A Novel Recognition Algorithm for XQPSK Based on Phase Difference Annular Statistics and SVM

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***Abstract*—A novel recognition algorithm based on phase difference annular statistics and support vector machine (SVM) is proposed to classify BPSK, QPSK, OQPSK and SOQPSK modulation schemes. The proposed algorithm exploring the characteristics of phase difference including the first-order and second-order triangle distance, variance, slope and kurtosis, to analyze the probability density of degree spread, the degree deviation from symmetrical distribution and the normal distribution. The feature parameters are input into a SVM classifier which has the advantages of generality and robustness. Compared with existing classification algorithms, the proposed algorithm can classify these four types of modulation schemes especially for signal with low signal to noise ratio (SNR). The proposed feature extraction method has less computational complexity, more stability. This algorithm improves the reliability and accuracy of the recognition by using the ring statistics and SVM classifier.**

***Index Terms*—modulation recognition, annular statistics, phase difference, SVM, SOQPSK**

I. INTRODUCTION

Modulation recognition is an intermediate step between signal detection and data demodulation. It plays a very important role in military and civilian applications. For military use, it is mainly utilized for surveillance, communications, electronic warfare, and threat analysis [1]. In modern warfare, the transmission of battlefield information relies mainly on radio communication. Hence communication reconnaissance is one the main aspects of electronic warfare. In the design of communication intelligent intercept receiver, the recognition of modulation schemes for receiving communication signal is one of its most important functions. In civilian applications, modulation recognition is mainly used in radio management, such as spectrum management, spectrum monitoring, interference recognition and signal positioning. BPSK QPSK, OQPSK and SOQPSK modulation schemes have been applied to various military and civilian communication systems. Therefore, it is of great significance to study the recognition of these four types of modulation schemes.

There exist plenty of research on modulation classification for MPSK signals, but very few attentions have been paid on the special MPSK signals such as SOQPSK. However, SOQPSK is a very important modulation scheme which has been used in the U.S. military MIL-STF 188-181 UHF satellite communication standard [2] and the airborne telemetry standard IRIG 106 [3].

In [4], Chunyun Song proposed a method of the classification and parameter estimation based on the statistical and spectral characteristics of the instantaneous phase difference. It can separate BPSK, QPSK, OQPSK and $\pi/4$QPSK signals from each other and success rates are higher than 96% for SNR larger than 10dB. In [5], Dibyajyoti Das proposed a cumulant based automatic modulation classification method to classify QPSK, OQPSK, 8-PSK and 16-PSK over additive white gaussian noise channel. The method classifies signals using the fourth-order zero-conjugate cumulant of backward differences of the received noisy signal. It can achieve perfect classification at SNR=9 dB with sample size N=2000. In [6], Zhao Fucai proposed a feature extraction method based on wavelet packet transform modulus maxima matrix. It can classify eleven digital modulation schemes in a wide range of SNR with high success rates. In [7], Wu Dan proposed a new scheme of automatic modulation classification using wavelet analysis and wavelet support vector machine (WSVM). It can separate MASK, MPSK and OQPSK with success rates larger than 96.5% when SNR is not lower than 3dB.

This paper focus on the problem of classification of BPSK, QPSK, OQPSK and SOQPSK under the similar framework of hierarchical digital modulation classification using phase difference. In this paper, a novel recognition algorithm based on phase difference annular statistics and SVM is proposed to classify BPSK, QPSK, OQPSK and SOQPSK modulation schemes. The proposed algorithm firstly performs a Hilbert transform. Then extraction of the non-folding phase of the signal is followed to get the phase difference. Finally, the first-order and second-order triangle distance of phase difference, variance slope and kurtosis are calculated as the classification features.

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II. Problem Formation

The BPSK signal has 0 and π phase. When the binary code element changes, there is $\pm\pi$ of carrier phase jump. QPSK has $\pm\pi/4$ or $\pm 3\pi/4$ phase. When the binary code element changes, there is $\pm\pi/2$ or π of carrier phase jump. OQPSK modulation scheme evolves from QPSK. The former manages to eliminate $\pm\pi$ of carrier phase jump, when the code group changes, there is only 0 or $\pm\pi/2$ of carrier phase jump. SOQPSK is a constant-envelope modulation scheme with continuous phase witch improves spectral efficiency compared with QPSK and OQPSK [8].

