Journal of Southeast University (English Edition) Vol. 33, No. 4, pp. 432 - 436 Dec. 2017 ISSN 1003—7985

Signal classification system using global-local feature extraction algorithm

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Abstract: A continuous wavelet transform (CWT) and global-local feature (GLF) extraction-based signal classification algorithm is proposed to improve the signal classification accuracy. First, the CWT is utilized to generate the time-frequency scalogram. Then, the GLF extraction method is proposed to extract features from the time-frequency scalogram. Finally, a classification method based on the support vector machine (SVM) is proposed to classify the extracted features. Experimental results show that the extended binary phase shift keying (EBPSK) bit error rate (BER) of the proposed classification algorithm is 1.3×10^{-5} under the environment of additional white Gaussian noise with the signal-to-noise ratio of -3 dB, which is 24 times lower than that of the SVM-based signal classification method. Meanwhile, the BER using the GLF extraction method is 13 times lower than the one using the global feature extraction method and 24 times lower than the one using the local feature extraction method.

Key words: continuous wavelet transform (CWT); support vector machine (SVM); global-local features; signal classification

DOI: 10.3969/j.issn.1003 - 7985.2017.04.007

Recently, binary signals have been received considerable attention in communication systems. In order to improve classification performance, a maximum-likelihood detection metric adopting max-log approximation was proposed to make the performance analysis tractable[1]. A simple iterative cancellation demodulator was proposed in Ref.[2], and this method can predict the performance exactly. Ref.[3] utilized differentially coherent detection to reduce system complexity. A new lock detector structure used for phase lock loops was proposed in Ref. [4]. In Ref. [5], several analytic image methods were proposed to extend the notion of the 1D analytic signal to 2D analytic signal. Chen et al. [6] proposed a new approach for the nonlinear demodulation based on the support vector machine (SVM) and the bit error rate (BER) performance can be improved significantly by using the SVM classifier. However, these methods only consider the features in the time domain.

There are many methods proposed to derive time-frequency features[7-8], in which wavelet transform is a wise choice to extract time-frequency features. Wavelet-based methods have been shown to be effective for many applications such as signal evaluation, signal analyzing and signal detection[9-10]. In this paper, we apply the wavelet transform-based method to the signal classification system.

Fang et al. [11] proposed a binary signal classification method based on continuous wavelet transform and feature extraction. However, there are many redundant features in the direct extracted features vectors, and this paper did not use any feature reduction method in the feature extraction process. Feature reduction is a surprising work in the classification system[12]. Processing the feature information by some pretreatment methods such as feature strengthening and background subtraction, can help reduce the redundant features[13-14]. Choosing appropriate feature vectors can better reflect the signal characteristics, and, therefore, increase the accuracy and reliability of the signal classification[15].

This paper proposes a signal classification system. The system utilizes the SVM classifier to achieve classification. We adopt the continue wavelet transform (CWT) to generate a wavelet scalogram, which includes both the time domain and the frequency domain features. The proposed system is fulfilled by four modules, which are modulation, channel, demodulation and estimation. The modulation module modulates the symbols to signal waveform. The demodulation module preprocesses the signal waveform. This module is composed of the filter bank, CWT, and redundant features reduction. The filter bank in this paper is composed of an impulse filter and a band-pass filter. CWT is utilized to generate the wavelet scalogram, and we construct an adaptive wavelet to achieve CWT. The wavelet scalogram output by CWT is mixed with noise features and redundant features, and several templates are introduced in this paper to process the wavelet scalogram. A pretreatment method is proposed as the final procedure in the demodulation module to reduce the redundant features, and the wavelet scalogram after pretreatment has more obvious features. The

Received 2017-06-10, **Revised** 2017-10-20.

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Foundation items: The National Key Technology R&D Program (No. 2012BAH15B00), the Scientific Innovation Research of College Graduates in Jiangsu Province (No. KYLX150076).

