A Novel Method for Wireless Communication Signal Modulation Recognition in Smart Grid

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Abstract —Dynamic spectrum access technology and cognitive radio technology are research directions in new types of wireless communications business in smart grid. Modulation recognition technology of wireless communication signals is the premise of wireless communication in smart grid dynamic spectrum access technology and the cognitive radio technology. Currently, high computation complexity happens when the existing support vector machine (SVM) identifies multi-class problems, and the modulation recognition rate is not ideal when the receiving signal noise ratio (SNR) is low. For these two problems, high-order cumulants used in this article can have good anti-noise performance. To begin with, high-order cumulants can be extracted as the characteristic value of signal. Then, SVM is conducted training. Finally, the recognition algorithm routine of conventional SVM is promoted. After this process presented in this article, the simulation result showed that the corresponding average modulation recognition rate can increase by more than 25% than the situation when individually using conventional SVM. Especially, when SNR is 5dB, the recognition rate can reach 90% and the system prone to be achieved, which shows that high-order cumulants has wide application prospect in the application aspect of smart grid dynamic access wireless communication technology.

Index Terms—Smart grid dynamic spectrum access, high-order cumulants, feature extraction, SVM, modulation recognition

I. Introduction

At present, the communication technology in smart grid includes types of wired and wireless communication and fibre Optical Communication Technology is the main and predominated technical means of power system communication cable. It hosts the relay protection of power line, safety remote control, electric power, telephone, high-definition video, video monitoring, data network remote automation and a variety of other information communication businesses which are from single to complex and from small particles to large data. But for 35kV low-pressure placement of electricity such as cable communication mode which has many spots, wide areas and complex environment, adopted wire communication falls down. Therefore, wireless communication becomes the inevitable choice. However, with the significant improvement of the communication traffic in the smart grid, the frequency of the wireless communication resources which can be used in the smart grid are limited. Thus, exploring the wireless communication which has higher spectrum efficiency, high reliability, high adaptability and high maintainability has become a problem in the development of intelligent electric power communication and this problem needs to be urgently solved [1]. Hence, in the smart grid, dynamic spectrum access technology and cognitive radio technology are hotspots in the research of smart grid wireless communication technology research. Especially in the case of spectrum scarcity, using spectrum sensing and spectrum access technology can achieve the real-time and reliable information transmission of the power grid control information, business information, scheduling information. Meanwhile, they can effectively reduce the fees generated by the spectrum leasing. And the modulation recognition of wireless communication signal is an important foundation in spectrum sensing, spectrum access, cognitive wireless electronic technology [2], [3]. Modulation recognition is widely used in signal detection, information interacting, interference query and some aspects in wireless communication of military and civil use, and is a basic problem for spectrum sensing in cognitive radios. Therefore, how to continuously innovate in extracting characteristic value and classifier algorithm becomes one of the important ways in the modulation recognition research [4], [5].

According to the references [6]-[9] which discuss the recognition of multiple problems, high computational complexity exists when using modulation recognition method of the classifier based on the conventional SVM. Especially under the low SNR, the recognition rate of the modulation signal is unsatisfactory. In the reference [10], [11], the combination of K-mean value clustering algorithm and SVM is applied. The detailed process is the characteristic value of the signal is extracted firstly. Then, the constellation of the signal is rebuilt through clustering

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algorithm. After this step, the function values of different clustering centers can be computed through the effective function so that these function values can be as characteristics values while grading algorithm is applied to train the SVM classifier. The entire process can achieve the modulating recognition of the signals and improve the performance of recognition under low SNR.

On the basis of the above methods, the use of satisfactory anti-noise performance which exists in high-order cumulants is applied in this paper. The entire process is that the higher-order cumulants is firstly extracted as the signal characteristic value which is then sent to the process of clustering optimization. After this step, the SVM is trained. For this process presented in this paper, the program of conventional SVM recognition algorithm can be improved and the recognition of wireless communication signals can be achieved. This method can effectively resist the Gaussian white noise and the bad effects because of the signal constellation rotation caused by the initial phase, and effectively avoid the problem of over learning and local convergence in the neural network way.

This paper summarizes the drawbacks of conventional SVM, clustering and SVM combined modulation recognition so as to present that it is necessary to improve conventional SVM recognition algorithm program based on the combination of higher-order cumulants and SVM. Section 2 and 3 respectively introduced the higher-order cumulants and method of SVM classification. Section 4, focuses on the principle of signal recognition based on higher-order cumulant and SVM. All kinds of modulation recognition simulation results and comparative analysis are given in Section 5. Finally, conclusion is made in Section 6.

