# Improvements on Transient Signal Detection for RF Fingerprinting

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***Abstract*—The detection of the transient signal plays a significant role in RF fingerprinting for transmitter devices. This paper proposes modifications on two transient signal detection methods, namely, Bayesian change point detection and phase based detection. For initial tests, Bluetooth signals captured in the laboratory are used for performance analysis of the proposed methods. Preliminary results show that the proposed methods can be used in RF fingerprinting of wireless devices.**

***Keywords*—Wireless networks; Bluetooth signals; RF Fingerprinting; Transient signal detection.**

## I. Introduction

A secure identification of devices in a wireless network has an important concern for the network security [1]. Wireless network security has been challenging with complicated threats day by day [2]. The classification and identification of wireless devices are very important because of security and reliability concerns [3]. Radio Frequency (RF) Fingerprinting is considered as a promising approach to improve wireless network security [4]. It identifies uniquely wireless devices that exchange messages among the network [5]. RF Fingerprinting is a process by which radio transmitters can be identified uniquely. Extraction of the features of the transmission signals that are transmitted from different wireless devices plays a significant role in RF fingerprinting. RF fingerprinting starts with extracting distinctive features from the transient signal at the beginning of the transmission. Wireless devices have distinct and unique transient signal features depending on their analog circuits [6], [7]. In literature, there are many proposed methods that are used to detect the transient starting point and the end point.

Bayesian change point detection method is widely used to detect the start of transient signal, and it is based on amplitude characteristics of the transient. The Higuchi's method is used, in the Bayesian detection technique, to calculate the fractal dimension [6]. The importance of the fractal dimension comes from the characterization of the degree of the data correlation. Another approach used to detect the start point exploits the phase characteristic of the transient [8]. The phase of the signal in the transient part has a linear slope so this can be used to distinguish the signal start from the noise. In doing this, firstly, the phase vector consisting of bins is calculated, and the variance of each bin is used to see the slope [6].

In this paper, improvements regarding with the methods discussed above are presented. In section 2, these two improvements are introduced to detect the start and the end of the transient. In section 3, performance of the improved methods is presented by using test signals captured from Bluetooth signals of several mobile phones. Finally, section 4 draws some conclusions.

## II. RF Fingerprinting Start and End Detection Methods

In this section, we will introduce improvements to two methods used to detect the start of transient signal. These methods are Bayesian change point detection and Transient Detection Based on Phase Characteristic. As a basis Bayesian change point detection is considered firstly.

### A. Bayesian change point detection

The Higuchi's method is used, in the Bayesian detection technique, to calculate the fractal dimension. The importance of the fractal dimension comes from the characterization of the degree of the data correlation. The Higuchi's method can be applied to the sampled transient signal in the form of an uniform time series, $x(i),\ i = 1, 2, \dots, N$. A new series can be generated from the given original uniform time series as

$$x_k^m : x(m), x(m+k), \dots, x\left(m + \left[\frac{N-m}{k}\right] k\right) \quad (1)$$

where $m = 1,\ 2,\ 3, \dots,\ k;$ and $k$ is integer number, and [ ] denotes the integer part. The length of the generated series is defined as:

$$L_m(k) = \frac{N-1}{\left[\frac{N-m}{k}\right] k^2} \left[ \sum_{i=1}^{\left(\frac{N-m}{k}\right)} |x(m+ik) - x(m+ki-k)| \right] \quad (2)$$

Take the average of all $L_m(k)$ to obtain the length of the series $L(k)$ for the given $k$ value. If the obtained length $L(k)$

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behaves as a power law like $L(k) \propto k^{-D}$, then the exponent D represents the fractal dimension of time series. Then, the exponent D can be obtained by taking the natural logarithm of the vectors $L(k)$, and k, followed by the application of the least square method. Once the fractal dimension D is obtained, the posteriori probability density function can be used to detect the transient starting point as follows [8]:

$$P\{m|D\} \propto \frac{\frac{1}{\sqrt{m(N-m)}}}{\left[\sum_{i=1}^{N} D_i^2 - \left(\frac{\sum_{i=1}^{m} D_i}{\sqrt{m}}\right)^2 - \left(\frac{\sum_{i=m+1}^{N} D_i}{\sqrt{N-m}}\right)^2\right]^{\left(\frac{N-2}{2}\right)}} \qquad (3)$$

where m=1, 2, 3, …, N represents the transient starting point, and is the length of the fractal dimension. For each m value, calculate the variances of the fractal dimension for the two sequences [1, 2, 3, …, m] and [m+1, m+2, m+3, …, N]. The probability is proportional to the differences between each two variances of successive sequences. Based on the fact that the fractal dimension values of the noise portion is higher than that of the transient signal, one can estimate the transient starting point easily. Because, this should be located at the point where we have the highest variance.

