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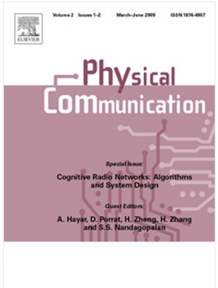

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A Robust Parameter Estimation of FHSS Signals Using Time-Frequency Analysis in a Non-Cooperative Environment

Abdulrahman Kanaa[*,1,2], Ahmad Zuri Sha'ameri[1]

[1]Department of Microelectronic and Computer Engineering, Faculty of Electrical Engineering, Universiti Teknologi Malaysia, Skudai 81310, Johor, Malaysia

[2]RISE, RISE ICT, Acreo, Applied Digitalization, Sweden

[*]abdulrahman.kanaa@ri.se

Abstract: Frequency hopping spread spectrum (FHSS) signals are widely implemented in both modern civilian and military applications. They are robust to channel impairments because of their low probability of interception. For applications that require the interception of FHSS signals, the signal parameters such as the hopping frequencies, hopping duration and hopping sequence should be accurately measured. In this paper, an accurate FHSS signal parameter estimation method is proposed based on quadratic time-frequency distributions (QTFDs). The extended modified B-distribution (EMBD) and the adaptive smoothed Wigner-Ville (SWWVD) are used which have the properties of high time-frequency resolution. The adaptive SWWVD requires no prior knowledge of the signal parameters since the kernel parameters are estimated from the signal characteristics and are compared to the EMBD which operates at the optimal kernel parameters. The proposed instantaneous frequency (IF) estimate method is compared to the time-frequency (TF) moments method and benchmarked with the Cramer-Rao lower bounds (CRLBs). The computational complexity of the IF estimation method is reduced by a factor of five compared to the TF moments method. Furthermore, the

results show that the IF estimation method outperforms moments method where the mean-squared error (MSE) of the hopping frequencies estimate meets at minimum SNR of -3 dB and the hopping duration estimate MSE meets the CRLB at SNR of 0 dB.

1. Introduction

Spread spectrum communication methods are widely implemented in military and civilian applications such as unmanned aerial vehicles (UAVs) or drones, telemetry tracking and command satellites, intelligent radio frequency controlled robots and cellular radios. The signal spectrum is intentionally spread beyond the bandwidth needed to send data [1] to overcome various types of jamming and multipath fading environments [2-7]. Two commonly used spread spectrum signals are the direct sequence spread spectrum (DSSS) and frequency hopping spread spectrum (FHSS). Both methods spread the spectrum using a code that can be generated using pseudorandom sequence [8]. For DSSS, the code modulates the information bearing signal while it changes the hopping frequency for FHSS. For commercial applications, the FHSS is used in Global System for Mobile Communications (GSM) to overcome the problem of frequency selective fading where the user is allocated various frequency channels based on the channel performance. The DSSS concept is used in code division multiple access systems where every user pair is allocated a unique code. Both methods in military application are used to reduce the probability of intercept [9, 10].

It is also important for the military for intelligence gathering. In electronic warfare, three main tasks are performed which are electronic support (ES) electronic attack and electronic protect [11]. Among the three tasks, ES is more related to spectrum monitoring where the process is to search, intercept, locate, and analyse radiated electromagnetic energy to support military operations [12]. UAVs and drones have recently been the subject of increasing interest for their use in military airstrikes [13]. However, the security matters in UAV technology have not been well addressed. Analysing these security issues requires information about FHSS signals which are used in the radio frequency controllers. Once accurate information is obtained, EA can be performed against the target system.

The analysis of FHSS signals required a method suitable for representing time-varying signals. Time-frequency (TF) analysis is suitable since it produces a representation for time varying signals jointly in both time and frequency [14]. There are two general classes of time-frequency distributions (TFDs), linear TFD and quadratic TFD (QTFD) [14]. Linear TFD like short time Fourier transform (STFT) suffers from time-frequency resolution trade off. On the other hand, QTFDs like Wigner-Ville distribution provides a good time-frequency resolution at the drawback of cross terms [14, 15]. Thus, a variety of TFDs which is much application dependent have been introduced. However, if the kernel function is chosen properly, the QTFD can provide an accurate representation.

TFDs like spectrogram and WVD are not able to resolve two closely spaced signals in the time–frequency domain. As a result, B-distribution (BD) was introduced in [16] that has shown a superior performance compared to other TFDs in terms of high time frequency resolution and energy concentration. However, the BD does not satisfy most of the conventional properties of QTFDs. In addition, BD does not provide a lowpass 2-D function which performs filtering on the auto-terms that are concentrated at the origin of the Doppler-lag domain [16]. Moreover, no direct component amplitude estimation from BD is possible. Consequently, the modified B-distribution (MBD) has been introduced in [17], which has a normalization factor and a lag independent kernel. The QTFD satisfies most of the desirable properties of TFDs.

Nevertheless, the low-pass 2D function filters the terms which are far from the origin in the Doppler direction and preserves the cross-terms in the lag direction in the Doppler-lag domain. That results in the remaining artefacts in the frequency direction of the TFD. As a result, the extended modified B-distribution (EMBD) is introduced which uses the MBD kernel in both lag independent kernel and Doppler-independent kernel. EMBD is a separable kernel TFD [18]. The EMBD is a recent QTFD [19] that is used to analyse time-varying signals. It is shown that the method outperforms other TFDs in cross-terms suppression and preserves a high time-frequency resolution. In a non-cooperative environment where priori information of the signal parameters are unknown, adaptive methods such as adaptive smoothed windowed Wigner-Ville distribution (SWWVD) [20] are implemented. The resulting time-frequency distribution (TFD) is comparable to the optimal kernel. Thus, the EMBD and adaptive SWWVD are used in this paper to obtain the TFD.

Once the TFD is obtained, the next step is to estimate the FHSS signal parameters. Different approaches are implemented in [21, 22]. The method introduced in [22] showed a performance improvement by around SNR of 1 dB compared to [21] in the root mean-squared error to estimate the hopping frequency and hopping duration. However, estimating instantaneous frequency (IF) from the first moment introduced an additional complexity compared to estimating the IF from the peaks of the TFD [23]. In addition, the method was shown to be able to estimate the IF of a multicomponent signal. Another work uses the Cohen-assignment joint TFD in [24] to estimate FHSS signal parameters. However, the assumption of perfect knowledge of transmitted signal parameters may not be applicable in a non-cooperative environment. The TFD of FHSS signal was generated using the STFT [25, 26]. Due to the time-frequency resolution trade off, multiple STFTs are required to estimate the hopping duration [25]. Compressive sensing was used to estimate the hopping frequencies [27]. Since the hopping intervals are assumed known, additional methods have to be introduced before the method could be used in a non-cooperative environment.

S-transform is a type of TFD used in [28] to estimate FHSS parameters. The resulting TFD provided good time resolution for all frequency components. However, the frequency dependent window produced good frequency resolution at low frequency while causes smearing at high frequency. As a result, the FHSS signal parameters could only be estimated accurately at a relatively high SNR of above 5 dB. To overcome the shortcomings of the previous works, a new approach based on the QTFD is introduced to improve on the estimation of FHSS signal parameters.

The focus of this work is on the estimation of the hopping parameters of the FHSS signal and not on the estimation of the modulation parameters of the information bearing signal. This paper is organized as follows. Section 2 describes the problem and defines the FHSS signal model. Time–frequency analysis methods are discussed in Section 3. The suggested FHSS signal parameters estimation algorithms are presented signal in Section 4. In Section 5, we demonstrate results for the presented TFDs along with the results for each step of the parameters estimation algorithms, in addition to Monte Carlo performance evaluation results and CLRBs for each method. The findings are concluded in Section 6.

2. Problem definition

Since FHSS signal is non stationary, time-frequency signal analysis (TFSA) is an appropriate method to first represent the signal and then estimate the FHSS signal parameters. The TFSA methods should provide high resolution in TF representation with minimum artefacts like cross terms. Furthermore, efficient algorithms have to be implemented to estimate the FHSS signal parameters.

