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Automatic Modulation Classification Based on Novel Feature Extraction Algorithms

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ABSTRACT In order to solve the problems that the accuracy of modulation recognition algorithms of MSK and MQAM signals is not ideal under the condition of low signal-to-noise ratio (SNR) in Additional White Gaussian Noise (AWGN) environment, two novel features, the differential nonlinear phase Peak Factor (PF) and the reciprocal of amplitude envelope variance of cyclic spectrum at zero frequency cross section after difference and forth power processing, are constructed, which can complete the recognition of MSK signal and the classification of MPSK and MQAM signals respectively. This paper proposes a mixed recognition algorithm based on the two new features and other classical features, and design a tree shaped multi-layer smooth support vector machine classifier based on feature selection algorithm (FS_DT-SSVM) to recognize eleven kinds of digital modulation signals. The simulation results illustrate that the algorithm can achieve the classification of the modulation signals {2FSK, MSK, 2ASK, 4ASK, 8ASK, 2PSK, 4PSK, 8PSK, 16QAM, 32QAM, 64QAM} with small SNR. When the SNR is not less than -1dB, the recognition rate of the classifier for all signals exceed 97%, which validates the effectiveness of the proposed modulation recognition algorithm.

INDEX TERMS Automatic modulation classification, novel feature extraction, smooth support vector machine, feature selection.

I. INTRODUCTION

The automatic modulation classification (AMC) technology of communication signal is widely used in modern military war and civil electromagnetic supervision, which provides technical basis and guarantee for the realization of intelligent signal reception and processing. In recent decades, AMC technology has been explored continuously and many algorithms derived from it can be roughly divided into two categories: decision theory method based on likelihood function (LB) and statistical pattern recognition method based on feature extraction (FB). Among them, FB has been favored by researchers in the past decade due to its advantages of stable overall performance and low computational complexity. This method generally consists of two parts: feature extraction and classifier design.

In the feature extraction subsystem, the features which can represent the characteristics of signal are extracted by analyzing the time domain or transform domain information of signal in many aspects. As the core content of FB approach, the discrimination of signal characteristics directly affects the performance of modulation classification. In recent years, with the improvement of feature types and extraction methods, some new features based on classical feature extraction algorithms have been proposed and applied in modulation recognition. In [1], [2], authors successfully classify the modulation signals such as MSK and MPSK by using the cyclic spectrum characteristic image analysis method and enumerating the differences between the characteristic parameters obtained from training and test data through Hamming distance measurement. In [3], a new feature is constructed based on the fourth and sixth order cumulants and a neural network classifier is designed to classify nine kinds of signals including MSK and MQAM signals. More recently, authors combine the information entropy features of the signal with the feature selection algorithms and use five different ensemble learning classifiers to complete the classification of a variety of digital modulation signals [4]. In another work, compressive temporal higher order cyclostationary statistics is proposed in [5]. And likewise, in order to solve the problem of limited use of cyclic cumulant features at high sampling rate, the author of [6] introduces the compressed sensing

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framework into the modulation recognition system and studies the new features reported by [5] as the comparison target. Although in recent years, many high-quality new features have been proposed, the research process of new feature extraction is more difficult due to the requirements of innovation and practical engineering effectiveness. In particular, the new features that can complete recognition of MSK signal and classification of MPSK and MQAM signals are rarely proposed, and thus this paper will study the above two problems and realize the extraction of the two new features. At the same time, with the machine learning (ML) theory was widely applied in the field of modulation recognition in the past decade, the focus of modulation recognition research is moving towards another equally important core technology, classifier design. Therefore, as the important algorithm of ML, dictionary learning used in [7] with a block coordinate descent algorithm to identify the modulation format of the received signal and prove the convergence of the algorithm and quantify its convergence speed in a closed form. And meanwhile, a hierarchical polynomial classifier based on the high-order cumulant feature is designed in [8] to complete the modulation pattern recognition of MPSK and MQAM signals in Gaussian white noise and fading channels respectively. In [9], the author designs a new classifier and verifies its validity by folding the received signal and combining the different symmetry axis difference of modulation format with the theory of Kolmogorov-Smirnov test. On the other hand, improvement and design of support vector machine classifier (SVM) is also one of the research hotspots in the study of classifier. In [10], the CHKS smooth function as an alternative loss function was introduced into the algorithm of SVM classifier so as to design a new type of smooth support vector machine (SSVM), which was compared with the SSVM with sigmoid function in terms of time complexity and classification performance. And recently, other researchers introduce gray-scale algorithm into the training process of SVM and combines the feature parameters extracted by K-means clustering algorithm to complete the modulation pattern classification of MPSK and MQAM signals [11]. Moreover, the author of [12] uses the mathematical structure of the wedge product on the SVM to extend the support vector machine to the support spinor machine, and extends the original field from the vector field to the spinor field, so as to establish a new classifier model on the mathematical principle of the SVM.

However, in the related research articles, the researchers mostly use the average recognition rate of modulated signals to show the effectiveness of the modulation recognition algorithm and ignore the individual recognition rate of each signal. Although this method can effectively show the classification performance of the algorithm, it may also make the over fitting of some signals under low SNR ignored. As a result, this paper will focus on the classification of more comprehensive modulation signal set and take the individual recognition rate of each modulation signal as a significant standard to measure the effectiveness of the algorithm. Firstly, features of eleven kinds of digital signals are extracted and the properties of two new features are analyzed. Then, tree shaped multi-layer smooth support vector machine classifier based on feature selection algorithm (FS_DT-SSVM) is designed. Finally, the corresponding experimental data are used to train and test the classifier model and analyze the experimental results.

