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LS_SVM Parameters Selection Based on Hybrid Complex Particle Swarm Optimization

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Abstract

It is important to select parameters in the research area of support vector machine. For this reason, parameters selection for least squares support vector machine (LS_SVM) by hybrid complex particle swarm optimization is proposed in this paper. The proposed method reduces the disadvantage of traditional PSO in local optimum. Simulation of function estimation problem demonstrates t that LS_SVM based hybrid complex particle swarm optimization has better global optimization ability than LS_SVM based traditional PSO.

Keywords: Least squares support vector machine; Particle swarm optimization; Complex method; Fault classifications

1.Introduction

Through rigorous mathematical theory, Vapnik [1] put forward the support vector machine (SVM) in 1995. From the rigorous mathematical theory, it demonstrated and implemented that the small sample can maximize the accuracy of pattern classification and data fitting methods. SVM is successfully used in speech recognition, text recognition, fault identification and other research field [2].

In 1999, least squares support vector machine (LS-SVM) was developed for classification and function estimation by Suykens [3]. LS_SVM works with equality instead of inequality constraints and a sum square error cost function as it is used in training of classical neural networks. Consequently, this method is solved by a set of linear equations, instead of by quadratic programming. This reformulation greatly simplifies the problem. In spite of all these attractive features, one of LS-SVM drawbacks is that people can not choose SVM parameters easily. These parameters in LS-SVM need to find their optimal values in order to minimize the expectation of test error. The direct method for people is to do a lot of experiments to select parameters. But this method wastes much time, but without any optimal value. Paper [4] uses cross validation to determine parameters. But it wastes a lot of computer memory and CPU time. Recent years, some scientists used particle swarm optimization (PSO) to select the optimal parameters [5]. The PSO algorithm has a special ability to simplify the implementation and to quickly converge to a good

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solution. But, PSO is easily to get a local optimal value [6].

In this paper, particle swarm optimization algorithm based on the complex algorithm [7] is proposed. The use of the superior local optimization ability of complex algorithm, it greatly reduces the particle swarm algorithm into local optimal possibility. Experiments demonstrate the effect of the proposed method in this paper.

2.LS_SVM Parameters Selection Based on Hybrid

Complex Particle Swarm Optimization

2.1.The introduction of the parameters selection

In the LS-SVM model, the appropriate parameters are selected by the PSO algorithm. As what has been mentioned above, C and σ^2 become the swarms, then the dimension of the swarms is two. These swarms can be expressed as following:

$c_i = [c_{i1} \quad c_{i2} \cdots \quad c_{id}], \sigma_i^2 = [\sigma_{i1}^2 \quad \sigma_{i2}^2 \cdots \quad \sigma_{id}^2]$.In function regression, the fitness function is the sum square error between the real output data of the system and the output data of the LS-SVM model in the same input. But in classifiers, the fitness function is the precision of classify. The process obtaining the parameters by the PSO from LS-SVM model is as following:

Step 1: Take the parameters (c, σ^2) as swarms and initialize a population of particles with random positions and velocities;

Step 2: By using the training samples for objective system and parameters (c, σ^2) obtained by the particles of PSO, the regularized risk function $\min J(w,e) = \frac{1}{2} w^T w + \frac{1}{2} c \sum_{i=1}^{N} e_i^2$ can be optimized and the Lagrange multiplier set α_i can be obtained. Then LS-SVM model can be deduced.

Step3: Evaluate the objective values of all particles as fitness function. In function regression problem, the fitness function is $f(c, \sigma^2) = \sum_{i=1}^{N} (y_{SVM} - y)^2$; in classification problem, the fitness function is:

$$f(c,\sigma^2) = \frac{\sum_{i=1}^{N} Inv(abs(sign[\sum_{i=1}^{N} a_i y_i \varphi(x_i)\varphi(x) + b] - y))}{N} \tag{1}$$

2.2.Complex algorithm

In complex algorithm, the worst vertex can be eliminated through the compare of every fitness value. For this reason, the new polyhedron moves closer to the feasible region. Each vertex in the iterative process is constantly moving to the point of optimal fitness value until this algorithm meets the convergence criteria. As what has been mentioned above, c and σ^2 become the vertexes, then the dimension of the vertexes is two. These vertexes can be expressed as following: $(c_i, \sigma_i^2), i = 1 \cdots m$. In function regression, the fitness function is the sum square error between the real output data of the system and the output data of the support vector interval regression model in the same input.

2.3.LS_SVM Parameters Selection Based on Hybrid Complex Particle Swarm Optimization

Step 1: Take the parameters (c, σ^2) as swarms and initialize a population of particles with random positions and velocities;

Step 2: By using the training samples for objective system and parameters (c, σ^2) obtained by the particles of PSO, the regularized risk function $\min J(w,e) = \frac{1}{2} w^T w + \frac{1}{2} c \sum_{i=1}^{N} e_i^2$ can be optimized and the Lagrange multiplier set α_i can be obtained. Then LS-SVM model can be deduced.

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Step 4: Set pbest of each particle equal to each particle current position. Objective value of pbest equal to current position's objective value. Moreover, set gbest and its objective value equal to the position and objective value of the best initial particle.