2.1 Signals model

In this section, the FHSS signal characteristics are described first followed by the description of the problem to be analysed. The received signal is assumed to be down converted from radio frequency band to intermediate frequency band and the sampling frequency for the discrete time representation normalized at 1 Hz. The term frequency used throughout this paper refers to the signal frequency at intermediate frequency.

The hopping frequency of FHSS signal changes periodically at each hopping duration according to a pseudorandom number. The information bearing signal could be any of the commonly used digitally modulation method. For this paper, phase shift keying (PSK) and quadrature phase shift keying (QPSK) signals are selected. The hopping rate is assumed to be slow where one or more symbols are carried within single hopping duration. The FHSS signal can be described as [2]

$$x(t) = \sqrt{2P}\sum_{k=0}^{N_h-1}\Pi_{T_h}(t-kT_h)\sum_{i=0}^{N_s-1}\Pi_{T_s}(t-iT_s)\exp(j2\pi(f_k)t+\phi_i+\phi_k) \qquad (1)$$

where P is the average signal power within a hopping duration, T_s is the symbol duration for the information bearing signal, N_s is the number of symbols per hopping duration, N_h is the total number of hops, f_k is the hopping frequency within a k-th hopping duration, ϕ_k is phase at the beginning of a k-th hopping duration, ϕ_i is phase associated with symbol “s” and T_h is hopping duration.

The box function of an interval T is defined as

$$\Pi_{T_h}(t) = \begin{cases} 1 & \text{for} \quad 0 \le t \le T \\ 0 & \quad \text{elsewhere} \end{cases} \tag{2}$$

where the symbols T_h and T_s are used for the hopping duration and symbol duration respectively.

The FHSS signals are defined in Table 1 at the normalized set of hopping frequencies. 4FHSS and 8FHSS signals are presented which consist of 4 and 8 hopping frequencies, respectively. In practice, the sampling frequency is in the order of 10^6 where f_s =16x10^6 Hz and for example, $f_{h.k}$=3.25x10^6 Hz. However, to generalize the method f_s is normalized to 1 Hz which will result in $f_{h.k}$=3.25x10^6/16x10^6=0.2031 Hz. The hopping sequence describes the frequency changes of the FHSS signal.

Table 1 Hopping parameters

Signal	**Hopping duration T_h (samples)**	**Normalized frequency $f_{h,k}$ (Hz)**
4FHSS	160	0.2031 0.2344 0.2656 0.2969
8FHSS	160	0.2031 0.2344 0.2656 0.2969 0.3281 0.3594 0.3906 0.4219

The frequency f_k changes its value at every k-th hopping duration and the actual frequency is selected from any of the frequencies listed in Table 2 [29]. The actual frequency of the signal at a given time instant depends on the hopping sequence. Based on the signal parameters in Table 2, an example for a 4FHSS signal can be described by following hopping sequence:

$[f_1\ f_2\ f_3\ f_4] = [f_{h,2}\ f_{h,1}\ f_{h,3}\ f_{h,4}] = [0.2344\ 0.2031\ 0.2656\ 0.2969]$

The received signal can be as

$$y(t) = x(t) + v(t) \tag{3}$$

where $v(t)$ is additive white Gaussian noise. The implemented modulation schemes are defined in Table 1.

To analyse FHSS signal, TFSA methods are suggested in the following section. The TFSA methods aims to present the signal with a high resolution in both time and frequency domains. The representation is used as a preliminary stop to accurately estimate FHSS signal parameters.

2.2 Justification to estimate hopping parameters

Together with DSSS signal, FHSS signal is a low probability of intercept (LPI) signal [30, 31]. It requires a precise knowledge of the signal parameters in order to analyse and demodulate the signal. For FHSS signal, a perfect knowledge of the hopping frequencies, hopping duration and hopping sequence is crucial. The signal is spread in frequency over a wide bandwidth where the hopping frequency changes according to a pseudorandom pattern which is only known to the communicating parties. As a result, every transmitted hopping duration has a different hopping frequency which makes it difficult to the interceptor to detect and analyse. If the FHSS signal parameters are unknown, an adaptive, fast and accurate parameters estimation method has to be implemented. In addition, the presence of noise further complicates the analysis of the signal and the estimation of its parameters.

3. Time-frequency analysis

The QTFD possesses desirable properties such as local energy concentration, IF, first moment visualization and reduced interference [14]. Those properties make it suitable to represent non-stationary signals. The QTFD can be described as follows [14]

$$\rho_z(t,f) = \int_{-\infty}^{+\infty} G(t,\tau) \underset{(t)}{*} K_z(t,\tau) \exp(-j2\pi f\tau) d\tau \tag{4}$$

where $G(t, \tau)$ is the time-lag kernel function, $\underset{(t)}{*}$ denotes convolution in time and $K_z(t, \tau)$ is the bilinear product of the analytic signal of interest $z(t)$ that can expressed as follows

$$K_z(t,\tau) = z(t+\frac{\tau}{2}) z^*(t+\frac{\tau}{2}) \tag{5}$$

A separable kernel enables independent control of smoothing in time and lag and can be expressed as [14]

$$G(t,\tau) = g_1(t) g_2(\tau) \tag{6}$$

where $g_1(t)$ and $g_2(\tau)$ are the time-smooth function and the lag-window function, respectively. By substituting (6) into (4), the resulting QTFD can be described as

$$\rho_z(t,f) = \int_{-\infty}^{+\infty} g_1(t) \underset{(t)}{*} K_z(t,\tau) g_2(\tau) \exp(-j2\pi f\tau) d\tau \tag{7}$$

The QTFD in (7) is also known as the smoothed windowed Wigner-Ville distribution (SWWVD) [20]. The cross-terms are attenuated by a lag window $g_2(\tau)$ in the lag-domain which removes non-oscillatory cross terms, and a time smooth function $g_1(t)$ which acts as a low pass filter to eliminate cross-terms with time oscillatory components. The separable kernel parameters have to be defined to maximize the auto-terms, minimize smearing, and attenuate the cross terms [32]. The extended modified B-distribution (EMBD) is uses the MBD kernel in both lag independent kernel and Doppler-independent kernel. EMBD is a separable kernel TFD [18]. The Doppler-lag kernel for EMBD is given by

$$g(\upsilon,\tau) = G_1(\upsilon) g_2(\tau) = \frac{\int_{-\infty}^{+\infty} \cosh^{-2\beta}(t) \exp(j2\pi\upsilon t) dt}{\int_{-\infty}^{+\infty} \cosh^{-2\beta}(t) dt} \cosh^{-2\alpha}(\tau) \qquad (8)$$

where α and β are positive and real parameters that are adjusted to preserve the auto terms and attenuates the cross terms.

The quadratic time-frequency distribution of the EMBD can be described as [35]

$$\rho_z(t,f) = \int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} g(v,\tau) * A_z(v,\tau) g_2(\tau) \exp - j2\pi(vt - f\tau) dv d\tau \qquad (9)$$

In a non-cooperative environment, where the signal parameters are unknown, adaptive methods have to be used to estimate the kernel parameters. The adaptive smooth-windowed Wigner-Ville distribution (adaptive SWWVD) derived from (7) features adaptive procedures to estimate time-smooth function $g_1(t)$ and lag window $g_2(\tau)$. The time-smooth function is estimated from the signal duration estimated from the power spectrum of the signal while the lag window is estimated from the smoothed magnitude autocorrelation of the signal. Both adaptive SWWVD and EMBD are used as the TFDs and the paper focuses on the estimation of FHSS signal parameters from the resulting TFDs.

4. Hopping parameters estimation

Once the TFD of the signal is obtained, the next step is to estimate the FHSS signal parameters: hopping frequencies, hopping duration and hopping sequence. Two different approaches for FHSS signal parameters estimation are presented which are the time-frequency (TF) moments method [22], and the IF estimation method.