The rest of this paper is organized as follows: Section II introduces the feature extraction algorithm. Section III proposes design principle of the FS_DT-SSVM classifier. The experimental environment, data and simulation results are described and analyzed detailedly in Section IV. Section V gives the conclusion of the paper and demonstrates the existing problems and the direction of the research work in the next stage.

II. FEATURE EXTRACTION

For the set of digital modulation signals to be recognized {2ASK, 4ASK, 8ASK, 2PSK, 4PSK, 8PSK, 2FSK, MSK, 16QAM, 32QAM, 64QAM}, this section analyzes two new feature extraction algorithms firstly and then extracts other nine existing features of each signal including instantaneous information features, cyclic spectrum features and high-order cumulant (HOC) features.

A. DIFFERENTIAL NONLINEAR PHASE PEAK FACTOR

When there are MSK, 2FSK, MASK, MPSK and MQAM signals in a modulation recognition system, it is not easy to distinguish MSK signal from other signals. In [13], enlightening from the key point of constant envelope of MSK signal, author first judge whether the signal is an equal-amplitude signal to distinguish MSK, 2FSK and AM signal, and then recognizes MSK signal by using the feature reflecting instantaneous frequency compactness. Method in [14] is proposed to distinguish MSK and PSK signal from ASK and FSK signal and then to identify MSK and PSK signals by using spectral features. These methods all adopt the step-by-step recognition method, which first use different feature parameters to recognize MSK signal and one or more other signals, and then construct different features to recognize MSK signal. Therefore, when using this method to recognize MSK signal, it is necessary to construct different features, which makes the algorithm difficult to have strong adaptability. In this paper, a new feature, differential nonlinear phase peak factor (PF) is proposed, which can directly identify MSK signals from 2FSK, MASK, MPSK and MQAM signals.

MSK signal is a kind of phase continuous signal and the nonlinear part of the phase presents continuous and uninterrupted characteristics. At the time of symbol transformation, the nonlinear phase will only show no significant change due to the influence of Gaussian white noise. However, ASK, PSK, QAM signals and 2FSK signal with discontinuous phase do not have continuous nonlinear phase characteristics, which will be accompanied by dramatic phase change at symbol switching time. In order to extract and observe the characteristics of phase jump caused by symbol switching conveniently, the nonlinear phase of signal is processed by difference, normalization and absolute value. In this section, five representative signals including MSK, 2FSK, 2ASK, 2PSK and 16QAM, are selected for simulation. The signal parameter setting was: number of symbols is 30, information rate is 500bit/s, carrier frequency is 2000Hz, sampling rate is 8000Hz, and the SNR is 20dB. The frequency deviation of 2FSK signal is 600Hz. and the simulation results are shown in Fig. 1.

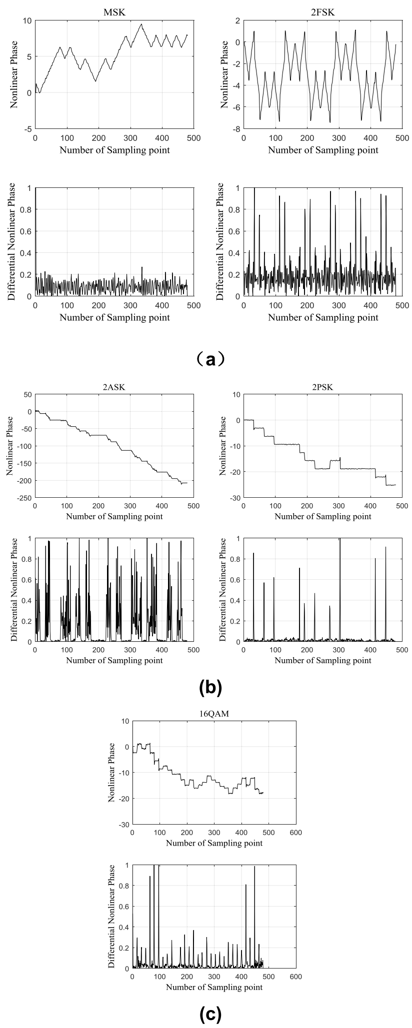

FIGURE 1. Nonlinear phase and differential nonlinear phase of five signals: (a) MSK and 2FSK signal; (b) 2ASK and 2PSK signal; (c) 16QAM signal.

