Parameter Optimization and Application of Support Vector Machine Based on Parallel Artificial Fish Swarm Algorithm

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Abstract—**Parameters selection of support vector machine is a very important problem, which has great influence on its performance. In order to improve the learning and generalization ability of support vector machine, in this paper, proposed a new algorithm -parallel artificial fish swarm algorithm to optimize kernel parameter and penalty factor of support vector machine, improved the loop body of artificial fish swarm algorithm to avoid the missing of the optimum solution, and proved its validity by testing with some test functions; used the optimal parameters in a non-specific persons, isolated words, and medium-vocabulary speech recognition system. The experimental results show that the rates of speech recognition based on support vector machine using the new algorithm are better than those of using the traditional artificial fish swarm algorithm in different signal to noise ratios and different words. Especially, the support vector machine model based on the new algorithm can still maintain better recognition rates in lower signal to noise ratios. So the new algorithm is an effective support vector machine parameter optimization method, which makes the support vector machine not only have good generalization ability, but have better robustness.**

Index Terms—**artificial fish swarm algorithm, parallel artificial fish swarm algorithm, support vector machine, speech recognition**

I. Introduction

Support vector machine (SVM) [1] is a new generation machine learning method based on statistical learning theory. According to the limited sample information, it seeks the best compromise between model complexity and learning ability to obtain the best generalization ability. The algorithm has been widely used in text classification, handwriting recognition, image classification, bioinformatics and other fields [2]. As a pattern recognition method, SVM has a strong classification capability, and the essence of speech recognition system is a multi-class classification system, So SVM applied to speech recognition system has enormous potential for research [3] [4] [5]. Studies have shown that [6] [7] [8] the kernel function parameters and the penalty factor of the SVM affect its classification ability seriously. When the values of the Kernel function parameters and the penalty factor are appropriate, the classification of SVM will enhance significantly. So far, however, there are not some particularly effective methods about the optimization of SVM parameters [9]. Artificial fish swarm algorithm (AFSA) [10] [11] [12], an optimization algorithm based on the simulation of fish behavior, has simple structure, its parameters adjustment is simple and it is more suitable for computer programming processing. But, the main loop of the basic AFSA selects only one of the three behaviors (chasing behavior, swarming behavior and feeding behavior) to execute. This optimization results may be stagnant or easy to miss the better solution, the optimization results may be not very satisfactory. Therefore, this paper proposed an improved artificial fish swarm algorithm - parallel artificial fish swarm algorithm (PAFSA), improved the loop body of AFSA to avoid the missing of the optimum solution, used PAFSA to optimize the kernel function parameters and the penalty factor of SVM, and applied the optimal parameters to a speech recognition system which based on SVM, finally, obtained perfect results.

II. SVM Classification Principle

SVM was originally proposed for the case of linearly separable classification problem. However, practical problems are almost non-linear separable, so the studies of non-linear separable algorithms are particularly important. For the nonlinear problem, it can be transformed into a linear problem in another space (feature space), and the optimal separating hyperplane can be selected in the feature space, which makes the distance between the hyperplane and the different types of samples maximal, so as may achieve maximal

Sponsored by Natural Scientific Foundation of China (61072087) and Scientific and Technological Research Projects (Social Development) of Shanxi Province of China (20120313013-6).
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doi:10.4304/jsw.8.3.673-679

generalization ability. The non-linear transformation of SVM is realized by the kernel function in the low-dimensional space (need to satisfy the Mercer conditions) instead of the inner product calculating of the high-dimensional space, thus avoiding the computation complexity caused by the increase of the dimension [13].

For the linearly inseparable training sample set, need to introduce non-negative slack variables ξ_i, i = 1, 2,…, l, thus the problem of solving the optimal hyperplane is

$$\left.\begin{aligned} &\min(\frac{1}{2}\|w\|^2 + C\sum_{i=1}^{l}\xi_i) \\ &s.t.\ \ y_i(w\cdot x_i + b) \ge 1-\xi_i \end{aligned}\right\} \quad (1)$$

