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Original article

Emitters Classification based on Steady State BT Signal Features

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ABSTRACT

Aims. *The aims of this study were to verify the enhancement wireless networks' security, and the identification of specific emitters.* ***Methods***. *A novel technique was introduced to enhance the security of wireless network. The technique was built up based on the use of radio frequency (RF) fingerprinting for Bluetooth (BT) signals. Five emitters represented as mobile phones were considered to classify them. Two hundred and fifty BT signals were collected from these emitters. Portions of steady state of the BT signals studied. The applied methods were a detection method based on energy envelope was used to detect the portions, and the variational mode decomposition (VMD) method was applied to generate the intrinsic mode functions (IMFs). Features which represented as statistical information were extracted from the obtained IMFs. The Tree classifier was applied to the extracted feature to classify the introduced emitters.* ***Results***. *The results demonstrated a high percent of correct classifications (93.5% through 100%).* ***Conclusion***. *The results demonstrated the robustness of the features, the functionality, and the activeness of the introduced method; consequently, a high degree of wireless network security was achieved.*

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INTRODUCTION

Recently, wireless network has become an essential issue in establishments, organizations, and companies, where wireless networking plays an extremely important role in transmission data [1]. Radio frequency (RF) fingerprinting plays an important role in the network security. RF fingerprinting demonstrated robustness in both high- end and low-cost receivers [2]. RF fingerprinting enhanced the security at physical layer of wireless networks; RF fingerprinting was utilized to identify and classify wireless devices emitters [2–4]. Many wireless networks signals were studies to improve the wireless network security. Empirical Mode Decomposition (EMD) method and the Hilbert–Huang transform (HHT) were applied to analyze GSM signals [5]. Blue tooth (BT) signals were used as a database to identify wireless emitters. EMD and HHT were applied to transient stages of the BT signals to generate RF fingerprinting classifying mobile phones devices [6]. There were more decomposition techniques by which the wireless signals can be decomposed to intrinsic mode functions such as, the Ensemble empirical mode decomposition (EMD) [7], and The variational mode decomposition (VMD) method [8]. The later was applied to the transient BT signals to classification and identification of specific emitters [9].

The VMD which is a modern decomposition method was used for many engineering problems [10-13]. In our study the VMD technique was used with the steady state portion of BT signal to classify and identify wireless specific emitters. The first step of our research was the data collection which is explained in section-2 (the first subsection), where The BT signals were captured in a good conditions laboratory environment. The data were collected from different brands, different models, and different serial numbers of mobile phones. In order to get rid of undesired frequencies of the collected data, Band Pass Filter (BPF) was applied to the data. The filtered signals were centered and normalized before implementing the detection process. The detection process was accomplished by using energy envelope. The VMD method which explained in section-2 (the second subsection) was applied to the determined

steady state portions of the BT signals in section-2 (the third subsection) . The generated IMFs consecutive with the reconstructed signals were the output of the VMD implementation. The instantaneous parameters which were the instantaneous amplitude, phase, and frequency were the first step of the features extraction that demonstrated. The considered features in our study were statistical metrics, namely variance, kurtosis, and skewness. Each of them was obtained from each instantaneous parameter to the generated set of nine features. The extracted features were evaluated in section-2 (the fourth subsection) to guarantee a good classification of emitters before implementing the classifier. The classification process which explained in section-2 (The fifth subsection) was divided into two parts. These parts were the train and test part. Firstly, the classifier which is the Tree classifier was trained via a percent of feature data-base, and then the rest of the data used to test the classifier. In section-3 the scatter plot and the confusion matrix expressed the result of the classifier implementation, where the percent of the correct classification and identification for each emitter are demonstrated.
The main objective of our study was the enhancement of the wireless networks security, in order to protect communication networks from some threats such as signal interception, spoofing or jamming. In our study, the mobile phones were used as emitters. These emitters were subjects to successive processes. The objectives of applying these processes were the classification and identification of the emitters.

METHODS

The methods that were applied in this study were data collection technique, variational mode decomposition analysis method, and features extraction and graphical evaluation technique, and classification method. The data collection technique is a technical method by which the BT signals were captured by means of an oscilloscope in a laboratory. The VMD method was applied to the collected data in order decompose the BT collected signals. Once the signals were decomposed features are extracted from them. The extracted features were evaluated by a graphical evaluation technique before applying the classifier. The classification method was applied to the evaluated features in order to generate the final results which are expressed as scatter plot and confusion matrix of tested data.