Citation: Fang Lanting, Wu Lenan, Zhang Yudong. Signal classification system using global-local feature extraction algorithm[J]. Journal of Southeast University (English Edition), 2017, 33(4): 432 - 436. DOI: 10.3969/j.issn.1003 - 7985.2017.04.007.

estimation module in this system can be divided into three procedures, namely, features extraction, features reduction and signal detection. This paper utilizes the global-local features (GLF) extraction method. We extract the local features from each scale of the scalogram and the global features global structure of the scalogram. After that, the principle component analysis (PCA) is used to find a low dimension surface to process the features. Finally, we adopt the SVM classifier to predict the signal.

1 System Model

The system block diagram is shown in Fig. 1. The proposed system consists of three modules: modulation, demodulation and estimation.

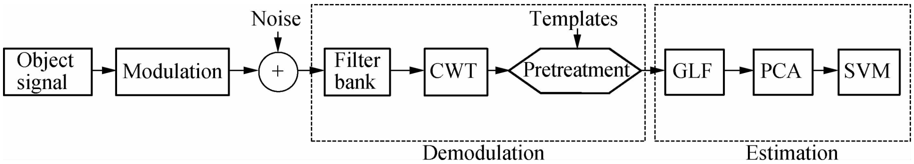

Fig. 1 System model

1.1 Modulation

The signal used to test our system is EBPSK, the modulated symbols g_1 and g_{-1} can be given by

$$g_1(t)=\begin{cases}\sin(2\pi f_c t+\theta) & 0\leqslant T<KT\\ \sin(2\pi f_c t) & KT\leqslant T<NT\end{cases}$$

$$g_{-1}(t)=\begin{cases}\sin(2\pi f_c t) & 0\leqslant T<(K+r_g)T\\ \sin(2\pi f_c t+\theta) & (K+r_g)T\leqslant T<(2K+r_g)T\\ \sin(2\pi f_c t) & (2K+r_g)T\leqslant T<NT\end{cases}$$

where θ is the modulating angle; $T=N/f_c$ is the temporal length of a symbol, and parameter f_c represents the carrier frequency; and N is the number of carriers in a symbol; $\tau=K/f_c$ is the phase modulation temporal length; and r_g is the guard interval.

1.2 Demodulation

1.2.1 Filter bank and CWT

The composite signal at the channel output is given by

$$z=g_d+pn$$

where n is i. i. d. standard Gaussian noise sample and p is the noise standard deviation.

The major indicator of the communication system is the bit error rate (BER). A filter module is used to enhance the gap between the signal and noise, and h is the impulse response of the filter module. The filter module output is given as

$$y=z*h$$

where $*$ is the convolution operation.

Time-frequency features indicate a two-dimensional energy representation of a signal in terms of the time domain and frequency domain. However, not all the methods are non-stationary compatible and suitable for time-frequency quantification or non-stationary feature extraction purposes. In this study, we select CWT to represent the signals. This representation is adaptive to signal non-stationaries, providing a high time-frequency resolution and it is robust to noise in the signals. CWT is the calculation of the cross covariance between the signal and the wavelet function, which is shifted in time and stretched in scale. Let ψ be the wavelet function, and the CWT of the signal y is given by

$$\boldsymbol{C}=\langle y,\psi_{a,b}\rangle=|a|^{-1/2}\int y(t)\psi^*\left(\frac{t-b}{a}\right)$$

where the wavelet scalogram $\boldsymbol{C}$ is a matrix including the information both in time and frequency; parameter a is the scale factor, representing the frequency related stretch; b is the shift factor in the time domain; and $\psi_{a,b}$ is a wavelet function with zero mean.

1.2.2 Pretreatment

Mathematical functions which are defined in the time domain and frequency domain have been usually used as redundant reduction methods for time-frequency domain features. Hence, the study of pretreatment for time-frequency features has recently become an important issue in classification.

The demodulation module receives the channel output signal. After this, we transform the signal through the filter bank and the CWT to yield the wavelet scalogram. There are significant differences between the wavelet scalogram generated by the signal 1 and signal −1. Pretreatment added in this module is used to further enhance the gap between the two signals.

This paper uses the templates to restrain the noise features. Let T_1 and T_2 be the thresholds for $\boldsymbol{L}_1$ and $\boldsymbol{L}_2$, respectively.

