IHS-LSSVM Based Brain CT Image Classification

He Sheng[1], Chen JieDong[2], Hou YongJin[1]

1. Department of Computer Engineering, Guangdong Industry Technical College, Guangzhou, 510300 China
2. Department of Automobile Engineering, Guangdong Industry Technical College, Guangzhou, 510300 China

Abstract
In order to improve brain CT image classification accuracy and solve LSSVM parameter optimization problem in the classifier, a brain CT image classification model with improved harmony search algorithm optimized LSSVM (IHS-LSSVM) is proposed in this article. In detail, firstly, LSSVM parameter is regarded as the tone combination of different musical instruments; then, the optimal parameter is found through the "tone tuning" of the harmony search algorithm and meanwhile the optimal position adjustment strategy of PSO (Particle Swarm Optimization) algorithm is also introduced therein during the optimizing process to improve the capability of the algorithm for jumping out of the local minimum; finally, the brain CT image classification model is established according to the optimal parameter and meanwhile the simulation test is also carried out to verify the performance of the model. The simulation result shows: relative to the comparison model, HIS-LSSVM can not only improve brain CT image classification accuracy, but also accelerate the classification speed, thus to be more suitable for the real-time classification requirements of brain CT images.
Key words: BRAIN CT IMAGE CLASSIFICATION, LEAST SQUARES SUPPORT VECTOR MACHINE CLASSIFIER, HARMONY SEARCH ALGORITHM, PARTICLE SWARM OPTIMIZATION ALGORITHM

1. Introduction

In recent years, hospitals have collected massive brain CT image data of the patients along with the continuous updating and perfection of the radio-diagnostic equipment, so how to mine the information from these image data to assist doctors for diagnosis becomes more and more important. Therein, the image classification is an important research content of brain CT image data mining, so how to establish a brain CT image classification mode with high classification accuracy and fast classification speed will undoubtedly become the research hotspot in CAD (Computer-Aided Diagnosis) field [1].

Actually, the brain CT image classification is a mode recognition problem, and the classification result is closely related to the selection and the optimization of the classifier. At present, the brain CT image classifiers mainly include Bayes method based brain CT image classifier, neural network based brain CT image classifier and SVM based brain CT image classifier [2,3]. Therein, the Bayes method based brain CT image classifier and the neural network based brain CT image classifier are both based on the "large sample" theorem, and under the condition of large samples, the above two classifiers can both have good classification results; however, the brain CT images belong to small-sample and high-dimension data and can be easily caught in such defects as local extremum and overfitting, and the classification accuracy of the above two classifier cannot meet the aided diagnosis requirements of brain CT images [4]. As an improved SVM, LSSVM (Least Squares Support Vector Machine Classifier) is based on structural risk minimization principle and can easily conquer such defects as the overfitting of neural network and the slow training speed of the standard SVM, thus to be widely applied to brain CT image classification[5,6]. LSSVM parameter can directly influence brain CT image classification results, and in order to solve the above problem, scholars have proposed such algorithms as GA (Genetic Algorithm), PSO algorithm, simulated annealing algorithm and ant colony algorithm to optimize LSSVM parameter, but these algorithms all have some disadvantages which can influence the brain CT image classification accuracy of LSSVM [7-9]. As a metaheuristic search algorithm based on the simulation of the harmony principle of the band in musical performance, HS algorithm has strong parallel and global search capabilities and accordingly can provide a new research tool for LSSVM parameter optimization [10].

In order to improve LSSVM based brain CT image classification accuracy, the improved harmony search (IHS) algorithm is introduced into LSSVM parameter optimization in order to establish HIS-LSSVM based brain CT image classification model. Meanwhile, the simulation experiment is also carried out to verify algorithm validity.

2. HIS Algorithm and LSSVM

2.1. LSSVM

As a machine learning algorithm established on the basis of statistical learning theory, LSSVM aims at properly optimizing the model complexity and the risk according to the limited sample information in order to obtain the best generalization ability [11]. If the training set is (x_i,y_i), wherein i=1,2,…,n, and n denotes the size of the training samples, and $x_i \in R^m$ is the sample input, and $yi \in \{1,-1\}$ is the output, then the linear function of LSSVM in high-dimensional characteristic space is as follows:

$$f(x) = w^T \varphi(x) + b \tag{1}$$

In the formula, ω is weight vector and b is the offset.

