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A novel recognition approach for radar emitter signals based on on-line independent support vector machines

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Abstract: Radar emitter signal recognition is one of the key procedures in signal processing of Electronic Intelligence. To enhance the ability of online recognition to meet the requirement of modern electronic warfare, A novel recognition approach for radar emitter signals based on on-line independent support vector machines is presented in this paper. Based on the cascade feature extraction of radar emitter signals, the on-line independent SVM is applied to effectively construct the basis vectors of SVM by incremental mode and make full use of the signal data information, then, an automatic online recognition system based on data driven are implemented. Experiment results shows that the method can achieve high accurate recognition rate even at lower SNR, and has good characteristics of rapid identification and less memory.

Keywords*: Radar emitter signal, Signal recognition, On-line independent SVM*

1. Introduction

Radar emitter signal recognition is one of the key procedures of radar electronic scout system. More drastic as modern electronic warfare being, new complex radar systems are set into use and become dominant. The modulating methods of inter-pulse, intra-pulse and intra-group of modern radar signals are diverse and complicated. Further more, as different modulating methods are penetrative with each other, the radar signals become denser and electromagnetic circumstance is more complicated, radar signals are overlapped in parameter space. These result in poor inerratic signals, and traditional signal identification methods based on five regular parameter features are unsuitable to modern electronic countermeasure [1-3]. Five conventional parameter features are radio frequency (RF), time of arrival (TOA), pulse amplitude (PA), pulse width (PW) and pulse width (PW) respectively. Meanwhile, modern electronic and information warfare need equipments not only to be intelligent, automatic, real-time, and error-tolerant, but also of learning and judgment ability [4-5]. Hence, it is hopeful to improve the performance of modern electronic countermeasure equipment by applying advanced pattern recognition technologies based on extracted intra-impulse features.

Recently, all kinds of radar emitter signal interleaving methods were proposed based on pattern recognition technologies such as clustering [6-10], artificial neural networks (ANNs) [11-14], support vector machines (SVMs) [16-17], etc. As an unsupervised learning method, clustering can be described as dividing a set of observations into some disjoint groups, called clusters, according to some kind of measure and evaluation criterion. However, the accuracy of radar emitter signal recognition methods based on clustering are unsatisfied because there is no prior knowledge to be used. Artificial neural networks are widely applied to radar emitter signal recognition because of its nonlinear mapping and learning capability. But the structure of ANN is difficult to determine and ANN have limitations on generalization rise that can be overfit to the data. Support vector machines (SVMs), based on statistical learning theory, and are applied in the areas of pattern recognition and machine learning because of the high accuracy and good generalization capability. But the standard SVMs train the models by batch-wise and the size of SVM solution grows linearly with the number of training samples taken into account. Once a new observation or training sample come forth, the SVM models must be retrained to improve the capability of classifier, this limits the application of SVM in the area of radar emitter signal recognition. Recently, several on-line learning algorithms have been developed for SVMs [18-20], but in all cases there is no attempt to reduce the growth of the solution.

On-line Independent Support Vector Machines (OISVMs) is a new on-line SVM algorithm proposed by

F. Orabona et al. [21]. OISVMs construct the hypothesis via a subset of the samples seen so far called basis; new samples are put in the basis only if they are linearly independent in the feature space from the current basis. As opposed to similar algorithms, OISVMs produce smaller models and with bounded testing time. Moreover, it reaches near-optimal performance while retaining the good generalization power of standard SVMs. In this work, a novel radar emitter signal recognition method is proposed by introducing the OISVMs classifiers for intra-impulse features, which are proposed by us in previous research. Experiment results show that the proposed method is of good accuracy and can learning classifier on-line.

The organization of this paper is as follows. The basic OISVM is briefly described in the next section; the automatic online recognition system based on data driven is proposed in Section 3; Section 4 presents and analyzes the experiment results. Finally, summary and conclusions are given.

