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Investigation of Steady State Features in Emitters Classification

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Abstract:
The security of the communication network has become an important issue. Because of most wireless communication networks are exposed to different types of penetrative attacks such as stray, spoofing, and interaction of communication signals. Radio Frequency (RF) Fingerprinting has provided a promising solution for communication network security. In this study, RF fingerprinting of steady state potion of Bluetooth (BT) has been applied to solve this problem. Set of Bluetooth (BT) signals has been collected from different mobile phones to generate a preliminary raw data set. Successive of preparation processes applied to the collected BT signal data set to generate signals' features data. These processes are converting signals from text to digital, cantering and normalizing the digital BT signals, determination of steady sate portions, and Hilbert-Huang Transform (HHT) along with Empirical Mode Decomposition (EMD). By applying HHT, and EMD to the signals Time Frequency Energy Distributions (TFED) are obtained. By means of the signals' energy envelopes and the signals' steady state, and their TFEDs, signals' features are extracted. The extracted features represent the input data set of classifiers. A learning machine technique is applied to classify and identify the transmitter device. Part of data set is used to learn the classifiers, while the rest of the data is used to test the classifiers performance. The performance of the classifiers is evaluated for different levels of signal to noise ratio (SNR). The results of this study demonstrate the usability of steady state of RF fingerprinting for BT signals at physical layer security of wireless networks, and the effectiveness of the applied processes and introduced classifiers.

Keywords: Bluetooth, Hilbert-Huang Transform, Steady State, Radio Frequency Fingerprinting, Empirical Mode Decomposition.

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التحقق من ميزات الحالة المستقرة في تصنيف البواعث

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الملخص
أمن شبكة الاتصالات أصبح الان مسألة مهمة؛ وذلك بسبب أن معظم شبكات الاتصالات اللاسلكية تتعرض لأنواع مختلفة من الهجمات الاختراقية كالإشارات الطائشة، والانتحال، والتفاعل بين إشارات الاتصال. إن بصمات الترددات الراديوية (RF) قدمت حلاً واعداً لأمن شبكات الاتصالات. في هذه الدراسة، تم تطبيق بصمات الترددات اللاسلكية لجزء الحالة المستقرة للشارة البلوتوث (BT) لحل هذه المشكلة. تم جمع مجموعة من إشارات البلوتوث (BT) من هواتف محمولة مختلفة لإنشاء مجموعة بيانات أولية.

طبقت عمليات تحضير متعاقبة على مجموعة بيانات الخاصة بإشارات BT المجمعة لإنشاء بيانات ميزات هذه الإشارات. تعمل هذه العمليات على تحويل الإشارات من إشارات نصية إلى إشارات رقمية، وضبط إشارات BT الرقمية ومركزتها عند الصفر، وتحديد أجزاء الحالة الثابتة، وتطبيق تحويل هيلبرت-هوانغ (HHT) جنبًا إلى جنب مع طريقة تحليل الوضع التجريبي (EMD) . من خلال تطبيقHHT ، و EMDعلى الإشارات تم الحصول على توزيعات الطاقة بالتردد الزمن (TFED). عن طريق أغلفة طاقة الإشارات وحالة ثبات الإشارات ووحدات TFED الخاصة بها تم استخراج ميزات الإشارات. هذه الميزات المستخرجة تمثل مجموعة بيانات الإدخال للمصنفات. تم تطبيق تقنية تعليم الالة لتصنيف وتحديد أجهزة الإرسال. استخدام جزء من مجموعة البيانات للتعرف على المصنفات، بينما استخدمت باقي البيانات لاختبار أداء المصنفات. قيم أداء المصنفات لمستويات مختلفة من نسب الإشارة إلى الضوضاء(SNR) . وضحت نتائج هذه الدراسة إمكانية استخدام الحالة المستقرة لبصمات الترددات اللاسلكية لإشارات BT في أمان الطبقة المادية للشبكات اللاسلكية، وفعالية العمليات المطبقة والمصنفات المستخدمة.

الكلمات المفتاحية: بلوتوث، تحويل هيلبرت-هوانغ، الحالة الثابتة، بصمات ترددات الراديو، تحليل الوضع التجريبي.

Introduction

ONE of important issues in communication network systems is the networks security. The wireless networks are exposed to different types of threats such as spoofing, interception, and stray. These threats are considered as main forms of penetrations. Enhancing the wireless network security is concern by extensive studies. The mobile cell phones are considered as the widely used wireless network devices. Multiple security approaches are interested in mobile phone network security [1]. Radio Frequency (RF) fingerprinting is used to be a solution of the wireless network security deficiency at physical layer.