According to the structural risk minimization principle and based on the comprehensive consideration for fitting error and function complexity, formula (1) can be converted into the following formula:

$$\min_{w,b,e} J(w,e) = \frac{1}{2} W^T W + \frac{\gamma}{2} \sum_{i=1}^{n} e_i^2 \qquad s.t.\ \ y_i = w^T \varphi(x) + b + e_i, i = 1,2,\cdots,l \tag{2}$$

In the formula, γ is the regularization parameter and e_i is the forecast error.

Formula (2) is converted into unrestraint dual optimization problem through the introduction of Lagrange multiplier, namely:

$$L(w,b,e,\alpha) = J(w,e) - \sum_{i=1}^{l} \alpha_i \left(w^T \varphi(x_i) + b + e_i - y_i \right) \tag{3}$$

In the formula, a_i is Lagrange multiplier.

According to KKT condition, the following formula can be obtained:

$$\begin{bmatrix} 0 & el^T \\ el & Q + \gamma^{-1} I \end{bmatrix} \begin{bmatrix} b \\ a \end{bmatrix} = \begin{bmatrix} 0 \\ y \end{bmatrix} \tag{4}$$

For the nonlinear classification problem, kernel function can be introduced to convert the problem into high-dimensional characteristic space solution. Moreover, compared with other kernel functions, the radial kernel function (RBF) has less parameters and good performance, so it is selected as the kernel function of LSSVM. Therein, RBF is defined as:

$$K(x_i, x_j) = \exp\left(-\left\| x_i - x_j \right\|^2 / 2\sigma^2 \right) \tag{5}$$

In the formula, σ is the width parameter of the radial kernel function.

Finally, LSSVM classification decision function is as follows:

$$f(x) = \operatorname{sgn}\left(\sum_{i=1}^{n} \alpha_i \exp\left(-\left\| x_i - x_j \right\|^2 / 2\sigma^2 \right) + b \right) \tag{6}$$

According to LSSVM classification principle, LSSVM learning performance is related to parameters γ and σ, so it is necessary to select most rational γ and σ values in order to obtain satisfactory brain CT image classification accuracy.

2.2. Improved Harmony Search (IHS) Algorithm

HS algorithm is based on the simulation of the tone tuning of the band and always aims at realizing perfect harmony. Such thought for solving decision optimization problem has been successfully applied to the combinational optimization problem [12]. In HS algorithm, the "tone tunings" of the candidate solutions are independent of each other, without information sharing mechanism, thus to be easily caught in local minimum. In order to conquer such defect, the optimal position updating strategy of PSO algorithm is introduced therein to "tune the tones" on the basis of the "best harmony" in the harmony memory and reserve the tone tuning parameter and meanwhile prevent the "tone tuning" process from being weakened. The working process of HIS algorithm is as follows:

Step 1: initialize such parameters as harmony memory considering rate (HMCR), harmony memory size (HMS), band width (bw), pitch adjusting rate (PAR) and number of iteration (NI).

Step 2: assume the problem solution as $X^k = \{x_1^k, x_2^k, \cdots, x_n^k\}$, then initialize the candidate solutions as the random values within the value range of each dimension of the vector, namely $x_i^k = Rnd(L(x_i^k), U(x_i^k))$, wherein $X^k \in R^n$, $k \in [1, HMs]$, $i \in [1, n]$, and then calculate the fitness function value of each initial solution.

Step 3: randomly generate two numbers r1 and r2 and randomly select one solution Xj from the harmony memory, and then generate a new solution according to the following rule:

$$\begin{cases} x_i' = x_i' & , r_1 < HMCR, r_2 \geq PAR \\ x_i' = Rnd(x_i^{gBest} - bw, x_i^{gBest} + bw), r_1 < HMCR, r_2 \geq PAR \\ x_i' = Rnd(L(x_i'), U(x_i')), r_1 \geq HMCR \end{cases} \tag{7}$$

In the formula, x_i^{gBest} is the optimal candidate solution corresponding to the i^{th}-dimension solution vector in the harmony memory.

The introduction of the optimal position updating strategy of PSO algorithm is favorable for not only considering the optimal candidate solution value in the harmony memory, but also reserving *bw* parameter, thus to realize the information sharing between the optimal candidate solution and the new solution.

Step 4: if the fitness value fit(X') of the new solution is superior to the candidate solution value in the harmony memory, then use X' to replace the solution with worst fitness in the harmony memory.

Step 5: check whether the termination condition can be met; if not, return to Step 3 for continuous iteration.

