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Frequency Hopping Spread Spectrum Recognition Based on Discrete Fourier Transform and Skewness and Kurtosis

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Abstract

Modulation recognition is the ability to recognize the modulated signal of unknown modulated scheme. Frequency hopping spread spectrum (FHSS) signal recognition can be carried out by using the effective parameters of feature extraction (FE), and the classifier. This paper specifies the FHSS recognition based on using discrete Fourier transform (DFT) for feature extraction. The numbers of FE are reduced by applying skewness and kurtosis to DFT, adaptive neural fuzzy inference system (ANFIS) as classifier. MATLAB programs are designed to execute signals generation without noise, signal corruption with additive white Gaussian noise (WGN) at signal-to-noise ratio (SNR) with the range (-3, 0, 5, 10, 15, 20, 25) dB, FE parameters, and classification. The simulation of proposed recognition approach shows that the system is robust, high performance even at low SNR, and low complexity of classifier because of reduced ANFIS input.

Keywords: Frequency hopping spread spectrum, discrete Fourier transform, skewness and kurtosis, and adaptive neural fuzzy inference system.

INTRODUCTION

Modulation recognition is increasingly important in civilian, commercial and military applications [1], It is used for cognitive radio, spectrum surveillance and management, software defined radio, source identification, threat assessment, and so on [2].

Frequency hopping spread spectrum (FHSS) systems have many advantages, such as low probability of interception, high security, resistance to a multipath propagation environment, anti-interference, and anti-jam, then they are attractive in many applications like military and GSM [3]. The recognition of FHSS signals is a challenge and an important task in communication fields. Spread spectrum (SS) signals classification are based on Wigner-Ville distribution and neural network [4]. Based on compressive sensing, the frequency hopping signal was identified [5]. Machine (SVM) with wavelet kernels were used for identification of FHSS signals [6]. In this paper the recognition processes consists of feature extraction [FE], and soft computing technique as a classifier. Skewness and kurtosis are applied to discrete Fourier transform (DFT) of FHSS signals to produce the (FE). Adaptive neural fuzzy inference system (ANFIS) was used as a classifier. This paper is organized as follow: Section II, explains briefly the FHSS signals. Section III, demonstrates the feature extraction using DFT, and skewness and kurtosis. Section IV, presents the classifier. Section V, presents the methodology and simulation analysis. The paper is concluded in section VI

FREQUENCY HOPPING SIGNALS

FHSS is a type of spread spectrum (SS), the carrier hops from one frequency to other randomly according to the pseudo-noise (PN) sequence generator, with a fixed bandwidth. The frequencies are varied from single frequency to another pseudo-randomly. The selection of number of frequencies and hopping rate are affected by: rate and type of information being sent, distance to the near possible interferer, and any amount of redundancy is used [7]. The transmitted SSFH signal is demonstrated by

$$y(t) = s(t)\cos\left(2\pi f_j t + \emptyset_j\right) \quad jT_{\mathrm{h}} \le \mathrm{t} < (\mathrm{j}+1)\mathrm{T_h} \quad \ldots\ldots(1)$$

where s(t) is the baseband signal, $\emptyset_j, f_j$ is the phase and carrier frequency after jth hop, $\frac{1}{\mathrm{T_h}}$ is frequency hopping rate.

SSFH can be classified into slow-frequency hopping (SFH), and fast-frequency hopping (FFH). In SFH, the symbol rate is larger than the frequency hop, while the FFH, the frequency hop is larger than the symbol rate [8].

FEATURES EXTRACTION:

The different types of digitally modulated signals have different characteristics. The selection of proper features are the big challenge for the recognition performance of the signals. The dimension of the modulated signals is reduced, the new reduced data with discriminative characteristics represents the feature extraction (FE) [9]. The increase in the numbers of FE, will increase the system complexity, and training time of the classifier. In this paper the extracted features by DFT, are reduced by skewness and kurtosis.