It can be seen from the observation of nonlinear phase in the Fig.1 that MSK signal phase is continuous and does not have dramatic changes, while 2FSK signal has phase connection part close to the vertical direction, and moreover, 2ASK, 2PSK and 16QAM signal phase has sharp change characteristics similar to ladder shape. In addition, the figure of differential nonlinear phase feature demonstrates that only discrete spectral lines value of MSK signal does not have more than 0.5, and the other four signals have obvious discrete spectral lines. Therefore, this paper uses 0.5 as the threshold to judge whether there are discrete spectral lines in a signal. Finally, differential nonlinear phase peak factor (PF) is defined as:

$$PF = \frac{sum(nor(diff(\phi_{NL}(i)))\,|_{nor(diff(\phi_{NL}(i)))>th})}{mean(nor(diff(\phi_{NL}(i))))} \tag{1}$$

$$\phi_{NL}(i) = \phi(i) - \frac{2\pi i f_c}{f_s} \tag{2}$$

$$\phi(i) = \theta(i) + C(i) \tag{3}$$

where, $\phi_{NL}(i)$ is nonlinear phase, $\phi(i)$ is unwrapped phase, $\theta(i)$ is instantaneous phase obtained by Hilbert transform, $C(i)$ is corrected phase sequence. $nor(\cdot)$ means to normalize the data and limit the range to [0,1], $diff(\phi_{NL}(i))$ represents difference processing of nonlinear phase $\phi_{NL}(i)$, $sum(\cdot\,|_{condition})$ means to compare the results of difference and normalization with the conditions and to sum the parts exceeding the threshold and then to calculate the ratio with the normalized difference phase average value. PF represents the ratio of the sum of the normalized differential nonlinear phase peak values to the normalized differential nonlinear phase average value.

For the Differential nonlinear phase peak factor, Monte Carlo experiments are performed 100 times on each signal and the PF of 11 kinds of digital signals is shown in Fig. 2.

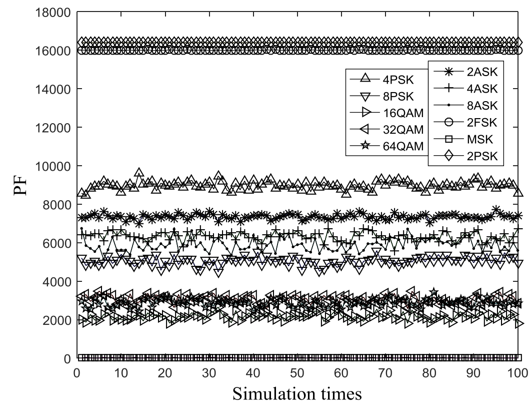

FIGURE 2. Differential nonlinear phase peak factor of 11 signals.

In Fig. 2, the bottom part is MSK signal simulation curve and the maximum value is not more than 100. Likewise, 16QAM signal is the closest to MSK signal and its value is about 2000, which is quite different from MSK signal. Therefore, the modulation identification between MSK signal and 2FSK, MASK, MPSK, MQAM signal can be carried out by using the feature parameter.

B. NOVEL FEATURE BASED ON CYCLIC SPECTRUM

The classification of PSK and QAM signals has been a difficult problem in the field of modulation recognition. In the previous research, these two kinds of signals cannot be distinguished by common cyclic spectrum features. Generally, PSK and QAM signals can be identified by high-order cyclic cumulant features or constellation clustering features, but these methods need to introduce new feature algorithm.

The calculation method of higher-order cyclic cumulant is different from that of higher-order cumulant, which is necessary to introduce variables to calculate the cyclic autocorrelation function of signal so that the calculation amount is greatly increased. In addition, the modeling and clustering process of constellation also need to establish a new computing system, and carrier deviation will seriously affect the correct recognition of modulation mode. Therefore, based on characteristic parameter Y_1 that is the normalization of the reciprocal of the amplitude envelope variance of cyclic spectrum at zero frequency cross section, the new feature Y_2 is constructed by the difference and forth power pretreatment of signals, and the effective distinction between the high-order MQAM signal and the MPSK (M = 4, M = 8) signal is realized successfully.

Feature parameter Y_2 and parameter Y_1 are calculated in the same way, and Y_1 is defined as:

$$Y_1 = \frac{1}{\frac{1}{N}\sum_{i=1}^{N}(y_i - y_0)^2} \tag{4}$$

$$y_0 = \frac{1}{N}\sum_{i=1}^{N} y_i \tag{5}$$

where, N is the number of Sampling points at zero frequency cross section, y_{i} is amplitude value of each point.

The difference between the two feature parameters lies in the fact that Y_2 needs to perform difference and forth power operation on the signal first, and then calculate the reciprocal of the amplitude envelope variance of the cyclic spectrum at zero frequency cross section. Principle block diagram of feature Y_2 extraction algorithm is shown in Fig.3.

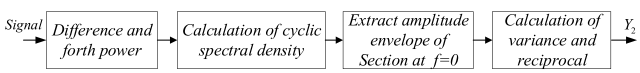

FIGURE 3. Principle block diagram of feature Y_2 extraction algorithm.

Traditional cyclic spectrum feature Y_1 cannot distinguish 4PSK and 8PSK signals from high-order QAM signals, while new feature Y_2 shows the difference between phase shift keying signal and orthogonal amplitude modulation signal in the zero frequency cross section of cyclic spectrum, which is convenient to classify high-order QAM, 4PSK and 8PSK signals. Simulation experiments are carried out on each signal in the noise-free environment, and the simulation value of feature parameter Y_2 of signals to be identified is shown in Fig. 4. It can be seen from the figure that the simulation values of feature parameter Y_2 of MQAM, 4PSK and 8PSK signal are quite different and easy to recognition.