3. IHS-LSSVM Based Brain CT Image Classification

3.1. LSSVM Parameter Range Pre-Estimation

Before optimizing LSSVM parameter, it is necessary to pre-estimate the parameter range. Since the kernel function can be regarded as the coverage of the sample on the neighboring sample, thus the kernel parameter σ can be related to the sample distance. For all training samples, σ is limited in the following range:

$$k_1 \, d_{\min} = \sigma_l < \sigma < \sigma_u = k_2 \, d_{\max} \tag{8}$$

In the formula, d_{min} and d_{max} respectively denote the average minimum distance and the average maximum distance of the training set.

(1) Lower bound σ_l: if the radius of RBF is less than 0.003 (small probability event), then the present sample of LSSVM only slightly influences the neighboring sample and the fitting phenomenon can easily appear, so it is necessary to set $k(x_i,x_j)$=0.003 to obtain σ_l=0.2935$d_{\min}$.

(2) Upper bound σ_u: SVM more significantly influences the near sample rather than the faraway sample, so the larger the σ value, the wider the corresponding coverage range. Specifically, σ_u=12.29$d_{\max}$.

According to the above analysis, it is necessary to approximately set k_1=0.3 and k_2=13 and set σ parameter range as [0.001, 1000].

γ parameter range cannot be easily determined, so it is set as [1, 1000] according to relevant experience.

3.2. Brain CT Image Classification with IHS Optimized LSSVM Parameter

(1) Collect brain CT image data and carry out denoising and enhancing pretreatment to improve image quality.

(2) Extract image features: adopt the textural features of the gray-level co-occurrence matrix as the classification features, namely: pixel grey level and angular second-order distance, deficit, entropy and relevant textual features; then, determine training sample set and prediction sample set.

(3) Different dimensions of the feature data can cause large data range change. In order to prevent the features with large value from weakening the attribute with small value, it is necessary to normalize the features to narrow down the range as [0, 1], namely:

$$x_{ik}' = \frac{x_{ik} - \min(x_i)}{\max(x_i) - \min(x_i)} \tag{9}$$

In the formula, x_{ij} denotes the j^{th} value of the i^{th} feature, $\min(x_i)$ and $\max(x_i)$ respectively denote the minimum value and the maximum value of the i^{th} feature.

(4) Set γ and σ ranges and relevant parameters of HS algorithm.

(5) Initialize harmony memory to have m initial solutions and make each X correspond to one group of parameter (γ, σ), and then calculate the fitness value (brain CT image classification accuracy) of each individual in the harmony memory.

(6) Generate new individual X' according to formula (7) and calculate the fitness value of new individual; if the fitness value of this individual is su-

perior to the maximum fitness value in the harmony memory, then use X' to replace the individual corresponding to the maximum fitness value in harmony memory (HM).

(7) Set the number of iterations as k=k+1, if k is more than the maximum number of iterations NI, then take (γ, σ) corresponding to the optimal individual as the optimal parameter of LSSVM; or else, return to Step (6) for continuous iteration.

(8) Retrain LSSVM classifier according to optimal parameter combination (γ, σ) and establish optimal brain CT image classifier.

(9) Adopt the optimal brain CT image classifier established thereby to classify the test sample set.