Data collection technique

The main goal of our study is the investigation and analysis of classification and identification of wireless emitters. This goal was achieved by using pure real data and accurate applied approaches. The considered signals, in this work, were a Bluetooth transmission signals. These signals were collected from different cell phones. The difference between the studied phones was taken based on brands models and serial numbers. The BT signals were captured in a good conditions laboratory environment, where the laboratory equipment is completely isolated from outside disturbances. Moreover, there were no running devices or equipment inside the laboratory. We keep no change in the ambient temperature and humidity inside the laboratory; because the change in environmental conditions may decrease the performance of identification accuracy. In our study, five cell phones each with fifty records were considered.

Table 1. The studied mobile phones

Class No	Brand	Model
1	Huawei	G5 A*
2	Huawei	G5 B*
3	I-Phone	5S
4	I-Phone	6S
5	L G	G4

** A and B denote to different serial numbers*

The mobile phones from which the BT signals were captured are listed in Table 1. Once the signals were captured, they saved as text data. The carrier frequency of BT signal is between 2400 MHz and 2483.5MHz. The signals were received by a typical modem antenna and then transmitted to an (TDS7404 DSO) Oscilloscope (4GHz). The distance between the cell phone and the antenna is kept constant to guarantee same accuracy of transmitted signals.
An analogue to digital converter (ADC) was utilized to digitize the captured signals. The ADC has at least 4.8 GHz sampling frequency; because for a 2.4 GHz signal, ADC must be at least 4.8 GHz sampling frequency. Based on these techniques BT signals were recorded by using 20 GHz sampling frequency. As an example, typical form of collected signals is shown in Fig. 1. It was collected from LG-G4 mobile phone.

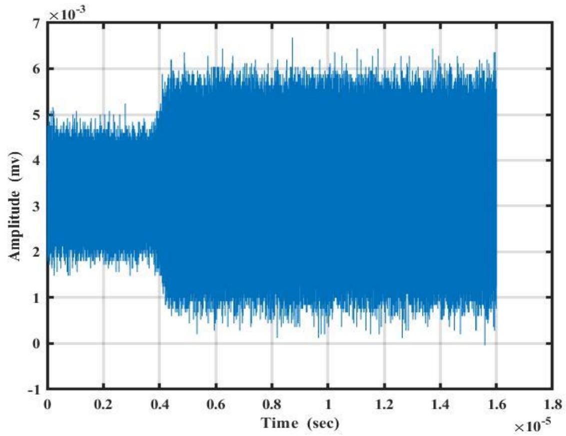


Figure 1. A typical form of a collected BT signal

Despite a good conditions laboratory, the recorded signals still have undesired frequency components. Filtering process is necessary to get rid of these undesired frequency components. The considered filter in our case is the Band Pass Filter (BPF); BPF that has a cut off frequencies 2400 MHz and 2485 MHz passes only ISM2400 band. The signal that is illustrated in Fig. 1 was filtered by means of BPF. Fig.2 shows the BT signal after filtering process.

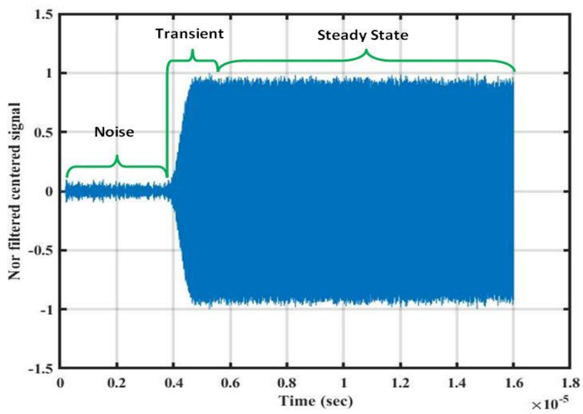


Figure 2. Three regions of filtered normalized BT signal

Figure_2 illustrates the three regions of the filtered normalized signal, namely, noise, transient, and steady state regions. The normalization process is necessary to shift the signals' amplitudes to the same level. Also, it makes the transient detection process easier and more applicable for all studied signals. The steady state stage which its duration is too long was considered in this study. Due to that long duration, we assigned the duration of each signal steady state as the length of its associated transient portion, where the energy envelope of each normalized filtered centered signal was used to detect its transient region [6]. The assigned steady state portion and the energy envelope of a BT signal are shown in Fig 3, where the length of the transient portion equals the steady state portion length.