The identification and classification of wireless communication devices can be accomplished via of RF fingerprinting technique [2]–[4]. The wireless hardware can be identified by spectral power density fingerprints [2]. The primary user emulation attacks are mitigated by means of RF fingerprinting [3]. Low-end software-defined cognitive radio networks are used to accomplish this mitigation. RF finger printing is confirmed as an effective enhancing security technique for wireless communication networks [5]. The study that introduced in [6], [7] states that RF finger printing is utilized to identify individual wireless transmitters. An approach constructed based on Hilbert-Huang transform (HHT) is used to identify specific Emitters [6]. Time-frequency energy distributions (TFED) of signals transient stages are obtained by means of HHT [8]–[10]. According to a study presented in [6] HHT is considered as a self-adaptive signal analysis method; therefore, no initial information is required in signal analysis. However, a study [7] proposed Specific Emitters Identification (SEI) method based on high order cumulants generate signal’s energy trajectory. SEI is implemented to transient stages of the GSM signals [6], [7]. In the classification and identification of transmitting devices, the first step is the collection of pure data. The next major step is determining the portion from where the features extracted. In this study, the features are extracted from a portion of steady state stage. The length of this potion is determined to be equal to the length of transient stage of the same signal. Therefore, firstly, the transient of the mobile BT signals must be detected. Many approaches are implemented to detect the signals transient stages [5], [11], [13], [16], [18]–[23].

Another important step is the extracting of features from signals. In this study the features are extracted from the determined steady sate portions and TFEDs. TFEDs are generated by applying the HHT to the considered signals. The last step in this study is usage of a learning machine technique to classify the transmitter devices.

In this study, the data is collected in appropriate laboratory conditions. Ten cell phone devices are considered as transmitter classes. The cell phones are different in brands, models, and serial numbers. Fifty BT signals are collected from each cell phone. A high sampling rate oscilloscope is utilized to collect the signals. Steady sate portions of the BT signals are where unique features are extracted from. The extracted features are divided into two groups, namely overall and subtle groups. These groups together construct the data set of learning machine input. The extracted features are graphically evaluated by Box plot and scatter plot before implementing the learning machine approach. The data set is divided into two parts, as well. Train part data set which is used to learn the classifiers, and test part of data is used to evaluate the performances of the classifiers. Both the extracted overall and subtle features represent the input data of the introduced classifiers. Seven different types of classifiers are introduced in this study. The performances of the classifiers and the robustness of the features are examined for different SNR levels. The paper is organized as follows; section 2 describes the applied methods which include the data acquisition techniques, signal processing approaches, Empirical Mode Decomposition (EMD), and Hilbert Spectrum (HS) methods. In section 3, Extracting features from steady state portions of signals. Section 4 presents the learning machine and classification. In section 5, the classifiers’ performances with noisy signals is evaluates. Section 6 presents results discussion. Section 7 conclusion of the work is introduced.

Methods

A. DATA ACQUISITION

The method by which the BT signals collected accomplished by utilizing a commercial Wifi antenna and a high sampling rate oscilloscope. The captured BT signals were collected in an appropriated Laboratory environment. The laboratory is located in an underground (-2) floor, where other instruments, equipment, and devices are witched off. The environmental conditions such as ambient temperature and humidity are stable and suitable for such a neat work. These laboratory conditions are helpful for accurate analysis, and precise identification and classification performances. The BT signal was transmitted The BT signal were transmitted to the oscilloscope, of type (TDS7404 DSO4 GHz/20 GSPS), via the commercial Wifi antenna that is operating at 2.4 GHz ISM band. Fig. 1 shows the devices that used in the data acquisition process. Ten different cell phones are considered in this study. The phones are different in brands, models, and serial numbers. The considered ten mobile phones are listed in Table 1. The lengths of BT captured signals approximately about 261000 samples for each signal, where the signals are sampled at 20 GHz frequency. During the data collection, we make sure that there no any noise or disturbance in the laboratory may affect the acquisition process. In addition to that the distance between the mobile phone that the signal transmitted from and the WiFi antenna is kept at 30 cm for all phones, in order to guarantee that all signals are transmitted in same conditions.