A- Discrete Fourier Transform

A discrete Fourier transform (DFT) is defined at discrete times, and can be calculated via fast Four transform (FFT). The output of DFT is:

$$X(k) = \sum_{m=0}^{N-1} x(m) e^{\frac{-j2\pi mk}{N}} \qquad k = 0, \ldots, N-1 \qquad (2)$$

where x(k) is the output of FFT at k_{th} point, x(m) is the m_{th}

time sample of input signal, and N is the number of sample point [10].

B- Skewness and Kurtosis

Skewness characterizes the degree of symmetry of a probability density function (PDF) around its mean. Kurtosis characterizes the degree of relative peakedness compared with the normal distribution of the PDF. Skewness and Kurtosis represents the third and fourth order moments, which are the concepts of expected values

$$.\mu_j = \sum_{j=0}^{M-1} (\boldsymbol{S_i} - \boldsymbol{\mu})^j \, \boldsymbol{f}(\boldsymbol{S_i}) \qquad (\mathbf{3})$$

where the mean value $\mu = E(X)$, j is the order of moment, M is the data length. The auto-moment is [11] :

$$E_{S,p+q,q} = E[S^p (S^*)^q] \qquad (4)$$

Therefore:

$$skewness = E[S^3 (S^*)^0] = E(S^3) = \mu_3$$

$$kurtosis = E[S^4 (S^*)^0] = E(S^4) = \mu_4$$

CLASSIFIER

Fuzzy Inference system (FIS) is a model that maps crisp input to crisp output through a set of fuzzy rules and membership functions (MFs). In general FIS consists of fuzzification, rule base and inference engine, and defuzzification. Mamdani, and Takagi-Sugeno-Kang are the most commonly types of fuzzy inference system. The lake of learning capability, is the main disadvantage of FIS. In this paper adaptive fuzzy inference system (ANFIS) was utilized as a classifier. ANFIS is a hybrid system based on Takagi-Sugeno-Kang FIS, which employs the learning and adaptive learning capabilities of artificial neural network (ANN), to find the parameters of FIS. The fuzzy rules and input-output fuzzy membership functions (MFs), are tuned using the learning algorithms of ANN, like gradient descent and least square. More details may be found about ANFIS at [12][13].

METHODOLOGY AND ANALYSIS OF SIMULATION

FHSS signal can be commonly represented as in equation (1). MATLAB programs were designed to perform the whole system of signal generation, feature extraction, and classification. The recognition system is shown in Figure (1).