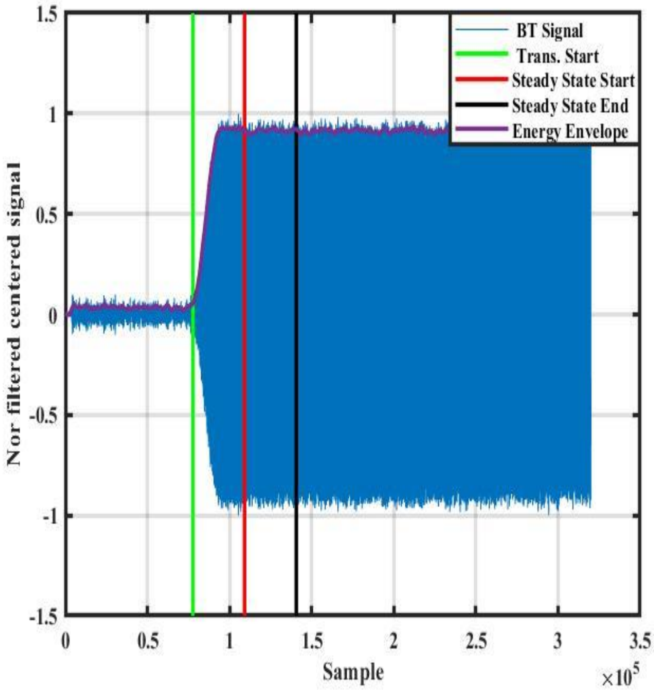


Figure 3. Assigned steady state portion of filtered normalized BT signal

Once the steady state portion for each signal had been determined, the BT signals'features were extracted from the steady state regions. In this study the features were extracted after applying the variational mode decomposition technique to the steady state portions.

Variational mode decomposition method

An entirely non-recursive variational mode decomposition model was firstly introduced by K. Dragomiretskiy and D. Zosso [8], where the decomposed signal modes were extracted simultaneously. The model generates a package of modes and their associated center frequencies. The summation of these modes reproduced the original signal [8]. VMD Technique works based on the Wiener filtering concept, and constructed analytic signal [9]. The analytic signal was generated by applying Hilbert transform to the original signal. The real value of the analytic signal was decomposed into number of modes. Each mode has limited bandwidth. The modes were estimated to be compacting around associated center frequencies determined along with the decomposition. The estimation was accomplished by smoothing the demodulated signal via Wiener filtering. The generated constrained variational problem can be expressed as following: [8]

$$min_{\{u_k\},\{\omega_k\}}\left\{\sum_{k=1}^{K}\left\|\frac{\partial}{\partial t}\left[\left(\delta(t)+\frac{j}{\pi t}\right)*u_k(t)\right]e^{-j\omega_k t}\right\|_2^2\right\} s.t. \quad \sum_{k=1}^{K}u_k = x(t), \tag{1}$$

The minimization problem that given in eq.(1) is used to minimize $\{u_k\}, and\ \{\omega_k\}$, where $\{u_k\} = \{u_1,\ u_2, \dots\ u_K\}$, and $\{\omega_k\} = \{\omega_1,\ \omega_2, \dots\ \omega_K\}$ are the intrinsic modes function IMF, and the associated center frequencies, respectively, $x(t)$ represents the IMF summation, the asterisk (*) denotes a convolution operation between to arrays, $\delta(t)$ is a function of time drag delta, and $\|.\|_2^2$ is L_2 norm-squared, such that the summation of the generated modes equals the original signal. Considering this condition, a quadratic penalty function can be introduced multiplied by Lagrangian multiplier to address the minimization problem in Eq. (1) [8, 14].

$$L(\{u_k\},\{\omega_k\},\lambda) = \alpha \sum_{k=1}^{K}\left\|\frac{\partial}{\partial t}\left[\left(\delta(t)+\frac{j}{\pi t}\right)*u_k(t)\right]e^{-j\omega_k t}\right\|_2^2 + \left\|f(t)-\sum_{k=1}^{K}u_k(t)\right\|_2^2 + \langle\lambda(t), f(t) - \sum_{k=1}^{K}u_k(t)\rangle, \tag{2}$$

where $\langle.,.\rangle$ denotes the inner product of two vectors. The flow chart of the VMD method can be given as following:

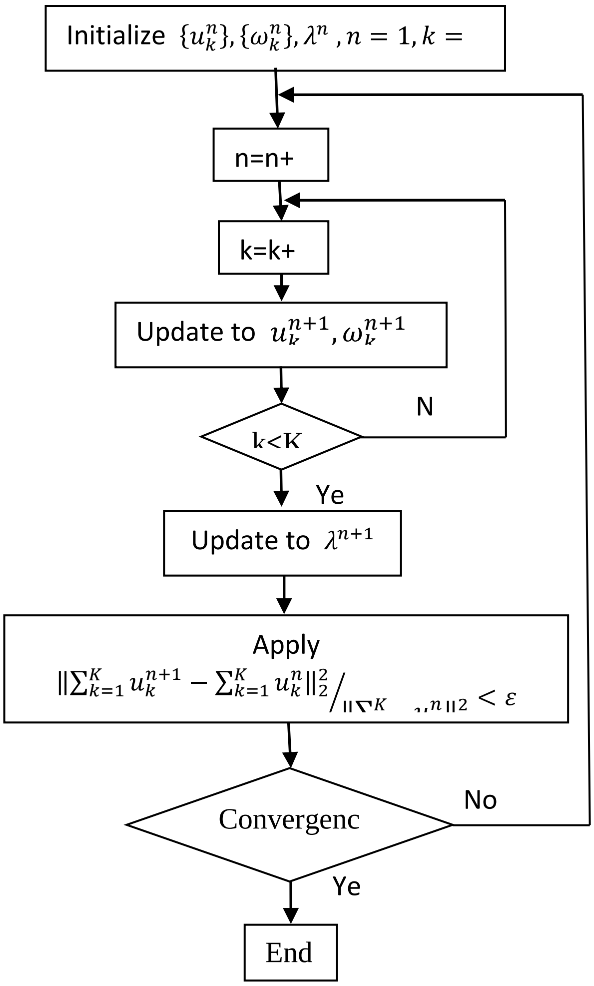


Figure 4. Flow chart of The VMD method

Updating the modes, the center frequencies, and the Lagrangian multiplier can be done as following:
The modes can be updated, in time domain, based on the following equation:

$$u_k^{n+1}(t) = min_{u_k}\left\{\alpha \left\| \frac{\partial}{\partial t}\left[\left(\delta(t) + \frac{j}{\pi t}\right) * u_k(t)\right] e^{-j\omega_k t} \right\|_2^2 + \left\| f(t) \sum_{k=1}^{K} u_k(t) + \frac{\lambda(t)}{2} \right\|_2^2 \right\} \quad (3)$$

For simplicity the rest can be updated based on spectral domain as

$$\omega_k^{n+1} = min_{\omega_k}\{\int_0^{\infty} (\omega - \omega_k)^2 |\hat{u}_k(w)|^2 d\omega\}, \quad (4)$$

where $\hat{u}_k(w)$ is the k^{th} mode in spectral domain. Eq. (4) can be solved as

$$\omega_k^{n+1} = \frac{\int_0^{\infty} \omega |\hat{u}_k(w)|^2 d\omega}{\int_0^{\infty} |\hat{u}_k(w)|^2 d\omega} \quad (5)$$

The Lagrangian multiplier can be updated as

$$\lambda^{n+1} = \lambda^n + \tau\left(f(t) - \sum_{k=1}^{K} u_k^{n+1}(t)\right) \quad (6)$$

Where τ represents a numeric value specifying the time-step of the dual ascent [15]. Based on the aforementioned procedure the introduced method (VMD) can be applied to the collected data

VMD method implementation

The introduced method was applied to the steady state portions of the collected data. A typical form of those portions is shown in Fig. 3, where the end and start of the steady state portion is illustrated. The main goal of VMD method implementation is to obtain the instantaneous amplitude, phase, and frequency of the reconstructed signals. The reconstructed signal was built by summing up the original signal IMFs. These IMFs were generated by applying VMD method to the original signal. The original signals were the steady state portions of the collected BT signals. Along with parameters the original signal declared as input to the VMD algorithm. These parameters are defined as follows:

- α: a balancing parameter for increasing the procedure accuracy.
- τ: a time-step of the dual ascent.
- K: denotes the number of IMFs
- DC: a conditional parameter. If true, the frequency of first mode is put and kept at DC (0-freq).
- Init: an initialized parameter given as the following:
  - ➢ For one-dimensional data:
- If init = 0, then all omegas start at 0.
- Else if init = 1, then all omegas start uniformly distributed.
- Else if init = 2, then all omegas initialized randomly.
  - ➢ For Two-dimensional data:
- If init = 0, then all omegas start at 0.
- Else if init = 1, then all omegas start initialized randomly.
- Tol: represents a tolerance of convergence criterion (typically for one-dimensional and 1e-6).

The results of the VMD implementations were the IMFs. Bunch of features can extracted from the reconstructed signal $x(t)$ that was generated from IMFs summation. In our study the features were extracted from the instantaneous amplitudes $a(t)$, phases $\emptyset(t)$, and frequencies $inf(t)$ of the reconstructed signals. These signals must be converted to analytic signal before obtaining the instantaneous parameters as follows:

$$x^a(\mathrm{t}) = x(\mathrm{t}) + \mathrm{j}\mathcal{H}x(\mathrm{t}), \quad (7)$$

where $x^a(\mathrm{t})$ is the generated analytic signal, and the Hilbert transform of $x(t)$ is expressed as

$$\mathcal{H}x(\mathrm{t}) = \frac{1}{\pi}\int_{-\infty}^{\infty}\frac{x(\tau)}{t-\tau}d\tau, \quad (8)$$

which gives the quadratic component $x_q^a(\mathrm{t})$of the analytic signal, whereas its in-phase component is

$$x_p^a(\mathrm{t}) = x(\mathrm{t})\ . \quad (9)$$

So that the analytic signal is given as

$$x^a(\mathrm{t}) = x_p^a(\mathrm{t}) + \mathrm{j}x_q^a(\mathrm{t}) \quad (10)$$

The analytic signal instantaneous parameters can be obtained as

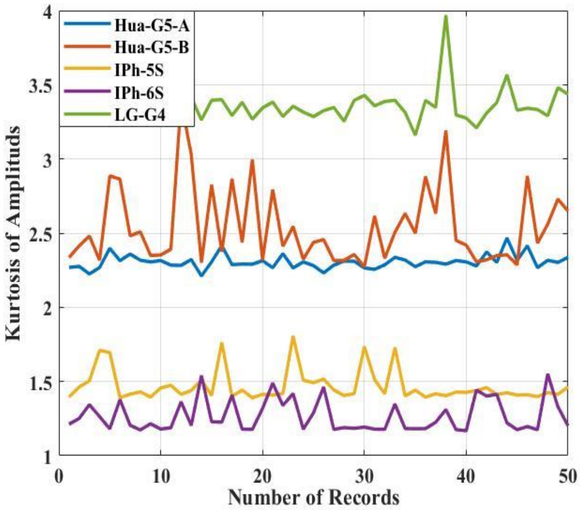
$$a(t) = \sqrt{\left(x_p^a(\mathrm{t})\right)^2 + \left(x_q^a(\mathrm{t})\right)^2} \quad (11)$$

$$\emptyset(t) = tan^{-1}\left[\frac{x_q^a(t)}{x_p^a(t)}\right](12)$$

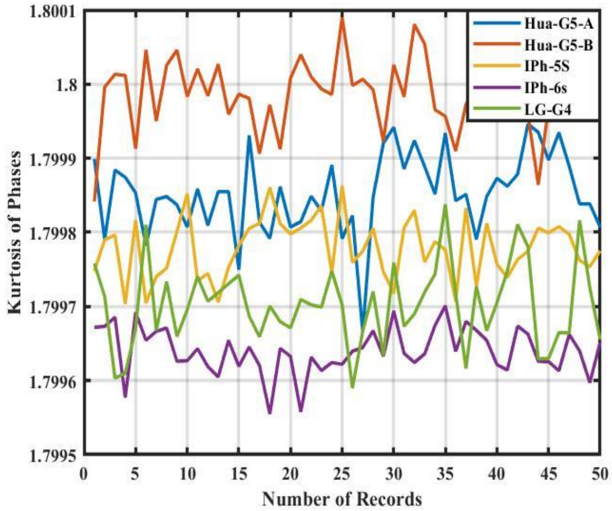
$$inf(t) = \frac{1}{2\pi}\frac{\emptyset(t)-\emptyset(t-1)}{\Delta t} \quad (13)$$