C. OTHER CLASSIC FEATURES

1) INSTANTANEOUS FEATURES

Maximum value of power spectral density of central normalized instantaneous amplitude is defined as:

$$\gamma_{\max} = \frac{\max |FFT\,[a_{cn}(i)]|^2}{N} \tag{6}$$

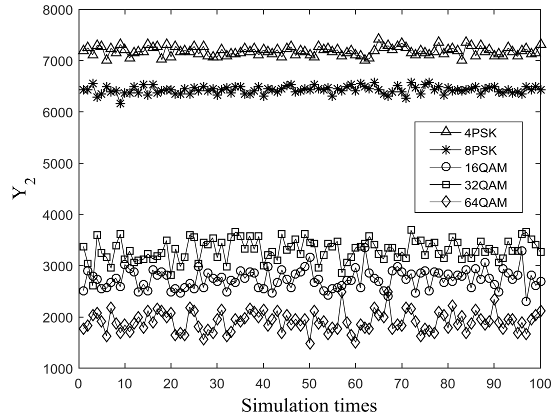

FIGURE 4. Simulation value of feature Y_2 of signals to be identified.

where, $a_{cn}(i)$ is central normalized instantaneous amplitude of signal, N is the number of sampling points, and the derived formula is as follows:

$$\begin{aligned} m_a &= \frac{1}{N}\sum_{i=1}^{N} a(i) \\ a_n(i) &= a(i)\big/ m_a \\ a_{cn}(i) &= a_n(i) - 1 \end{aligned} \tag{7}$$

Standard deviation of signal instantaneous amplitude is:

$$\sigma_{xi} = \sqrt{\frac{1}{N}\left[\sum_{i=1}^{N} a^2(i)\right] - \left[\frac{1}{N}\sum_{i=1}^{N}|a(i)|\right]^2} \tag{8}$$

2) CYCLIC SPECTRUM FEATURES

The number of spectral lines normalized at zero frequency cross section can recognize MASK, 2PSK, 2FSK and MSK signals from other signals. In the normalized zero frequency cross section of the cyclic spectrum, the spectral correlation characteristics of different modulation modes are not same. There are two obvious spectral lines on the normalized zero frequency cross section of MASK and 2PSK signals. And the number of spectral lines of 2FSK and MSK signals is 4, while the number of spectral lines of MQAM, 4PSK and 8PSK signals is more on this section.

And the feature Y_1 that is normalization of the reciprocal of the amplitude envelope variance of cyclic spectrum at zero frequency cross section is defined as the formulas (4) and (5).

3) HOC FEATURES

In this paper, five features based on HOC are extracted:

$$A_1 = \left|C_{60}^2\right| \Big/ \left|C_{40}^3\right|, \quad A_2 = \left|C_{63}^2\right| \Big/ \left|C_{40}^3\right| \tag{9}$$

$$F_1 = |C_{42}| / |C_{21}|^2 \tag{10}$$

$$F_2 = |C_{80}| / |C_{42}|^2 \tag{11}$$

$$B = |C_{40}| / |C_{42}| + |C_{41}| / |C_{42}| \tag{12}$$

III. CLASSIFIER DESIGN

Classifier is an important part in the system of modulation recognition, which is responsible for the decision of modulated mode classification. In order to realize the multi-classification of eleven kinds of digital modulated signals, this paper proposes a tree shaped multi-layer smooth support vector machine classifier based on feature selection algorithm (FS_DT-SSVM).

A. SMOOTH SUPPORT VECTOR MACHINE

Support vector machine (SVM) is to transform the classification problem into a convex quadratic optimization problem with linear constraints. It can effectively solve the problems of model selection, under learning and over learning, which has the perfect mathematical form, intuitive geometric interpretation and good generalization ability. SVM has been successfully applied to the problem of classification of modulation modes of communication signals because of its small number of artificial parameters and ease of use. However, in conventional SVM, the objective function of quadratic programming problem does not have second-order smoothness, especially causing large error in solving the problem of signal classification with low sampling rate and small SNR. To resolve these problems, Lee and Mangasarian introduced the sigmoid smooth function and proposed the smooth support vector machine (SSVM) [15]. The Related research shows that the SSVM not only inherits the advantages of the classical SVM algorithm, but also uses the effective numerical operating algorithm to solve the objective function with the smooth loss function, which makes the SSVM have better classification ability.

B. FEATURE SELECTION ALGORITHM

Feature selection (FS), also known as feature subset selection or attribute selection, refers to selecting a feature subset from all features to make the constructed model better.

1) BEST FIRST SEARCH

The best first search algorithm is a kind of complete search algorithm and a special location search algorithm. The algorithm is described as follows: Firstly, N elements with the highest evaluation are selected as element subsets, which are added to a priority queue and the subsets with the highest evaluation are obtained from the queue each time. And then all the sets generated after adding an element to this subset are enumerated, and these element sets are added to the queue.

2) SEQUENCE FLOATING FORWARD SELECTION

Sequence floating forward selection (SFFS) algorithm is a heuristic search algorithm and a form of sequence floating algorithm. The initial set of the algorithm is an empty set. In each round, a subset X is selected from the unselected features, so that the evaluation function is optimal after adding subset X, and then subset Z is selected from the selected features, so that the evaluation function is optimal after removing subset Z.

C. DESIGN OF FS_DT-SSVM

In this paper, the idea of feature selection is applied to the selection of the signals to be classified at each node and the selection of the optimal feature combination of training node classifier in the classification algorithm, so that the decision tree classifier (DT) and SSVM are combined to design FS_DT-SSVM.