B. SIGNAL PROCESSING

Even though we were very careful about the purity of the collected data, it's inevitably still some noises produced by the sampling oscilloscope. A FIR filter, namely a Band Pass Filter (BPF) was used to get rid of the undesired frequency components [13]. The Band Pass Filter is a digital filter by which only ISM2400 band is passed. Thus, the processed signal can be manipulated. All considered signals were centered such that their means are zeros, then the signals were normalized. The normalization which is a technique implemented to each signal individually to make its maximum amplitude is unity. The normalization process is needed to ensure that all studied signals have unity maximum amplitudes. This is helpful to compare different signals' features each other. The length of steady state potions for each signal is determined based on associated transient stage; because the steady state portions for the signals are too long. So, for each record, firstly, the transient stage was detected by means of energy envelope of whole associated signal. The length of the steady state portion equals the length of the corresponding transient stage, and start from the end of it. HHT is implemented to the generated steady state portions. Applying the HHT, generated data is considered as a source to extract the signal subtle features, whereas the signal overall features are extracted from the steady state portions before applying the HHT. Both the extracted overall and subtle features represent the input data of the introduced classifiers. Ten different models of five brands were selected for the experiments. For each model, two different (series or serial number) cell phones were acquired. By this manner, a database of 10 mobile phones has been created with 50records for each device; so that the database is composed of 500 records. This number of records was adequate to investigate the performance of the classifiers and the features' robustness. Table 1 lists the devices, brands and models. Here, 1 and 2 indicate two different serial numbers of the same brand and model devices. A typical form of a steady state portion is shown in Fig. 2.

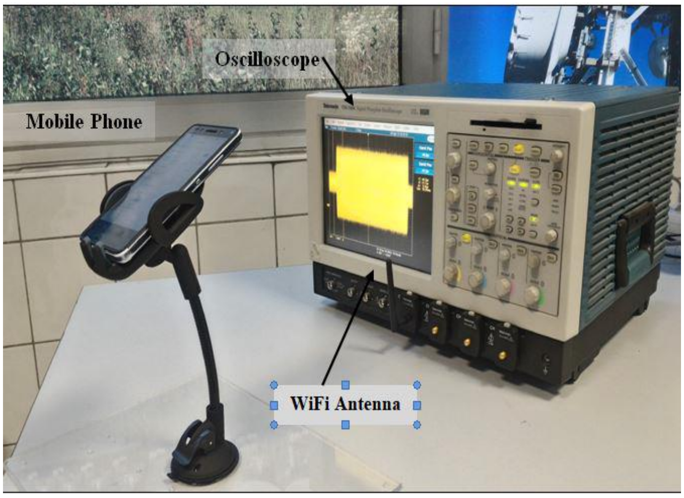

Figure 1: Illustration of signal acquisition Process.

Table 1. The Studied Mobile Phones.

Class No.	Brand	Model
1	Huawei	G5 1*
2	Huawei	G5 2*
3	I-Phone	6S Plus 1
4	I-Phone	6S Plus 2
5	I-Phone	5S 1
6	I-Phone	5S 2
7	LG	G4 1
8	LG	G4 2
9	SamSung	Note3 1
10	SamSung	Note3 2

* 1 & 2 mean two different serial numbers.

The steady state portions of all signals are subject to successive processes to generate the classification database set. The EMD is a method by which each record of the steady state portions is prepared to apply HHT to it. The EMD Method is explained in the following subsection.

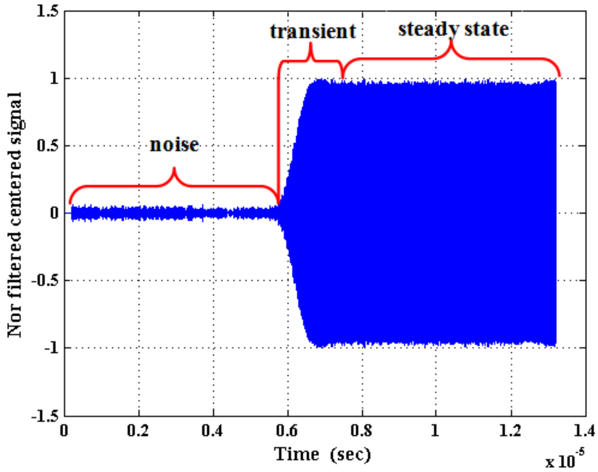

Figure 2: Typical BT signals captured in a laboratory.

C.EMPIRICAL MODE DECOMPOSITION

The EMD is a complex systematic way, involves successive processes to extract the IMFs of each record. Each record rep- resents a steady state portion of a signal. The extreme points are located for each record. The lower and upper splines are formed via the minimum and maximum points, respectively. The mean of the splines is taken for the considered record to extract its IMFs [28], [29] based on a sifting process [30]. The generated IMFs are series of sub-signals different in their frequencies and amplitude. Two compulsory conditions must be satisfied to generate each IMF [6]. Once the IMFs are generated, the Hilbert transform is applied to each extracted IMFs to generate their instantaneous characteristics which are the instantaneous amplitude (IA), instantaneous phase (IPH), and Instantaneous Frequency (IF) [5], [28]. The Hilbert Spectrum (HS) which is three dimensional distributions by which the energy of the signal can be demonstrated is generated from the IMFs' instantaneous characteristics.

