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Speech Emotion Features Selection Based on BBO-SVM

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***Abstract*—In order to solve the problem that the emotion feature dimension is too high in speech emotion recognition, an optimization method based on BBO-SVM for invariant set of elements is proposed. BBO-SVM method optimizes the original lower-level speech emotion feature set with higher dimension combining the optimization characteristics of the Biogeography-Based Optimization algorithm (BBO) and the classification training ability of support vector machine (SVM), the purpose is to obtain feature set with low dimension and rich emotional information. This paper first extract 1582-D emotional feature set for each speech file using openSMILE and then randomly divided it into multiple feature subsets, which are used as the original population of BBO algorithm. Corresponds the feature subset to the index of the BBO algorithm. At last, grouping and screening the high redundancy features using BBO. The final results are obtained by multiple iterations, and the cross validation results of support vector machine are used as the criteria for evaluating the generated subsets in the iterative process. The result shows that, for the original speech feature set with high dimension and contains a lot of redundant information, the BBO-SVM method can filter them to obtain feature set with rich emotional information and few redundant components. This provides an optimized feature basis for the establishment of emotion model, which can improve the efficiency of speech recognition process and obtain better recognition results at the same time.**

***Keywords*—Biogeography-Based Optimization, SVM, feature selection, speech emotion recognition**

I. Introduction

With the development of artificial intelligence technology, more and more intelligent equipments go into tens of thousands of households, and people's expectation to what intelligent equipment can do become higher and higher. In order to achieve natural and harmonious human-computer interaction, developing a technology that allows machines to accurately understand human emotions is imminent. Speech is one of the most direct and natural ways of human communication. Voice not only contains complex semantic information but also a wealth of emotional information, and voice signal is easier to capture compared to other physiological signals. The current speech processing technology is also relatively mature, which makes the speech emotion recognition become one of the most important directions in human emotion research. In recent years, speech recognition technology has made great progress in all aspects, such as semantic identification, speaker recognition, voice and emotion recognition. It had also played an important role in some social service practice, such as distance education, telephone customer service and emotional treatment and so forth.

The basis of emotion recognition is extract useful features from speech signals. At present, the features mainly include prosodic features, spectral features, sound quality features and other acoustic features [1]–[4]. In recent years, many scholars have suggested that speech is an unstable signal over time, therefore, its helpful to improve the accuracy of speech recognition by extracting nonlinear features, such as chaotic features [5]–[7]. A large number of features are used in speech recognition, good results can be obtained by the training of various machine learning methods. However, the increasing number of speech feature dimension brings more redundancy characteristics, which will affect the result of recognition. If we can find a set of low dimensional and sufficient features to characterize the emotion contained in the speech signal, it will greatly reduce the processing time and improve the efficiency of recognition.

How to find the most contributing subset in high dimensional features, many scholars have done relevant work. In paper [8], the author uses ant colony algorithm to optimize the original feature space; In paper [9], the original feature set was optimized by the two-time feature selection method; Paper [10] uses Markov blanket to select a feature subset with higher characterization ability for each kind of emotion; There are many related papers, which reduced the characteristic dimension, at the same time, improved the emotion recognition rate [11]–[16]. In this paper, an optimization method based on BBO-SVM for the invariant elements of set is proposed, which utilizes the biogeography optimization algorithm (BBO) to select and optimize the original feature set, and uses the cross validation result of support vector machine as a standard for evaluating subset. The method iteratively optimizes the original high-dimensional feature set, get the compressed feature subset, and the effect of the speech emotion classification is also considerable.

This paper is organized as follows. It introduces Biogeography Based Optimization algorithm in Section 2 and describes BBO-SVM method in more details in Section 3. Simulation experiment and result analysis based on BBO-SVM algorithm

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are presented in Section 4. Section 5 is the final conclusion part of this paper.