II. The Characteristic Value of Spectrum Dynamic Identification in the Smart Grid

In the smart grid, in order to obtain the information such as user's real-time demand, electricity consumption, and guide the user independently adjust electricity demand for balancing electricity supply and demand power grid, reducing energy waste and relieving the pressure of power supply support, the utilization of limited spectrum resource used in communications is especially important. In order to improve the utilization rate of spectrum, the extraction of characteristic value used for dynamic spectrum recognition is critical. In this paper, the higher-order cumulants of signal are obtained as the characteristic value of spectrum dynamic identification. The higher-order cumulants has good anti-noise performance and is widely used in signal processing. In general, the transmission signal and Gaussian noise is independent of each other in the channel, and the cumulants of Gaussian noise higher than that of the second order is zero. Therefore, a high-order cumulants converted from the received signal is used so as to eliminate Gaussian noise [12], [13].

Assume that we are in a continuous and synchronous environment while synchronization of the time synchronization and carrier, and waveform restoration have been achieved, then a complex baseband sequence can be written as:

$$r(i) = s(i) + n(i) = \sum_{k=1}^{L} \sqrt{E} a_k e^{j\theta_c} p(i-k) + n(i) \tag{1}$$

For (1), E means k information symbol, L is the length of the observation sequence, E and T_d are symbol energy and duration respectively, θ_c is early phase of the carrier, $p(t)$ is impulse response of channel, $\mathbf{n}(t)$ is white Gaussian noise and its mean is 0, additive variance is σ^2. The higher-order cumulants of receiving signals can be expressed as:

$$\begin{gathered}\mathbf{C}um_m(\mathbf{r}_1, \mathbf{r}_2, \cdots, \mathbf{r}_k) = \mathbf{C}um_m(\mathbf{s}_1 + \mathbf{n}_1, \cdots, \mathbf{s}_k + \mathbf{n}_k), \\ k = 1, 2, \cdots,\ s_k + n_k\end{gathered} \tag{2}$$

As the transmission signal and Gaussian noise are independent of each other, according to the properties of the cumulants, cumulants of received signal can be written as:

$$\mathbf{C}um_m(\mathbf{r}_1, \mathbf{r}_2, \cdots, \mathbf{r}_k) = \mathbf{C}um_m(\mathbf{s}_1, \mathbf{s}_2, \cdots, \mathbf{s}_k),\ m > 2 \tag{3}$$

$\mathbf{x}^*(k)$ is Complex conjugate, $\mathbf{M}_{pq}$ is the higher order original moment of signal at a certain moment and can be defined as

$$\mathbf{M}_{pq} = E\left[\mathbf{x}(k)^{p-q}(\mathbf{x}^*(k))^q\right] \tag{4}$$

For stable complex signals, four and six order cumulants can be defined as [14], [15]:

$$\mathbf{C}_{40} = \mathbf{C}um[\mathbf{x}(k), \mathbf{x}(k), \mathbf{x}(k), \mathbf{x}(k)] = \mathbf{M}_{40} - 3\mathbf{M}_{20}^2 \tag{5}$$

$$\mathbf{C}_{41} = \mathbf{C}um[\mathbf{x}^*(k), \mathbf{x}(k), \mathbf{x}(k), \mathbf{x}(k)] = \mathbf{M}_{41} - 3\mathbf{M}_{21}\mathbf{M}_{20} \tag{6}$$

$$\begin{aligned}\mathbf{C}_{42} &= \mathbf{C}um[\mathbf{x}^*(k), \mathbf{x}(k), \mathbf{x}(k), \mathbf{x}^*(k)] \\ &= \mathbf{M}_{42} - \left|\mathbf{M}_{20}\right|^2 - 2\mathbf{M}_{21}^2\end{aligned} \tag{7}$$

$$\begin{aligned}\mathbf{C}_{60} &= \mathbf{C}um\left[\mathbf{x}(k), \mathbf{x}(k), \mathbf{x}(k), \mathbf{x}(k), \mathbf{x}(k), \mathbf{x}(k)\right] \\ &= \mathbf{M}_{60} - 15\mathbf{M}_4\mathbf{M}_2 + 30(\mathbf{M}_{20})^3\end{aligned} \tag{8}$$

$$\begin{aligned}\mathbf{C}_{63} &= \mathbf{C}um\left[\mathbf{x}(k), \mathbf{x}(k), \mathbf{x}(k), \mathbf{x}^*(k), \mathbf{x}^*(k), \mathbf{x}^*(k)\right] \\ &= \mathbf{M}_{63} - 9\mathbf{M}_{41}\mathbf{M}_{21} - 6(\mathbf{M}_{21})^3\end{aligned} \tag{9}$$

Modulus operation can make the value of cumulants separate from the initial phase signal. Therefore, the characteristics classification based on the cumulants for Gaussian noise and the constellation rotation is very stable.