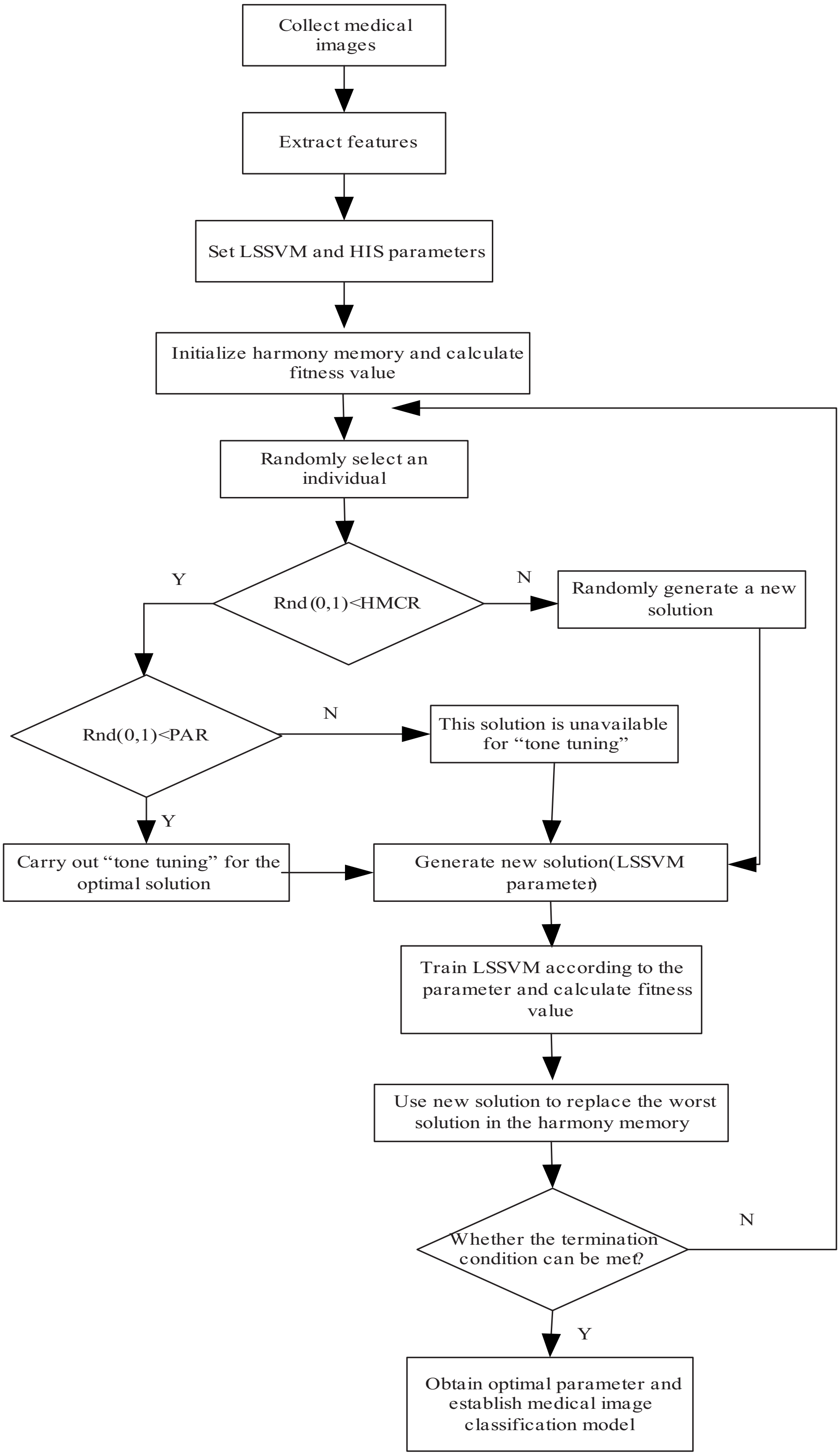
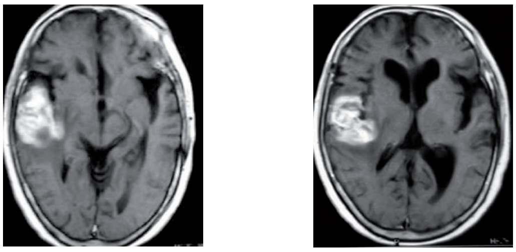


Figure 1. Brain CT Image Modeling and Classification Flow

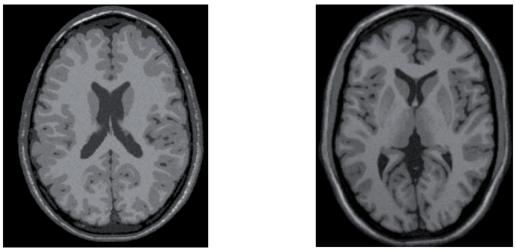
4. Simulation Experiment

4.1. Data source

Matlab 2009a is adopted to realize the algorithm in the platform (CPU: Intel Intel(R) Dual 2.3GHZ, RAM 3GB, Windows XP). Therein, the data are obtained from the online image library of McConnell Brain Image Center of McGill University, and include normal brain CT images and abnormal brain CT images, namely 500 training samples and 100 test samples. Additionally, the normal brain CT image and the abnormal CT brain image are respectively as shown in Fig. 2.