II. Biogeography-Based Optimization – BBO

A. Background

In nature, biological populations are distributed within a range of geographical regions with distinct boundaries, known as habitats. For each habitat, Habitats suitability Index (HSI) can be used to indicate the appropriate species survival index [17]. For habitat in nature, there are many factors that can affect HIS, such as temperature, humidity, vegetation, soil quality and land area. These influence factors are called Suitability Index Variables (SIV). The change of SIV will cause the change of species in habitat. In general, high HSI habitats have a larger number of species, and low HSI habitats have fewer species. In the habitat with high HSI, there are more species and more fierce competition. Therefore, some individuals of species will choose to move out to their neighboring habitats, that is to say, the species emigration rate is high in habitats of high HSI; However, due to the abundance of species in the habitats with high HSI, few species can be moved in, so the species immigration rate in the high HSI habitats is low. Conversely, habitats with low HSI have lower species emigration rate and higher immigration rate. For low HSI habitats, the HSI of the habitat can be improved because of the influence of species migration on habitat environment. But if the HSI remains low, that indicates resources are scarce in the region, the invasive species will be in danger of extinction; When some species are extinct, such habitats will have a chance to move in large numbers of new species. Therefore, the dynamic changes of species distribution in low HSI habitats are more obvious than those of high HSI. In order to simplify the representation, Fig. 1 depicts a simple linear mathematical model of the species diversity of habitats, wherein represents the immigration rate and represents the emigration rate, both of which are functions of the habitat species number S; I indicates the maximum immigration rate, E indicates the maximum emigration rate, s_0 indicates the number of species in which the immigration rate and the emigration rate reach equilibrium. s_{max} indicates the largest number of species [18].

Formula (1) can be obtained from the above diagram:

$$\lambda_S = I(\frac{1-S}{S_{max}}), \mu_S = \frac{ES}{S_{max}} \tag{1}$$

Assuming that the probability of a habitat just accommodate s species is P_s. From time t to time$(t + \Delta t)$, the change of P_s is as formula (2).

$$\begin{aligned} P_s(t+\Delta t) = P_s(t)(1-\lambda_s\Delta t - \mu_s\Delta t)+ \\ P_{(s-1)}\lambda_{(s-1)}\Delta t + P_{(s+1)}\mu_{(s+1)}\Delta t \end{aligned} \tag{2}$$

The left side of the equation indicates the probability of owning a species of S at the time$(t + \Delta t)$, and there are three cases on the right side of the equation that shows in formula (2). First, there were S species at time t, and one species immigrated; Second, there were S species at time t, and no immigration or emigration occurred between t and $(t+\Delta t)$; Third, there were S species at time t, and one species emigrated. As shown in formula (3).

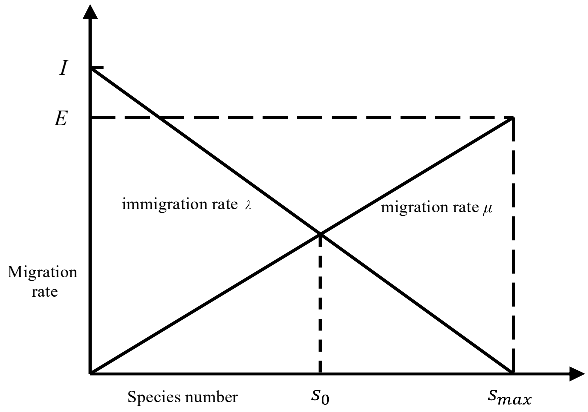

Fig. 1. Migration model of habitat species

$$\begin{cases} -(\lambda_s+\mu_s)P_s+\mu_{(s+1)}P_{(s+1)} & S=0 \\ -(\lambda_s+\mu_s)P_s+\mu_{(s+1)}P_{(s+1)}+\lambda_{(s-1)}P_{(s-1)} & 0<S<S_{max} \\ -(\lambda_s+\mu_s)P_s+\lambda_{(s-1)}P_{(s-1)} & S=S_{max} \end{cases} \tag{3}$$

B. BBO Algorithm

Biogeography-Based Optimization algorithm(BBO) is a new intelligent optimization algorithm based on biogeography theory, which was proposed by Simon in 2008, has good convergence and stability. Similar to many other heuristic algorithms, BBO is also based on population, it regards each solution of the population as a habitat, the goodness of the solution as the HSI of the habitat, and each component of the solution as an SIV. It can solve the optimization problem by simulating the effect of migration and mutation in biogeography on population.

