Detection and Estimation of Frequency Hopping Signals Using Wavelet Transform

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***Abstract*—For receiving frequency hopped spread spectrum signals, one needs to first detect the presence of signal in wideband environment and then estimate the hop parameters such as hop time and hop frequency. In this paper we investigate the application of wavelets for the detection and estimation of frequency hopping signals. For detection we propose a method using discrete stationery wavelet filter banks. We compare our results with a method using polyphase filter using Fast Fourier Transform and energy detector. For estimation, we make use of discrete stationery wavelet transform for finding the hopping time by extracting the features from an image obtained from the phase information extracted from the received signal. We present simulation results in additive white Gaussian noise channels that show good detection and estimation at low SNRs.**

I. Introduction

Frequency hopping spread spectrum (FHSS) is a popular communication technique used in military radio communications. To design cognitive radio for military applications, one needs efficient algorithm for detection and estimation of frequency hopping signals.

In this paper, we use discrete stationary wavelet methods for the detection and estimation of frequency hopping signals. Discrete wavelet transform (DWT) provides sufficient information both for analysis and synthesis of the original signal, with a significant reduction in computation time. Also DWT captures different frequency information hidden inside the signal by analyzing it at different scales, which acts like different filters for a signal [1]. The signal is passed through a series of high pass filters to analyze the high frequencies and through low pass filters for analyzing low pass frequencies.

For the reception of frequency hopping signal, first we need to detect it. We propose a new method using stationary wavelet filter banks, which shows better detection performance than method using the polyphase filter banks and Fast Fourier transform (FFT) [2]. Estimation of frequency hopping signals requires calculation of time of hop and frequency of hopping. Time hop estimation problem can be viewed as an edge detection problem [3]. Wavelet transform has been widely used in image processing for feature extraction [4]. For the estimation of frequency hopping signal we first extract the phase information from the temporal correlation function (TCF) of received signal. Then, by using denoising techniques, we apply the discrete stationary wavelet transform for feature extraction, which gives us the time of hopping.

For estimation and detection of frequency hopped signal, various methods have been proposed in the literature [5], [6], [7]. These approaches include energy detector, single channel FFT, polyphase filter bank, maximum likelihood approach etc. and their variants by using windowing functions and frequency smoothing. A comparison of these techniques is done in a paper by William J. L. Read in [8]. Maximum likelihood detection shows the best performance but it may not be practical to implement it, as it requires knowledge of the modulation type. Single channel FFT does not provide good detection performance and has poor sidelobe suppression. Energy detector does not have good performance in negative SNR region. Filter banks are widely used to detect signals having frequency content in a wide range. Detection through polyphase filter banks using FFT was proposed in [2].

Estimation of various frequency hopped signal parameters e.g. time of hop, frequency of hop, must be determined for complete reception of the signal. Various methods have been adopted for the estimation of these parameters, both for coherent and non-coherent case. Wavelet transform has been widely used in image processing for feature extraction [9], [10], [4]. In [2], [3], authors have used redundant discrete wavelet transform for extraction of time of hop in a frame of a frequency hopped signal. Our method is based on non-coherent detection of frequency hopped signal using redundant discrete wavelet transform and 2-D Gaussian filters for denoising.

This paper is organized as follows. In section II, the signal model and some of its parameters are discussed. In section III, detection of frequency hopping signal using discrete wavelet filter bank is given. In section IV, an algorithm to detect the hopping time of frequency hopping signal is proposed. In section V, some simulation results for additive white Gaussian noise channel is presented, and finally, we conclude in section IV.

II. Signal Model

The frequency hopping signal is modeled as follows:

$$x(t) = A \sum_{k} rect_{T_h}(t - kT_h - \theta) e^{j2\pi f_k (t - kT_h - \theta)} + w(t) \quad (1)$$

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with $0 < t < T$, where

$$rect_{T_h}(t) = \begin{cases} 1 & t \in (-T_h/2, T_h/2) \\ 0 & \text{elsewhere} \end{cases}$$

f_k is the hop frequency, belonging to a given finite alphabet $f_1, f_2, ..., f_N$, T_h is the duration of each hop, and $w(t)$ is additive white Gaussian noise.