III. The Classifier for Spectrum Dynamic Identification in the Smart Grid

In the smart grid, in order to improve the spectrum efficiency, except for extracting the signal spectrum cumulant as characteristic value in the dynamic identification, the match choice of the appropriate classifier is also very important. In this paper, using the SVM as the classifier of modulation recognition for communication signals can achieve the dynamic spectrum identification. For solving cognitive problems of nonlinear and complex spatial model, learning algorithm of SVM has superior performance, and can be used for machine learning in which function is similar with a small training set. Compared with other similar algorithms such as neural network, fuzzy learning machine *et al*, SVM has many advantages, the most outstanding advantage is high general ability of obtaining better results from training.

The classical learning method in solving the problem of a specific learning is based on the empirical risk minimization principle, but in statistical learning theory, the principle of minimizing risk is adopted, and the principle can be described as follows [16], [17]:

Defining probability density function as $F(z)$ and loss function as $Q(z,a), a \in \Lambda$ on space $\mathbf{Z}$. The goal is minimized risk function as following:

$$R_{emp}(a) = \frac{1}{l}\sum_{i=1}^{l} Q(z,a_i) \tag{10}$$

The minimized function $Q(z,a_0)$ is approximately equal to $Q(z,a_l)$ typical (10) when empirical risk function is the minimized, which is called the principle of empirical risk function minimization. But after practice, it can be proved that the obtained result based on empirical equality function minimization principle is not always the best, such as for over fitting phenomenon and the low degree of generalization ability. Thus, when solving the problem of small sample, the extensive use of empirical risk minimization principle is not appropriate which exposes the necessity of a new criterion named the structural risk minimization principle. The basic idea of this principle is how to minimize the empirical risk and confidence interval. SVM can realize the principle of structural risk minimization and its principle is as follows [18], [19]:

Assume that the training set $(\mathbf{x}_i, \mathbf{y}_i)$, $i = 1, \cdots n$, $\mathbf{x} \in R^d$, $\mathbf{y} \in \{+1, -1\}$ can satisfy the following decomposition of hyperplane:

$$\boldsymbol{\omega}\mathbf{x} + b = 0 \tag{11}$$

If vector set can be error-free decomposed, separated hyperplane and the shortest distance between positive and negative samples are maximum. More specifically, assume that all of the training data meet the following limits:

$$\mathbf{y}_i [\boldsymbol{\omega} \cdot \mathbf{x}] - 1 \ge 0, i = 1, \cdots, n \tag{12}$$

The hyperplane which is limited by above formula and makes $\varphi(\boldsymbol{\omega}) = \|\boldsymbol{\omega}\|^2$ minimizes is called the optimal separating hyperplane. The training points which meet the demands of the above formula are called support vector. For a set of training set, in order to find out the hyperplane, convex quadratic programming problem needs to be solved. The detailed process is meeting the demand of the above formula, then minimum:

$$\varphi(\boldsymbol{\omega}) = \frac{1}{2}(\boldsymbol{\omega} \cdot \boldsymbol{\omega}) \tag{13}$$

The Lagrange multiplier is introduced to solve this problem so that the optimal decision function is:

$$f(\mathbf{x}) = \operatorname{sgn}\{(\boldsymbol{\omega}^* \cdot \mathbf{x}) + \mathbf{b}^*\} = \operatorname{sgn}\left\{\sum_{i=1}^{n} \mathbf{a}_i^* \mathbf{y}_i (\mathbf{x}_i \cdot \mathbf{x}) + \mathbf{b}^*\right\} \tag{14}$$

Among them, $\operatorname{sgn}(\cdot)$ is symbolic function. For data which are inseparable, if the dot product $(\mathbf{x}_i \cdot \mathbf{x})$ is replaced by kernel function $K(\mathbf{x}_i \cdot \mathbf{x}')$, the input space can be transferred into a new feature space. So the quadratic programming problem can be changed to be:

$$Q(\mathbf{a}) = \sum_{i=1}^{n} \mathbf{a}_i - \frac{1}{2}\sum_{i,j=1}^{n} \mathbf{a}_i \mathbf{a}_j \mathbf{y}_i \mathbf{y}_j K(\mathbf{x}_i, \mathbf{x}_j) \tag{15}$$