1) Migration Operation: The purpose of the migration operation is to transfer information between different solutions, in which the optimal solution tends to propagate its own information to other solutions, whereas the poor solution tends to receive information from other solutions. In the implementation, each iteration of the BBO algorithm will examine every solution H_i in the population. The immigration rate and the emigration rate were λ_i and μ_i, that is to say, each component has the probability of λ_i to be modified; If immigration, a solution H_j to move out is selected from the population by the migration rate μ_j, and then replace the current component of H_i with the corresponding component of H_j. After all the components of H_i have been executed, a new solution $H_i{}'$ is generated. The algorithm compares the fitness of H_i and $H_i{}'$ and then keep a solution with higher fitness in the population. The procedure for the migration operation is described in Fig. 2 by pseudo code, where D indicates the dimension of the problem, or in other words the length of the solution vector, and rand() is used to generate a random number within $[0, 1]$.

```
Migration Operation
for d=1 to D do
    if rand()<λ_i then
        Choose anther habitat H_j from populations
        with the probability of emigration rate μ_j;
        H_i(d) ← H_j(d);
    end if
end for
```

Fig. 2. Migration operation pseudo code

2) Mutation operation: Some unexpected events can dramatically change the property of natural habitats, accordingly changing the HSIs of these habitats and leading to significant changes in the number of species. The BBO algorithm modeled this situation as SIV mutation. Formula (3) describes the probability of a species in a habitat, which determines the mutation rate of the habitat. When the number of species is too large or too small, the probability of species is relatively low; Probability of species quantity is higher when the number of species is medium.

Correspondingly, the BBO algorithm gives each solution H_i of the population an associated probability number of species P_i, The probability of the solution with high or low fitness is lower, while the probability of moderate fitness is higher. π_i, the mutation rate of H_i, is inversely proportional to the probability of species number, of which, π_{max} is a control parameter. The expression of π_i is as follows:

$$\pi_i = \pi_{max}(\frac{(1 - P_i)}{P_{max}}) \tag{4}$$

In the specific implementation, each iteration of the BBO algorithm will examine every solution H_i in the population, and make sure that each component of the solution have the probability π_i to mutate. Assuming that it is a continuous optimization problem, the value range of the D dimension of the problem is $[l_d, u_d]$, the BBO mutation operation process can be described by the pseudo code in Fig. 3.

```
Mutation Operation
for d=1 to D do
    if rand()<π_i then
        H_i(d) ← l_d + rand() * (u_d − l_d);
    end if
end for
```

Fig. 3. Mutation operation pseudo code

III. BBO-SVM EMOTION FEATURE SELECTION MODEL

A. Design idea

The goal of BBO-SVM optimization algorithm is to select a subset which make the emotion classification rate higher, and it also make sure that the contents of each vector in the original feature set remains the same after the progress of optimization. Therefore, the selection of the speech feature set is transformed into an optimization problem, as formula (5):

$$\begin{cases} \text{Max F=SVM.CrossValidation}(R^*) \\ R = (R_1^*, R_2^*, \cdots, R_m^*), R_i^* \cap R_j^* = \emptyset \\ R_a^* = (x_{a1}, x_{a2}, \cdots, x_{an}), i \neq j, x_i \neq x_j \\ a \in (1, 2, 3, \cdots, m) \\ m, n, a, i, j \in Z^+ \end{cases} \tag{5}$$

In this formula, F is the result of cross validation result of support vector machines, as the objective function to evaluating the optimization problem; R is original emotion feature set; R_a^* is a subset of the features obtained after partitioning R. There is no cross characteristic vector between different feature subsets, and there is no same eigenvector in each feature subset.