D. HILBERT SPECTRUM

The Time Frequency Energy Distribution (TFED) is the result of the HS of IMFs' instantaneous characteristics. The energy distribution is given as a function of time and frequency [31], [32]. A complex procedure is needed to obtain HS.

This procedure illustrates how the record energy summing up in time segments and frequency bins. The major steps for generating HS can be described as following:

1) For each record
2) Upload the generated instantaneous characteristics of the IMFs of the record.
3) Determine the upper limit of frequency scale SULFS.
4) Obtain the scaled instantaneous frequency SIF from the following equation:

$$S_{1F} = \frac{\mathrm{ULFS}}{\max(\mathrm{IF_S})-\min(\mathrm{IF_S})} * \mathrm{IF_s} \quad (1)$$

where *IFs* are the instantaneous frequencies of all IMFs.

5) Select the number of frequency bins (FB) and the number of time segments (TS), and define the bin space as $\frac{ULFS}{FB}$.

6) For each IMF, obtain the HS as a weighted sum of CIA at the m^th frequency bin along time segments as

$$HS_b(m,t) = CIA_b(t)w^m(t)\,, \quad (2)$$

Where b represents the index of imf, $CIA_b(t)$ is the corresponding instantaneous amplitude to the imf_b. The weight factor.

$w^m(t)$ = 1, if the S_{1F}(t) lies in the m_{th}frequency bin, else $w^m(t) = 0$.

7) Construct the overall HS of the record by using the following formula

$$HS= \sum_{b=1}^{B}\left(HS_{\mathrm{b}}(m,t)\right), \quad (3)$$

Where B is the number of the IMFs of the record. A Typical form of HS generated from captured BT Steady state portion is shown in Figures 3, and 4. Here, the time frequency energy distribution is illustrated as normalized amplitude distribution over the time and frequency plane. Fig 3 illustrates the concentration of BT signal energy at 2.4GHz.

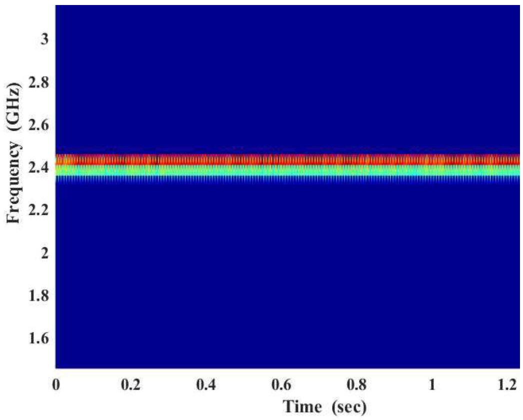

Figure 3: The concentration of BT-signal energy at 2.4GHz

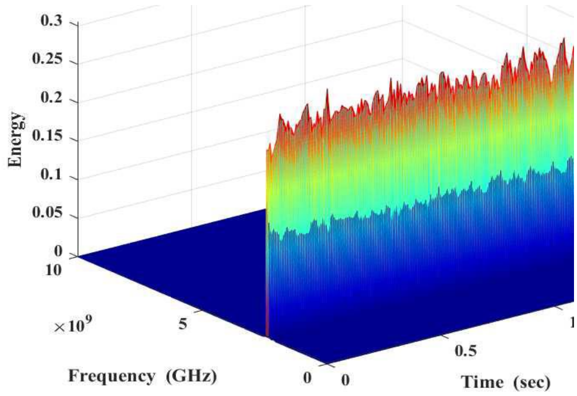

Figure 4: Typical Hilbert spectrum sample of BT signals

III. FEATURES EXTRACTING

The features of each record can be extracted from the record itself or from the TFED of the record. The features that extracted from the record is called overall features, while that are extracted from the TFED are called subtle features. In general, the BT signal features can be extracted from both the transient signal and steady state signal [35], [36]. A RF fingerprinting technique utilized the steady-state potion of the RF signal. In which the features are extracted by means of Higuchi Fractal Dimension technique [37].

Different classification performance might be obtained depending on the signal type and extracted features. This has been extensively demonstrated in the literature for different signals. For instant, some studies interested in extracting features from steady state portion signal are [35], [38]–[40] ,while other studied are concern in transient signals features [6], [7], [12], [16], [17]. In this study, the features are extracted from a part of the steady state potion of signals. The part, of the steady state, that from which the features are extracted are started from the end of the corresponding transient and have the associated transient length. Uniquely identifying features (fingerprints) of the transmitters are existed in the transmitted BT signals. By means of these unique features RF fingerprinting can be developed. The features could be directly extracted from the steady state portion of the signal or along with its associated time frequency energy distribution.