2. On-line Independent

Support Vector Machines (SVM) has been applied to classification, regression and computer vision widely. For classification, the SVM attempts to place a boundary between the two different classes, and orient it in such a way that the margin is maximized.

Let $\{\mathbf{x}_i, y_i\}_{i=1}^{l}$, with $l \in \mathbf{Z}^+$, $\mathbf{x}_i \in \mathbf{R}^m$, and label $y_i \in \{-1,1\}$, be the full training set, classification can be taken as problem

$$\min_{\mathbf{w},b} \frac{1}{2}\|\mathbf{w}\|^2 + C\sum_{i=1}^{l}\xi_i^p \tag{1}$$

s.t.

$$y_i(\mathbf{w}\cdot\mathbf{x}+b) \ge 1-\xi_i \tag{2}$$

where, ξ_i is slack variable in case the samples are not linearly separable, $C \in \mathbf{R}^+$ is an error penalty coefficient and is usually 1. Introduce l pair of parameters α_i, $u_i \ge 0$, $i = 1,...,l$. Using Karush-Kuhn-Tucker optimality conditions, we obtain the approximating function expressed as

$$f(\mathbf{x}) = \sum_{i=1}^{l}\alpha_i y_i \mathbf{x}_i \cdot \mathbf{x} + b \tag{3}$$

To improve the discriminative power of an SVM , the x_i 's are mapped to feature space via a non-linear mapping $\phi(\mathbf{x})$. Then, Eq.(3) can be rewritten as

$$f(\mathbf{x}) = \sum_{i=1}^{l}\alpha_i y_i K(\mathbf{x}_i,\mathbf{x}) + b, \tag{4}$$

where, kernel function $K(\mathbf{x},\mathbf{y}) = \phi(\mathbf{x})\cdot\phi(\mathbf{y})$.

In the solution of (4), most of α_i are equal to zero; those $\mathbf{x}_i$'s corresponding to nonzero of α_i 's are called support vectors, which construct the solution of (4).

The standard SVM algorithm is meant to be used batch-wise training. To extend it to the on-line setting, different approaches have been proposed [18-20]. But the potentially endless flow of training samples of the on-line setting will bring sooner or later to an explosion of the number of support vectors, and hence of the testing time [21].

If some of the support vectors are linearly dependent on the others in the feature space, some of them can be expressed as a function of the others. In these cases different, possibly sparser, expression can be obtained. According to this property, Orabona et al. proposed the OISVM algorithm, whose solution is based on selected independent basis vectors in the feature space. The algorithm can be summed up as two step [21]: 1) check whether the current sample is linearly independent from the basis in the feature space; if it is, add it to basis; 2) incrementally optimize the classifier.

After l training examples, suppose the indices of the vectors in the current basis are $\mathcal{B}$. When the algorithm receives $\mathbf{x}_{l+1}$, it has to check if it is linearly independent or not from the basis vectors. How well a single vector is linearly independent from a matrix of vectors already known to be full-rank can be transformed to how well the vector can be approximated by a linear combination of the vectors in the matrix; then let

$$\Delta = \min_{\mathrm{d}}\left\|\sum_{j\in\mathrm{B}} d_j\varphi(\mathbf{x}_j) - \varphi(\mathbf{x}_{l+1})\right\|. \tag{5}$$

Applying the extremum condition and kernel trick to equation (5), we can obtain

$$\Delta = k(\mathbf{x}_{l+1},\mathbf{x}_{l+1}) - \mathbf{k}^T\tilde{\mathbf{d}}, \tag{6}$$

where, $\mathbf{k} = [k_1 \ \ k_2 \ \cdots \ k_l]^T$, $k_i = K(\mathrm{x}_i, \mathrm{x}_{l+1})$, $\tilde{\mathrm{d}} = \mathrm{k}_{BB}^{-1}\mathrm{k}$ is the solution of (5), and $\mathbf{k}_{BB}$ is the restriction of kernel matrix $\mathbf{K}$ to the rows and columns corresponding to the indices in $\mathcal{B}$. Using the matrix inversion lemma, after the addition of a new sample the new inversion matrix $\mathrm{K}_{\boldsymbol{BB},\ \mathrm{new}}^{-1}$ can be computed as