Decision function can be written as follows:

$$f(\mathbf{x}) = \operatorname{sgn}\left\{\sum_{i=1}^{n} \mathbf{a}_i^* \mathbf{y}_i K(\mathbf{x}_i \cdot \mathbf{x}) + \mathbf{b}^*\right\} \tag{16}$$

This is SVM, and its basic ideas can be described as follows: first of all, transforming the input space as a multi-dimensional feature space by nonlinear mapping, then achieving nonlinear mapping by the proper kernel function, finally finding out the best separation hyperspace in the feature space.

IV. The Principle of Signal Modulation Recognition Based on Higher-Order Cumulants and SVM in the Smart Grid

This paper uses the high order cumulants and SVM combined modulation recognition method to achieve the dynamic identification of frequency spectrum in the smart grid. First of all, the feature parameters are extracted from each signal based on higher-order cumulants and then are used to combine the signal types so as to become a training vector quantity and form a training set. Then known type of characteristic parameters in the training set is used to train Support Vector Machine (SVM). In other words, the training vectors are used as constraint condition for solving the optimal classification function. Finally, in the recognition phase, characteristic parameters of input signals are extracted. The input signals are identified, and signal modulation type is determined. In order to make the SVM classifier can accurately conduct the signal modulation recognition, the training program debugging and optimization of the SVM classifier are very important in the training phase. The related details are shown as follows.

TABLE I: SIMULATION COMPARISON OF CALCULATION COMPLEXITY

Computation time (seconds)	T_{2PSK}	T_{4PSK}	T_{8PSK}	T_{16QAM}	T_{4ASK}	T_{2FSK}	T_{MSK}
Conventional training algorithm	84.47	83.36	82.57	83.35	85.02	86.29	95.85
Total	600.91						
Combined algorithm	63.49	63.38	62.59	63.36	75.07	66.26	65.83
Total	449.98						

A. Classifiers are Trained (Offline) and to Identify Signals (Online)

Training and recognition are the two independent program. For the original program, each parameter of the original program is directly assigned to the classifier, which means the program only has recognition. At this moment the main work is adding and modulating SVM training process in the code composer studio. Even though the modulation is successful, time-consuming too long problem sometimes appears after the modulation. Since the classifier is offline, if using empirical data to build a classifier library under various environmental conditions and sex ratio, the corresponding classifiers can be modulated when the signals come, which saves time and resources which can be consumed in the original training.

B. The SVM Modulation Recognition

For the original program debugging, the applied signal parameters are ideal, such as the input signal $f_s = 8KHz, f_c = 2KHz$. However, the parameters of the signal used in the practical application are obviously larger. When directly using the parameters of signal in actual situation ($f_s = 61.44MHz, f_c = 10.7MHz$), errors, slow running time and other related problem will happen in the program. Especially for extraction of center frequency, time-consuming obviously takes place.

V. SIMULATION AND PERFORMANCE ANALYSIS

The computational complexity and convergence are simulated. Modulation recognition of seven kinds of modulating signal which contain 2PSK, 4PSK, 8PSK, 16QAM, 4ASK, 2FSK,and MSK are simulated by adopting regularly SVM based on BP algorithm, combined modulation recognition algorithm based on higher-order cumulants and SVM respectively under the situation that the simulation parameters is given as follow: the frequency of main carrier is 4*MHz*, frequency of sampling is 61.44*MHz*, The symbol rate is 5*M* baud, the data length is 2048 and the SNR is: -2dB,0dB,4dB,8dB,10dB respectively, The statistic of correct recognition rate is obtained when each situation is experimented for 1000 times.

A. The Computation Complexity of the Combined Algorithm Based on Higher-Order Cumulants and SVM

In the Table I, T_{2PSK}, T_{4PSK}, T_{8PSK}, T_{16QAM}, T_{4ASK} ,T_{2FSK}, T_{MSK} respectively represent the time that various target signal are identified and trained under different SNR, different training algorithm. According to the simulation data (in Table I), the duration of combined training algorithm based on higher-order cumulants and SVM is 449.98 seconds. This duration is obviously lower than the duration of the conventional SVM training algorithm (600.91 seconds), which shows the computation complexity of the algorithm used in this paper is lower than the conventional algorithm.