The objective function value in (5) is expressed by the cross validation result of support vector machine, because support vector machine has excellent learning performance, that is suitable for many different classification problems, so it is widely used in emotion recognition as classifier. In this paper, each iteration produces a set of feature subsets that are different from the previous generation, so we need to compute the recognition rate of each subset in each iteration, and support vector machines can improve performance greatly.

To use the BBO algorithm to filter and optimize the speech emotion feature set, it is necessary to match the concepts in emotional feature set with the related concepts in the BBO algorithm. According to the optimization model of this paper, their corresponding relationships are shown in Fig. 4:

Fig. 4 shows the correspondence between the main concepts in the BBO algorithm and the BBO-SVM emotion feature selection model. It shows that the subset of the original feature sets corresponds to the solution of the BBO optimization problem. Through the finite iterative calculation, the optimal solution of the problem is obtained, that is, the optimal subset of the emotion feature set. During the iteration, the results of the SVM cross-validation for each subset correspond to the HSI of geographical environment, which also serves as the criterion to judge the subset of emotional features and the basis to sorting subsets; Each vector of the emotion subset corresponds to the SIV of each habitat in the geographical environment.

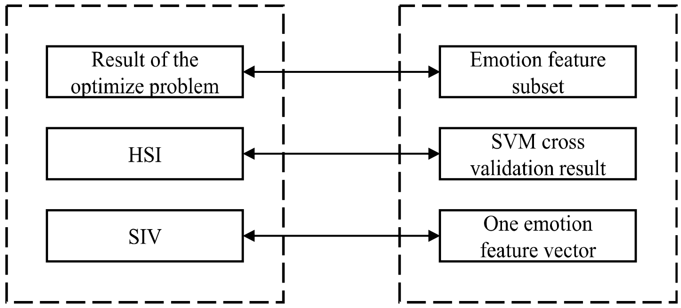

Fig. 4. BBO corresponds to feature selection model

Using BBO algorithm to optimize the speech emotion feature selection is to reduce the dimension of the original high-dimensional feature set, that is to say, remove redundant feature information, and simultaneously retain the feature subset which greatly contributes to emotion recognition and division. In this process, the specific values of the eigenvector in the original feature set should not be modified. Compared with the original BBO algorithm, the BBO-SVM feature selection optimization process has retained the migration operation of BBO algorithm, and removed the mutation operation, because the mutation operation will change the value of SIV itself.

B. BBO Emotion Feature Selection Algorithm

Fig. 5 shows a feature optimization flowchart based on the BBO-SVM model.

As shown in Fig. 5, according to the optimization process of BBO algorithm, the steps using BBO algorithm to select and Optimize emotion feature set are as follows:

- Step 1: Initialize the BBO control parameters. Maximum population size – N; The number of eigenvectors contained in each population – M; Maximum iterative times – Gen; Maximum migration rate – I; Maximal emigration rate – E; Elite retention number – Keep; Global migration rate – P.
- Step 2: Obtain the original feature set $X = (x_1, x_2, \cdots, x_n)$ by extracting the speech feature, where X is a two-dimensional array of m*n, and $x_i (i \in [1, n])$ represents a feature vector of m*1 dimension of one feature set. X is randomly divided into N subsets with equal number features, each feature subset contains M vectors, and no repeated feature vectors between any two feature subsets. Where m,n is determined by the dimension of the original feature set, M,N is selected according to the parameter set in Step 1.
- Step 3: Calculating habitat suitability index HSI. The HSI of the subset is obtained by using cross validation result of support vector machines. According to the result, the immigration rate and the emigration rate of each subset are calculated. As the formula (1).