Extracted features evaluation technique

The instantaneous parameters that had been obtained in the previous section were exploited in signal features extractions. Five BT signals were captured from different mobile phones each with fifty records. Three instantaneous parameters were obtained from each reconstructed signal. Three features were extracted from each instantaneous parameter. The features are statistical criteria, namely variance, kurtosis, and skewness of the instantaneous parameters.



a- Kurtosis of all signals Ins. Amplitudes



b- Kurtosis of all signals Ins. phases

Figure 4. Two different extracted features

It is inferred from Fig. 4 that the kurtosis of the instantaneous amplitudes more robust than the kurtosis of the phases. That is because of the intersections between the features of records, which is clearly intersected to each other in the phase kurtosis features. However, it's helpful to distinguish the records of Huawei-G5-B from those of LG-G4, and IPhone-5s records from IPhone-6s records, which are close to each other in the kurtosis of amplitudes' features.

Another criterion by which the robustness of the extracted features can be investigated is the Box plot. By means of the box plot the interference among the signals extracted features can be seen. Moreover, the percentage of the signal features concentration can be demonstrated. The box plot which is shown in Fig. 5 can be marked by the following six criteria: The 25th percentile, lower adjacent, outlier value, the median, upper adjacent, and the 75th percentile. The 25th percentile is a value of the considered data group at which 25% of the data values are less than it. A 50% of the data group or the Inter-Quartile Range (IQR) is located between the 25th percentile and the 75th percentile. The median criterion which is illustrated by a red line in the box middle represents the 50 th percentile. What are known as whisker boundaries are represented by the lower and upper adjacent lines. These boundaries are determined by multiplying a value (generally 1.5) times the IQR, and subtracting or adding it to the 25th percentile or the 75th percentile, respectively. The outlier values represent the values of the data group that are out of the whisker boundaries.

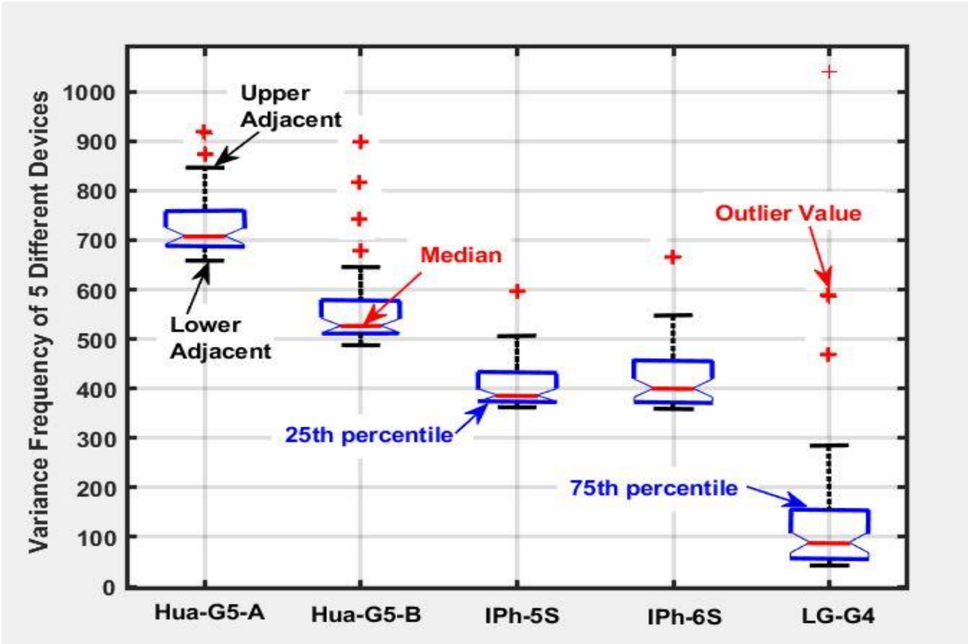


Figure 5. The box plot criterion

It is concluded, from the box plot that shown in Fig.5, that the interference of the variance frequency features of the signals was so perspicuous. The percentege of the interference of the features of Iphone-5s and Iphone-6s was so large, whereas the LG-G4 variance frequency feature is completly separated, except two outlier value recordes. These two record might be interpreted by the classifiers as a features of Iphone-5s or Iphone-6s signals.