This paper presents a SVM recognition algorithm based on phase difference annular statistics. Phase difference is used to improve the recognition accuracy of QPSK and OQPSK signals. It can be seen from the definition of QPSK and OQPSK signals that they have the same phase constellation. Therefore, the SVM recognition algorithm based on phase-loop statistics is not able to distinguish the signal directly. However, the phase hopping pattern of QPSK and OQPSK signals is different, and the constellation diagram after phase difference is different, as shown in Fig. 1.

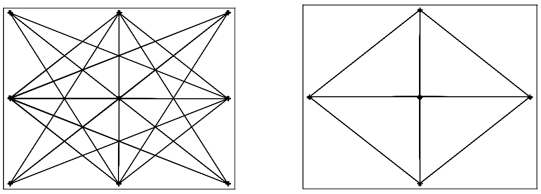

Figure 1. Phase difference constellation of QPSK and OQPSK.

A. Annular Statistics Definition

In modern signal analysis and processing, high-order statistical analysis is a common method, which is widely used in the field of signal interception detection and reconstruction, parameter extraction, equalization and synchronization. The commonly used statistical tools include variance, slope and kurtosis. Variance data reflects the probability density of degree spread. Slope reflects the degree deviation from symmetrical distribution. Kurtosis reflects the degree deviation from normal distribution, which is the degree of sharpness.

The annular statistic is mainly used for the statistical analysis of the data samples with angle value, which can be regarded as a random variable with circular distribution. In linear statistics, the moment of circular random variable is defined in the form of probability density function. Variance, slope and kurtosis are defined in the form of the moment of annular data, and the calculation of its statistics is also estimated by sampling data to obtain its theoretical value.

If $\Phi = \{\theta_k\}$ is the data sample of K value in $[-\pi, \pi]$ range, the first-order triangle distance of Φ is defined as:

$$\mu_1 = \frac{1}{K}\sum_{k=0}^{k-1} e^{j\theta_k} \tag{1}$$

Similarly, the p-order triangle distance of Φ is defined as:

$$\mu_p = \frac{1}{K}\sum_{k=0}^{k-1} e^{jp\theta_k} \tag{2}$$

We can put the p-order triangle distance of Φ as the first-order triangular distance of Φ^p.

Therefore, we give the definition of the variance, slope and kurtosis based on the p-order triangle distance:

Variance: $\sigma^2 = 1 - |\mu_1|$

Slope: $r = |\mu_2|\sin\left(\angle\mu_2 - 2\angle\mu_1\right)/\left(\sigma^2\right)^{3/2}$

Kurtosis: $\kappa = |\mu_2|\cos(\angle\mu_2 - 2\angle\mu_1 - |\mu_1|^2)\left(\sigma^2\right)^2$

In order to analyze the variance, slope and kurtosis of the p-order triangle distance defined above, the discrete time model of phase-modulated signal can be expressed as follows.

$$s[k] = A(t)e^{j\varphi(t)}\big|_{t=kT_s} \tag{3}$$

where $A(t)$ is the instantaneous amplitude of the signal, and T_s is the sampling interval.

BPSK signal phase difference has carrier phase jump of 0 or $\pm\pi$. QPSK signal phase difference has carrier phase jump of 0, $\pm\pi/4$, $\pm\pi/2$, $\pm 3\pi/4$ or $\pm\pi$. OQPSK signal phase difference has carrier phase jump of 0, $\pm\pi/4$ or $\pm 3\pi/4$. The signal envelope of SOQPSK is strictly constant with continuous phase and forming pulse being a continuous function. Its phase difference is within $[-\pi, \pi]$. Therefore, the phase difference of the above signals can be regarded as a circular variable and the calculation of the circular statistics defined above applies.

B. SVM

SVM is a method of pattern recognition and machine learning based on statistical learning theory. Its main idea is via some nonlinear mapping to establish an optimal separating hyperplane as a decision surface structure. In the high dimensional space, the linear discriminant function is constructed to realize the nonlinear discrimination in the original space, so that the separation edge between the positive and the negative cases is maximized [9]. It is not necessary to know the specific form of the nonlinear mapping mentioned above, but to calculate the inner product of high dimensional space through the kernel function, which can overcome the calculation difficulties caused by the increase of dimension. At the same time, the properties of special optimization functions defined in SVM can guarantee that the machine has a better generalization ability, which is unique to support vector machines.

Using SVM to realize the recognition of BPSK, QPSK, OQPSK and SOQPSK signals, it is necessary to construct a multi-classifier, select the appropriate kernel function, and select the optimal parameter. The selection of these key parameters is described below.