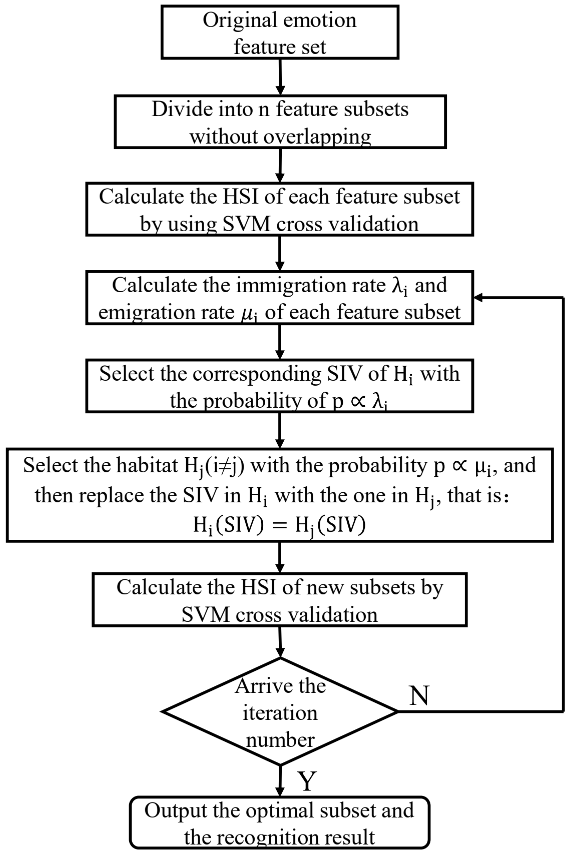

Fig. 5. BBO-SVM emotion feature selection flowchart

- Step 4: Migration operation. A new population is updated by using the immigration rate and the emigration rate. Subsets are sorted according to the fitness index HSI. The two groups with the highest fitness are the elite populations, which are retained in the new population after the iteration. Recalculate the habitat suitability index (HSI) and update the optimal solution.
- Step 5: According to the maximum number of iterations to determine whether the end of optimization, if end, output the optimal subset; if it did not reach the maximum number of iterations, go to Step 3.

IV. Experimental Simulation

A. Data Sources and Preprocess

1) Emotional speech database: In order to verify the application of BBO-SVM model in speech emotion recognition, this paper chooses the audio files in Berlin emotional speech database to process. The database consists of seven types of emotions: medium, happy, angry, sadness, disgust, boredom and fear. Because the quantity of each kind of audio emotion files is different, and the minimum is 46, therefore, this experiment chooses 40 audio files for each kind of emotion, and the total number of audio files is 40*7=280.