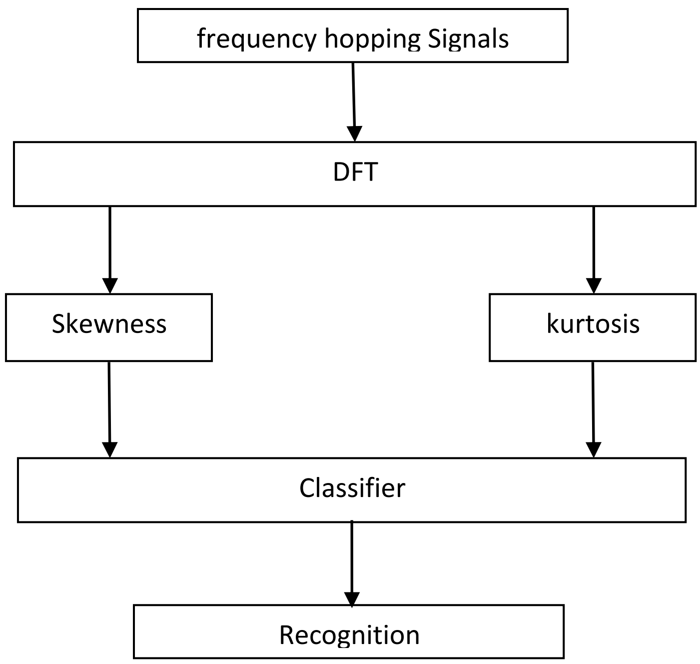

Figure 1. Recognition system

The random data sequence was generated, gray code was implemented for even bits, and then followed by BPSK modulation of the signal. Six carrier frequencies were used to create the spread signal. The carrier frequency is periodically hopped following the spreading code. FHSS was generated, 3000 simulated signals had been generated. Additive white Gaussian noise (AWGN) is added for different signal-to-noise ratio (SNR) in the range (-3, 0, 5, 10, 15, 20, 25) dB. Fig. (2) demonstrates the FHSS signal at 25dB. The FE plays the key role for recognition and the performance of the system. In order to reduce the complexity of the system, the selected FE should fewer as far as possible. FFT was applied to the signals which are corrupted with noise. Fig. (3) shows the DFT of the SSFH signal at 25dB.

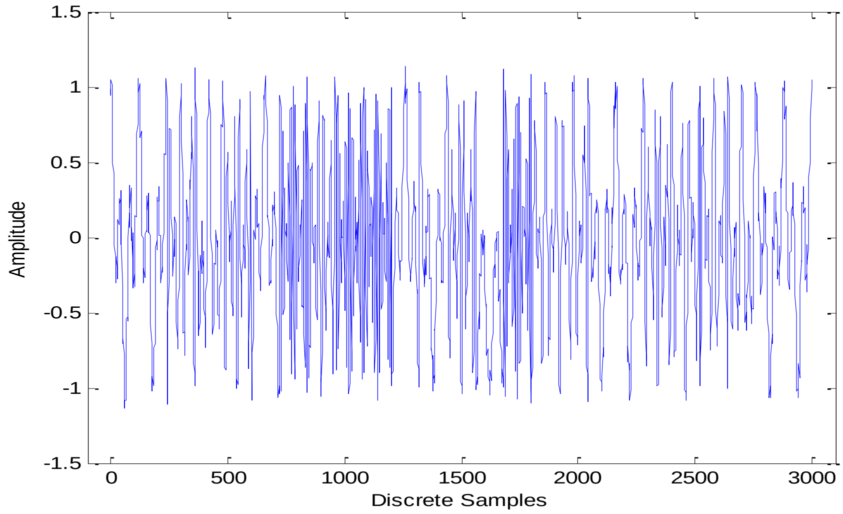

Figure 2. Frequency hopping signal at 25 dB

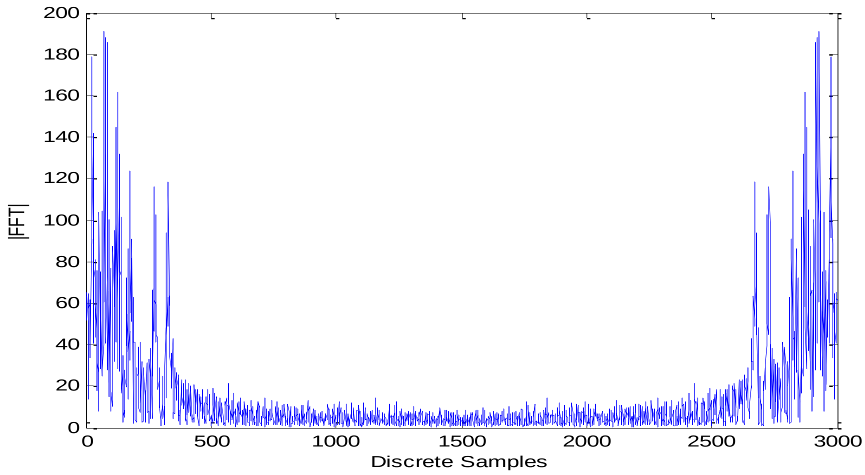

Figure 3. DFT of FHSS at 25dB

High number of FE are produced, then skewness and kurtosis are applied to FFT, thus the FE are mapped into another reduced features which posses the discriminating facilities of FHSS signal. Figure (4) shows the final FE that train the classifier. This approach reduces the raining time as well as the complexity of the classifier. From the figure, it is clearly shown that the extracted feature exhibits acceptable discriminating facilities even in low SNR, but has better performance at SNR≥ 10dB. Skewness and kurtosis represent the two inputs to the stage of ANFIS classifier. The structure of ANFIS and the training parameters used in this paper are shown in table 1.