4.1 TF Moments method

The first method presented is the TF moments method that involves the computation of the first frequency moment which represents the mean frequency and the second frequency moment about the mean which provides the variance at a given time instant. Instead of the reassigned QTFD used in [22], both the adaptive SWWVD and EMBD are used to obtain the TFDs. The resulting TFDs produced are more accurate and have less cross terms present in the frequency transitions of the TF plane. The work presented in [21] first applied the FFT to the maxima of the SWVD to find hopping duration. Next, the hopping frequencies are estimated by summing up the SWVD within a hopping duration for all frequencies and then finding the maximum value which produces the hop frequency. Further improvement was proposed in [22] for FHSS signal parameters estimation. It uses the first and the second moment around mean frequency to measure hopping sequence and hopping duration, respectively.

The TF moment method is clarified further in this section. The hopping frequencies are estimated from the peaks of the energy spectrum (E_z) which is obtained from the frequency marginal [33] that is expressed as

$$E_z(f) = \int_{t=0}^{T} \rho_z(t,f)\,dt = \left|Z(f)\right|^2 \tag{10}$$

From the energy spectrum, the hopping frequencies are estimated as

$$\hat{f}_h = \arg\left\{\max_f \left[E_z(f)\right]\right\} \qquad 1 \le h \le M_h \tag{11}$$

where M_h is the number of hopping frequencies which is assumed to be known, $M_h = 4$ for 4FHSS and $M_h = 8$ for 8FHSS.

The second stage is to find the hopping sequence and the following steps are applied:

The first TF moment which is also shown to be the IF [14] is expressed as

$$f_i(t) = \frac{\int_0^T f\,\rho_z(t,f)\,df}{\int_0^T \rho_z(t,f)\,df} \tag{12}$$

Next, the second TF moment about the mean that is also the frequency variance [14] is defined as

$$\sigma_f^2(t) = \frac{\int_0^T f^2 \rho_z(t,f)\,df}{\int_0^T \rho_z(t,f)\,df} - f_i^2(t) \tag{13}$$

Taking the square root of the frequency variance $\sigma_f(t)$ results in the effective bandwidth [33]. The value of $\sigma_f^2(t)$ is maximized when the hopping frequency changes its values at the transition time instant. The effective bandwidth at the transition time instant represents the frequency distance between the current and following hop. Thus, the hopping instant $\hat{t}_{h,k}$ at which the frequency transition occurs is

$$\hat{t}_{h,k} = \arg\left\{\max_t \left[\sigma_f^2(t)\right]\right\} \qquad 0 \le k \le N_h - 1 \tag{14}$$

where the value of hopping instant can range $0 \le k \le N_h - 1$ and N_h is the total number of hops within the signal interval T.

The hopping duration $\hat{T}_{h,k}$ for a given instant k can be estimated by finding the time difference between hopping instants $\hat{t}_{h,k}$ along signal duration T as follows

$$\hat{T}_{h,k} = \hat{t}_{h,k} - \hat{t}_{h,k-1} \qquad 0 \le k \le N_h - 1 \tag{15}$$

The averaging of $\hat{T}_{h,k}$ for all hops N_h results in the estimate of the hopping duration

$$\hat{T}_h = \frac{1}{N_h} \sum_{k=0}^{N_h - 1} \hat{T}_{h,k} \tag{16}$$

Once the hopping frequencies $\hat{f}_h$ and the hopping durations $\hat{T}_{h,k}$ are estimated from (11) and (14) respectively, the hopping sequence can be estimated from the following steps. First, the average value of $f_i(t)$ is calculated within the hopping duration T_h using

$$f_{avg,k} = \frac{1}{\hat{T}_{h,k}} \int_{t=\hat{t}_{h,k-1}}^{\hat{t}_{h,k}} f_i(t)dt \tag{17}$$

The absolute difference between $f_{avg,k}$ and the hopping frequencies set $\hat{f}_h$ is

$$D_{h,k} = \left| f_{avg,k} - \hat{f}_h \right| \tag{18}$$

For a 4FHSS signal, $\hat{f}_h$ is a set of four estimated frequencies. Thus, there are four different values of $D_{h,k}$ for a hop instant k. The hopping frequency $\hat{f}_{h,k}$ is selected for a k-th hop instant is based on the minimum difference of the set $D_{h,k}$ as

$$\hat{f}_{h,k} = \arg\min_{k}(D_{h,k}) \tag{19}$$

The process is repeated for all values of k until all $\hat{f}_{h,k}$ are estimated which represents the hopping sequence.

4.2 IF estimation method

The use of IF estimation is to characterize time-varying signals and estimate the signal parameters [14]. Extending its use for FHSS signals, the IF estimation from the peaks of the TFD is

$$\hat{f}_i(t) = \arg\left\{\max_f \left[\rho_z(t,f)\right]\right\} \quad 0 \le t \le T \tag{20}$$

The IF obtained from (20) is shown to provide accurate results in previous works such as [34]. Unlike the TF moment method, the IF estimation method utilizes the IF to estimate the hopping frequencies. From the IF estimation, a histogram (hist) of the estimated IF is constructed. The histogram provides the number of occurrences of the IF.

From the histogram the IF, the hopping frequencies are estimated as follows

$$\hat{f}_h = \arg\left\{\max_f \left[\text{hist}(\hat{f}_i)\right]\right\} \qquad 1 \le h \le M_h \tag{21}$$

Once the hopping frequencies are determined, the second step is to find the hopping duration from the derivative of the IF estimation

$$\frac{df_i(t)}{dt} \simeq \left|f_i(t) - f_i(t+\Delta t)\right| \qquad 0 \le t \le T \tag{22}$$

where Δt is the time difference between two consecutive IF estimations.

The IF of the FHSS signal changes instantly at every hopping interval. Consequently, the derivative of the IF at the time instant where the transition occurs is maximum (23). The maximum value represents the IF difference between the current hopping frequency and the subsequent hopping frequency which is expressed as

$$\hat{t}_{h,k} = \arg\left\{\max_t \left[\frac{df_i(t)}{dt}\right]\right\} \qquad 0 \le k \le N_h - 1 \tag{23}$$

Hence, the peaks are spaced at hop intervals. By detecting the peaks from (23) and finding the distance between them as in (15), the hopping duration can be estimated by applying (16). Instead of using the TF moments, the hopping sequence is estimated based on the IF estimation. The average value of the IF estimation measured for every *k*-th hop is

$$f_{IF,avg,k} = \frac{1}{\hat{T}_{h,k}} \int_{t=\hat{t}_{h,k-1}}^{\hat{t}_{h,k}} \hat{f}_i(t)dt \tag{24}$$

The absolute difference between $f_{IF,avg,k}$ and the hopping frequencies set $\hat{f}_h$ based on (25) is

$$D_{h,k} = \left| f_{IFavg,k} - \hat{f}_h \right| \tag{25}$$

The hopping sequence can be derived by substituting the absolute difference into (19).

4.3 Performance evaluation and CRLBs

The performance of the suggested algorithm is evaluated based on the variance of the parameters measured. The variance of the frequency hopping estimation is measured as

$$\mathrm{Var}(\hat{f}_i) = \frac{1}{T_h} \int_{t=0}^{T_h} (\hat{f}_i(t) - f_i(t))^2 dt \tag{26}$$

where $\hat{f}_i$ is the estimated hopping frequency at every hopping duration T_h and f_i is the transmitted FHSS signal hopping frequency. Once the hopping frequency variance is obtained, the results are compared with CRLB for frequency estimation. The CRLB for frequency estimation is given in In this paper, the FHSS signal, if observed within a hopping duration can be viewed as a sinusoid signal. Therefore, the CRLB for FHSS signals where the IF is estimated from the peak of the TFD can be defined as [35]

$$\mathrm{Var}(\hat{f}_i) \geq \frac{12}{(2\pi)^2 T_h (T_h^{\ 2} - 1)\mathrm{SNR}} \tag{27}$$

where SNR is the ratio of signal power to the noise power.