III. PROPOSED ALGORITHM

A. The Choice of SVM Parameters

1) Choice of kernel function

Combined with the above analysis, the structure diagram of SVM is presented, in Fig. 2. As can be seen from the figure, the key of SVM algorithm is based on the nonlinear transformation of support vector, which is realized through kernel function (K in Fig. 2). Therefore, the proper selection of kernel function is directly related to the results of SVM algorithm. At present, the commonly used kernel functions are linear, polynomial, radial basis and two-layer perceptron kernel function, etc. Their expressions are as follows:

Linear kernel function:

$$K(x, x_i) = x^{\mathrm{T}} x_i \tag{4}$$

Polynomial kernel function:

$$K(x, x_i) = (\gamma x^{\mathrm{T}} x_i + r)^p, \gamma > 0 \tag{5}$$

Radial basis kernel function:

$$K(x, x_i) = \exp(-\gamma \left\| x - x_i \right\|^2), \gamma > 0 \tag{6}$$

Two-layer perceptron kernel function:

$$K(x, x_i) = \tanh(-\gamma x^T x_i + r) \tag{7}$$

Based on the radial basis kernel function (also called Gaussian kernel function), that's because studies show that the radial basis function is better than that of other kernel function when lacking prior knowledge of the chosen process. Meanwhile, the radial basis kernel function also has the inherent simplicity of polynomial kernel function.

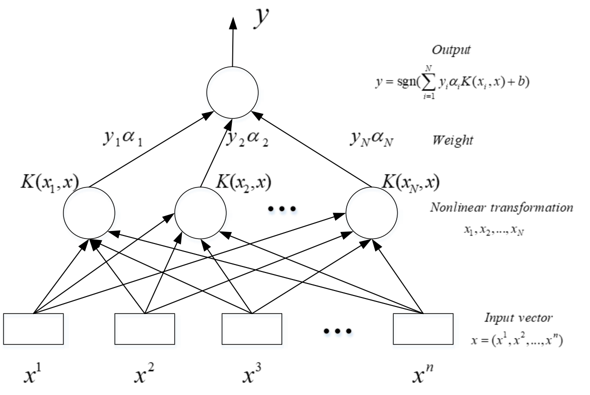

Figure 2. The schematic diagram of SVM structure.

2) Penalty parameter C and kernel function parameter g optimization

After selecting the kernel function, to achieve a better classification, it is necessary to optimize the penalty parameter C and the kernel function parameter *g* of SVM. In this paper, cross validation is used to select the optimal parameters. The specific idea of this method is: Let the parameters C and *g* within a certain range of values. For a fixed parameters C and g, use the training set as the original data set. And the K - CV (K - a fold cross validation) method is used to verify the classification accuracy of the training set under the parameters C and *g*. Finally the group C and *g* corresponding to the training set with highest verified classification accuracy are chosen as the optimal parameters [10]-[12].

3) The construction of a multi-classifier

In this paper, the Libsvm classifier based on the one-to-one construction method to identify QPSK, OQPSK and SOQPSK signals is adopted.

The idea of one-to-one is: one SVM is designed between any two types of samples so that the *k* types of samples need to design $k(k-1)/2$ SVMS [13], [14]. When classifying an unknown sample, use pairs of SVMS for comparison, and eliminate a SVM classifier after a comparison. The winner will continue to compete until only one winner is left. Finally, the final winner SVM classifier determines the category of test samples.

B. Identification Scheme

The algorithm block diagram of classification recognition of BPSK, QPSK, OQPSK and SOQPSK signals using SVM is shown in Fig. 3.

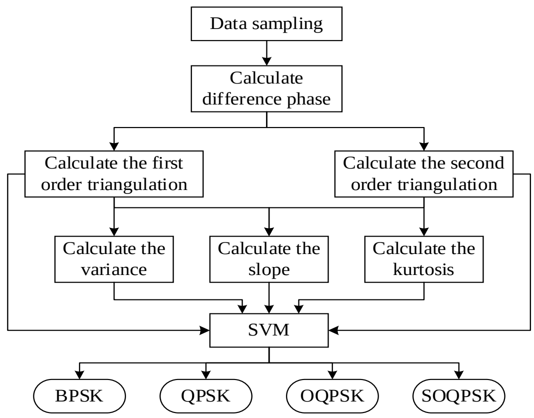

Figure 3. The flow diagram of algorithm.

The detailed steps of the algorithm are as follows:

Step 1. Oversample on the received signal.