$$\mathrm{K}_{\boldsymbol{BB},\ \mathrm{new}}^{-1} = \begin{bmatrix} & & 0 \\ \mathrm{K}_{\boldsymbol{BB}}^{-1} & & \vdots \\ & & 0 \\ 0 & \cdots\ 0 & 0 \end{bmatrix} + \frac{1}{\Delta}\begin{bmatrix}\tilde{\mathrm{d}} \\ -1\end{bmatrix}\begin{bmatrix}\tilde{\mathrm{d}}^T & -1\end{bmatrix}. \tag{7}$$

Given tolerance factor $\eta \ge 0$, if $\Delta \ge \eta$, then $\mathbf{x}_{l+1}$ is linearly independent with respect to the basis, and the $l+1$ sample is added to $\mathcal{B}$.

In the feature space, SVM classification can be transformed to the unconstrained minimization problem

$$\arg\min_{\beta} \frac{1}{2}\boldsymbol{\beta}^T\mathbf{K}_{BB}\boldsymbol{\beta} + \frac{1}{2}C\sum_{i=1}^{l}\max(0, 1-y_i\mathbf{K}_{iB}\boldsymbol{\beta})^2. \tag{8}$$

When a new sample $\mathbf{x}_{i+1}$ is available, we can calculate the solution of (8) by Newton method.

Different from existing SVM, OISVM solution can be bounded by setting the parameter η to speed up the training and testing time as well as reduces the using memory [21].

3. The Scheme of Proposed Radar Emitter Signal Recognition

3.1 The scheme of the proposed radar emitter signal recognition

The scheme of data driven radar emitter signal identification is showed in Fig. 1. Firstly, feature parameters are extracted from radar emitter signal samples with class label. Then a set of OISVM models are trained as classifier. In the phase of application, when a new radar emitter signal is received, the signal features are extracted as the inputs of OISVM models and the signal is recognized. The classification outcome will be confirmed by engineers. One hand, identification result can be used to support the decision-making, at the other hand, this outcome can be used to train the OISVMs online to improve its performance.

It is shows from Fig.1 that the classification capability of proposed method is enhanced by using the label information of train samples and the SVM classifiers. What's more, OISVM classifiers can be constructed by incremental training the data in history fault database or by training the on-line affirmed fault samples. By online learning, the classification ability can be improved.

3.2 Feature extraction of instantaneous frequency

Instantaneous Frequency (IF) as the research hotspot of non-stationary signal processing, is an important parameter to describe the characters changed with time [22]. The extracting method of IF features has been proposed in our previous research [22]. In this work, the extracting method of IF features is applied to six kind of typical radar emitter signals i.e., linear frequency modulation (LFM),

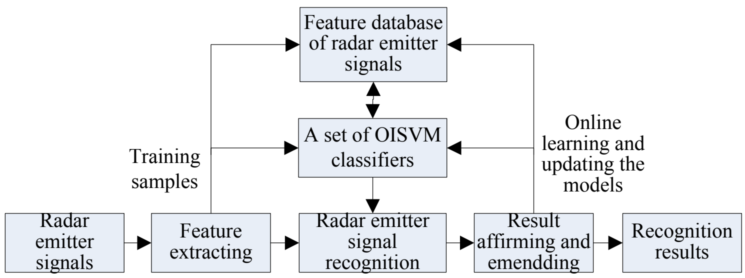

Figure 1. The scheme of radar emitter signal recognition method based on OISVMs.

binary phase shift keying (BPSK), non-linear frequency modulation (NLFM), binary frequency shift keying (BFSK), quadri-phase shift keying (QPSK), conventionality pulse (CP). Then, to reflect the difference of these signals, the derived characteristics are extracted from IF features as follows.