In order to establish the tree-shaped classifier model, the best first search method is introduced and used for reference in the process of selecting the signals to be classified at each node. However, the search object is modified from the feature type to the signal type, and the signal subset is selected from the signal set to be identified by using signal modulation category as the initial evaluation criterion, and then the classification accuracy of the optimal feature selection result of the node classifier is used as the search evaluation function to search the subsets of signals to be classified according to the stop criterion that it is not less than the expected accuracy threshold.

Therefore, the combination of the signal to be identified and the optimal feature of each node is selected completely by this method, and so as to establish a multi-classifier model. And The principle of node training data selection of FS_DT-SSVM classifier is shown in Fig. 5.

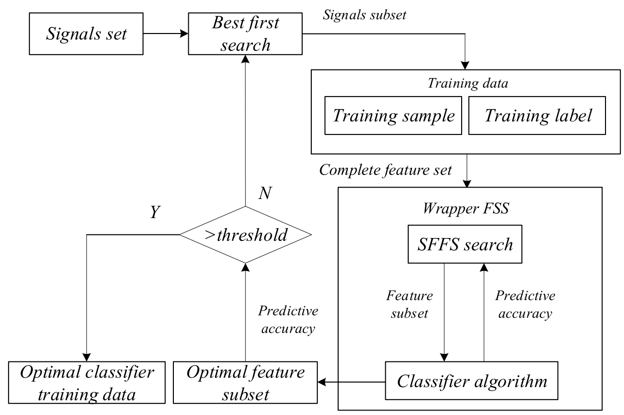

FIGURE 5. The principle of node training data selection of FS_DT-SSVM classifier.

As shown in Fig. 5, the training data selection process at any non-leaf node of the decision tree is as follows:

First of all, different kinds of signal samples in the signal set to be identified are marked, and the marking rules are determined by the results of the best first search of the signal set to be identified. The signal subset generated by the search algorithm and its signal complement set relative to the signal set to be identified are marked with two different labels respectively.

Then, under the condition of determining different signal markers, SFFS is used to select the feature combination which is most suitable for SSVM classifier training and has the greatest contribution to modulation signal classification at different non-leaf nodes of decision tree classifier.

Finally, the predictive accuracy of the optimal feature combination selected by the feature selection algorithm is compared with the accuracy requirement threshold value. If the threshold value is not reached, the subset search of the signal set to be identified will continue. If the threshold value is reached, the optimal training data of the node will be output, which is the signal classification expectation and feature combination for training of this node classifier will be determined.

IV. RESULT AND DISCUSSION

A. EXPERIMENTAL ENVIRONMENT AND DATA

In the MATLAB simulation experiment, this paper simulated eleven digital signals including 2FSK, MSK, 2ASK, 4ASK, 8ASK, 2PSK, 4PSK, 8PSK, 16QAM, 32QAM and 64QAM. Signal parameters are set as follows: carrier frequency is 2000Hz, sampling frequency is 8000Hz, signal length is 2048, digital signal symbol rate is 500 Symbol/s. The baseband signal random code formed by rectangle pulse, and the number of symbols is 128, The noise is Gaussian white noise.

Data set includes training set and test set. The training set contains 36300 samples: SNR is from −10dB to 20dB with 3dB interval, each of which has 300 samples per signal. The test set contains 60500 samples: SNR is from −10dB to 20dB with 3dB interval, each of which has 500 samples per signal.

B. EXPERIMENTAL RESULT AND DISCUSSION

1) EXPERIMENT OF FEATURE EXTRACTION

In the experiment of feature extraction, this paper conducts 100 times Monte Carlo simulation for each modulation signal under different SNR, and then takes the average value to get the change trend of different features with SNR. The variation curve of the two new features with the SNR is shown in Fig. 6. The variation curve of other classic features with SNR is shown in Fig. 7.

It can be seen from the curve changes shown in Fig. 6(a) that the PF distinguishes the MSK signal from others more clearly when the SNR is more than 8dB. However, when the SNR is less than 8dB, the difference between the features of 2FSK and MSK signals gradually reduces, but it may still make contribution to the classification of the two signals by combining the PF with other features. When the SNR is equal to 8dB or less than −4dB, the change curves of the two kinds of signals almost coincide. At this time, it can hardly identify any signals. In Fig. 6(b), Reciprocal of the amplitude envelope variance of cyclic spectrum at zero frequency cross section after difference and forth power processing Y_2 can distinguish almost all signals above 5dB, especially MPSK and MQAM signals can be still classified effectively at −1dB. When the SNR is less than −4dB, the discrimination degree of the feature to the signal decreases gradually, and it almost loses effect at −7dB.