We have considered that the frequency range is fixed from 1 MHz to 24 MHz for our setup, and minimum hopping time, T_{hop_min} is chosen to be equal to 256 sample points. At a sampling rate of 50 MHz, this translates into a minimum hopping time of 5.12 μs. The minimum frequency differential, Δf, for frequency hops was chosen to be 1KHz. These parameters are same as in [2] and [3].

III. Detection of Frequency Hopping Signal Using Stationary Wavelet Filter Bank

We use stationary wavelet filter banks for the detection of frequency hopping signals [11]. An overview on wavelet filter bank is given in [13] [12]. Classical DWT is not time-invariant transform. However, Stationary Wavelet Transform (SWT) overcomes the lack of translation-invariance of the DWT by removing the downsamplers and upsamplers in the DWT and upsampling the filter coefficients by a factor of 2^{j-1} in the j^{th} level of the algorithm [14]. The detection algorithm can be summarized as follows.

1) Two dimensional discrete stationary wavelet transform is applied to the received signal.
2) After wavelet processing, we get a transformed matrix. From this matrix, the maximum value is chosen as the test static Z_N for comparison with the threshold Z_T.
3) The threshold value is determined by processing a number of matrices created using R noise realizations for a given signal to noise ratio (SNR). These R noise realizations are set to achieve the desired probability of false alarm. The threshold value Z_T is chosen as the smallest of the 10 largest Z_N test statistics. The number of R realizations required is then given by

$$R = \frac{10}{P_{fa}} \quad (2)$$

where P_{fa} is the desired probability of false alarm, which is maintained constant as SNR is varied.
4) The R matrices are regenerated with the R noise realizations and signal of interest present. The Z test statistics from these signals are then compared with the threshold Z_T and probability of detection is given by P_d is

$$P_d = \frac{\sum(Z > Z_T)}{R} \quad (3)$$

In Fig. 1 we compare the performance of redundant discrete wavelet filter bank with energy detector and polyphase filter bank using FFT. It is clearly shown that discrete wavelet filter bank provides the best performance among these three methods.

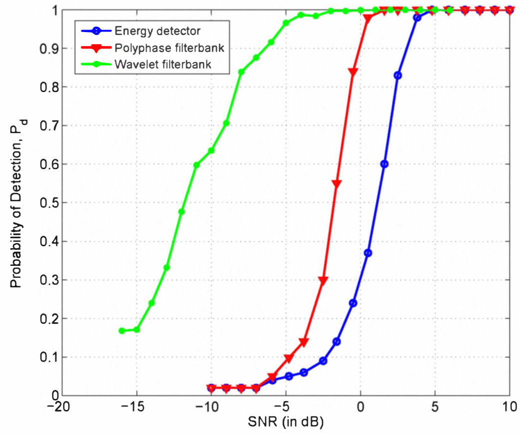

Fig. 1. Comparison of Wavelet filter bank based detection with polyphase filter bank using FFT and energy detector

IV. Estimation of Hop Time of Frequency Hopping Signal

We consider a method using discrete wavelet filter banks for estimation of hop time. The algorithm can be summarized as follows.

1) We take a real signal and transform it to an analytical signal. We consider the analytical frequency hopping signal $x(k)$ of the following form corresponding to two-hop frequency hopped system

$$\begin{aligned} x(k) \quad = \quad & e^{2\pi j f_1 k}\left[u(k) - u(k - T_{hop})\right] + \\ & e^{2\pi j f_2 k}\left[u(k - T_{hop} + 1) - u(k - T)\right] \end{aligned} \quad (4)$$

for $0 < k < T$, where T_{hop} is the time of hop (or change in frequency) from f_1 to f_2, and where $u(k)$ is the unit step function.
2) The data is partitioned into frames of duration equal to T_{hop_min} which in our case is chosen to be 256 sample points, so as to ensure that there is atmost one hop in a frame.
3) We calculate the *temporal correlation function* (TCF) of a signal $x(k)$ (for each frame), defined as:

$$TCF_x(k, \tau) = x(k + \tau)x^*(k - \tau), \quad (5)$$

where k is the absolute center time and τ is the lag time, expressed in number of samples.
The resulting TCF function is given by