Step 1. Suppose the IF sequence is $f_{IF}(n)$, $n = 1,2,\cdots,L$, compute the correlation coefficient R,

$$R = \frac{\sum_{i=1}^{n}(f_{\mathrm{IF}} - E(f_{\mathrm{IF}}))(nT - E(nT))}{\sqrt{\sum_{i=1}^{n}(f_{\mathrm{IF}} - E(f_{\mathrm{IF}}))^2}\sqrt{\sum_{i=1}^{n}(nT - E(nT))^2}};$$

(9)

Step 2. Normalize f_{IF1} by formulation (9), and calculate the mean and variance of f_{IF1}, noted as E_{IF1} and σ_1.

$$f_{\mathrm{IF1}} = f_{IF} / \max(f_{\mathrm{IF}}); \quad (10)$$

Step 3. Compute the difference between the maximum value and the minimum value of IF, noted as $sub(f_{\mathrm{IF1}})$

Step 4. Map $f_{IF1}(n)$ to $g(n)$ according to eq. (10), and calculate the mutation number N_{p} of $g(n)$,

$$g(n) = \begin{cases} 1, & |f_{\mathrm{IF1}} - E_{\mathrm{IF1}}| > 5\sigma_1 \\ 0, & \text{otherwise}; \end{cases} \quad (11)$$

Step 5. Transform the first normalized sequence f_{IF1} according to $f_{\mathrm{IF2}} = |f_{IF1} - E_{IF1}|$, then normalize f_{IF2} and calculate $E_{\mathrm{IF2}}, \sigma_2$.

Step 6. Construct derived characteristic vector $CCV = [R, E_{\mathrm{IF1}} - E_{\mathrm{IF2}}, \sigma_1 - \sigma_2, E_{\mathrm{IF2}}, N_{\mathrm{p}}, sub(f_{\mathrm{IF1}})]$.

Step 7. End.

The statistics in CCV can improve the anti-noise ability, and the derived parameter $E_{\mathrm{IF1}} - E_{\mathrm{IF2}}$, $\sigma_1 - \sigma_2$ can exhibit the difference in all kinds of radar emitter signals. These will enhance the performance of recognition methods.

3.3 Recognition based on OISVMs

1) OISVM algorithm

The OISVM algorithm is discribed as follows [21]:

Initializing η, B and β;

For each time step $t = 1,\ldots,l$

While (not termination condition) do

Update independence index Δ using (6) and (7)

If ($\Delta > \eta$)

Add the sample into the base, $B = \{B, t\}$
End if
Calculate the best solution using Newton method
End do
End for

2) Parameter selection

The tradeoff between computation efficiency and accuracy should be considered to assign value η. Larger η is, faster the algorithm is and smaller the number of support vectors is and the storage of kernel matrix sized on, but the model is more coarse. We find it is satisfied to set $\eta = 0.1$ when training samples are normalized to zero mean and variance 1.

3) Multi-radar signal recognition

OISVM are formulated for classifying two classes, but there are more than two types of radar emitter signals in practical. Either one-versus-one classifier or one-versus-all classifier can be used for multi-radar emitter signals classification. In one-versus-one classifier, OISVM models are built for every pair of classes. This results in $p(p-1)/2$ OISVM classifiers, where p is the number of signal type. In one-versus-all classifier, only p OISVM classifiers are used. For the radar emitter signal recognition, we recommend to use one-versus-all classifier.

4. Simulation Analysis

In this section, we report the experimental evaluation of OISVMs, All the experiments are running on computer Lenovo M7160 (CPU frequency is 2.93GHz , with 2G memory) , the simulation software was developed in MATLAB 7.1.