2) Preprocess and original features extraction: Since this paper mainly verifies the effectiveness of the proposed feature

```
/////////////////////////////////////////////////////////////////
/// > openSMILE configuration file for emotion features <      ///
///   Based on INTERSPEECH 2010 paralinguistics challenge      ///
///   Pitch, Loudness, Jitter, MFCC, MFB, LSP and functionals  ///
///                                                            ///
///   1582 1st level functionals:                              ///
///     (34 LLD + 34 delta) * 21 functionals                   ///
///    +(4 LLD + 4 delta) * 19 functionals                     ///
///    + 1 x Num. pitch onsets (pseudo syllables)              ///
///    + 1 x turn duration in seconds                          ///
///                                                            ///
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Fig. 6. Low level feature set extracted by emobase2010.conf file

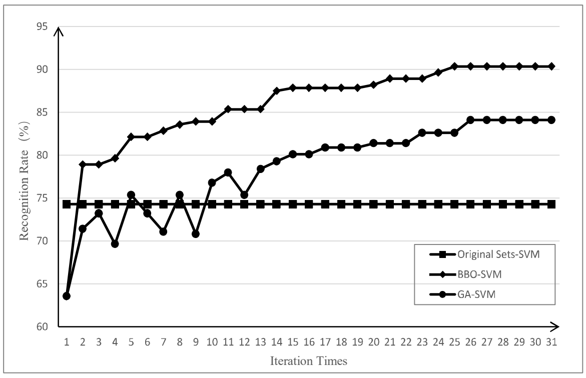

Fig. 7. The optimal subset recognition rate varies with the number of iterations

selection algorithm, the pre-processing of speech signals and the extraction of basic emotional features are not described in detail. For feature selection algorithms, the larger the original feature set size is, the more likely to filter out the optimal subset. Therefore, it is necessary to extract enough features before optimization. This paper choose OpenSMILE to process audio files and extract features. OpenSMILE is used for signal processing and machine learning feature extractor, its basic function is the speech signal feature extraction. There are lots of configuration files for researchers to choose to process speech signal [19]. In this paper, the file "emobase2010.conf" file is selected to extract the speech features, and a total of 1582 dimensional low level speech features are extracted as the original feature set. The interpretation of the 1582 dimensional low level speech features in the configuration file is illustrated in Fig. 6.

3) Emotion recognition algorithm: This paper choose support vector machine to recognize emotions. The support vector machine is used to train the feature subset generated in every iteration of the optimization algorithm, and then obtained the cross validation result, that is, the emotional recognition rate. This result is also used as an evaluation standard for the iterative results.

B. Simulation Experiment and Result

Parameter initialization is performed in Step 1 of the algorithm flow in the third chapter. Since openSMILE extracts 1582 dimensional feature sets from 280 audio files, this paper sets the population size is N=14, and the number of feature vectors contained in each population is M=113. According to the experience of many iterative experiments, the maximum iteration number Gen=50 is selected, and the optimal fitness value can be guaranteed in the 50 iteration process. This paper set the maximum immigration rate and emigration rate of I=E=1, elitist retention number Keep=2, and global migration rate P=1. After the parameters are set, the iterative operation is performed according to the optimization step.

In order to compare the BBO algorithm and other mainstream optimization algorithms in the process of speech emotion feature selection optimization, this paper chooses another optimization algorithm for feature select optimization. Since Genetic Algorithm (GA) is similar to BBO algorithm, it also can optimal feature sets without change the internal numerical feature vector. Therefore, under the same parameter settings, the GA algorithm is selected to optimize the speech emotion feature set, and the cross validation value of SVM is also used as the classification result.

The simulation results of emotional feature selection optimization using BBO algorithm and GA algorithm are shown in Fig. 7, Fig. 8 and table I.