(a) Abnormal CT Image



(b) Normal CT Image

Figure 2. Brain CT Image

4.2. Comparison Method and Evaluation Index

In order to make IHS-LSSVM classification results comparable, GA optimized LSSVM (GA-LSSVM) and PSO optimized LSSVM are taken as the comparison models. Therein, the performance evaluation indexes of the model are sensitivity and specificity which are specifically defined are as follows:

$$sensitivity = \frac{t\_pos}{pos} \times 100\% \tag{11}$$

$$specificity = \frac{t\_neg}{neg} \times 100\% \tag{12}$$

Therein, t_pos T denotes the number of the normal brain CT images correctly identified; pos denotes the number of the normal brain CT images; t_neg denotes the number of the abnormal brain CT images correctly identified; neg denotes the number of the abnormal brain CT images.

4.3. Result and Analysis

Firstly, the features of normal and abnormal brain CT images are respectively extracted and normalized; then, these features are taken as the input vectors of LSSVM and the image categories are taken as the output vectors; then, the training samples are input into LSSVM for learning, and GA, PSO and IHS algorithms are respectively adopted to optimize LSSVM parameter (γ, σ); finally, the optimal parameter as shown in Table 1 are obtained.

Table 1. Optimal LSSVM Parameters of the Algorithms

Parameter Optimization Algorithm	γ	σ
GA	28.311	2.292
PSO	40.405	2.136
IHS	51.026	2.150

The optimal parameters as shown in Table 1 are adopted to respectively establish GA-LSSVM based brain CT image classifier, PSO-LSSVM based brain CT image classifier and IHS-LSSVM based brain CT image classifier, and then the test sample set is classified to obtain the result as shown in Table 2. According to Table 2, compared with GA-LSSVM and PSO-LSSVM, IHS-LSSVM has obtained optimal classification result, with high classification accuracy both for normal and abnormal brain CT images. Meanwhile, the specificity of IHS-LSSVM more approaches to 100%, thus indicating that there is only a small possibility for the error classification of abnormal brain CT images and this is expected by the medical experts. Moreover, the comparison result shows that HS can obtain better LSSVM parameter, thus to be favorable for improving brain CT image classification accuracy.

Table 2. Classification Algorithm Comparison

Algorithm	Sensitivity (%)	Specificity (%)
GA-LSSVM	90.04	90.28
PSO-LSSVM	91.32	91.80
IHS-LSSVM	92.18	92.09

In order to verify the validity of the improvement on standard HS algorithm, the standard HS algorithm is adopted for the simulation experiment, and the results for 5 times of this simulation experiment are as shown in Table 3. According to Table 3, the classification performance of IHS-LSSVM is superior to that of HS-LSSVM and the training time is obviously reduced to significantly accelerate the brain CT image classification speed. In fact, IHS-LSSVM can find better LSSVM parameter to reduce the quantity of support vector points and the sample storage volume as well as accelerate convergence rate, thus to be more consistent with the real-time and online requirements for modern brain CT image classification.

Table 3. Comparison of the Brain CT Image Classification Performances of HS-LSSVM and HIS-LSSVM.

Test No.	HS-LSSVM		
	Sensitivity	Specificity	Training Time
1	91.35	91.07	2.66
2	91.71	91.47	2.52
3	92.82	91.65	2.56
4	92.25	91.95	2.47
5	91.29	91.79	2.32
Mean	91.88	91.59	2.51

Test No.	IHS-LSSVM		
	Sensitivity	Specificity	Train Time
1	92.18	92.09	2.18
2	92.05	92.22	1.95
3	92.51	92.41	2.02
4	92.44	92.30	1.90
5	91.98	92.24	1.83
Mean	92.23	92.25	1.98

Conclusions

In order to solve LSSVM parameter optimization problem during brain CT image classification and modeling process, a brain CT image classification model with improved harmony search algorithm optimized LSSVM (IHS-LSSVM) is proposed in this article. The simulation result shows that IHS algorithm can not only better solve LSSVM parameter optimization problem, but also improve the brain CT image classification accuracy and efficiency. Since the automatic classification of brain CT images is related to feature selection, the combinational optimization of feature selection and LSSVM parameters should be further researched.

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Network Hotspot Prediction Model Based on GA-WRVM

Zhang Yongjun[1,2], Ma Jialin[1,2], Liu Jinling[1],Xiao Shaozhang[1]

1. Faculty of Computer Engineering , Huaiyin Institute of Technology, Huaian, Jiangsu, 223003, China
2.College of Computer and Information, HOHAI University, NanJing, Jiangshu, 211100, China

Abstract
In order to improve the prediction accuracy of hotspots events, this paper has proposed network hot events prediction model based on GA-WRVM. Firstly, a weighted coefficient is added to the noise variance of each sample data to get a WRVM, and then the combined kernel function is used to replace single kernel of RVM and kernel