The features that can be directly extracted from the steady state portion of the signal, for instant, the summation of the steady state portion signal or the its slope. Some other features can be extracted from the steady state portion's instantaneous characteristics. These generally represented as statistical moments of instantaneous amplitude, phase and frequency distribution [6].

Some processes can be applied to extracted features to improve their robustness. The normalization is one of the necessary processes that are applied to the extracted features. It's helpful in comparing two or more devices according to two or more features. The features that are extracted from the studied records are listed in Table 2. The features are classified into three groups. The first features group is extracted directly from the steady state signal (overall features). The second and third groups of features are extracted from the HS of BT signals (subtle features). Total of 15 features with their labels are listed in the table. By means of the extracted features, a set data of mobiles' features are constructed. One of the goals of this work is examination of the effectiveness of the generated features' set. This can be accomplished by graphically observing the features and evaluating the classification performance. Moreover, Performance of classifiers is generally evaluated by using confusion matrix. However, the receiver operating characteristics (ROC) curve and the area under the ROC curve (AUC) can additionally be used in evaluations. These performance metrics can visualize the performance of classifiers [47], [48]. The learning algorithms require high-quality training data to generate the model. Therefore, the training data must be evaluated to generate an accurate decision classifier model [42].

Table 2: Rf Fingerprints.

Feature group	Feature name	Feature label
Steady state signal And its energy envelope	Duration of steady state portion	f_1
	Summation of steady state signal energy	f_2
	Summation of energy envelope of steady state	f_3
	Variance of energy envelope of steady state	f_4
	Std of steady state signal inst. phase	f_5
	Entropy of steady state signal inst. Phase	f_6
TFED of the transient signal a long time axis	Length of sum of energy along time axis	f_7
	Slope of summation of energy along time axis	f_8
	Variance of sum of energy along time axis	f_9
	Polyfit coefficient of sum of energy along time axis	f10
	Maximum of sum of energy along time axis	f11
	Mean of summation of energy along frequency axis	f12
TFED of the transient signal along frequency axis	Slope of Nor. sum of energy along frequency axis	f13
	Max entropy of sum of energy along frequency axis	f14
	Summation of sum of energy along frequency axis	f15

By means of the box plot graphical technique, the robustness of the features can be examined. By analyzing the box plot the performance of classification can be predicted, and the features' discrimination capability can be expected. Five major criteria can adequately describe the construction of a typical box plot as shown in (Fig. 5). These criteria can be listed as following: The lower adjacent, the 25th percentile, the median, the 75th percentile, and the upper adjacent. The 25th percentile is a value of a certain data group at which 25% of this data group values are less than it. The interquartile range (IQR) which represents a 50% of the data group are located between the 25th and 75th percentiles lines. This means that 25th of the data values are greater than the 75th percentile value. The median criterion, which is located in the middle of the data box plot, and illustrated by a red line, represents the 50% percentile. The lower and upper adjacent represent the lower and upper whisker boundaries, respectively. the values of these boundaries can be calculated by multiplying a value (usually 1.5), for each data, times the IQR, and subtracting or adding the result to the 25thpercentile or the 75th percentile, respectively.

The rest of the data values that are out of the whisker boundaries are considered as outliers' data [41]. Any feature is considered as a completely separable feature, if the box plot criteria of any device are separated from the boxes' values of other considered devices. The nearly separable feature is a feature where only the whiskers or outliers of a certain device box are inseparable.

The entropy of the steady state signals' instantaneous phases (IPH), which is shown in (Fig. 5) is considered as one of most robustness discriminate features. For example, in this feature, the phone or device number 6 (refer to Fig. 5) is considered as a completely separated device, so that the entropy of the steady state signals' instantaneous phases feature is consider as a completely separable feature for the device or phone. Some devices can't be completely separated by suing the entropy of the steady state signals' instantaneous phases. In this case, another feature can compensate this deficiency. For example, the phones number 4, and 5 can't completely separate by means of the entropy of (IPH) feature. The standard deviation (STD) of (IPH) feature, (refer to Fig. 6), can compensate this shortage; because these phones (numbers 4, and 5) are completely separated, if the STD of (IPH) is considered. The entropy of (IPH) and the STD of (IPH) represent examples of most robustness features, whereas, there are some weakness features, one of them is normalized summation of steady state portion energy feature (see Fig. 7), where most of the devices are nearly separated or completely not separated. In the device's classification, the shortage of this feature can be compensated by other features.