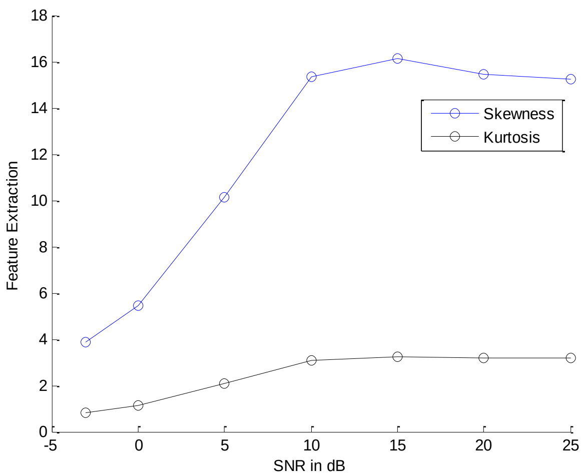

Figure 4. Features extraction for different SNR

Table 1

The structure of ANFIS and training parameters

Number of inputs	2
Number of fuzzy rules	9
Number of nodes	35
Number of linear parameters	9
Number of nonlinear parameters	18
Number of fuzzy MFs	3
Input MFs type	Triangular MF
Output MFs type	Constant
Training error at 20 epochs	$4.57235*10^{-6}$
Learning rule	Hybrid (least square errors and back propagation)

The important representation of recognition process is the surface graph which is shown in Fig. (5) . The surface graphs shows the influence of FE (skewness and kurtosis) to the output (recognition ratio) of FHSS signal, number 1 in the vertical axis represent correct recognition. From the graph the recognition region represents a wide area at high and low values of FE, but the high values are more wider, which are extracted at SNR ≥ 10dB. Then the recognition system exhibits a high recognition ratio and it is close to 100% even at low SNR

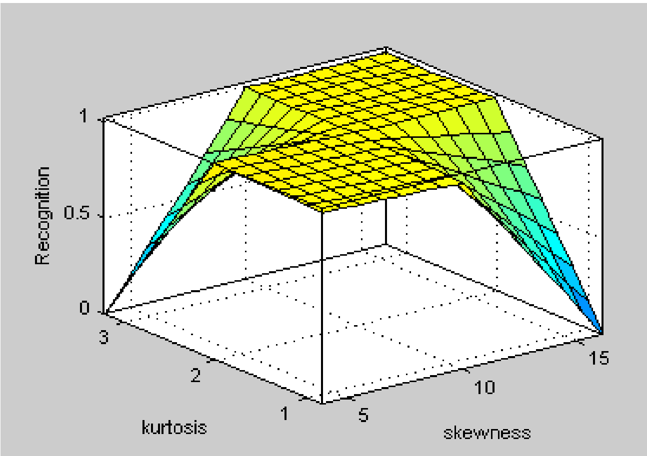

Figure 5. Surface graph

CONCLUSION

The effective FE of the modulated signals is crucial for recognition of these signals. DFT had been introduced as an effective tool for extracting the features of FHSS signals. In order to reduce the FE parameters, skewness and kurtosis are applied to DFT. ANFIS was used for signal classification. The system was simulated at different values of SNR (-3, 0, 5, 10, 15, 20, 25) dB. The main advantages of this approach is high recognition ratio even if at low SNR, low complexity of the recognizer, and reducing the training time. This recognition approach could be modified as future work to recognize another types of digitally modulated signals like m- ary frequency shift key (MFSK).

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