Fig. 7 shows the change of the emotion recognition rate of the optimal subset in each iteration of the BBO algorithm and the GA algorithm, and it also provides the recognition rate of not optimized original set of features as a comparison at the same time. As shown in the figure, with the increase number of iterations, the two algorithms all show the optimization effect on the randomly assigned feature subset. After the random allocation of the original feature subset, the optimal recognition rate of 14 subsets is below 65%. For the BBO-SVM algorithm, in the first 5 iterations, the recognition rate of the optimal subset has changed obviously, reaching more than 80%; After 25-30 iterations, the recognition rate of the optimal subset reaches the highest, about 90%; The recognition rate has increased by about 30% relatively to the original subset. For the GA-SVM algorithm, in the first 15 iterations, the optimization effect of the feature subset is not stable, then gradually become stable. GA is also stabilize before the iteration 30, and the final recognition rate is about 84%. With the increment of iterative times, the recognition rate of the two algorithms goes beyond the recognition rate of the original feature set, and the BBO algorithm is better than GA algorithm.

Fig. 8 shows the average recognition rate of the BBO algorithm and the GA algorithm in each iteration of subsets. During the iterative process, the average recognition rate of the two algorithms is basically on the rise, so it can be seen that the BBO algorithm and the GA algorithm are optimized for all feature subsets. That is to say, the small contribution features will be eliminated, and the excellent features will be retained. It can also be seen that, the BBO algorithm is superior to the GA algorithm in the optimization of the overall feature subset

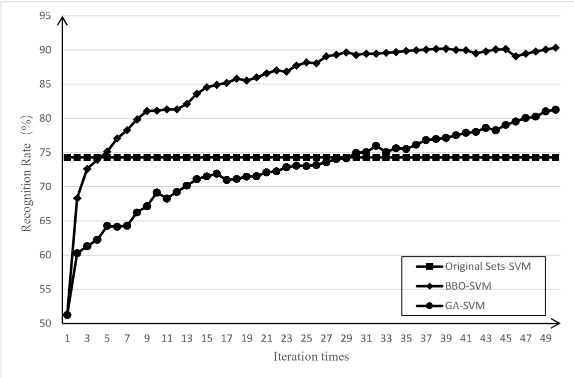

Fig. 8. The average recognition rate of subsets varies with the number of iterations

TABLE I
COMPARISON OF RECOGNITION RATE OF THREE FEATURE SETS

Feature Sets	Max Recognition Rate	Average Recognition Rate
Original-SVM	74.29%	
GA-SVM	84.11%	81.26%
BBO-SVM	90.36%	90.13%

in each iteration.

Table I gives the data of the simulation experiment. The data in the table is the result after using SVM training the original feature set, the set optimized by GA algorithm and the set optimized by the BBO algorithm respectively. The maximum recognition rate and average recognition rate of the three feature sets are compared in the table. It can be seen that the advantage of feature set optimized by BBO algorithm in model training.

Fig. 9 draws the variation of all feature subset recognition rates for each generation in the optimization of BBO-SVM algorithm. The points on each vertical line represent the recognition rate of all feature subsets in this iteration. We can see that after many iterations, the recognition rate of the whole subset is rising, and the optimization of the optimal subset in the later iterations is basically formed. In the later iterations, the algorithm continues to optimize the other subsets. Finally, the recognition rate of each feature subset is very considerable, and the average recognition rate is 90%. Multiple iterative optimization makes the different feature subsets have a lot of repeated feature vectors.

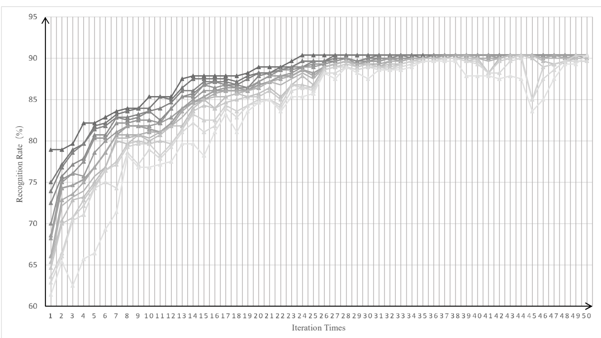

Fig. 9. Each generation subset recognition rate varies with the number of iterations

V. CONCLUSION

This paper presents an optimization method based on BBO-SVM for the invariant set elements. The BBO algorithm is used to optimize the subset of random distribution, and the cross validation of SVM is used as a criterion to judge the subset's excellence. The simulation results show that this method can effectively reduce the dimension of the original high dimensional collection and improve the accuracy of classification, and recognition rate using the optimized feature set can reach 90.4%. Compared with the simulation experiments with GA algorithm under the same conditions, it also shows the effectiveness of the proposed BBO-SVM algorithm in feature selection.

From the process of experiment simulation using MATLAB, we can conclude the feature selection in BBO is possible to be optimized in the following aspects. Firstly, the migration operation of BBO algorithm is based on the probability, and the random number generator is needed in MATLAB, so the generation function of random number has an effect on the migration operation. It is possible to eliminate features with a certain probability, which may be an excellent feature. Once eliminated, the loss is more serious. Secondly, in this paper, the size of the emotion feature subset is a fixed dimension. If possible, we should find a method to dynamically generate a subset with unfixed length, and it might get better results. In the follow-up study, we can make improvements by focusing on these aspects.

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