Where the penalty parameter C>0, it regulates the proportion between the confidence range and the empirical risk of SVM in the determinate feature space, it can determine the structural risk and the proportion between the maximum interval and the minimum error rate. When C is small, SVM has smaller punishment for the misclassified samples and smaller complexity of the learning machine, but the empirical risk value is larger; when C is larger, the punishment will get bigger. In (1), the first part makes classification interval as large as possible, while the second part makes error as small as possible. After introducing the kernel function $K(x_i, x_j)$, using Lagrange multiplier method may make the above optimization problem attribute to a quadratic programming problem, that is

$$\left.\begin{aligned} &\min_{\partial} W(\partial) = \frac{1}{2}\sum_{i=1}^{l}\sum_{j=1}^{l}\partial_i\partial_j y_i y_j K(x_i, x_j) - \sum_{i=1}^{l}\partial_i \\ &s.t.\ \ \sum_{i=1}^{l}\partial_i y_i = 0, \\ &\qquad 0 \le \partial_i \le C \quad i = 1,\cdots,l \end{aligned}\right\} \quad (2)$$

In (2), ∂_i is the Lagrange multiplier corresponding to the i th sample, it is essentially the solution of the convex optimization problem. When ∂_i is nonzero, the sample point x_i corresponding to it is a support vector. After solving the above problem, the corresponding decision-making function is

$$f(x) = \mathrm{sgn}[\sum_{i=1}^{l}\partial_i^* y_i K(x_i, x) + b^*] \quad (3)$$

$$b^* = y_j - \sum_{i=1}^{l} y_j \partial_i^* K(x_i, x_j), \forall j \in \left\{ j \middle| \partial_j^* > 0 \right\} \quad (4)$$

In (3) and (4), ∂_i^* ($\partial_i^* \ne 0$) is the optimal solution, b^* is the classification thresholds, and x is the sample which need to be identified.

Choosing different kernel function can be made into different support vector machine [14] [15] [16]. Commonly used kernel functions are as following:

(1) Linear kernel function:

$$K(x, x_i) = xgx_i$$

(2) Polynomial kernel function:

$$K(x, x_i) = [\gamma(xgx_i) + r]^q$$

(3) The Gaussian kernel function:

$$K(x, x_i) = \exp(-\gamma\|x - x_i\|^2)$$

(4) Sigmoid kernel function:

$$K(x, x_i) = \tanh(\gamma(xgx_i) + r)$$

In practical applications, the appropriate kernel functions and parameters is selected, according to the specific circumstances of the problem. Gaussian kernel has better adaptability, whether it is low-dimensional, high-dimensional, smaller sample and larger sample, Gaussian kernel function is applicable and it is a satisfactory function for classification [17]. In this paper, the Gaussian kernel function is selected as the kernel function of SVM, SVM optimization problem based on Gaussian kernel function is transformed into the following convex optimization problem:

$$\left.\begin{aligned} &\min_{\partial} W(\partial) = \frac{1}{2}\sum_{i=1}^{l}\sum_{j=1}^{l}\partial_i\partial_j y_i y_j \exp(-\gamma\|x - x_i\|^2) - \sum_{i=1}^{l}\partial_i \\ &s.t.\ \ \sum_{i=1}^{l}\partial_i y_i = 0 \\ &\qquad 0 \le \partial_i \le C \quad i = 1,\cdots,l \end{aligned}\right\} \quad (5)$$

The minimum of (5) depends on the choice of parameters C and γ . Best (C, γ) value can obtain the best performance of the SVM classifier. Parameter γ mainly affects the complexity of the sample data distribution in the high dimensional feature space. Because of different specific learning objects, different characteristic and no-fixed rule, parameter optimization has not yet formed a unified model, and this paper proposes a PAFSA to optimize C and γ in order to improve SVM performance.

III. The Design Of PAFSA

A. PAFSA Is Proposed

AFSA is a kind of bottom-up optimization strategy based on the model of the animal self-governing body, and it focuses on constructing animal self-governing body model using behavior-based on multi-parallel channel structure. The algorithm mainly uses feeding, swarming and chasing behavior and constructs the underlying behavior of the single fish. AFSA has a better ability of overcoming the local extremum to obtain the global extremum, and the algorithm only uses the objective function value, without specific information such as the gradient value of the objective function.