*B. Improved Bayesian change point detection*

The improvement proposed is considered to simplify the detection process. For this purpose, we compute summation of fractal trajectory entries and then get the difference vector. In this way we get rid of calculating the posteriori probability density function.

This improved technique is illustrated in flow chart in Fig.1 from which the transient signal can be located by the following steps:

- The transmission signal x(t) is divided into identical windows based on overlapping windowing technique.
- The fractal dimension (and trajectory) is computed by using Higuchi's method.
- Fractal trajectory is divided into bins.
- The summation of each bin's entries is taken. We take the difference of the summation vector from which the transient start and end points can be determined. The noise and steady parts have oscillations that make the differences contain positive and negative values in these portions, whereas the differences in the transient portion contain only positive values. In this improved technique, we avoided to calculate the a posteriori probability density function since we have to test every entry in the FT to check the maximum probability value that matches the transient starting point. Consequently, that will take time to try each entry thus increase the computational cost, whereas in the improved technique we divided the FT into windows.

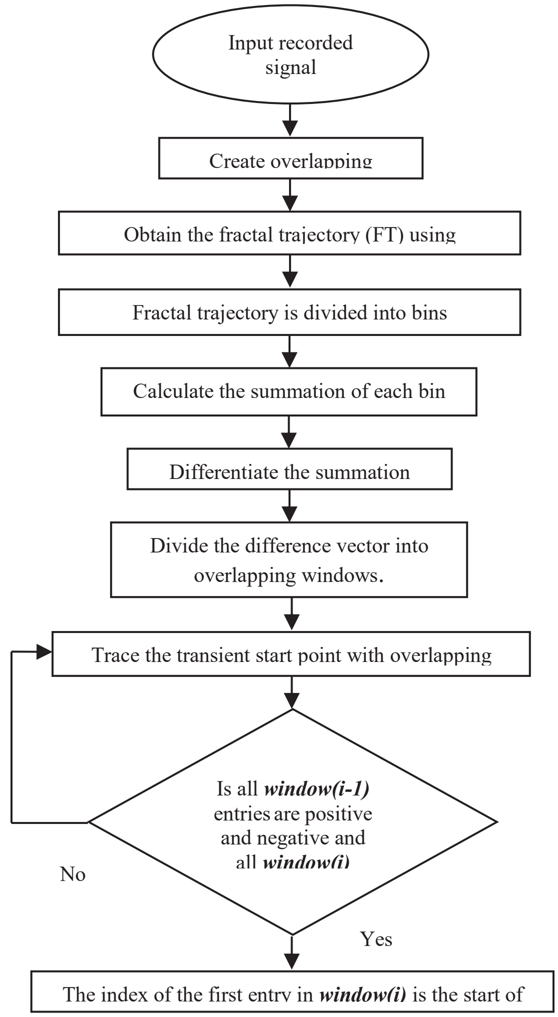


Fig. 1. Improved Bayesian change point detection.

*C. Phase Based method*

The Hilbert transform of the recorded signal is taken, and instantaneous amplitude, frequency and phase. This is very straightforward and will not be discussed in here. The signal instantaneous phase is unwrapped. The absolute value is taken for the unwrapped phase (*AV*) vector as discussed in [6]. The variances of the unwrapped phase (*AV*) vector, at the noise portion and the transient signal, are highly different as expected. Along the *AV* vector, the variances can be obtained based on bins of size *s* to generate a temporary variances (*TV*) vector as follows:

$$TV(i) = var\big(AV(d+1),\ AV(d+2),\ \ldots,\ AV(g)\big), \qquad (4)$$

where $i = 1,2,\ldots, N/_s$, $g = i \times s$, $d = g - s$, and Var() represents the phase variance. The fractal trajectory (FT) is obtained by taking the difference between each successive phase variances in TV vector. The slope of the phase is linear