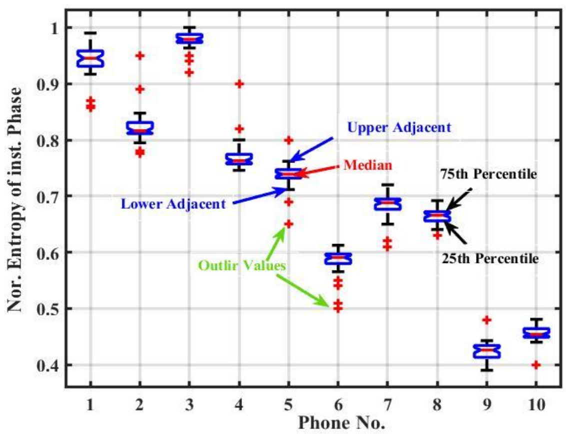

Figure 5: Nor Entropy of IPH

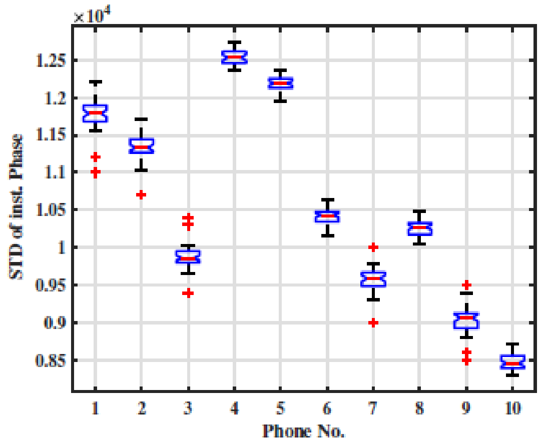

Figure 6: STD of IPH.

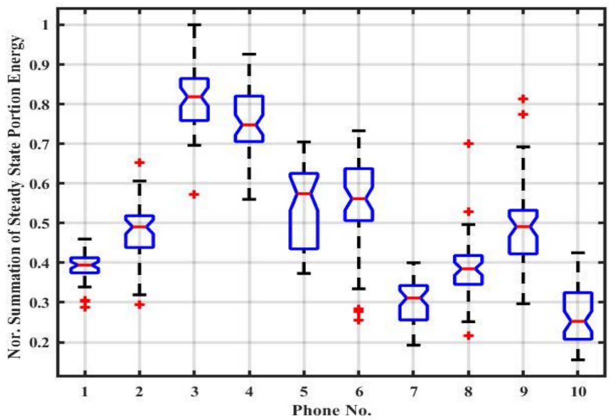

Figure 7: Nor. sum of steady state portion energy.

CLASSIFICATION

The extracted features that are discussed in the previous section are taken as input to the introduced classifiers. By using the application of classification in the Matlab software, the training and testing of the classifier can be done classification. By using the same application, the robustness of the input data (the extracted features) can be evaluated before implementing the training model and the testing classification. One of the criteria that can do such evaluation is the scatter plot in the classification learning software. The scatter plot which is shown in (Fig. 8), and (Fig. 9) evaluates peer-to-peer features. Figure (8) evaluates the effectiveness of two features.

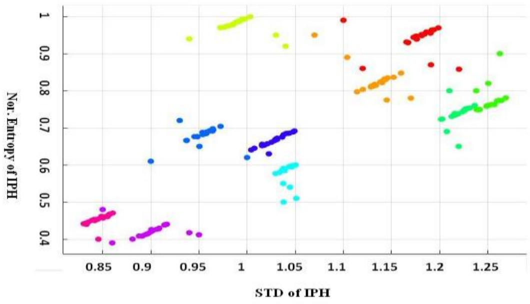

Figure 8: Scatter plot of STD Vs. Entropy of IPH

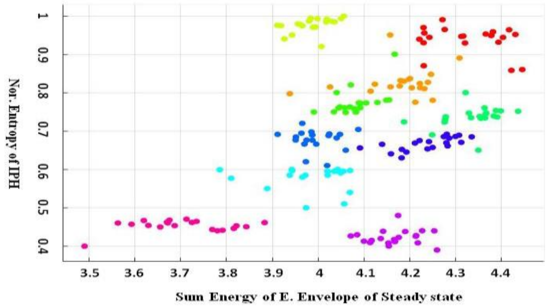

Figure 9: Entropy of IPH. Vs. Sum of Energy of SS Env.

These features are STD of (IPH), and normalization of (IPH) for the studied 10 mobile phones. It's clear from the Figure that there are ten groups of data with different colors, each of which represents trained set records of a certain device. As the data of each group be close together, the two features' discrimination capability increased. Consequently, the device that its color points are closer is more discriminated. So that, it's concluded from (Fig. 8), and (Fig. 9) that the data in Fig. 8 is more discriminated than that in 9.