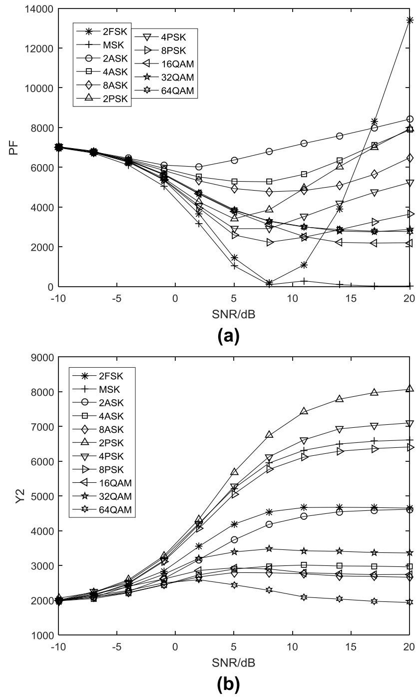

FIGURE 6. **The variation curve of the two new features with the SNR. (a) Differential nonlinear phase Peak Factor; (b) Reciprocal of the amplitude envelope variance of cyclic spectrum at zero frequency cross section after difference and forth power processing.**

Fig. 7(a) illustrates that the feature f_{0_number} can identify modulation schemes of {2FSK, MSK}, 2PSK, MASK and {4PSK, 8PSK, MQAM} under the condition that the SNR is not less than −4dB. While the feature Y_1 values shown in Fig. 7(b) can not only complete the classification of {2FSK, MSK, 2PSK} and MASK signal, but also has good discrimination on MASK signals and the distance between the signals is large. In Fig. 7(d), (f) and (h), the amplified variation curves show that the higher-order cumulant features A_1, A_2 and B can realize the classification of MASK and MPSK signals when SNR is not less than −1dB, but the features have differences in the intra-classification of these two types of signals. At the same time, compared with Fig. 7(j), feature F_2 can also contribute to the recognition between MASK and MPSK signals, and there is a distance between the values of 16QAM and 64QAM signal. In Figure 7 (k), it can be clearly shown that the feature F_1 can identify 2PSK signals from other signals and provide help for the intra-classification of MASK. When the SNR is more than −1dB, it can also contribute to the classification of 16QAM and 64QAM signals and the recognition of MSK signals. It can be seen from Fig. 7 (l) and (m) that the feature $\gamma_{\max}$ and the feature σ_{xi} can help the intra-classification of MASK and MQAM signals, but the feature curves of the related signals in the image have crossed and overlapped in some SNR ranges, which makes the features have different classification performance between the two types of signals, so there is the possibility of feature combination in the training process of the classifiers, and thus mutual make up the