Because the main loop of the basic AFSA only select one of the three behaviors (chasing behavior, the swarming behavior and the feeding behavior) to execute. This optimization results is easy to be stagnant or be missed, and it is not very satisfactory. Therefore, we propose an improved Parallel artificial fish swarm algorithm-PAFSA which reduces the probability of missing the better solutions. The improvement of PAFSA is made at the loop body, This method Divided into two paths after initialization execution, one path to perform the chasing behavior, feeding behavior is a random behavior, another path to perform the swarming behavior, and the feeding behavior is also a random behavior, by comparing the fitness value of the two behaviors, choosing the better result and recording in the bulletin board at the same time to update the individual to continue the iterative optimization. Figure 1 shows a flow chart for the parallel artificial fish swarm algorithm.

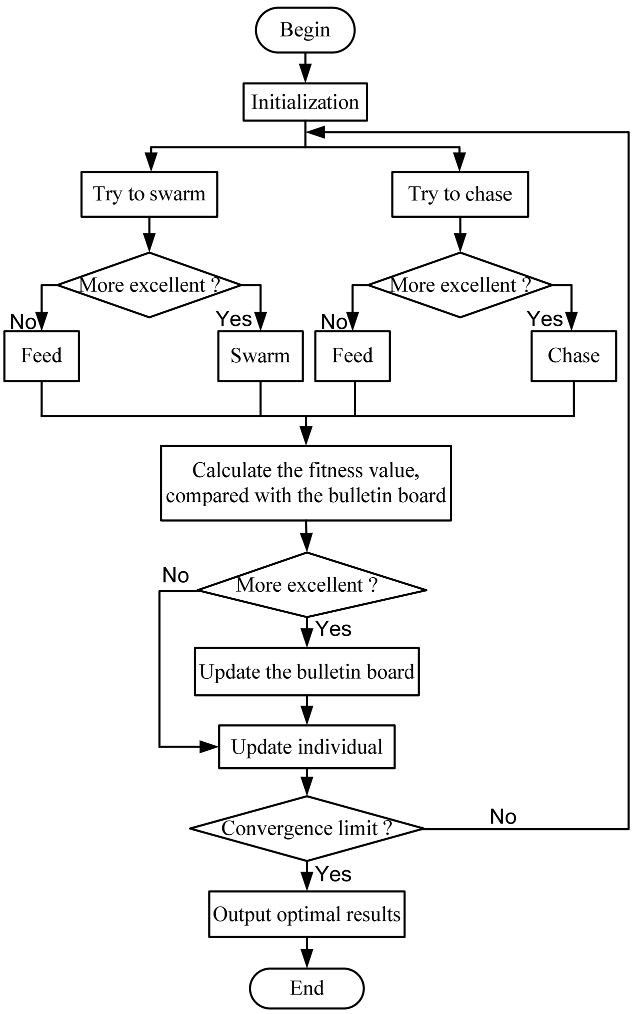

Figure 1. the Flow of PAFSA

B . PAFSA Algorithm Testing and Results Analysis

In order to test the performance of PAFSA, we select two typical test functions to be the objective function to test it.

Test function 1: GP-Goldstein-Price (n=2)

$$f_{GP}(x)=[1+(x_1+x_2+1)^2(19-14x_1+3x_1^2-14x_2+6x_1x_2+3x_2^2)]\times[30+(2x_1-3x_2)^2(18-32x_1+12x_1^2+48x_2-36x_1x_2+27x_2^2)]$$

$$-2\le x_i\le 2,\quad i=1,2$$

The global minimum value of this function is 3 within the scope of its definition domain, and optimal point is (0, -1). Its three-dimensional image is as figure2.

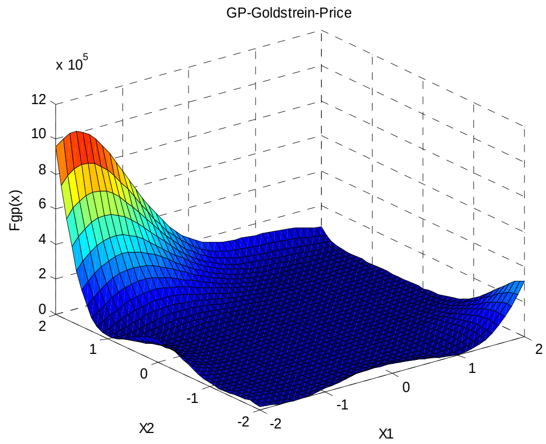

Figure 2. Image of GP-Goldstein-Price Function

Test functions 2: RA-Rastrigin (n =2)

$$f_{RA}(x)=x_1^2+x_2^2-\cos 18x_1-\cos 18x_2$$

$$-1\le x_i\le 1,\quad i=1,2$$

The function expression contains the polynomials and typical trigonometric function, its global minimum value is -2, and optimal point is (0, 0). Its three-dimensional image is as figure3.