4.1 Data generating

In order to verify the validity of the approach in this paper, the online recognition experiments based on data driven are carried out for the six typical radar emitter signals. The signal pulse width is 30μs, fs, and fc are 200MHz, and 10MHz respectively. the frequency bandwidth B of LFM are 20MHz and 30MHz. BFSK uses Barker codes with length 13 and its frequency is 20 MHz and 30MHz, BFSK uses Barker codes with length 7 and Frank code with length 16 is adopted for QPSK. For every kind of signals, Signal Noise Ratios (SNR) are varied from 0dB to 20dB every 2dB. Then 600 samples are generated for every signal type under each SNR, the first 500 of which are taken as training samples and the last samples are used to test the algorithms. The total number of training samples is 44000, number of test samples is 8800. The IFs of signals are extracted and normalized by the algorithm in 3.2. Additionally, as the IFs are normalized, Gaussian function $K(x, y) = e^{\frac{\|x-y\|^2}{\sigma}}$ with parameters $\sigma = 1$, $C = 0.1$ is served as kernel function.

4.2 Simulation scenarios

Four simulation scenarios are designed to exemplify the feasibility and performance of proposed radar emitter signal recognition method.

Experiment 1: Online learning ability testing. All the 44000 training samples are used to construct classification models, this experiment test the online learning ability of OISVMs for large number of training numbers.

Experiment 2: Classification ability testing in the case of small training samples.

Experiment 3: Testing the generalization ability of the classifier vary from tolerance factor.

Experiment 4: Influence of training samples diversity for the classification precision.

4.3 Simulation results and analysis

1) Online learning ability testing

All the 44000 training samples are trained one by one to construct 8 OISVM models, the tolerance factor η are set to 0.1. Fig. 2(a) and Fig. 2(b) show one of the model's training errors and number of support vectors (SVs) varying the number of training samples. It shows the number of SVs is small and the training error is large in the beginning of simulation procedure. More and more SVs obtained as training samples increasing, and training errors are fall down. When the number of training samples attained to 4000-5000, the number of SVs is 72, training error is 1.5%. a few additional SVs are obtained as the training samples increased from 5000, and there is nearly no improving in training errors because of the corelative of training samples in kernel space. The number of SVs is less than 90 all the samples are trained, because the size of basis vectors are restricted by the parameter η , this can reduce the redundancy samples and keep high recognition accuracy.

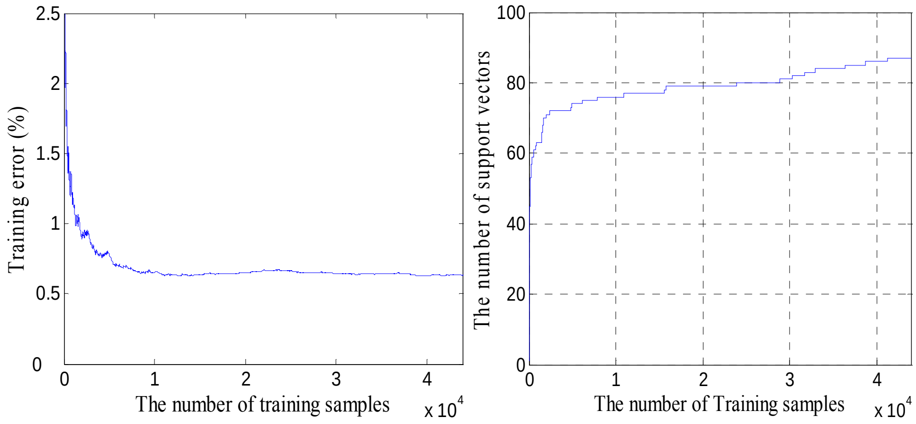

Figure 2. training errors and number of support vectors (SVs) varying the number of training samples

2) Classification ability testing in the case of small training samples

In order to demonstrate Classification ability of the proposed radar emitter signal recognition method, OISVMs are constructed by training 88, 440, 880 and 4400 samples, which are formed by extracted 1, 5, 10, 50 samples from every type of radar signal with every SNR respectively. The recognition rates for every signal and all signals varying with different SNR are displayed in Figure 3. It shows classification ability of OISVMs is very poor when the models are trained by one sample of each signal type with every SNR. But the accuracy improved great when the number of train samples increased, when the number of training samples attend to 4400, the recognition percent of proposed method is 80% even for BPSK with SNR=4dB, the most difficult to recognition signal in the situation of SNR=4dB, and the total recognition percent is 96.6%.