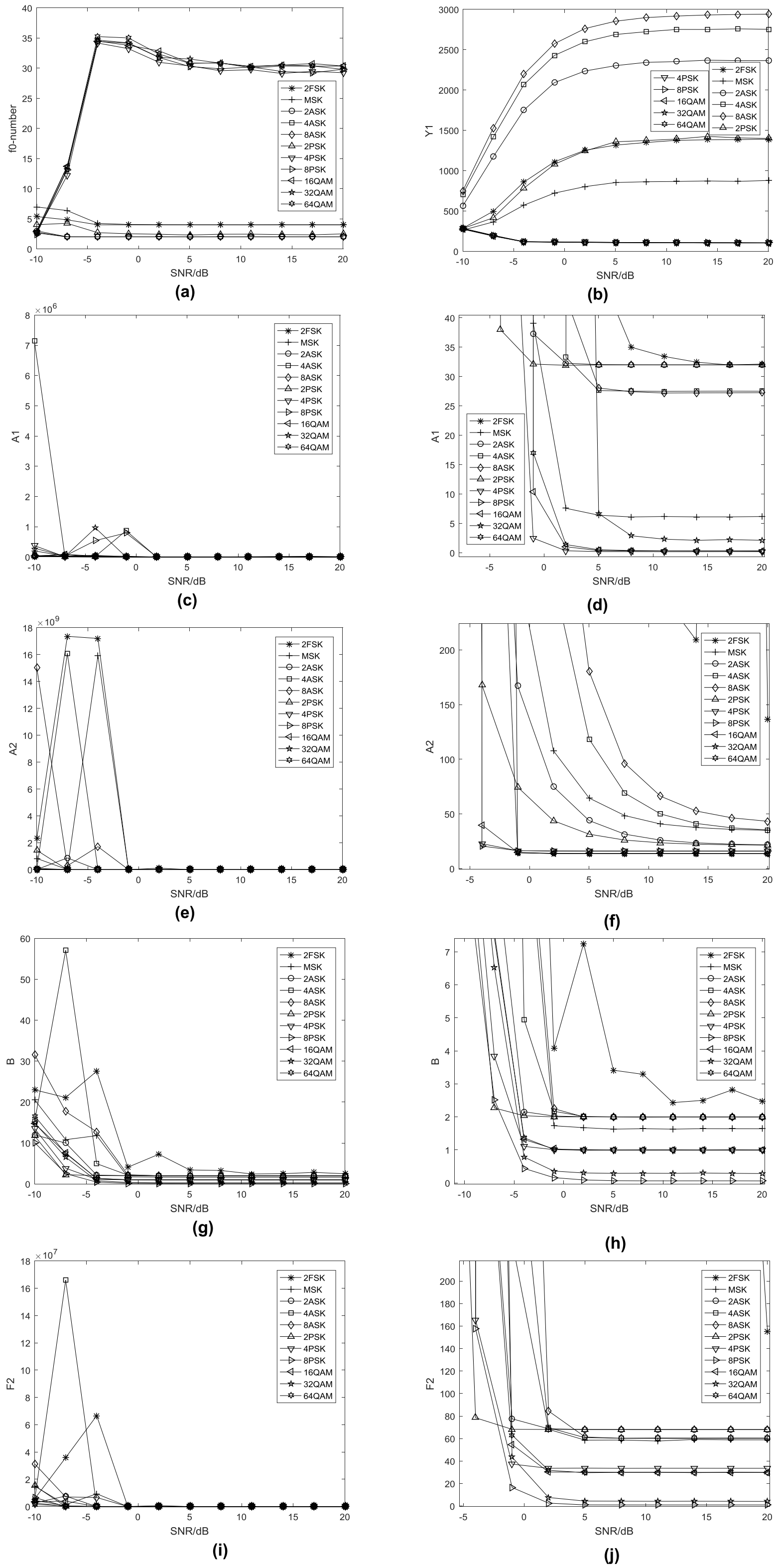

FIGURE 7. **The variation curve of other classic features with SNR. (a) The number of spectral lines normalized at zero frequency section; (b) The normalization of the reciprocal of the amplitude envelope variance of cyclic spectrum at zero frequency section; (c) High-order cumulant A_1; (d) Enlarged view of (c) where the SNR is more than −1dB; (e) High-order cumulant A_2; (f) Enlarged view of (e) where the SNR is more than −4dB; (g) High-order cumulant B; (h) Enlarged view of (g) where the SNR is more than −7dB; (i) High-order cumulant F_2; (j) Enlarged view of (i) where the SNR is more than −4dB.**

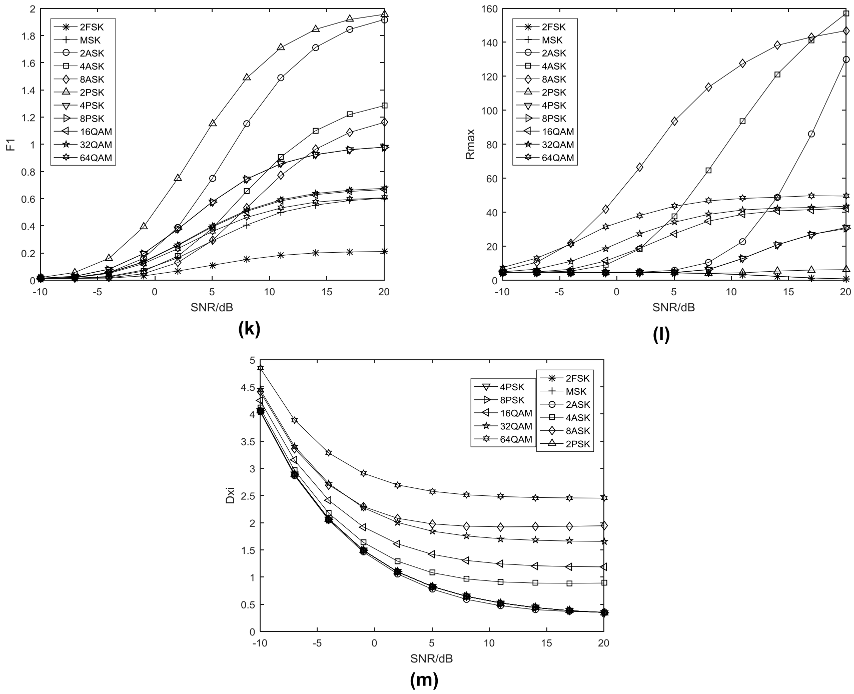

FIGURE 7. ***(Continued.)*** **The variation curve of other classic features with SNR. (k) High-order cumulant F_1; (l) Maximum value of power spectral density of central normalized instantaneous amplitude; (m) Standard deviation of signal instantaneous amplitude.**

disadvantages and improve the recognition rate of modulation signal.

2) EXPERIMENT OF MODULATION CLASSIFICATION

In the simulation experiment of modulation classification, this paper first establishes the classifier model according to the design principle of FS_DT-SSVM classifier mentioned above. Then the training data is used to train the classifier. Finally, the performance of the trained classifier is tested by the test data, and the modulation pattern recognition rate of the signal under different SNR is obtained. The principle structure of the optimal classifier model that is established in this paper is shown in Fig. 8. The letters and numbers of each non-leaf node in the decision tree represents the corresponding optimal feature subset, and the feature combination details are shown in Table 1.

According to the expected classification signal subsets and the optimal feature combination of each node of the classifier shown in Fig. 8 and Table 1, the analysis of the trend of each feature variation with the SNR in the feature extraction experiment can be verified. The differential nonlinear phase peak factor is applied to the classification of MSK and other signals, especially MSK and 2FSK signals. And the other two cyclic spectrum features make up for the defect of this feature in some SNR cases, thus enhancing the classification effect of the two signals. Likewise, another new feature Y_2 appears in the optimal feature combination options of all MPSK and MQAM inter-class and intra-class recognition node classifiers. This not only verifies the related analysis of

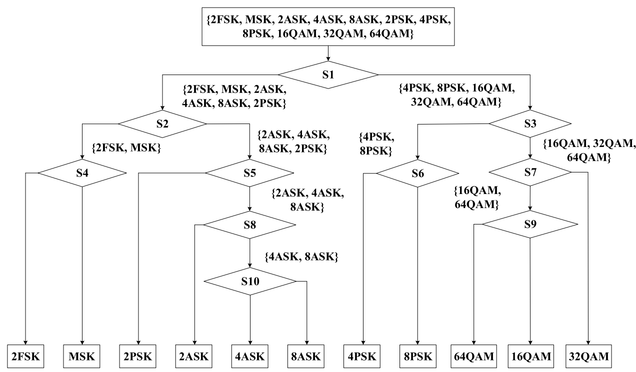

FIGURE 8. **Principle structure of the FS_DT-SSVM classifier model.**

this feature, but also directly reflects the contribution of this feature to the classification of the above two types of signals.