$$\begin{aligned} & TCF(k,\tau) = e^{2\pi j(2f_1)\tau}\left[u(k+\tau) - u(k+\tau-T_{hop})\right] \\ & \left[u(k-\tau) - u(k-\tau-T_{hop})\right] + e^{2\pi j(2f_2)\tau} \\ & \left[u(k+\tau-T_{hop}+1) - u(k+\tau-T)\right] \\ & \left[u(k-\tau-T_{hop}+1) - u(k-\tau-T)\right] \\ & +e^{2\pi[(f_2-f_1)k+(f_1+f_2)\tau]}\left[u(k+\tau) - u(k+\tau-T_{hop})\right] \\ & \left[u(k-\tau-T_{hop}+1) - u(k-\tau-T)\right] + \\ & \left[u(k-\tau) - u(k-\tau-T_{hop})\right]\left[u(k+\tau-T_{hop}+1)\right. \end{aligned} \quad (6)$$

$$-u(k+\tau-T)]$$
$$= TCF_1(k,\tau)+TCF_2(k,\tau)+TCF_{12}(k,\tau)$$

where $TCF_1(k,\tau)$, $TCF_2(k,\tau)$, and $TCF_{12}(k,\tau)$ are respectively the first, second and third non-overlapping terms in the TCF expression. $TCF_1(k,\tau)$ depends on f_1 and τ, and $TCF_2(k,\tau)$ is a function of f_2 and τ. However, $TCF_{12}(k,\tau)$, is a function of both f_1 and f_2 and τ.

4) We plot the TCF phase plot and the unwrapped phase of the TCF function. Fig. 2 presents the phase plot of an analytical frequency hopping signal $x(k)$ for frequencies $f_1 = 6.25MHz$ and $f_2 = 22.5MHz$, hopping time $T_{hop} = 208$ (samples), and for positive τ values. The combinations of the different shifted versions of the unit step functions force the TCF to take on non-zero values only within the overall triangular regions as shown in Fig. 2.

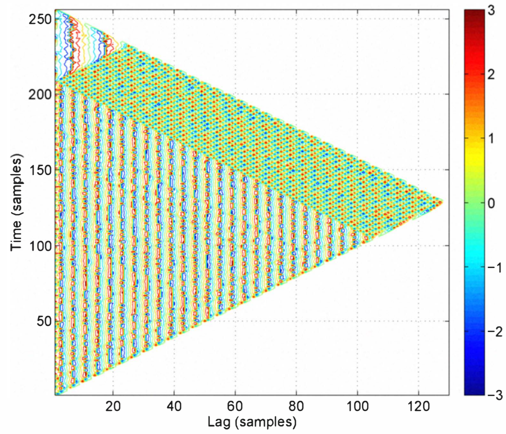

Fig. 2. Temporal Correlation Function of received frequency hopped signal

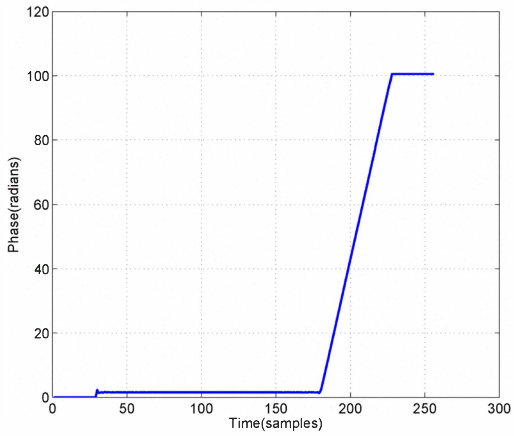

Fig. 3. unwrapped phase of the TCF function at $\tau = 30$

The frequency hopping time T_{hop} is located in the region where $TCF_1(k,\tau)$ ends and $TCF_2(k,\tau)$ begins. Also, we can note that for a given τ, the regions where $TCF_1(k,\tau)$ and $TCF_2(k,\tau)$ are defined are constant, while the phase behavior within the region where $TCF_{12}(k,\tau)$, is defined is linear. This fact is further illustrated in Fig. 3 where we plot the unwrapped phase of the TCF function for $\tau = 30$.

5) We apply a 2D Gaussian filter to the phase information of the TCF. The Gaussian smoothing operator is a 2D convolution operator that is used to remove noise. In 2D, a circularly symmetric Gaussian has the following form:

$$G(x,y) = \frac{1}{2\pi\sigma^2}e^{-\frac{x^2+y^2}{2\sigma^2}} \tag{7}$$

This algorithm differs from algorithm in [3] in this step.