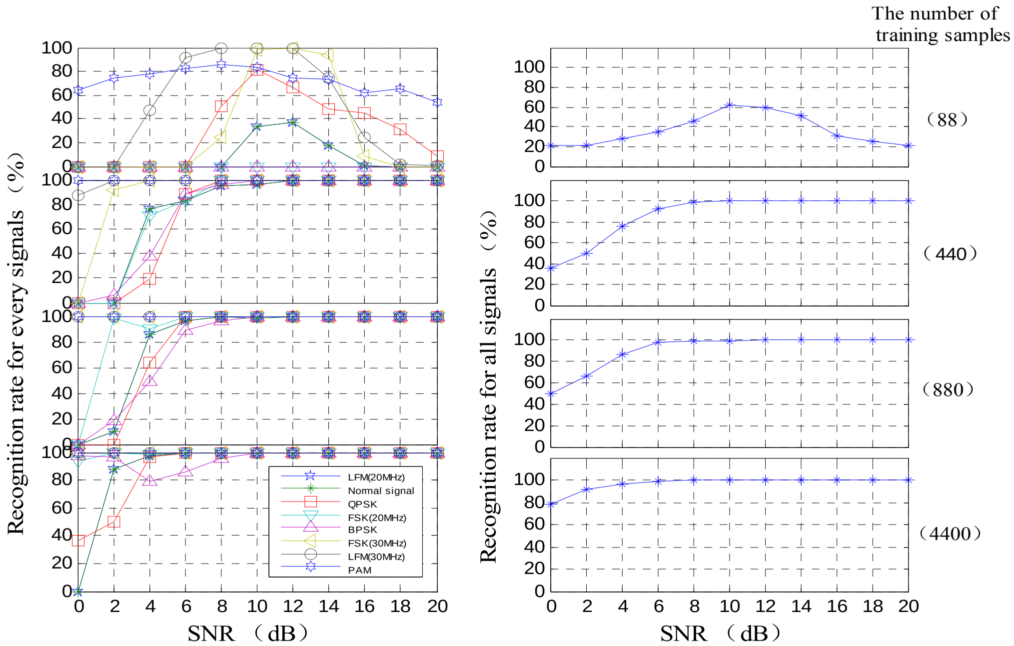

Figure 3. The recognition rates for every signal and all signals varying with different SNR

3) Testing the dependence of model generalization on tolerance factor

It is known from 2) high recognition can get when the number of train samples attained to 4400. In this experiment, 4400 samples, 50 samples for each type of radar signal with every SNR respectively, are trained for the OISVM models. The parameters η of OISVM models are set to 0.01, 0.1, 0.6 and 1 respectively. 8,800 samples are tested to evaluate the signal recognition accuracy. Simulation results are shown in Fig. 4. It is shown that the size of base vectors or num_{SV} , the number of support vectors, are determined by parameter η . When $\eta = 1$, $num_{SV} = 3$, the generalization performance is very poor. num_{SV} will increase and the accuracy will improved when

η decrease. When $\eta = 0.1$, the number of support vectors is 72, the signal recognition accuracy is very high with the cost of only 10K bytes memory to store the kernel matrix and take 40 seconds to training all the 44000 samples. Decreasing η further, when , the number of support vectors is 151,but the recognition accuracy is not increasing obviously. If η is set to zero, we can get comparative accuracy to $\eta = 0.1$, but the memory take up by kernel matrix will be nearly 4G bytes, and take more than 4 hours to complete the training procedure. So η controls the trade-off between accuracy and speed of OISVM models

4) Influence of training samples diversity to the classification accuracy

In this experiment, all training samples but samples with SNR of 12dB-20dB in experiment 2 are trained to construct OISVM models. The models are applied to testing samples. Simulation result is shown in Fig.5. It is shown that recognition accuracy is degraded when some type of training samples are absent. This means training samples need to be gathered to improving radar signal recognition accuracy, online learning is the important step to proposed method.