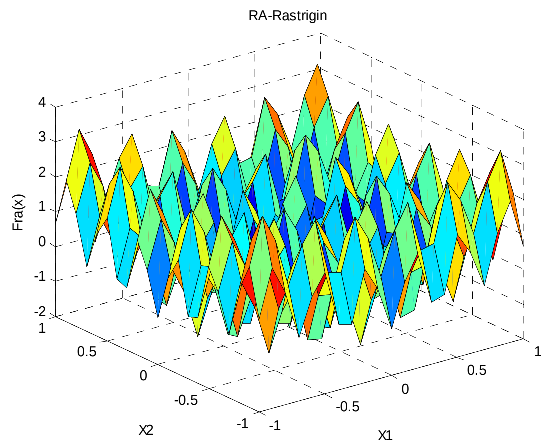

Figure 3. Image of RA-Rastrigin Function

In the experiments, basic particle swarm optimization (PSO), AFSA and PAFSA were used to analyze the test results by selecting the GP function and RA functions as test functions. Average minimum function value and the minimum were obtained by 30 times run independently. The results of experiments are shown in table I.

TABLE I.

THE COMPARISON OF OPTIMIZATION RESULTS AMONG PSO, AFSA AND PAFSA

Algorithm	Function / Value	f_{GP}	f_{RA}
PSO	Average minimum value	3.6679	-1.5958
	Minimum value	3.0016	-1.9660
AFSA	Average minimum value	3.3892	-1.5958
	Minimum value	3.0149	-1.9660
PAFSA	Average minimum value	3.0969	-1.9313
	Minimum value	3.0004	-1.9997

Figure 4 and Figure 5 show the convergence process contrast curve of the three optimization algorithms of PSO, AFSA and PAFSA, those methods were operated respectively for two test functions.

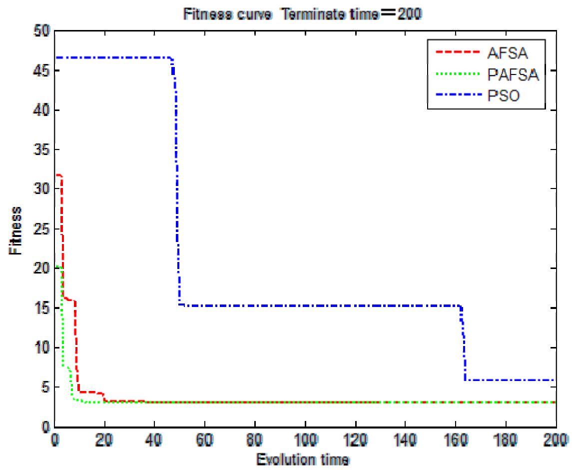

Figure 4. The optimization process for the GP-Goldstrein-Price function

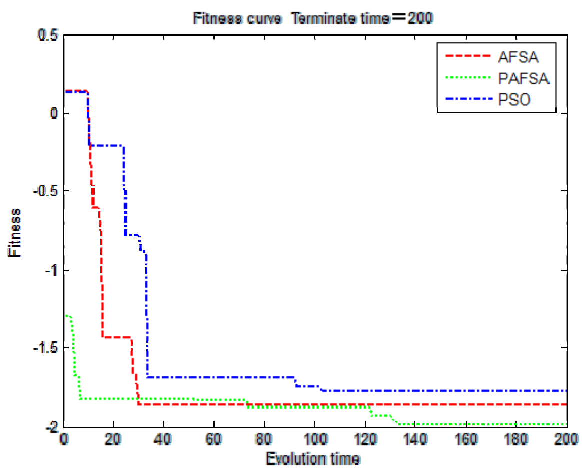

Figure 5. The optimization process for the RA-Rastrigin function

The experiments above indicate that optimization results of PAFSA are more close to the theoretical optimal value Relative to the AFSA and PSO algorithms, and PAFSA is superior to the other two algorithms in terms of search quality. PAFSA may find the global optimum quickly with the least iterations, it has better convergence.