Classification method

The extracted features are used as a data by which the mobile phones can be classified. These data was a subject to Tree classifier implementations as input data. The data was divided into two groups trained data and tested data. In our study the trained data represented 40% of the introduced data, whereas the tested data was 60%. Firstly, the classifier was trained by the trained group of data and then applied to the rest of the data to classify it. Before the classification process, its results can be expected by evaluate the trained process. This can be done by analyzing the scatter plot of the trained data.

RESULTS AND DISCUSSION

The final results of this study were the classification and identification results. The classification results divided in two parts, namely trained part and testing part, Once the testing part is done the emitters can be identified. The results from the training part can be evaluated before implementing the test part. By means of the scatter plot the training part can be evaluated. The scatter plot of the skewness amplitudes feature is plotted against the variance frequencies feature in Fig. 6.

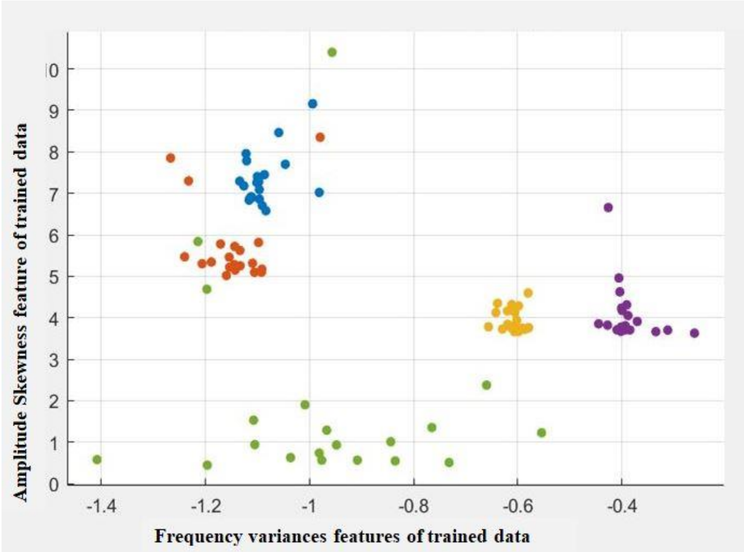


Figure 6. The scatter plot of two features.

It is inferred from Fig. 6, that the Tree classifier responded a good trained results, where each signal features were separately grouped. Of course, there were some records did not match the expected position in the scatter plot; but this is normal, because of the nature of data. For instance, in the scatter plot, two records of the green colour group were classified as red. The trained model was tested by the rest of the data, %60 of the data, which are 30 records for each signal. The classification process demonstrates a good test results. Fig. 7 which illustrates the confusion matrix demonstrated in average 96.7 % correct classification, where the records of BT signal of IPhone-6s and Huawei-G5-B were completely classified correct in 100%, whereas, the lowest correct classification percent (90%) demonstrated for LG-G4 records, where three records were misclassified. Two of them classified Huawei-G5-A and one record as Huawei-G5-B.