5. Conclusion

A novel recognition approach for radar emitter signals based on OISVM models is presented in this paper. The on-line independent SVM is introduced to effectively construct the basis vectors of SVM by incremental mode and make full use of the signal data information, then, an automatic online recognition scheme based on data driven is implemented. Four Scenarios are designed to testing the performance of proposed method. Simulation results show that the method can achieve high recognition accuracy even at lower SNR, and the algorithm is of low computing cost and need less memory to store kernel matrix.

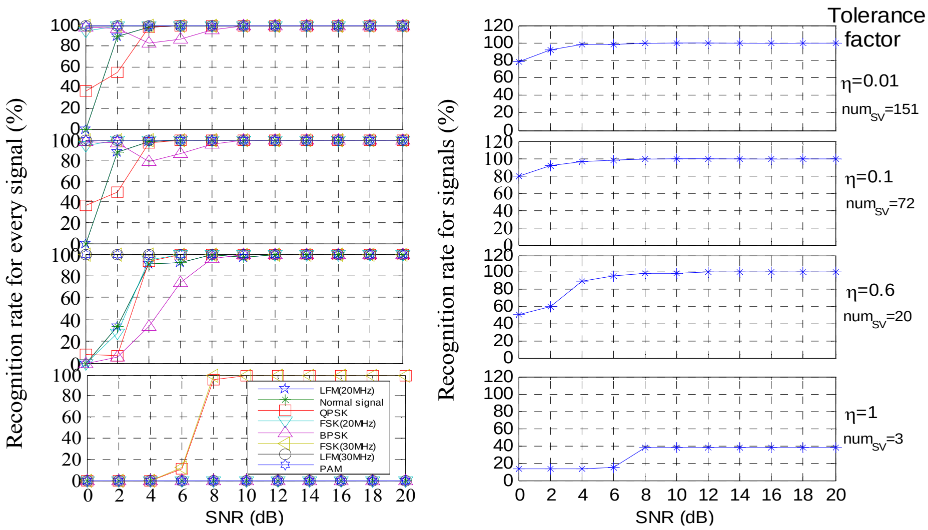

Figure 4. The dependence of model generalization on tolerance factor

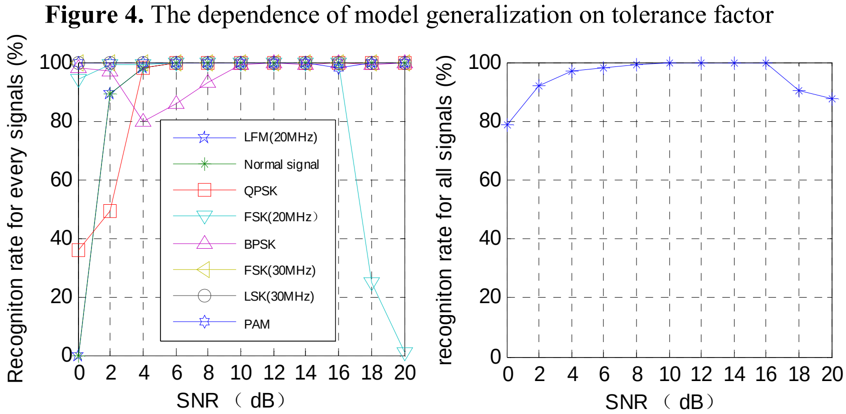

Figure 5. The classification accuracy when some training samples are removed

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