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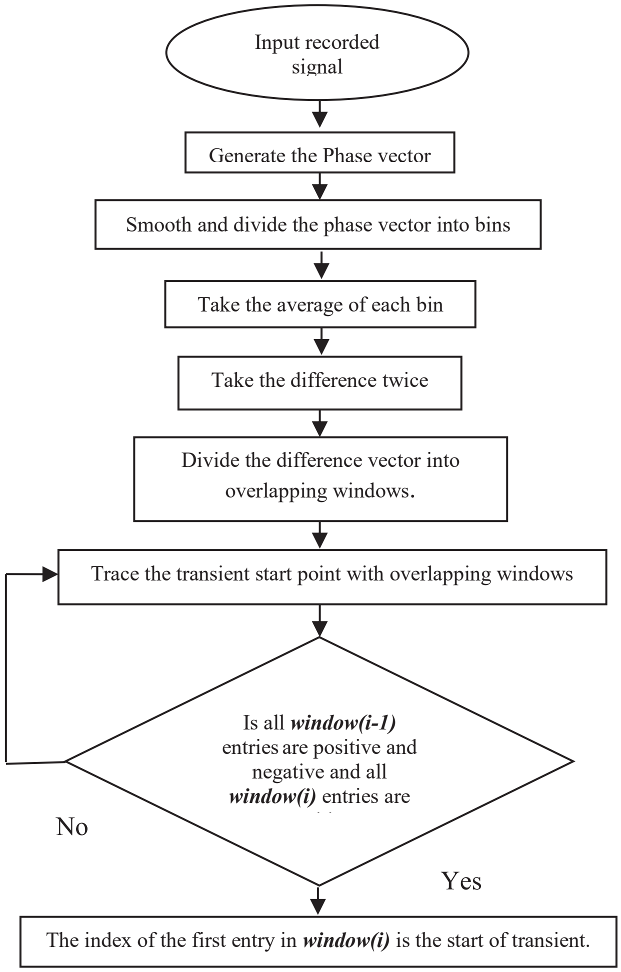



Fig. 2. Improved Bayesian change point detection

only at the transient duration. Based on this, the values of the variances on the AV vector do not change in the transient signal. That means the values of the fractal trajectory (FT) at this part are zero as shown in Fig.3-b. The value of fractal trajectory can be traced based on predetermined threshold (T).

The FT values are evaluated based on overlapping windows with a certain length ($L_{win}$). The values in each window are compared to the predetermined threshold as follows:

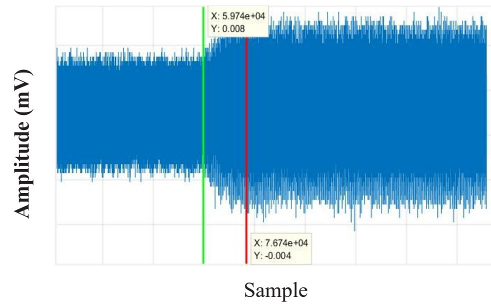
$$\mathrm{FT(i)},\ \mathrm{FT(i+1)}, \ldots, \mathrm{FT}(\mathrm{i}+\mathrm{L_{win}}) \leq \mathrm{T}, \qquad (5)$$

where $\mathrm{i} = 1, 2, \text{length } (\mathrm{FT} - \mathrm{L_{win}})$.

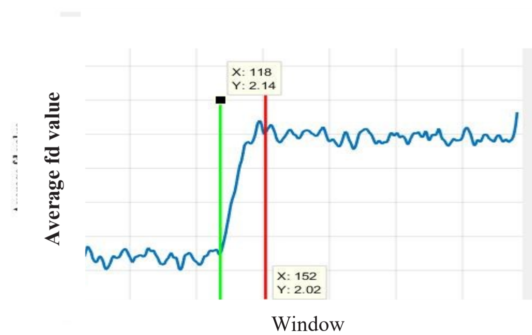
### *D. Improved Phase Based Method*

In this improvement, after obtaining the unwrapped phase vector (AV) as described in section C, the following procedure is proposed:

- The average of each window is obtained to distinguish the transient signal as shown in Fig. 3-b.
- The difference between each two successive points of the *TV* vector is taken twice to differentiate the transient portion that generates a difference vector.




a. The transmitted signal




b. The fractal trajectory

Fig. 3. Improved Bayesian change point detection applied to test Device 1

- In the difference vector there are positive and negative values in the noise and steady parts, whereas there are non-negative values in the transient signal due to the linearity.
- The difference vector is divided into overlapping windows to detect the transient signal. The transient signal will be located by the first entry of the first non-negative valued window.