Step 2. Extract the instantaneous phase of the signal and the differential operation is performed. Then, calculate the first-order and second-order triangle distance, the variance, kurtosis and slope of the distance.

Step 3. The first-order, second-order triangle distance, the variance, kurtosis and slope of the distance are used as inputs of SVM to identify BPSK, QPSK, OQPSK and SOQPSK signals.

The model of SVM is shown in Fig. 4.

The main process is: select pretreatment of the training set and testing set; choose the best penalty parameter C and kernel function parameter *g* using the above cross validation method. Then the SVM is trained with the training set. Finally, identify the signals with the model.

The preprocessing of data is the normalization of training set and test set. Data normalization method is one of the methods used in SVM before classification. Its purpose is to cancel the order of magnitude difference among different dimensional data, and to avoid error because of the greater difference between input and output data of classification.

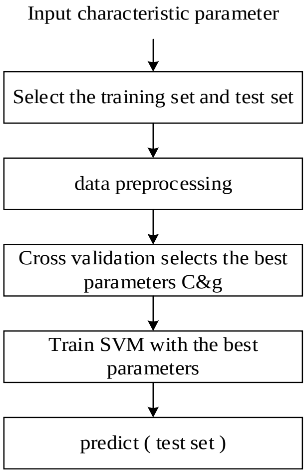

Figure 4. The model of SVM.

IV. Simulation and Analysis

A. Performance Analysis in Noiseless Environment

In order to verify the classification accuracy of the proposed algorithm, MATLAB is used to carry out the following simulation experiments. Simulation is set up as follows: The symbol rate is $3*10^5\ bit/s$. The symbol length is 1024. The carrier frequency is $3*10^5$Hz, and the sampling rate is $9*10^5\ bit/s$. 500 times of Monte Carlo experiments are carried out. There is no noise.

After data processing, a double-type matrix of 2000*5 is obtained, and 5 properties of 2000 samples are recorded. In the 2000 samples, 1 ~ 500 samples are the BPSK signal (defined as category 1), 501 ~ 1000 samples are the QPSK signal (defined as category 2), 1001 ~ 1500 samples are SOQPSK signal (defined as category 3), 1501 ~ 2000 samples are the OQPSK signal (defined as category 4). The first 100 samples for each signal set are taken as the train set, followed by 400 samples being the test set. The classification results are as follows:

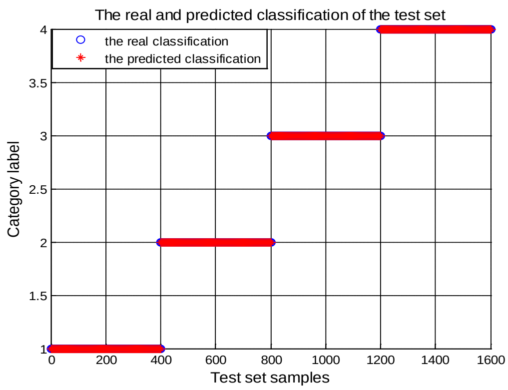

Figure 5. The real and predicted classification.

Fig. 5 and Fig. 6 show the result of classification with the phase difference annular statistic as the feature. The categories 1, 2, 3 and 4 in Fig. 5 represent BPSK, QPSK, SOQPSK and OQPSK respectively. Fig. 6 shows the concrete classification results by the confusion matrix. The simulation results of this part show that the proposed algorithm can distinguish the four signals perfectly in the no-noise environment. In other words, this algorithm has theoretical correctness and feasibility.

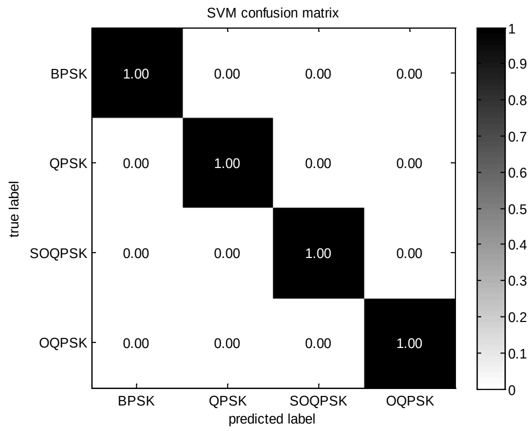

Figure 6. SVM confusion matrix.

B. The Influence of Noise on Classification Algorithm

The signal is added with Gaussian white noise, and the SNR range is -10 to 10dB. Fig. 7 shows the classification results of the algorithm under different SNR conditions.