6) After unwrapping phase information of TCF and smoothing it using Gaussian filtering, we take the derivative of phase angle at every lag τ. A Gaussian filtered signal at a value of $\tau = 30$ is shown in Fig. 4.

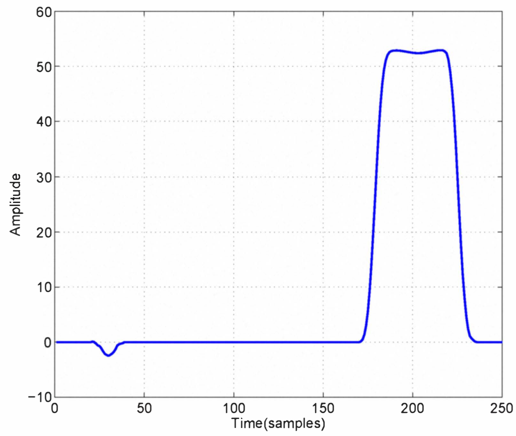

Fig. 4. Gaussian filtered signal at $\tau = 30$

7) Now, we finally take the RDWT at every value of τ using Haar wavelet [1]. The RDWT of filtered signal is shown in Fig, 5. The two dimensional RWT of the preprocessed TCF obtained at lag $\tau = 30$ using Haar wavelet is shown in Fig. 6.
8) Now, we perform a $45^0/135^0$ summation over the all the values of time lag τ. The resultant detection vector for SNR of 15 dB is shown in Fig. 7 whose peak gives us the information about the time of hopping of frequency hopping signal.
9) After forming the detection vector, we need to find out whether the hop has occurred in the frame or not. We use the variance of the detection vector as an indicator to determine whether a hop had occurred or not. The threshold, $T_{threshold}$ is chosen as a multiple, k, of the variance of the detection vector when no hop has occurred within the frame. The threshold determination is also guided by the fact that the cost associated with miss detection probability, P_m = [1 - probability of

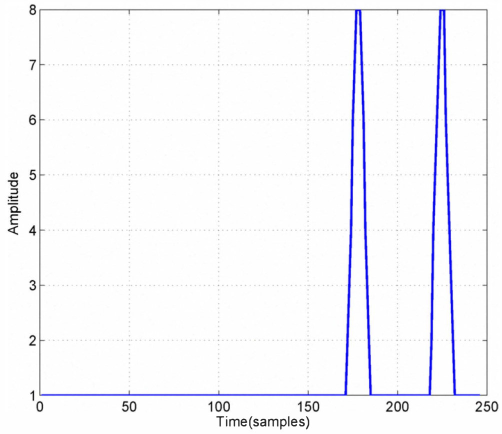

Fig. 5. RDWT of Gaussian filtered signal at $\tau = 30$

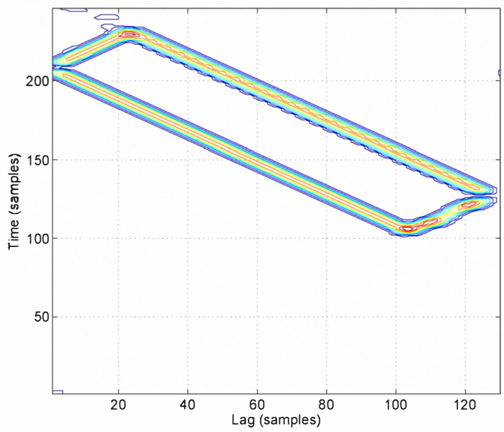

Fig. 6. 2D redundant wavelet transform of unwrapped TCF

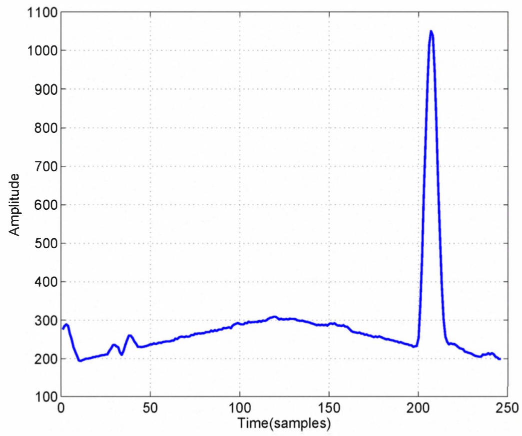

Fig. 7. Detection vector for 15dB

detection (P_d)] is more than the cost associated with the probability of a false alarm, P_{fa}.