The variance of hopping duration is measured based on the distance between peaks of the second moments and the derivative of IF and the results are calculated as

$$\mathrm{Var}(\hat{T}_h) = \frac{1}{N_h} \sum_{k=0}^{N_h - 1} (\hat{T}_h(k) - T_h)^2 \tag{28}$$

where N_h is the number of hops for the FHSS signal, T_h is the transmitted hopping duration which is assumed to be known and $\hat{T}_h$ is the estimated hopping duration for each hop *k*. The results are benchmarked by the CRLB for timing estimation as shown in [36]

$$\mathrm{Var}(\hat{T}_h) \geq \frac{3}{8\pi^2} \frac{1 + 2\mathrm{SNR}}{\mathrm{SNR}^2} \frac{1}{B_w T_h} \tag{29}$$

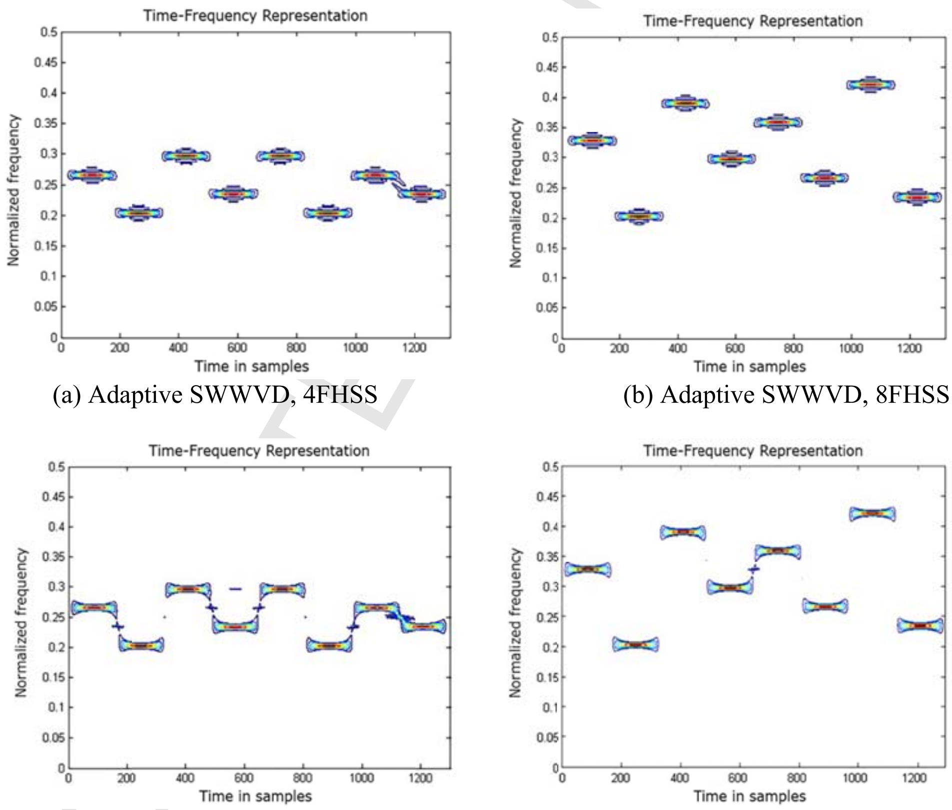
where B_w is the normalized bandwidth of a single hop.

5. Results

In this section, the TFDs using the adaptive SWWVD and EMBD are shown followed by the parameters estimation using the TF moments and the IF estimation method and lastly the computational complexity.

5.1 TFD results

In order to justify the hopping parameters estimation methods, a thorough comparison is made on the accuracy of TFD of the signal using the QTFD method described in Section 3. Figure 1 shows the TFD plots for 4FHSS and 8FHSS signals using the adaptive SWWVD and EMBD as defined in (7) and (8). The TFDs represents at which frequency and time instant the signal exists. Red colours indicate frequency content with higher power while blue colours indicate frequency content with very low power. By comparing adaptive SWWVD and EMBD, it can be seen that EMBD shows a higher level of cross terms at hop transition instant which in this example happens every 160th time sample. However, the results show a low level of cross terms compared to reassigned WVD [22] and higher time and frequency resolution compared to STFT and S-transform [28, 37].



(a) Adaptive SWWVD, 4FHSS (b) Adaptive SWWVD, 8FHSS

(c) EMBD, 4FHSS (d) EMBD, 8FHSS

Figure 1 The TFD for 4FHSS and 8FHSS signals

5.2 FHSS signal parameters estimation

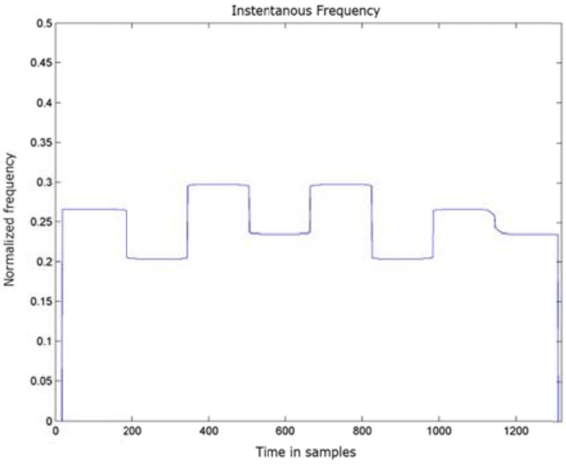
Further analysis on the TFDs should be performed to estimate FHSS signal hopping frequencies, hopping duration and hopping sequence. The analysis allows converting the TFDs to a simpler form and then extracts the FHSS signals parameters. In this section, the results of both the TF moments and the proposed IF estimation methods are discussed.

5.2.1 IF estimation

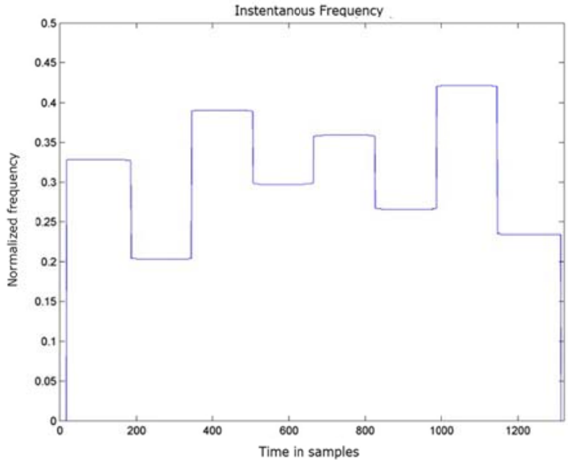
To obtain the IF from the TFDs, (12) and (20) are applied for TF moments and IF estimations methods, respectively. Figures 2 (a, b) show clearer IF estimations for adaptive SWWVD compared to Figures 2 (c, d) which show that the IFs for EMBD are less accurate especially at hop transitions . Therefore, the performance of EMBD will be negatively affected when hopping duration and hopping sequence are estimated. TF first moment results are shown in Figure 3 and the results look similar to IF estimation method.

5.2.2 Hopping frequencies estimation

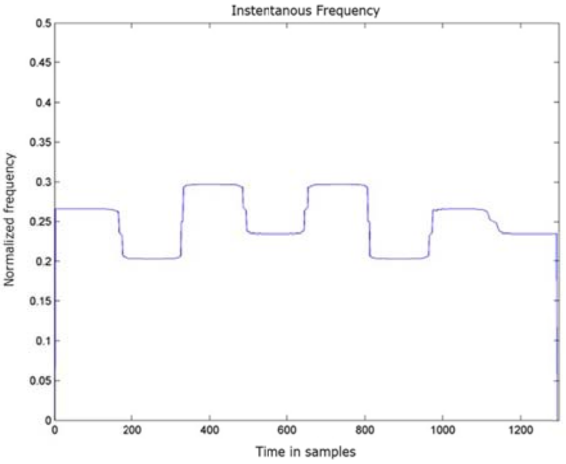
To estimate the hopping frequencies using TF moments method, the energy spectrum is calculated of the frequency marginal of the TFD (10). Figure 4 shows the energy spectrum based on TF moments method where the hopping frequencies are estimated from the peaks as defined in (11). It can be seen that the peaks occur at values close to the actual 4FHSS and 8FHSS signal frequencies defined in Table 1.