The classification process is divided into two parts training part and testing part. Firstly, part of the data (extracted features) is used for classifiers' training, then the trained classifiers test by the rest of the data. The data set is constructed from 15 extracted features. In this study the data is divided as follows, For each feature, 40% of that data which represents 200 records, each 20 records belong to a mobile phone, constructs the training data, while 60% of that data which represents 300 records, each 30 records belong to a mobile phone, constructs the testing data. Different types of classifiers are applied to the data. These classifies are listed in Table 3. Once a part of the data is trained, a confusion matrix generated. By the confusion matrix which is shown in (Fig. 10), and illustrates the percent of training performance, and also demonstrates which classes or devices data the classifier are learned well, and which ones not. Fig. 10, and Fig. 11 show the train confusion matrices that generated from applying the Fine Tree classifier, and Linear Discriminant classifier to the trained data, respectively. Training the applied classifiers, the rest of the data are used to test the performances of the considered classifiers. As an example, the results of testing the performances of the Fine Tree Classifier and the Linear Discriminant classifier are shown in Fig. 12, and Fig. 13, respectively.

Table 3: The Applied Classifiers.

Classifier Type.	Training percent	Testing percent
Fine Tree	98%	92%
Linear Discriminant	90%	96.3%
Quadratic Discriminant	76.5%	87%
Linear SVM	95%	92.3%
Quadratic SVM	86%	88.7%
Fine KNN	100%	81.3%
Medium KNN	86%	82%

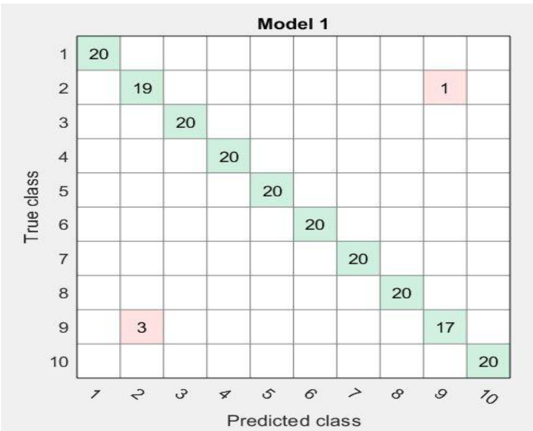

Figure 10: A confusion matrix generated by Fine Tree classifier.

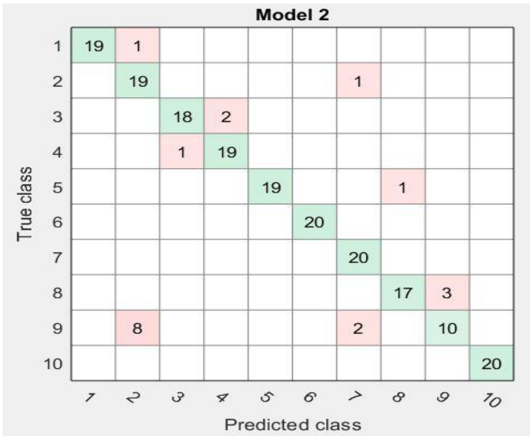

Figure 11: A confusion matrix generated by Linear Discriminant classifier

CLASSIFIERS' PERFORMANCES WITH NOISY SIGNALS

The performance of introduced classifies are examined for different levels of SNR. The SNR of the noisy steady state is calculated by obtaining the average energy of the noisy steady sate considered portion (SSP), and the average energy of the noise signal (n) as follows:

$$SNR = 10log_{10}\left(\frac{SSP}{n} - 1\right). \quad (4)$$

The introduced noise levels are added to the original signals. The noises are captured form the noise stage of each signal, and then multiplied by a factor to control the scales SNR levels. The scaled noise signal added to the steady state corresponding potion of the same signal. Three noise levels are studied (8-10), (12-15), and (18-23). Same processes that are applied to the high SNR data are applied to the three levels of noisy data. The results of performance testing classify are illustrated in Table 4.

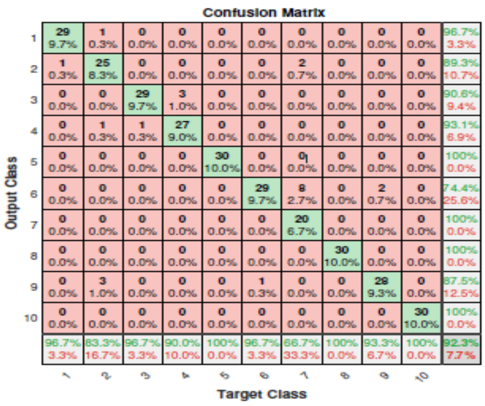

Figure 12: A performance testing matrix generated by Fine Tree classifier.