In this improved technique, whose flow chart is given in Fig. 2, we avoid using the threshold which is generally different in each signal. Moreover the average is taken instead of the variance which is more complicated technique given by Eq. (4). Since, in a certain manner we have to calculate some parameters before applying the variance, so that it is easier to calculate the average than the variance. This leads to simplification of the procedure for the detection of transient signal. In addition, the transient signal is more visible as shown in Fig. 3-b.

## III. Result and Discussion

The improved methods in sections B and D, namely, Improved Bayesian change point detection and Improved Phase Based Method were applied to some Bluetooth signals, which were recorded from different types of mobile phones. Fig. 3(a) shows a sample BT signal recorded in the laboratory (with 20Gsps sampling rate), which shows where the transient portion is located. Fig.3 (b) shows how the transient signal *is* detected by means of the fractal trajectory of the signal where the fractal trajectory is generated by proposed methods.

Moreover, the start and the end point of the transient part of the signal are also indicated.

The performance of the improved methods was evaluated with the respect to a reference method which was phase based method in [6]. The three methods were applied to five different devices each of which have five signal records were taken (total of 25 recorded signals). In evaluating the performance of the methods, the difference between the index number of the proposed method (IM-improved) and the reference method (PH-phase based) was used. This difference can be formulated as the error of each method, and given as follows:

$$\varepsilon_{IM} = \frac{|i_{PH} - i_{IM}|}{i_{PH}} \times 100 \tag{6}$$

where $\varepsilon_{IM}$ represents percentage error of the improved method, $i_{PH}$ indicates the index number of the start point detected by phase based method and $i_{IM}$ indicates the index number of the start point detected by either of the improved methods. Table I shows the mean value of the errors (μ), and the standard deviation (σ). With this limited test data, it has been observed that the maximum error is only 3.72%. The mean value and the standard deviation of the errors for both methods are comparable. It is inferred from the table I that the maximum and the minimum values of errors will not exceed 3.718% and 1.866%, respectively, for the improved phase based method. Similarly, for the improved Bayesian detection the maximum and the minimum values of errors will not exceed 3.145% and 1.585%. That means the start detection values of the proposed methods are close to each other based on these results.

## IV. Conclusion and Future Work

This paper presents improvements on two methods that have been widely used for detection the start point of transient signals in RF fingerprinting. The improvements avoid complex calculations such as the posteriori probability density function in Bayesian change point detection, and the variance computation in phase based detection. In this way we could reduce the computation cost, simplify the detection procedure and the transient signal is more visible in the fractal trajectory. In addition, the introduced improvements could detect the end point of the transient signal. These improvements were applied on twenty five BT signal records. The error statistics are provided, and the results are promising.

In future work, the improved techniques will be tested with extensive data (100+ devices). After transient signal detection, algorithms will be developed for extracting new features. By using those algorithms, the features that are unique for BT signals will be used for device classification. In literature, there are two main groups for feature extraction. The first one is advanced statistical features, namely, Variance, Kurtosis and Skewness of the instantaneous frequency, phase and amplitude [3]. The other one is time-frequency domain analysis which is discussed in [8]. It can be seen that there are several features that can be generated by using time frequency and energy distribution. By using the features that mentioned above classification can be done. The performance of the classification is highly dependent on the uniqueness of the features.

TABLE I. ERROR PERFORMANCE OF THE PROPOSED METHODS (OVER 25 RECORDED SIGNALS)

| Method | μ | σ |
|---|---|---|
| **Improved Phase Based** | 2.792% | 0.926 |
| **Improved Bayesian detection** | 2.365% | 0.780 |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