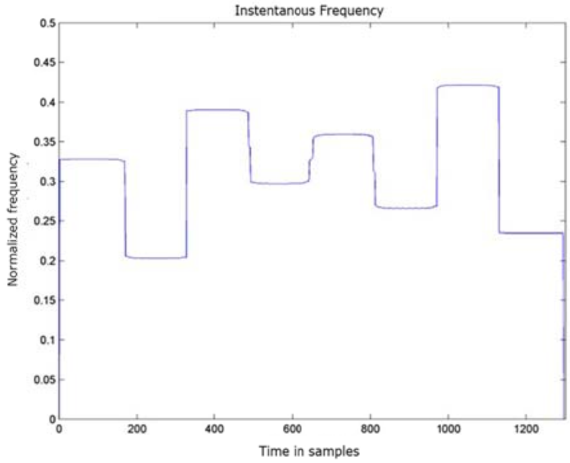
(a) Adaptive SWWVD, 4FHSS



(b) Adaptive SWWVD, 8FHSS

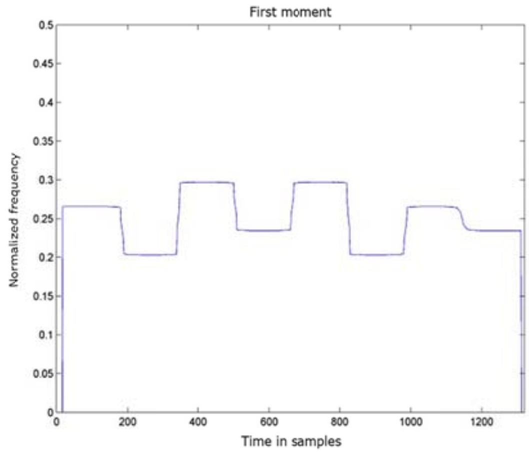


(c) EMBD, 4FHSS

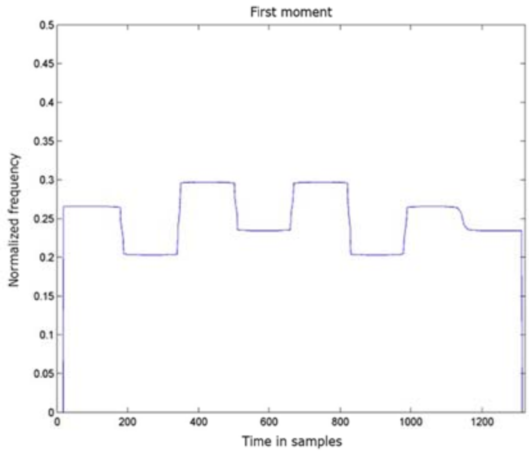


(d) EMBD, 8FHSS

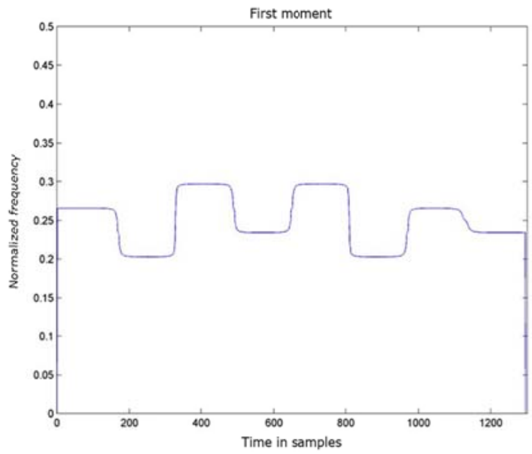
Figure 2 **IF estimation method:** IF estimation from the peaks of TFD.



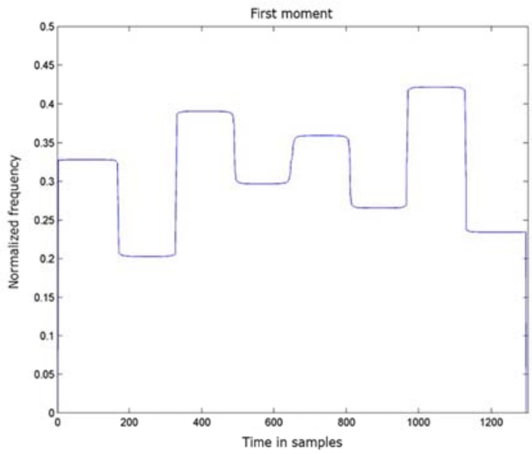
(a) Adaptive SWWVD, 4FHSS



(b) Adaptive SWWVD, 8FHSS



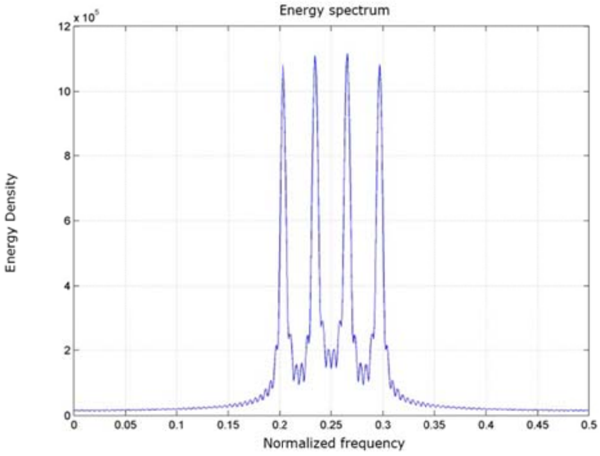
(c) EMBD, 4FHSS



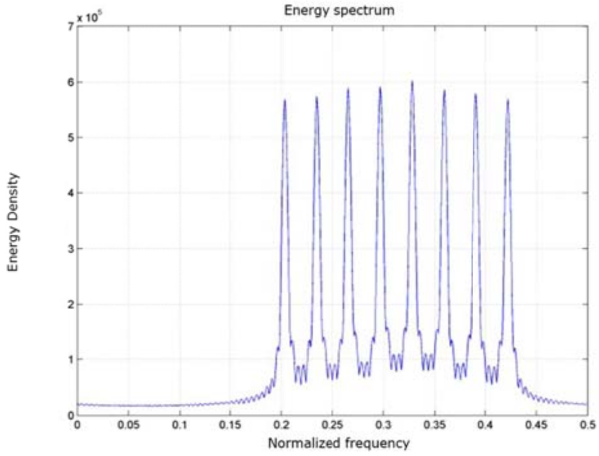
(d) EMBD, 8FHSS

Figure 3 **TF moments method:** IF derived from the first moment of the TFD.

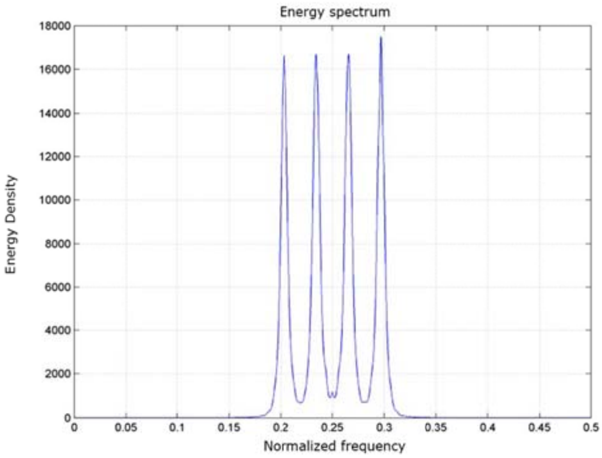
To estimate the hopping frequencies from the IF estimation method, the histogram of the IF derived from the peaks of the TFDs is constructed as shown in Figure 5. The whole range of normalized frequency is divided into N_{bins}. Figure 5 (a, b) represents 4FHSS signal where 4 different peaks can be seen and 8 peaks for the 8FHSS signal as shown in Figure 5 (c, d). The results observed in Figure 5 shows that the peaks of the histograms (21) accurately represent the actual signal frequencies. The estimated frequencies are considered as the hopping frequencies.