IV. PARAMETERS OPTIMIZATION OF SVM BASED ON PAFSA

The purpose of this paper is to get the optimal parameter set (C, γ), and uses it in a speech recognition system to obtain a higher recognition rate. The PAFSA idea proposed by this paper is as follows: Firstly, using the initial population, which is generated by the PAFSA, as parameters, carries on SVM model training and testing. In the experiments, the speech vocabulary is divided into two parts and one is used as the training sample and the other testing sample respectively, after the experiments, returned the recognition rate which was responding to the training sample. Then the chasing behavior, the swarming behavior and the feeding behavior are used to optimize the next generation of parameters. Newborn subgroup repeats this iteration until the termination conditions of PAFSA, and the optimal parameters and the optimal parameters model are the final prediction model. Figure 6 is the flow diagram of SVM parameters optimization based on the PAFSA.

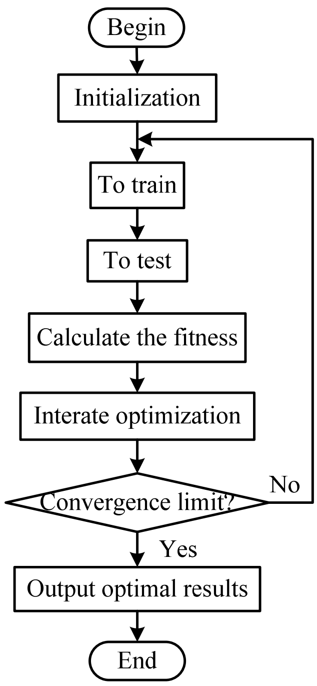

Figure 6. Flow diagram of SVM parameters optimization based on PAFSA

The specific steps of looking for the optimal solutions of parameters C and γ are as follows:

Step1: initialization. Generate an initial population which determine the scope of SVM parameter vector array (C, γ) and set up other parameters values of PAFSA.

Step 2: substitute the data set into the initial SVM model, and use the initial population to train training set. Then the trained model is used to test the testing data set. The recognition rate of the overall testing samples is converted to the fitness value of the model.

Step 3: according to the fitness value, the chasing behavior, the swarming behavior and the feeding behavior are used to generate the next generation of parameter array (C, γ) population for optimization of the better (C, γ).

Step4: using the parameters of the offspring (C, γ) population, re-training and testing the SVM, calculates the corresponding fitness value. If it satisfies with the termination condition for training in PAFSA, it goes to Step5, otherwise, it returns to Step3 to continue the operation.

Step5: ending training. Now, the parameters (C, γ) gotten is the final model parameters.

V. Experimental Results And Analysis

A. Speech Recognition System

Speech recognition system includes three main parts: pre-process, feature extraction and training recognition network. The pre-process includes pre-emphasis, window-adding and packetization and so on. A filter whose transfer function is $H(z) = 1\text{-}\alpha z^{-1}$ ($0.9<\alpha<1.0$) is used to realize pre-emphasis; and hamming window is used to realize window-adding and packetization. After pre-process, extract feature parameters of speech signal. At last, obtain recognition results by SVM classifier.

In this paper, speech feature we used is improved Me1-Frequency Cepstral Coefficient (MFCC) parameters. The process of traditional MFCC feature extraction is as follows. First, do pre-process, window-adding and packetization to speech signal. Second, obtain the spectrum by Discrete Fourier Transform (DFT). Then input speech energy spectrum into a bank of filters that are distributed equably in frequency, and obtain output of the filters. At last, compute logarithm of the output gotten in last step and do Discrete Cosine Transform (DCT). The value we gotten here is MFCC parameters. The improved MFCC parameters we used in this paper are using Bark Wavelet Transform instead of DCT [18], and MFCC parameters are transformed into Mel-frequency Discrete Wavelet Cepstral Coefficients (MFDWCs). MFDWCs can accord with auditory characteristics better and is better for SNR. Figure 7 is the process of improved MFCC parameters extraction.

