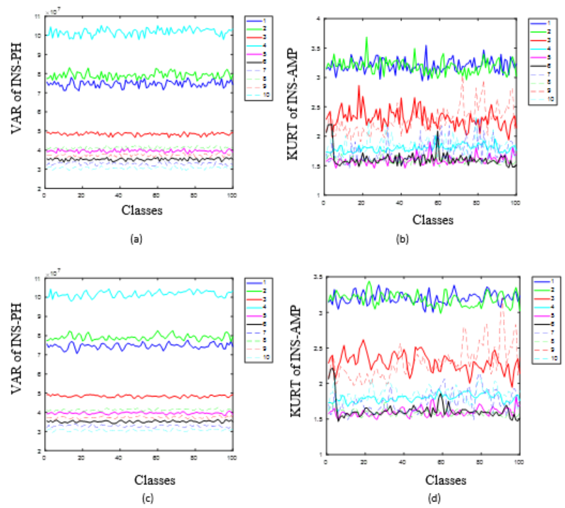

Fig. 4. Conventional plot of transient features.
(a) and (b) features before applying VMD, (c) and (d) features after applying VMD.

Classification results

In two scenarios, the categorization accuracy of 10 BT devices was examined in this study. In the first instance, we use nine transient characteristics to gauge classification performance in the absence of the VMD approach. Using nine characteristics from the reconstructed transients, we calculate the classification performance with VMD in the second example and compare it to the first case's classification performance. To create a classifier model, the LSVM classifier is used on training data.

Using the model that was produced, the test data is categorized according to the classifier's learning or training process. Fig. 5 shows the training confusion matrices based on 40% of datasets. According to the training confusion matrices, features without VMD show 96.3% and features with VMD show 98.8%, respectively. Plotting of the train data for 10 classes as a scatter plot displays the characteristics F1 (VAR of ins. phase) of the transient (see Fig. 6a). Fig. 6b displays the scatter plot of the same characteristics following the application of VMD. The features scatter plots indicate that, in comparison to the scatter plot without VMD, the features plots of each class record are closer to one another. To assess the classifier's performance following training, the LSVM classifier is tested using a subset of data that makes up 60% of the total data.

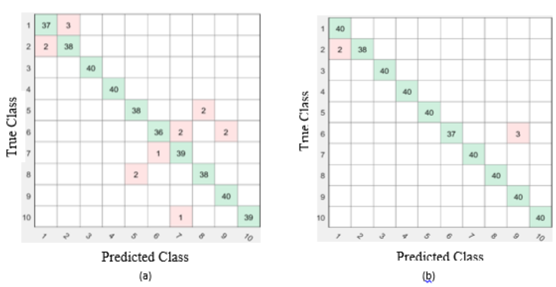

Fig.5. Confusion matrix based on 40% of train data : (a) without VMD, (b) with VMD

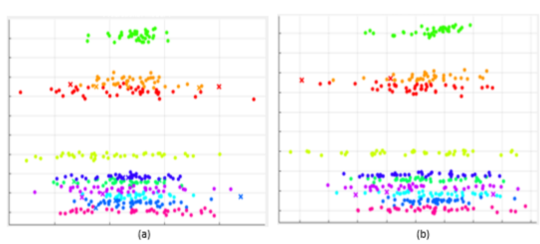

Fig.6. Scatter plot of data features (VAR): (a) without VMD, (b) with VMD

Comparing the VMD classification, however, 9.7% (58 transient) are accurately recognized as class 1 (Huawei G5 -A), while 0.3% (2 transient) are incorrectly categorized as class 2 (Huawei G5 -B). The testing reveals that the two distinct approaches perform differently. It was determined that 95% of the first instance (without VMD) and 97.3% of the second case (with VMD) had the proper categorization rate. In the confusion matrix for the first scenario, thirty and sixteen records (transients) out of six hand-crafted transients are misclassified as test data, respectively.

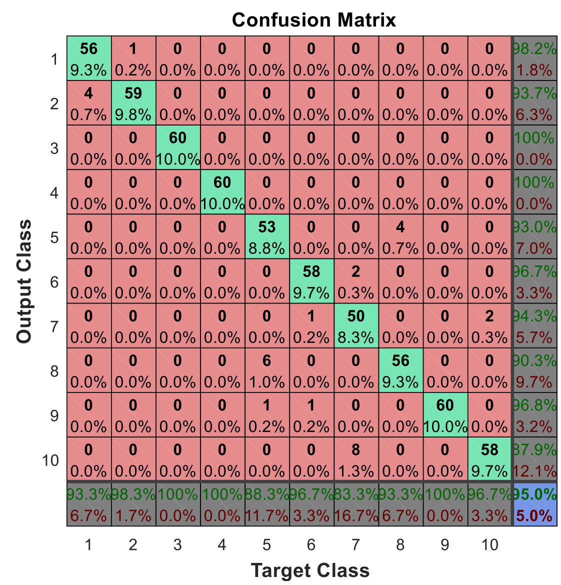

Fig.7 testing confusion matrix without VMD

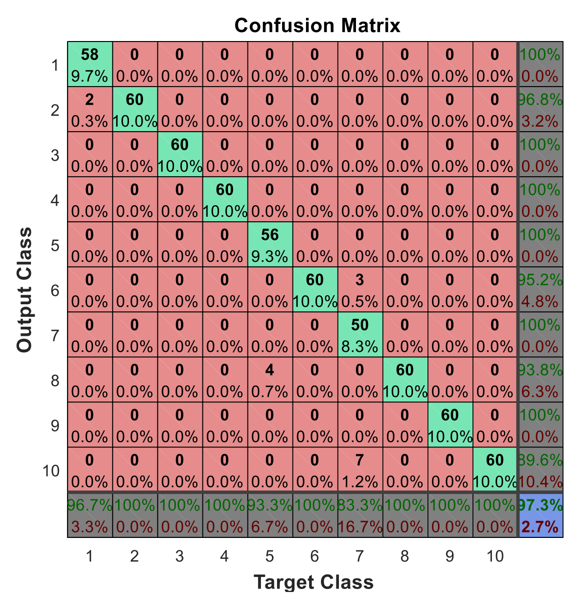

Fig.8 testing confusion matrix with VMD

Conclusion

The purpose of this study is to investigate the VMD's performance constraints when using RFF to enhance communication network security. A thorough analysis is conducted on the impact of the HOS characteristics (variance, skew, and kurtosis of instantaneous amplitude, frequency, and phase) that were recovered from the reconstructed transient on classification accuracy. There are three main phases to the RFF-VMD technique: For every mobile phone brand, two models were chosen in the initial round. For every mobile phone, a hundred transitory signals were created. In our investigation, the most often employed transient detection technique was based on the signal's energy envelope. Each Bluetooth transient signal is broken down into a number of band-limited modes in the second stage, and these modes are then combined to create the input transient signal. The third step involves extracting several statistical properties from the reconstructed transient signals, including variance, kurtosis, and skewness. Two plot types—a box plot and a traditional two-dimensional Matlab plot—are used to demonstrate the robustness of the retrieved features prior to applying the classifier. Lastly, the 10 BT classes (mobile phones) are classified using an LSVM classifier. The results of the classification performance showed that the suggested method (RFF with VMD) performs better than (RFF without VMD), with 2.3% greater accuracy. An effective technique to raise classification accuracy and subsequently communication network security is to extract features from Bluetooth (BT) transient signals using variational mode decomposition (VMD).

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