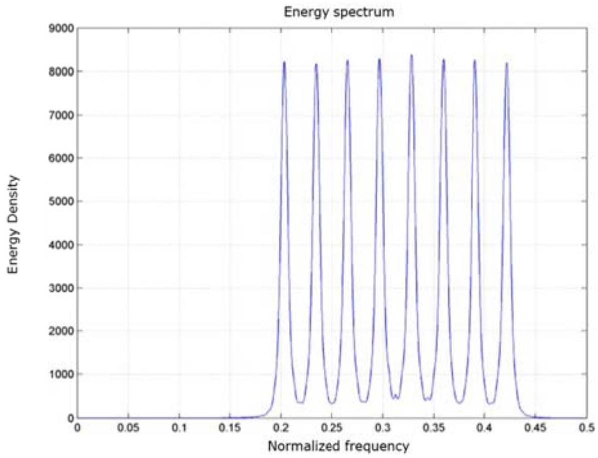
(a) Adaptive SWWVD, 4FHSS



(b) Adaptive SWWVD, 8FHSS

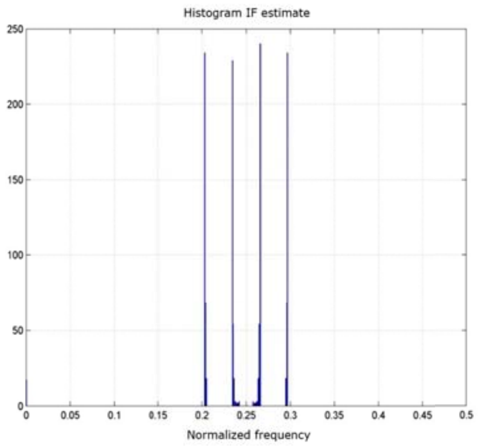


(c) EMBD, 4FHSS

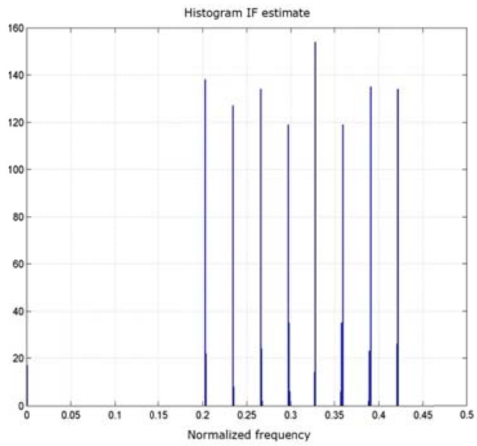


(d) EMBD, 8FHSS

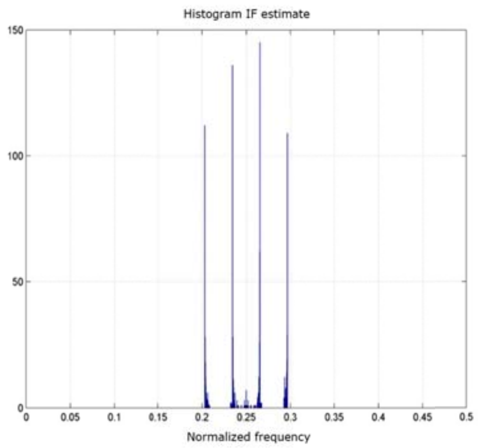
Figure 4 **TF moments method:** Energy spectrum of the 4FHSS and 8FHSS signals. The peaks of the energy spectrum represent the hopping frequencies.



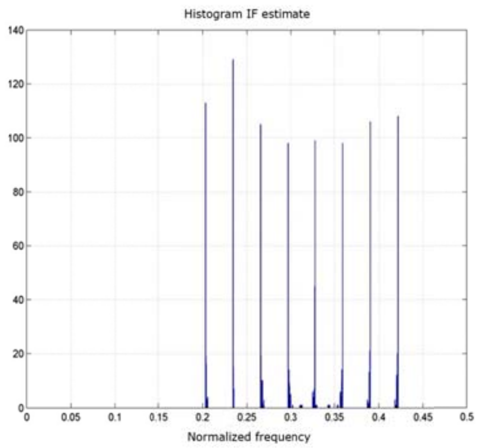
(a) Adaptive SWWVD, 4FHSS



(b) Adaptive SWWVD, 8FHSS



(c) EMBD, 4FHSS

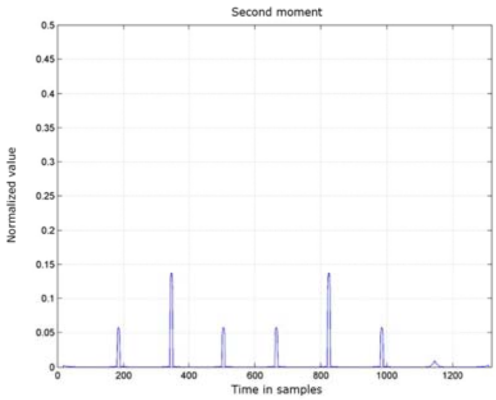


(d) EMBD, 8FHSS

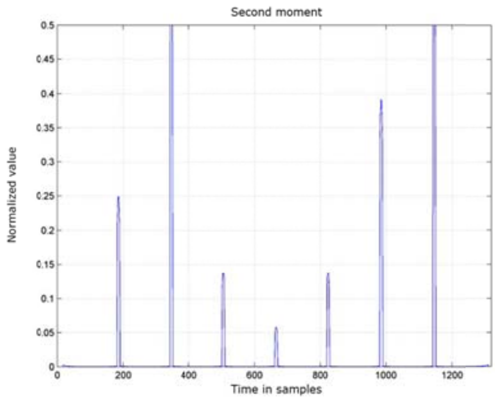
Figure 5 **IF estimation method:** Histogram of frequencies derived from the IF. Similar to the results in Figure 4, the peaks derived from the histogram correspond to the hopping frequencies

5.2.3 Hopping duration estimation

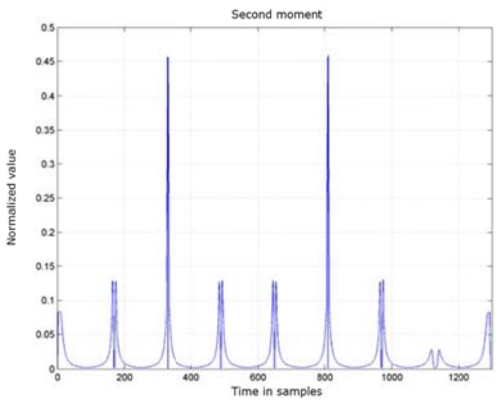
To estimate the hopping duration from the TF moments method, the second moment is calculated from (13) and the results are shown in Figure 6. It can be seen that the peaks occur at transition instants as shown in (14) and the spacing between the peaks indicates the hopping duration based on (15) which is close to the actual value defined in Table 1. However, Figure 6 (a, b) shows a better representation of the second moment in terms of peaks compared to Figure 6 (c, d) which shows multiple peaks at sample 840 which degrades the hopping duration estimation.