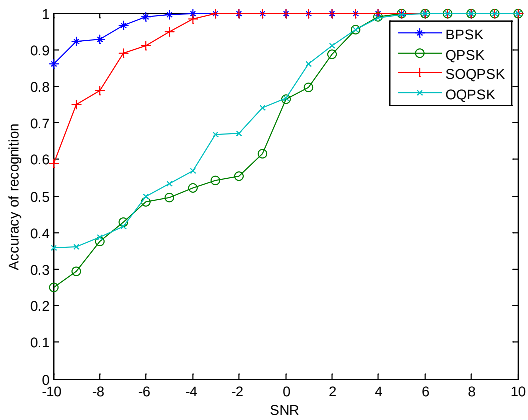

Figure 7. Accuracy of recognition at SNR from -10dB to 10dB.

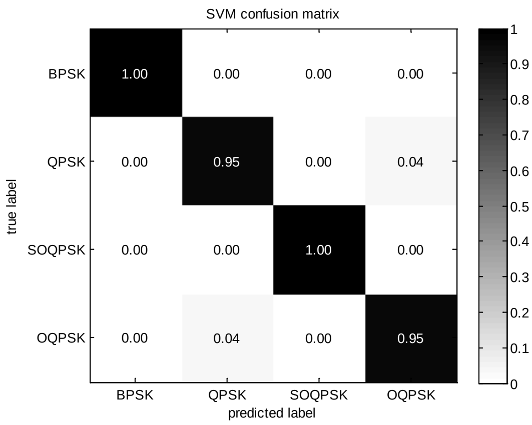

Figure 8. SVM confusion matrix at SNR=3dB.

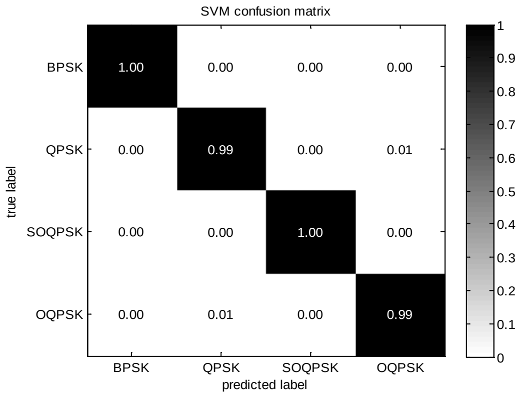

Figure 9. SVM confusion matrix at SNR=4dB.

It can be seen from the above figures that BPSK and SOQPSK modulation signals still have good recognition rate in lower SNR. The correct recognition rate of QPSK and OQPSK signals is more than 95% when the SNR is equal to 3dB. All signals have a correct recognition rate close to 100% when the SNR reaches 4dB. In the environment of Gaussian white noise, the phase information and the characteristic parameters of the signals would be affected. With the improvement of SNR, the recognition ability of the algorithm is better.

C. The Comparison of Different Normalization Methods

For different normalization methods and non-normalized pretreatment, the comparison of prediction classification accuracy of the final test set is shown in Table I. The accuracy shows the ratio of wrong classification over the total number of signals to be classified.

TABLE I. CONTRAST OF NOMALIZATION(SNR=3dB)

normalization methods	accuracy (%)	svmtrian parameter
No normalization	97.4(1559/1600)	‘-c 1 –g 0.25 –t 2’
[0,1] normalization	98.0(1568/1600)	‘-c 1 –g 0.25 –t 2’
[-1,1] normalization	98.0(1568/1600)	‘-c 1 –g 0.25 –t 2’

Depending on the state, normalization preprocessing can not necessarily improve the accuracy in SVM classification algorithm. From the above table, it can be seen that the normalization of data $[0,1]$ and the normalization of $[-1,1]$ can only improve the accuracy of the final classification very slightly.

V. CONCLUSIONS

To improve the signal recognition ability of BPSK, QPSK, OQPSK and SOQPSK, A novel recognition algorithm based on phase difference annular statistics and SVM has been proposed in this paper. Firstly, in the proposed algorithm, the classification of phase difference in characteristics improves the ability to identify the QPSK and OQPSK. At the same time, the phase difference has been further analyzed by using the classification characteristics of the first-order and second-order triangle distance, variance, slope and kurtosis based on annular statistics. Finally, SVM classifier has been used to realize the recognition of signals. The proposed algorithm greatly improves the signal recognition ability and still has good recognition performance with low SNR. This algorithm does not require prior information such as various parameters of signals. But it should be pointed out that SVM needs to learn before classification, which inevitably adds complexity.

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