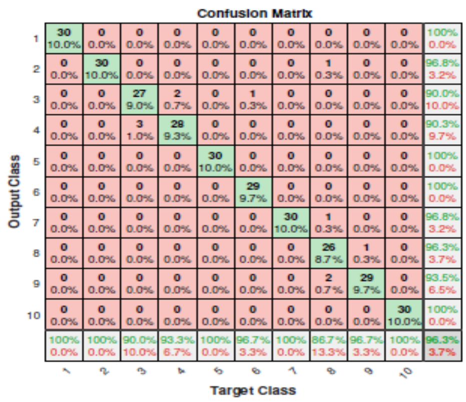

Figure 13: A performance testing matrix generated by Linear Discriminant classifier.

Table 4: Classifiers' test performances with different levels of SNR

Classifier	SNR		
	(8-10)	(12-15)	(18-23)
Fine Tree	75%	82.5%	86.4%
Linear Discriminant	52.3%	59.2%	79.7%
Linear SVM	78.6%	82.3%	81.6%

Results and discussion

The prepared data of the studied mobile phones' BT signals are divided into two groups. The steady state signals, the TFED of the steady state signals. The features are extracted from each group. The extracted features are evaluated before classifiers implementation. The evaluation of features is done by means of box plot technique and scatter plot demonstration. The evaluation result shows the robustness of some features such as STD of IPH and some partially separable features like summation of steady state portion energy, as illustrated in (Fig. 6), and (Fig. 7), respectively. The steady state portions records are subjected to EMD along with HHT techniques to generate HS. The result of these two complicated techniques applications was excellent and as expected. That is because all power concentration of HS at 2.4 GHz which matches the band frequency of the studied BT signals. The summation of TFED along time axis and along frequency axis generated two subgroups of features. The resultant features are also evaluated to grantee their robustness before introduced to classifiers.

As it's demonstrated in Table 3, the classifier training performance of the Fine Tree and the Linear Discriminant classifiers are 98%, and 90%, respectively. The x-label, and y-label of the trained confusion matrices' models are Predicted, and True classes, respectively. The true class is considered as the reference class of training process, and the predicted one is what we expect as a result from the training process. Referring to (Fig. 11), if class number9 is considered, one can notices that ten records out of twenty records are correctly classified, whereas eight records are classified as class number 2 and two records are classified as class number 7. A as result the performance of Linear Discriminant classifier training process is calculated as a percent (98%). The performances of the classifiers are evaluated by testing process. All the classifiers listed in Table 3 their performances are evaluated for both training and testing. (Fig. 12), and (Fig. 13) show the performance testing matrices generated by Fine Tree classifier (92.3%) and Linear Discriminant classifier (96.3%), respectively. The testing performances of the rest of applied classifiers are demonstrated in Table. 3. The results reflect a high degree of classifiers performances.

Conclusion

This study is concern in network communication security. RF fingerprinting is utilized to solve the security problem based on mobile phone BT signals. The signals are captured from ten different cell phones. each with fifty records. The cell phones are varying in brands, models, and serial numbers. A Band base filter was used to de-noising the collected signals. A part of steady state portion is where the signal feature extract from. The features are directly extracted from steady state signal, and also extracted from the HS of the steady state signal. The HHT along with EMD are used to generate HS or TFED, where the summation of energy along frequency and time axis are obtained as an array from each record. So that there are three groups of features which are features extracted from steady state portions, another two groups of features are extracted from summation of energy of TFED along time axis and frequency axis. The total extracted features are fifteen features. Some of which are considered as robustness features or separable features, such as STD of IPH, other features are partially separable features. By mean of these features, the devices or classes can be classified. The robustness of the extracted features can be investigated before applying the classification process. This accomplished by Box plot technique, and scatter plot demonstration. Preparing the features, the classification process is applied to features into two processes: training process, and testing process. Four types of classifiers are introduced, which are Tree, Discriminant, SVM, and KNN classifies. The data set of the features that is subject to the introduced classifiers are divided into train and test groups. Firstly, the classifiers are learned by means of the train data, and then their performances are evaluated by means of tested data. The testing process results, as illustrated in Table 3, demonstrated a high degree of machine learning. In order to evaluate the effectiveness of the applied methods and the performances of the introduced classifiers, the studied devices are classified for different levels of SNR. As shown in Table 4, the testing performances of the classifiers yielded a considerable percents of correct classifications. In general, the study proved the feasibility of usage the extracted features from the steady state potion of the BT signals as a data set from cell phone classifications. Consequently, the study showed the helpfulness of the RF fingerprinting of the steady sate portion in communication network security.

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