The local features pretreatment methods are given by

$$\boldsymbol{L}_1(i,j)=\begin{cases}1 & \boldsymbol{C}(i,j)>T_1\\ 0 & \text{else}\end{cases}$$

$$\boldsymbol{L}_2(i,j)=\begin{cases}1 & \boldsymbol{C}(i,j)<T_2\\ 0 & \text{else}\end{cases}$$

Some pretreatment methods are used in this section to enhance the global features. Since the signal is fixed with the noise, we need to restrain the noise and sharpen the signal information. The global pretreatment algorism in this paper is expressed as

$$S_1(i,j)=\frac{\max(\boldsymbol{C})}{\max(\boldsymbol{C})-T_1}(\boldsymbol{C}(i,j)-T_1)$$

$$S_2(i,j)=\frac{\min(\boldsymbol{C})}{\min(\boldsymbol{C})-T_1}(\boldsymbol{C}(i,j)-T_2)$$

where $\max(\boldsymbol{C})$ and $\min(\boldsymbol{C})$ represent the maximum value and minimum value in matrix $\boldsymbol{C}$, respectively.

1.3 Estimation

In this paper, we propose a GLF detection method to extract global and local features from the matrix output by the demodulation process. There are $N=2(m+1)$ features used in this paper. Most of them are local features, and the local feature vectors reflect the features in each scale and time. Small number features are global features, and the global vectors represent the information from the whole scalogram. The mathematical definitions and the related works of these features are listed below.

The features in different scales are different, and each scale carries important information concerning the local feature characteristics. We extract $2m$ local feature vectors in total. The top m feature vectors are extracted from each scale of feature matrix $\boldsymbol{L}_1$, and the bottom m feature vectors are extracted from each f scale of feature matrix $\boldsymbol{L}_2$. The number of the highlighted sections can represent the local features.

The calculation equations can be given by

$$v_i=\sum_{j=1}^{n}\boldsymbol{L}_1(i,j)$$

$$v_{i+m}=\sum_{j=1}^{n}\boldsymbol{L}_2(i,j)$$

where $i=1,2,\cdots,m$.

The global feature values v_{2m+1} and v_{2m+2} are defined as $v_{2m+1}=\sum_{i=1}^{m}\sum_{j=1}^{n}S_1(i,j)$ and $v_{2m+2}=\sum_{i=1}^{m}\sum_{j=1}^{n}S_2(i,j)$, respectively.

The GLF detection method extracts the global and local features for signals. In order to classify the signals effectively, we use PCA to extract most of the variance of the features. Then, we classify the signals based on the PCA output with SVM.

2 Performance

In order to validate the proposed methodology of binary signal classification introduced in Section 1, several simulations are performed to compare the proposed system with some existing algorithms. We compared our system with SVM without the CWT method, and with three feature-extraction methods (GLF, global features and local features). Meanwhile, the adaptive wavelet introduced in Section 1 is compared with other existing wavelets. All the simulations are performed under the condition of AWGN.

In the experiments, we use the binary simulation model. We use carrier frequency $f_c=30$ MHz and parameter $N=50$ to represent the power spectral density of the EBPSK signal. We use guard interval $r_g=20$, the modulating angle $\theta=\pi$ and sampling frequency $f_s=10$ MHz.

It is essential to choose the mother wavelet to make the easiest identification of the wavelet scalogram feature. Existing wavelet functions are divided into five main types: finite impulse response (FIR) filter wavelets, such as Haar, Daubechies (db), Coiflets (coif) and Symlets (sym); biorthogonal wavelets with a FIR filter, such as bior splines (bior); filter without FIR, but with a scale equation, such as Meyer (meyr) wavelets; wavelets without FIR filter or scale equation, such as Morlet (morl) and Mexican hat (mexh); complex wavelets with a finite impulse and a scale equation, such as complex Gaussian and Shannon. The selection of a particular wavelet function depends on the scalogram features to be extracted. Since the adaptive wavelet waveform can be adjusted as requested, using an adaptive wavelet can achieve superior results than existing wavelets.