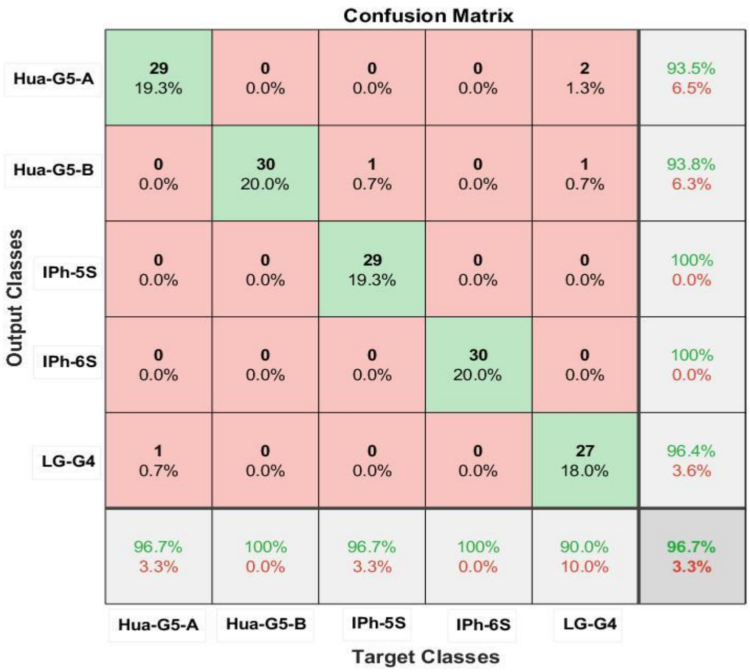


Figure 7. Confusion matrix of tested data.

CONCLUSION

The generated database of nine features was represented statistical features. This database of features was graphically evaluated as shown in Fig. 4, and Fig.5 before introduced as input data to the Tree classifier. Referring to the figures the evaluation of database indicated good classification results The classifier was trained by 40% of the input data. The scatter plot which is shown in Fig.6 showed a perfect forecasting to the test result of classification process. The trained model was tested by the rest of the data, %60 of the data. The classification demonstrated in average 96.7 % correct records identification, which is confirmed the robustness of the features that extracted from the steady state portion of mobile phones BT signals. Consequently, a high degree of mobile networks' security was achieved.

Disclaimer

The article has not been previously presented or published, and is not part of a thesis project.

Conflict of Interest

There are no financial, personal, or professional conflicts of interest to declare.

REFERENCES

1. ShiuY, and Chang S. Physical Layer Security in Wireless Networks: A Tutorial. IEEE Wireless Communications, April2011; 18(2): 66-74.
2. Ramsey BW, Stubbs TD, Mullins BE, Temple MA, Buckner MA. Wireless infrastructure protection using low-cost radio frequency fingerprinting receivers, International Journal of Critical Infrastructure Protection., 2015; 8: 27–39
3. Rehman SU, Sowerby KW, Coghill C. Radio-frequency fingerprinting for mitigating primary user emulation attack in low-end cognitive radios. IET Communication, 2014; 8(8): 1274–1284.
4. Padilla JL, Padilla P, Valenzuela-Valdes JF, Ramirez J. RF fingerprint measurements for the identification of devices in wireless communication networks based on feature reduction and subspace transformation, Measurement, 2014; 58: 468–475.
5. Yuan Y, Huang Z, Wu H, Wang X. Specific Emitter Identification Based on Hilbert–Huang Transform-Based Time–Frequency Energy Distribution Features. IET Communications. 2014; 8(13): 2404–2412.
6. Ali MA, Uzundurukan E, and Kara A. Assessment of features and classifiers for Bluetooth RF fingerprinting. IEEE Access. 2019; 7: 50524-50535.
7. Wu Z, and Huang N. E. Ensemble empirical mode decomposition: a noise-assisted data analysis method. Advances in adaptive data analysis. 2009; 1(1): 1–41.
8. Dragomiretskiy K. and Zosso D. Variational mode decomposition. IEEE Trans. Signal Process. 2014; 62(3): 531_534.
9. Aghnaiya A, Ali A. M, Kara A. Variational mode decomposition-based radio frequency fingerprinting of Bluetooth devices. 2019; 7: 144054-144058.
10. Isham M. F, Leong M. S, Lim M H, Ahmad Z A. Variational mode decomposition: mode determination method for rotating machinery diagnosis. Journal of Vibroengineering. 2018; 20(7): 2604-2621.
11. Lian J, Liu Z, Wang H, Dong X. Adaptive variational mode decomposition method for signal processing based on mode characteristic. Mechanical Systems and Signal Processing. 2018; 107: 53-77.
12. Padilla JL, Padilla P, Valenzuela-Valdes JF, Ramirez J. RF fingerprint measurements for the identification of devices in wireless communication networks based on feature reduction and subspace transformation, Measurement, 2014; 58:468–475.
13. Liu W, Cao S, Chen Y. Applications of variational mode decomposition in seismic time-frequency analysis. Geophysics. 2016; 81(5): 365-378.
14. Miao Q, Shu Q, Wu B, Sun X, Song K. A Modified Complex Variational Mode Decomposition Method for Analyzing Nonstationary Signals with the Low-Frequency Trend. Sensors. 2022; 22(5): 1801.