Step 5: Update the velocity and position of every particle according to equations (12) and (13).

Step 6: Evaluate the objective values of all particles.

Step 7: For each particle, compare its current objective value with the objective value of its pbest. If the current value is better, then update pbest and its objective value with the current position and objective value.

Step 8: Determine the best particle of the current population with the best objective value. If the objective value is better than the objective value of gbest, then update gbest and its objective value with the position and objective value of the current best particle.

Step 9: Calculate the fitness of each particle on behalf of the global optimum of the similarity with the target, if the value is less than the reference value C_sim, is that the risk of being trapped in the best, the next step of the finite complex-shaped mutation, or into steps.

Step 10: Determine whether the conditions for the establishment, not to set up a limited time, said variation has been completed and transferred directly to step 11, otherwise 20% of roulette mode selection range of complex-shaped particles as the initial vertex algorithm to a certain degree of accuracy for complex-shaped search, the search process, including reflection, expansion and compression process, the use of complex-shaped algorithm can get a local optimal solution, and will eventually replace the original complex form of the vertex selected particles. Home.

Step 11: determine whether the termination conditions are met, if not met, repeat from step 2 to run, or turn to the next step;

Step 12: Finally, obtain the LS-SVM model at the best optimal parameters and get the output data.

3.Experiment and illustration

To verify the effective of hybrid complex particle swarm optimization in the LS-SVM parameters automatically selection, two experiments are proposed and all of the experiments are carried out by Matlab7.0.1.

3.1.Function regression

Function regression problem is an important application for least squares support vector machine. This

paper takes the classic sinc function and additional noise term as a test function. In the interval [-10,10], 100 data is taken as training samples. 200 data are taken as test samples.
Functional form as follows:

$$y(x) = \sin(x)/x + \sigma N(0,0.1) \qquad x \in [-10,10] \tag{2}$$

PSO algorithm uses the fitness function which uses support vector machines fitted values ySVM and real values ytest error sum of squares $\sum_{i=1}^{200}(y_{SVM} - y_{test})^2$. by the proposed hybrid complex particle swarm optimization, the parameters optimized least squares support vector machine output and the fitting function (1) squared error between actual output are 0.1147. It shows the good fitting results. In order to comparison results, the paper also makes use of the traditional particle swarm algorithm for least squares support vector machines automatically selection the parameters of the work, the optimized parameters obtained, and, ultimately, the error sum of squares is 0.1192. Table I shows the parameters for the two methods. Figure 1 shows fitting results of least squares support vector machines based on hybrid particle swarm algorithm. Point represents the function (11) true curve. Solid line represents the use of hybrid particle swarm optimization for parameter selection least squares support vector machine fitting curve. Table 1 and Figure 1 show that the better effective of this proposed method.

Table 1: the parameters comparison between PSO and hybrid complex particle swarm parameters and fitting bias

method	γ	δ^2	Regression error
LS_SVM by PSO	43.19	0.625	0.1192
LS_SVM by PSO_HGA_EV	75.59	0.298	0.1147

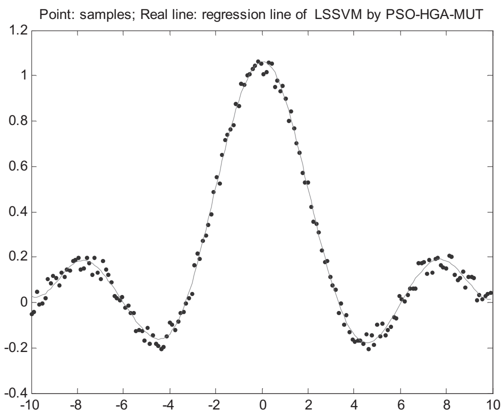

Figure 1: the fitting results for least squares support vector machine based on the hybrid complex PSO

4.Summary

In this paper, the hybrid complex PSO for the parameters selection is proposed. Experiments show that the hybrid complex particle swarm algorithm reduces the traditional PSO into a local optimum risk and improves the accuracy of parameters for least squares support vector

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References

[1] V. Vapnik, The Nature of Statistical Learning Theory, Springer, New York, 1995.

[2] Wan, Vincent; Campbell, William M., Support vector machines for speaker verification and identification, Neural Networks for Signal Processing - Proceedings of the IEEE Workshop 2, 2000:775-784.

[3] J.A.K. Suykens , J. Vandewalle, Least Squares Support Vector Machine Classifiers[J], Neural Processing Lettes, 1999, 9(3): pp293-300.

[4] Chapelle 0, Vapnik V, Bousquet O，et a1．Choosing Multiple Parameters for Support Vector Machines[J], Machine Learning，2002，46 (1): pp131—1 59.

[5] SHAO Xin-guang YANG Hui-zhong CHEN Gang. Parameters selection and application of support vector machines based on particle swarm optimization algorithm[J], Contril theory & application 2006 23(5).

[6] Kennedy, J, Eberhart, Particle Swarm Optimization, Proc. IEEE Int. Conf. on Neural Networks, Perth, 1995:, pp.1492-1948.

[7] Himmelblau D.M Applied nonlinear programming[M] New York: McGraw-Hill.1972