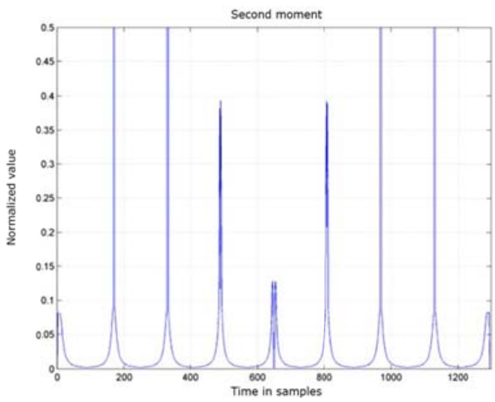
(a) Adaptive SWWVD, 4FHSS



(b) Adaptive SWWVD, 8FHSS



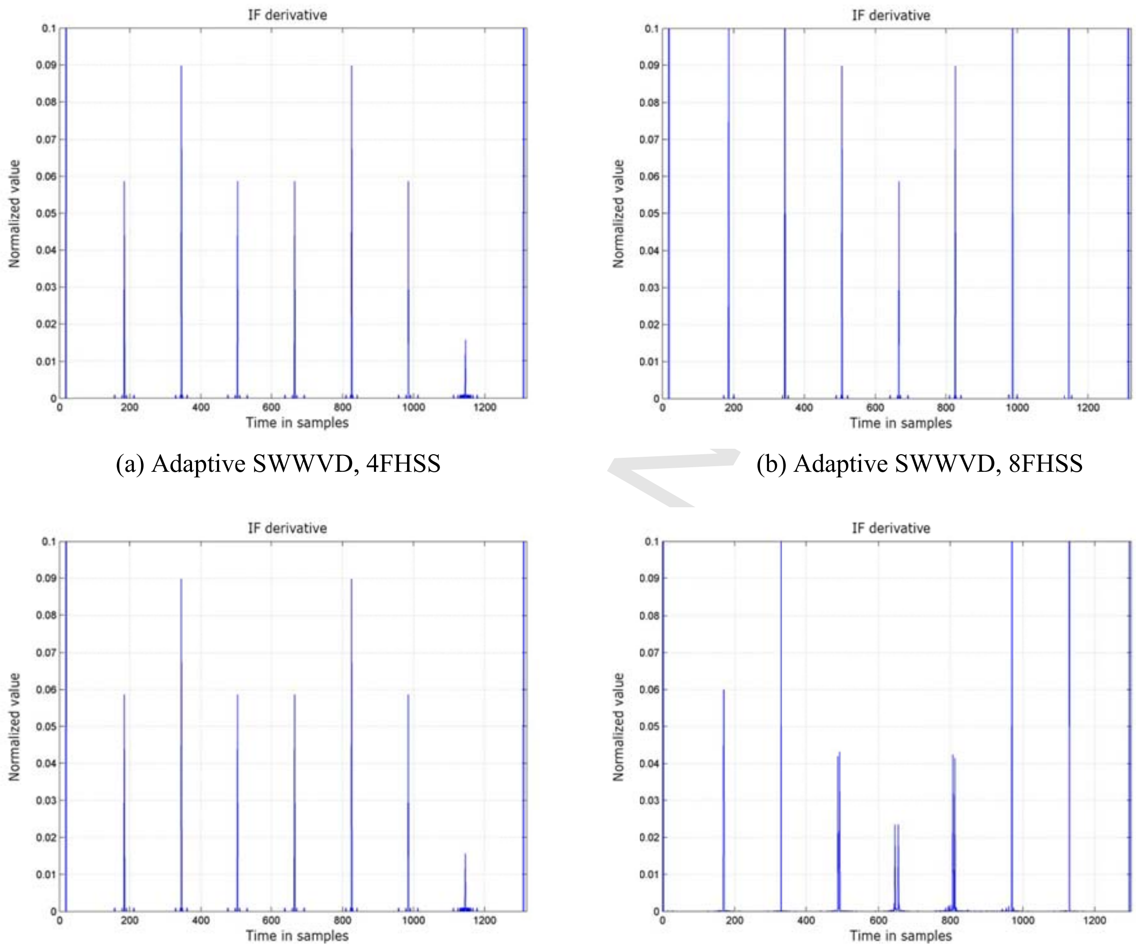
(c) EMBD, 4FHSS



(d) EMBD, 8FHSS

Figure 6 **TF moments method**: TF second moment derived from the TFD. The distance between the peaks represent the hopping durations.

For the IF estimation method, the IF derivative is calculated using (22). Unlike the second moment in Figure 6, the results shown in Figure 7 provide more precise representation of peaks in the IF derivative. The narrower peaks in the IF derivative improves the hopping duration estimation. However, the hopping duration estimation is better for the adaptive SWWVD compared to EMBD. In general, the estimated hopping duration is close to the actual for both the 4FHSS and 8FHSS signals as defined in Table 1.



(a) Adaptive SWWVD, 4FHSS

(b) Adaptive SWWVD, 8FHSS

(c) EMBD, 4FHSS

(d) EMBD, 8FHSS

Figure 7 **IF estimation method:** IF derivative. The intervals between the peaks represent the hopping durations.

5.3 FHSS parameters estimation Monte Carlo results comparison

In order to evaluate and compare the performance of each method, Monte Carlo simulations are performed. The SNR covers the range from -4 dB to 12 dB. For each SNR value, 300 different noise realizations are considered to find the mean-squared error (MSE) and the frequency sequence was changed randomly. The estimation variance of the hopping parameters is measured. The results are represented as the MSE. As shown in Figure 8, the numerical results indicate that the IF estimation method based on the adaptive SWWVD meets the CRLB and provides MSE of 60 dB for the hopping frequency estimation at SNR as low as -3 dB. On the other hand, the TF moments method based on the adaptive SWWVD could not hold a good performance at SNR above 1 dB and the MSE continues to derive away from the CRLB. However, at SNR above 0 dB, the IF estimation method based on the EMBD provides a performance close to the CRLB and the MSE continues to increase at higher SNRs at a difference of less than 5 dB. Finally, the worst performance is provided by the TF moments methods based on the EMBD where the MSE remains low at all SNRs.

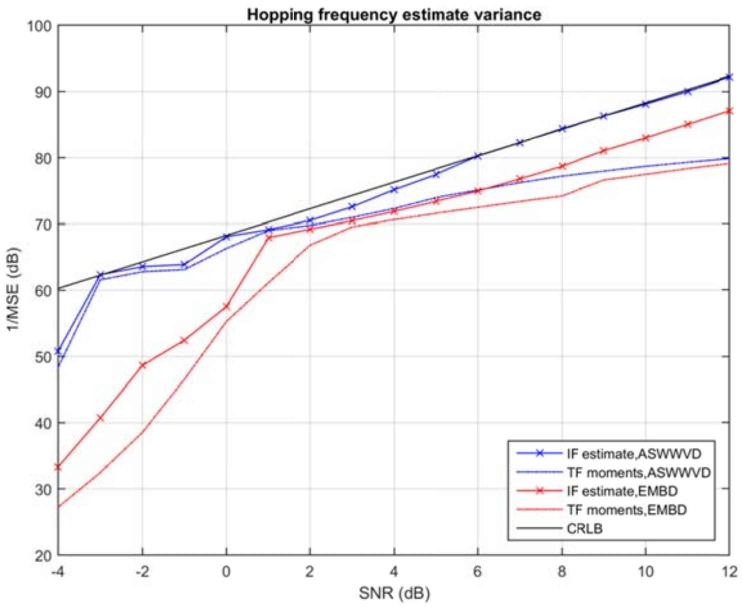


Figure 8 Hopping frequency estimate variance in comparison with the CRLB. IF estimation method derived from Adaptive SWWVD approaches CRLB at -3 dB

The results in Figure 9 show the MSE of the hopping duration estimation for the TF moments method and IF estimation method. The IF estimation method based on the adaptive SWWVD gives the best performance compared to the other methods by complying with the CRLB for hopping duration estimation at

SNR of 0 dB. The performances of the IF estimation method for both EMBD and adaptive SWWVD become similar at SNR greater than 8 dB. For the IF estimation method with EMBD, the MSE for hopping duration estimation remains less than the CRLB for SNR above 2 dB. For the TF moments method, the MSE for both adaptive SWWVD and EMBD are significantly less than the IF estimation method at SNR of above 4 dB. In general, the MSE for hopping duration estimate above SNR of 0 dB is proportional to the SNR.