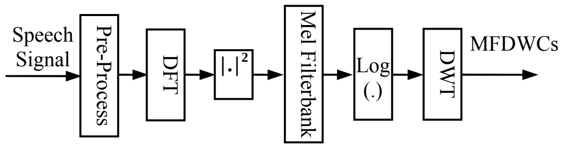

Figure 7. Extraction process of improved MFCC parameters

B. Multi-class Classification Algorithm

SVM itself is a classification method of two classes. For non-specific person and middle glossary quantity speech recognition system, it needs to classify N words, and this is a multi-class classification problem. The transformation from multi-class classification to two types is involved. This paper uses the "one-against-one" approach [19] in which $P=k(k-1)/2$ binary classifiers are constructed and each one trains data from two different classes to realize k classes multi-class classification SVM. In classification, a voting strategy is used: each binary classification is considered to be a voting where votes can be cast for all data points, in the end point is designated to be in a class with maximum number of votes.

C. Experimental Results and Analysis

In the experiments, the speech samples we used are isolated words, sampling frequency of speech signal is 11.02 KHz, the frame length N is 256 points and the frame shift M is 128 points.

The training samples database are pronunciations of 9 persons in 0 dB, 5 dB, 10dB, 15 dB, 20dB, 25dB, 30dB and clean environment, and the noise is Gaussian white noise which is artificially added. The Speech sample vocabulary is 10 words, 20 words, 30 words, 40 words and 50 words separately, each person pronounces each word three times. Thus, the categories of entire data set under different Signal to Noise Ratio (SNR) are 10, 20, 30, 40, 50, and corresponding training samples are 270, 540, 810, 1080, and 1350 respectively. The testing samples are pronunciations of other 7 persons in the same SNRs, each person pronounces each word three times, and so testing samples are 210, 420, 630, 840 and 1050 respectively.

Input features of the speech are the MFDWCs parameters in the experiments. Table II lists the speech recognition rates of SVM based on AFSA and PAFSA in the same experimental conditions, different SNRs and different words.

Observing the results in Table II, we may find that the speech recognition rates of SVM based on PAFSA are higher than the results of SVM based on AFSA in the same experimental conditions under different kinds of SNR and different words, especially when the SNR of the speech signal is lower, SVM based on PAFSA can still maintain a certain recognition rate. These indicate that SVM based on PAFSA proposed by this paper has strong anti-noise ability. Further, show that PAFSA is an effective method for parameter optimization of SVM. It not only makes SVM get better generalization ability, but also makes it get more robustness.

TABLE II.
THE COMPARISON OF SPEECH RECOGNITION RATES OF SVM BASED ON AFSA AND PAFSA(%)

Words	SNR / Methods	0 dB	5 dB	10 dB	15 dB	20 dB	25 dB	30 dB	Clean
10	AFSA	81.62	84.76	89.05	90.95	90.00	92.38	91.67	92.76
	PAFSA	86.19	89.52	94.76	94.29	95.71	95.24	94.76	96.67
20	AFSA	79.67	87.19	91.81	92.14	86.19	89.57	90.14	91.43
	PAFSA	82.86	91.43	93.81	94.92	94.52	93.57	93.27	93.81
30	AFSA	80.56	87.30	89.26	91.40	92.06	94.02	87.46	93.52
	PAFSA	85.24	87.62	93.65	95.25	95.71	94.60	92.78	94.32
40	AFSA	83.81	84.43	90.12	92.02	92.14	92.94	94.16	95.71
	PAFSA	84.17	91.79	93.45	93.85	94.88	95.01	95.60	96.19
50	AFSA	79.82	83.05	84.48	89.52	89.81	92.27	93.35	95.03
	PAFSA	80.43	89.90	92.00	94.29	94.38	95.90	94.19	95.26

VI. CONCLUSION

The choice of the kernel functions and its parameters directly affects the learning performance of SVM. The best classification and generalization ability of SVM model may be obtained when the most appropriate model is selected. In this paper, the SVM parameter set has been firstly optimized by PAFSA which was tested with the test functions, and compared with PSO and AFSA. Then it was supplied for a speech recognition system which is non-specific person, isolated words, medium vocabulary, by comparing to the rates of speech recognition of SVM based on AFSA, the results may verify effectiveness of PAFSA. It can be predicted that SVM will have broad development prospects in the field of speech recognition. Of course, it is certain that SVM still need to be in-depth studied in the future.

ACKNOWLEDGMENT

This work was sponsored by Natural Scientific Foundation of China (No.61072087), and Scientific and Technological Research Projects (Social Development) of Shanxi Province of China (No.20120313013-6). authors gratefully acknowledge them.

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