B. The Simulation of Convergence Performance

In Fig. 1, SVM is trained by using combined training algorithm based on higher-order cumulants and SVM, then its convergence performance is better than the training convergence performance of conventional SVM and it can reach the demand of design for targeted function when setting error of mean square is 0.011 by only iteration 280 steps.

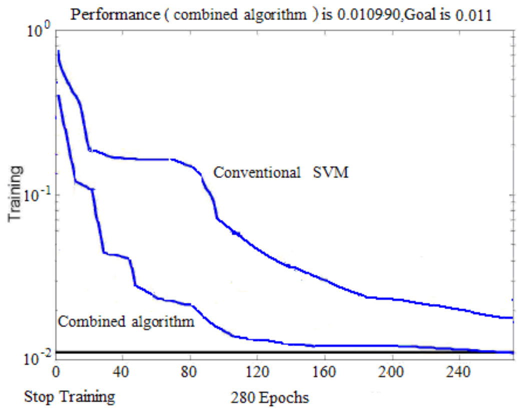

Fig. 1. The simulation diagram of training convergence performance

C. The Simulation of Modulation Recognition

The simulation of modulation recognition rate related to the conventional SVM classifier and combined modulation recognition algorithm is shown in Fig. 2 and Fig. 3 respectively.

In the Fig. 3, the correct recognition rate of signals such as BPSK, QPSK, 16QAM, 4ASK, 2FSK etc can reach 90% which have more improvement than that of Fig. 2. For 8PSK, MSK signals, as the difference of their high-order cumulants resolution is smaller, there will be a mistake of exporting MSK modulation system when conducting the modulation recognition of 8PSK. Similarly, when identifying MSK signal, there will be still a mistake of exporting 8PSK, especially under the situation that SNR is lower than 2dB. Therefore, the simulation experiment can be consistent with the theoretical analysis. However, even though under this situation, the modulation recognition of 8PSK, MSK are higher than that of Fig. 2 which is based on the conventional SVM classifier.

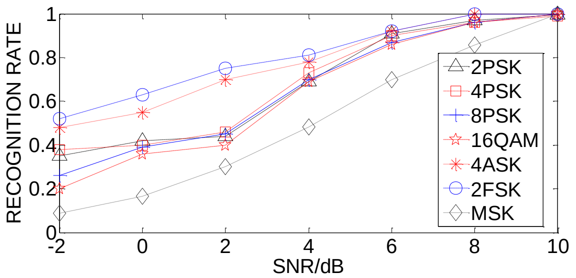

Fig. 2. The simulation of modulation recognition of conventional SVM

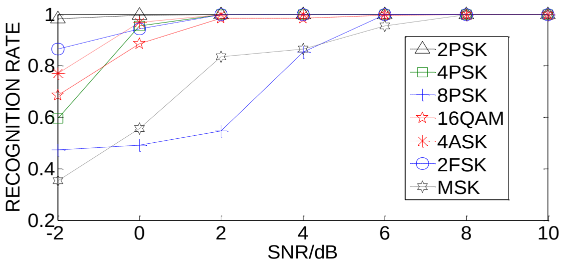

Fig. 3. The simulation of modulation recognition of combined algorithm based on higher-order cumulants and SVM

VI. Conclusions

In the modulation recognition of wireless communication signals presented in this paper is the basis of a new wireless communication technology in smart grid, namely dynamic spectrum access technology and cognitive radio technology. Adopting dynamic spectrum access technology and cognitive radio technology in smart grid wireless communication technology can improve the spectrum efficiency so they are of importance in the study of wireless communication signals modulation recognition in the smart grid. The combined algorithm of modulation recognition based on higher-order cumulants and SVM is put forward in this paper. High-order cumulants used in this article can have good anti-noise performance. To begin with, high-order cumulants can be extracted as the characteristic value of signal. Then, SVM is conducted training. Finally, the recognition algorithm routine of conventional SVM is promoted. The whole process achieves the modulation recognition of seven kinds of signals such as 2PSK, 4PSK, 8PSK, 16QAM, 4ASK, 2FSK, and MSK etc. meanwhile, compared with the conventional SVM modulation recognition, this process can overcome high computation complexity when identifying various problem so as to improve the recognition rate under low SNR. The simulation results show that the system recognition rate of modulation recognition is obviously enhanced compared with the conventional SVM modulation recognition.

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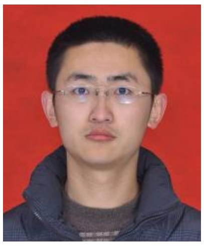

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