10) Once the hopping time is estimated, one can extract the signal frequencies by applying frequency analysis to the estimated hopping intervals to demodulate the actual message. In the case of false alarms, frequency analysis would show the same frequencies in two, or more, consecutive hopping intervals, resulting in no message degradation. However, a missed hopping time will result in degradation in the frequency estimation step, and hence errors in the decoded message.

V. Simulation Result

Simulations studies were conducted to test the detection and estimation algorithm proposed in this paper. Five hundred trial experiments were conducted for six different signal to noise ratios (SNR) between -3 to 15 dB. We simulated signals that had already been segmented into frames, so the problem was to determine whether a frequency hop exists within the given frame and to estimate the hopping time when a frequency hop is detected.

Communication signals were generated by choosing random hopping time, T_{hop}, and hopping frequencies f_1, f_2 selected randomly in a predefined range. The resulting signal is a signal with, at most, one hop which can be from any frequency, f_1, to any hopping frequency, such that $1MHz \leq f_1, f_2 \leq 24MHz$.

Simulations were conducted using a frequency hopping signal divided in frames of equal sizes. We considered a two hop system where frequencies f_1, f_2 were randomly chosen such that $1MHz \leq f_1, f_2 \leq 24MHz$. We observed that the proposed algorithm fails to detect the time of hopping if the hop is present within first 5% or last 5% of frame. This is because in this case, the triangular region in the TCF of the frequency hopped signal shown in Fig. 2 due to frequency f_1 is very small, and it is difficult to detect the edges and hence the time of hop. We have tabulated the detection statistics for the 500 experiments for each SNR using the above described estimation algorithm in Table I. Columns of Table I denote the probability of finding the time of hop within a given distance from the true hop, e.g. at SNR of 3 dB, the probability of detecting the hop within a 2 hop (1%) distance is 0.836, i.e. out of 500 trials, 418 times the hop was estimated within a 2 hop distance from the actual hop time.

TABLE I
Detection Statistics for hop in a frame

SNR	1%	5%	10%	15%	20%	30%
15	1	1	1	1	1	1
10	0.982	1	1	1	1	1
6	0.922	0.996	0.996	0.996	0.996	1
3	0.836	0.97	0.986	0.988	0.996	1
0	0.698	0.762	0.848	0.894	0.95	1
-3	0.528	0.892	0.924	0.95	0.974	1

We compare our results with those presented in paper [3]. In Table II, we tabulate the average distance of the estimated hop from the true time of hop for our proposed algorithm and the one proposed in [3].

TABLE II
COMPARISON OF AVERAGE DISTANCE (IN TERMS OF SAMPLES) FROM THE TRUE TIME OF HOP

SNR(in dB)	Results from [3]	Proposed Algorithm
15	2.22	0.77
10	2.70	1.13
6	5.46	1.64
3	10.48	2.53
0	28.48	7.15
-3	30.99	7.97

In Table III, we have tabulated the probability of detection, P_d, and the probability of false alarm, P_{fa} in detection of a hop for the selected threshold, $T_{threshold}$ for each of the six SNRs considered. The entries under the column labeled "k" denotes the multiple of the variance of the detection vector generated from a no hop frame for each respective SNR level and used as $T_{threshold}$.

TABLE III
DETECTION RESULTS FOR TIME OF HOP

SNR	k	P_d	P_{fa}
15	50	1	0
10	20	1	0.0196
6	13	1	0.1569
3	9	0.996	0.1961
0	7	0.982	0.3529
-3	5	0.858	0.3333

VI. CONCLUSIONS

In this paper a more efficient way of detection and estimation of frequency hopping signal is proposed using Discrete Wavelet Transform. For detection, results are compared with energy detector and polyphase filter using fast Fourier transform, and a gain of about 4-5 dB is achieved using wavelet filter banks. The method proposed in this work does not require any information about the modulation type or hopping pattern. Results also shows improved estimation of time of hopping in a frame.

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