Fig. 2 shows the BER of the proposed system and the SVM without the CWT method. It can been seen from Fig. 2 that the BER of the proposed method is 24 times lower than the BER of the SVM-based classification method with the SNR of −3 dB. Fig. 3 shows the performance comparison of the adaptive wavelet and other existing wavelets. It can be seen from Fig. 3 that the Morlet wavelet is more suitable to the EBPSK signal than other existing wavelets, and the adaptive wavelet is better than all the other studied wavelets. Fig. 4 compares the BER performance when using the GLF extraction method with using the global feature extraction method and local feature extraction method. Fig. 4 shows that the BER using the GLF extraction method is 13 times lower than that when using the global feature extraction method and 24 times lower than the one using the local feature extraction method when the SNR is equal to −3 dB.

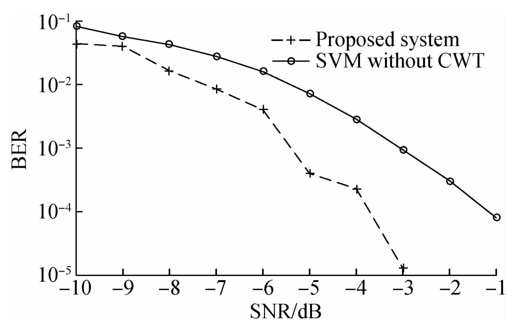

Fig. 2 Comparison of proposed algorithm and SVM without CWT

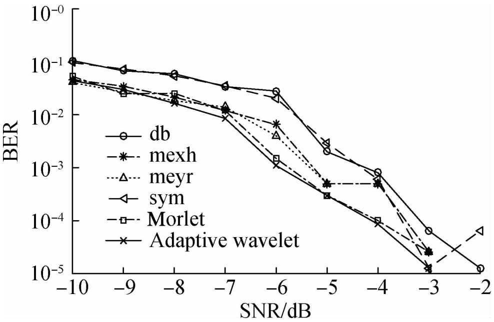

Fig. 3 Comparison of wavelets

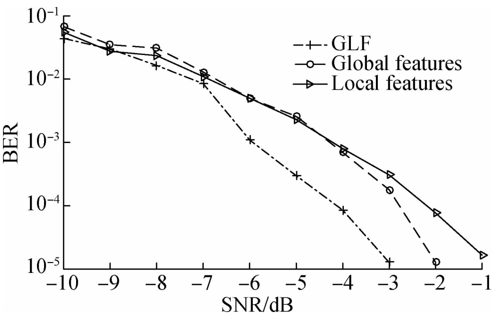

Fig. 4 Comparison of GLF, global features and local features

3 Conclusion

We propose a binary signal classification system utilizing the CWT-based time-frequency features. In our system, features are detected by the GLF extraction method. The simulation results reveal that our system yields a lower BER compared with the SVM without CWT. The proposed adaptive wavelet generates a lower BER than existing wavelets. In addition, we compare the proposed system adopting the GLF extraction method with the system using the global feature extraction method and local feature extraction method. Simulation results show that the BER performance of the system using the GLF method is better than the system using the global feature extraction method and that using the local feature extraction method.

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基于全局-局部特征提取算法的信号分类系统

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摘要:为了提高信号分类的准确度,提出了一种基于连续小波变换和全局-局部特征提取的信号分类算法.首先,对信号进行小波变换,生成时域-频域系数矩阵.然后,提出了一种全局-局部特征提取算法,该算法可以有效地提取时域-频域系数矩阵的特征信息.最后,使用支持向量机分析方法提取到的特征信息,输出分类结果.仿真结果表明,在信噪比为 −3 dB 的高斯白噪声环境下,所提出的信号分类算法对 EBPSK 信号分类的误码率为 1.3×10^{-5},该误码率比基于支持向量机的信号分类算法低 24 倍,同时,使用全局-局部特征提取算法的误码率比仅使用全局特征提取算法低 13 倍,比仅使用局部特征提取算法低 24 倍.

关键词:连续小波变换;支持向量机;全局-局部特征;信号分类

中图分类号:TP391