In order to further verify the effectiveness of the classification algorithm proposed, this paper establishes the experimental testing sample set that uses random sampling method to take samples of 100 from test set and can complete data testing experiment to obtain correct recognition rate of each signal. And then this paper repeats the above experiment 100 times and takes the average of these simulation results. The final correct recognition rate of the modulation pattern of each signal is shown in Table 2 and Table 3.

Through the research on the information of the correct recognition rate of modulation modes of eleven kinds of digital signals with the change of SNR shown in Table 2 and

TABLE 1. The optimal feature subset of training samples for each node classifier.

Node number	optimal feature subset
S1	f_{0_number} Y_1 F_1 PF
S2	f_{0_number} Y_1 F_1
S3	Y_2 B F_1 F_2 $\gamma_{\max}$ σ_{xi}
S4	f_{0_number} Y_1 F_1 PF
S5	Y_1 A_1 A_2
S6	Y_2 B F_1 F_2
S7	Y_2 $\gamma_{\max}$ σ_{xi}
S8	$\gamma_{\max}$ σ_{xi}
S9	Y_2 F_1 $\gamma_{\max}$ σ_{xi}
S10	$\gamma_{\max}$ σ_{xi}

TABLE 2. Correct specific recognition rate of modulation modes of 2FSK, MSK and MASK signals.

SNR	2FSK	MSK	2ASK	4ASK	8ASK
-10	0.5948	0.5053	0.8075	0.908	0.9884
-7	0.7548	0.7218	0.9848	0.9889	0.9977
-4	0.9432	0.95	0.9981	1	1
-1	0.9928	0.9762	0.9995	1	1
2	0.9992	0.9949	1	0.9998	1
5	0.9999	1	0.9993	0.9987	1
8	1	1	0.9996	1	1
11	1	1	1	0.9991	1
14	1	1	0.9968	0.9994	1
17	1	1	0.9994	1	1
20	1	1	1	1	1

TABLE 3. Correct specific recognition rate of modulation modes of MPSK and MQAM signals.

SNR	2PSK	4PSK	8PSK	16QAM	32QAM	64QAM
-10	0.4885	0.5151	0.4052	0.8667	0.903	0.8713
-7	0.9265	0.611	0.4783	0.986	0.9912	0.9954
-4	0.9984	0.8295	0.8812	0.9999	1	0.9982
-1	1	0.9962	0.9994	1	0.9998	1
2	0.9978	0.9989	1	1	0.9981	1
5	0.9996	0.9994	1	1	1	1
8	1	0.9979	1	1	0.9977	1
11	0.9979	0.9989	1	1	0.9999	1
14	0.998	1	1	1	1	1
17	1	1	1	1	0.9992	1
20	0.9995	1	0.999	1	1	1

Table 3, it can be seen that the recognition rate of all signals increases with the SNR increasing, and when the SNR is not less than -1dB, the recognition rate of all signals is above 97% and the recognition rate of MSK signal can even reach a high level of 97.62%.

However, when the SNR is not more than -4dB, the modulation pattern recognition rate of MSK and 2FSK signal drops rapidly, even reaches about 59% and 50% respectively at -10dB. At this time, it is almost impossible to recognize the two kinds of signals, which means that the feature PF gradually loses the ability of classification under low SNR and it is difficult to distinguish the modulation signals despite the assistance of other features.

Moreover, another new feature Y_2, contributes to the inter-classification between MQAM and MPSK signals and the intra-classification of MQAM signals, so that MQAM signals can maintain a good recognition rate under low SNR. However, according to the relevant experimental data in the chart, its effect in the classification within MPSK signals under low SNR is very limited. If the intra-class recognition rate of MPSK signal wants to be further improved, the other new features or feature combinations should be introduced.

V. CONCLUSION

In this paper, in order to solve two kind complex problems of communication signals modulation classification including MSK extracted from 2FSK and inter-classification of MPSK and MQAM, differential nonlinear phase Peak Factor (PF) and reciprocal of amplitude envelope variance of cyclic spectrum at zero frequency cross section after difference and forth power processing (Y_2) were proposed respectively. In addition, a tree shaped multi-layer smooth support vector machine classifier based on feature selection algorithm (FS_DT-SSVM) is designed to classify eleven kinds of digital signals including MSK and MQAM signals. Through the analysis of simulation results, it can be seen that PF has significant effect on MSK and 2FSK signal classification when the SNR is greater than 8dB. When the SNR is lower than 8dB, the classification effect gradually decreases, but when the SNR is not less than -4dB, it can still maintain good classification effect with the help of other features. Compared with the PF, feature Y_2 is more stable in low SNR and it can not only complete the inter-classification of MPSK and MQAM signals, but also contribute to the intra-classification of MQAM signals. Although these two features have some limitation, they can greatly reduce their own shortcomings and increase the modulation pattern recognition rate of the related signals with the help of other suitable features and FS_DT-SSVM classifier. At the same time, although the classifier can complete the modulation recognition of eleven kinds of digital signals well under the low SNR, the computation amount in the classification process increases and the recognition time becomes longer because the SSVM algorithm is applied to every node classifier. This is a problem to be solved in the follow-up study of this paper.

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