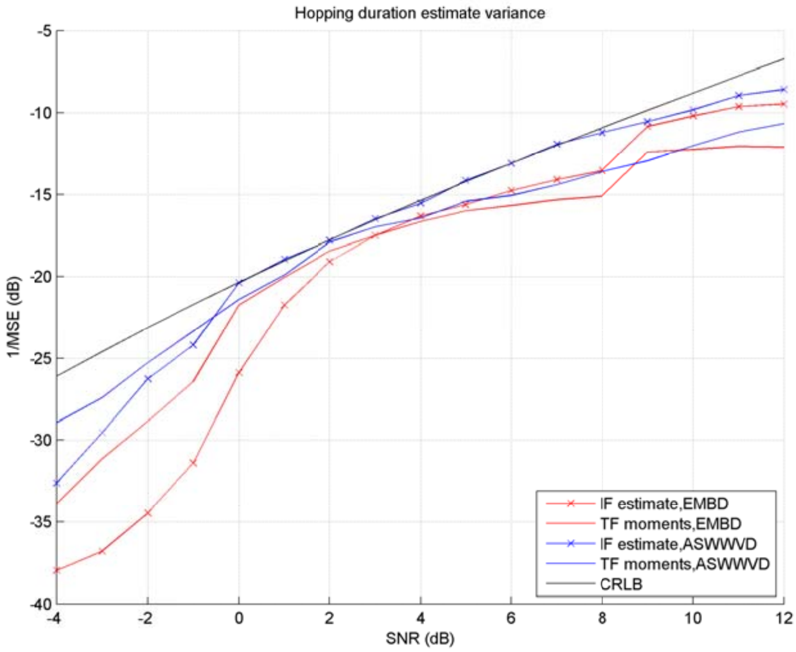


Figure 9 Hopping duration estimate variance in comparison with the CRLB. IF estimation method derived from adaptive SWWVD approaches CRLB at 0 dB.

5.4 Computational Complexity

Since the work can be implemented in an embedded system, the time and frequency domains are discretized and it is important to discuss the computational complexity (CC). The CC of this work can be addressed as two parts: the first part is on the discrete time-frequency distributions (DTFDs) while the second part is on the estimation of the FHSS signal parameters.

The total number of multiplication required to compute optimal SWWVD [20] is $(2N_\tau + N_{sm}N_\tau+0.5N_{2\tau}\log_2 N_{2\tau})N$ which requires a prior knowledge of signal parameter, where N is the signal length, N_τ is the window length, N_{sm} is the length of smoothing function, and $N_{2\tau}$ is the length that is multiple of 2 and is greater or equal to N_τ. However, the computation of adaptive SWWVD [20] has an additional complexity equals to $N_\tau[12N_r(4N_r+5)+0.5N_{2\tau}\log_2 N_{2\tau})]$ with the assumption of no prior knowledge of the signal, N_r is the length of window function used in the weight function. On the other hand, EMBD is a separable kernel distribution and the CC is $cP_hN\log_2 N+cP_hN_{th}\log_2 N_{th}+cN_{th}N_{freq}\log_2 N_{freq}$ as shown in [38] , where P is half the lag function $g_2[m]$ length, P_h is half P, N is half the signal length, N_{time} and N_{freq} are the dimensions of DTFD, N_{th} is half N_{time}.

The second part is related to FHSS parameters estimation methods. To estimate hopping frequencies using the TF moments method, it requires to compute the frequency marginal which takes a complexity of N_tN_f summation. Then the peaks detection algorithm is applied, which has a complexity of kN_t. [39], where k is the total number of peaks. The hopping duration estimation algorithm consists of three stages: first moment calculation which has a complexity of $2N_tN_f+N_t$ from (10), the second stage is to calculate second moment which takes a complexity of $2N_tN_f$ from (11), and followed by peaks detection algorithm as discussed above. To find the hopping frequencies in the IF estimation method, the IF is first estimated from (16) with complexity of N_tN_f. Then the construction of the histogram of IF has a complexity of N_t+N_{bins} where N_{bins} is the number of histogram bins [39]. The peaks detection algorithm complexity is kN_t. For hopping duration estimation, three additional steps are required which is the IF estimation that was previously calculated, followed by the IF derivative with N_t complexity and the peaks detection as previously described. Table 2 shows the CC of both the TFDs and the parameters estimation methods. Although the adaptive SWWVD has a higher complexity compared to EMBD, it provides a better performance and the kernel parameters of the adaptive SWWVD are calculated automatically. On the contrary, the finding of the optimal kernel parameters for the EMBD has to be done manually based on several trials to obtain the best results for the FHSS signal of interest. Between the two methods, the CC of the IF estimation method is reduced by around a factor of five compared to the TF moments method.

Table 2 Computational Complexity

Element	Adaptive SWWVD	EMBD	TF moments	IF estimation
Computational Complexity	$(2N_\tau+N_{sm}N_\tau+0.5N_{2\tau}\log_2 N_{2\tau})N+N_\tau[12N_r(4N_r+5)+0.5N_{2\tau}\log_2 N_{2\tau})]$	$cP_hN\log_2 N+cP_hN_{th}\log_2 N_{th}+cN_{th}N_{freq}\log_2 N_{freq}$	$N_t(5N_f+k+1)$	$N_t[N_f+2(k+1)]+N_{bins}$
Parameter Definition	$N=1024$ $N\tau=512$ $N_{2\tau}=512$ $N_r=75$ $N_{sm}=160$	$N=1024$ $N_{th}=256$ $P=512$ $P_h=P/2$ $N_{freq}=512$ $c=0.5$	$N_f=N_t=1024$ $K=7$	$N_f=N_t=1024$ $K=7$ $N_{bins}=512$
Computational Complexity	2.29×10^8	3.01×10^6	5.25×10^6	1.06×10^6

6. Conclusion

A robust adaptive method was introduced to estimate FHSS signal parameters such as hopping frequencies and hopping duration from the TFDs. Two different QTFDs were presented which are known as the adaptive SWWVD and EMBD. Both QTFDs showed a low cross terms compared to the previous work. Although, the adaptive SWWVD has a higher complexity compared to EMBD, it provides a better signal presentation without a prior knowledge of the FHSS signal parameters. Moreover, the complexity of the IF estimation method to estimate the signal parameters is lower by 5 times compared to the TF moments which reduces the FFHSS parameters estimation complexity. The simulation results show that the adaptive SWWVD with the IF estimation method can accurately estimate the FHSS parameters in a non-cooperative environment and meets the CRLB at SNRs as low as -3 dB and 0 dB for the hopping frequency and hopping duration estimate respectively.

7. Acknowledgment

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Abdulrahman Kanaa He obtained his B. Sc. in Electrical Engineering from the University of Aleppo, Syria in 2008, and received the Best Student Award in M. Eng. Electrical Engineering in 2012 from UTM, Malaysia. At present, he is pursuing his PhD in Electrical Engineering, UTM, Malaysia. His research interests include digital communications, signal analysis, cognitive radios and underwater signal processing.

Ahmad Zuri bin Sha'ameri He obtained his B. Sc. in Electrical Engineering from the University of Missouri-Columbia, USA in 1984, and M. Eng. Electrical Engineering and PhD both from UTM, Malaysia in 1991 and 2000 respectively. At present, he is the Head of the Microelectronic and Computer Engineering Dept and Head of the DSP Lab, Faculty of Electrical Engineering, UTM. His research interests include signal theory, digital communication over HF channels, machine condition monitoring, signal analysis and classification and information security. The subjects taught at both undergraduate and postgraduate levels include digital signal processing, advance digital signal processing, and advance digital communications. He has also conducted short courses for both government and private sectors. At present, he has published more than 90 papers in his areas of interest at both national and international levels in conferences and journals.