# An improved support vector machine based on particle swarm optimization in laser ultrasonic defect detection

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*Abstract:* Laser ultrasonic defect detection and classification has been widely used in engineering and material defect detection, **s**o detecting and classifying the defect targets accurately is significant. In order to obtain the higher classification accuracy, an improved support vector machine (SVM) based on particle swarm optimization algorithm is used as classifier in this paper. To search the optimal parameters of SVM, a new Tangent Decreasing Inertia Weight strategy particle swarm optimization (TPSO) algorithm is proposed to determine the optimal parameters for SVM. In addition, to further improve the classification accuracy, sparse representation is used to extract the target features from the real target echo waveform in experiment. Experimental results show that the proposed TPSO-SVM can achieve higher classification accuracy compared to the commonly PSO-SVM, classical SVM and BP neural network (BPNN) in the laser ultrasonic defect signals classification.

*Key-words:* Laser ultrasonic defect detection; Classification method; Support vector machine; Particle swarm optimization; Sparse representation.

## 1 Introduction

Nowadays, with the development of modern science and technology, ultrasonic nondestructive testing technology has become a multi subject cross engineering technology. So far, there have been some researches on the defect detection and defect classification based on machine learning [1-6]. Canonical support vector machine (SVM) and particle swarm optimization optimized support vector machine (PSO-SVM) are applied as classifiers in those studies.

Support vector machine proposed by Vapnik in 1995 [7], is a statistical classification method, which based on the structural risk minimization approach. It solves the classification problem by maximizing the margin of the separation beside the optimal hyper plane. The kernel function plays a very important role in the performance of SVM. The input data is mapped to a higher dimensional feature space by the kernel function, so that the classification problem can be linearly separable. There are many kinds of kernel functions, such as linear kernel, polynomial kernel, Gaussian kernel, and so on. The Gaussian kernel is frequently used in SVM, due to its excellent nonlinear classification ability. Support vector machines show many unique advantages in solving small samples, nonlinear and high dimensional pattern recognition, and to a certain extent, it overcomes the "dimension disaster" and "over learning" and other traditional difficulties. In addition, today, support vector machines have been widely concerned, and have made great progress, due to its solid theoretical foundation and a simple and clear mathematical model. At present, it has been successfully applied to solving pattern recognition, classification, approximation of functions, and time series prediction problems, such as speech recognition [8], text recognition [9], target detection and recognition [10, 11], fault diagnosis [12], financial time series forecast [13], and so on. However, in those applications, the performance of SVM depends upon the selection of SVM parameters. In other words, the parameters selection has great influence on the learning and generalization ability of SVM. Therefore, the selection of the optimal parameters is important to obtain an excellent performance of SVM. The parameters optimization of SVM has gained great attentions in the past several years. Such as, Shi and Zhou use grid search method and genetic algorithm to optimize SVM parameters, and then study the reliability of blasting vibration prediction of open pit mining using the optimized SVM model, and achieved good results [14]; Li, Xia, et al, with the combination of clustering method, ant colony algorithm and support vector machine (SVM) to construct an efficient and reliable classifier, and then use it to judge whether the network access is normal or not [15]; E. Avci choose the best subset of features in digital modulation classification with the support vector machine optimized by genetic algorithm [16]. But, grid algorithm method has disadvantages such as computationally intensive, time consuming and low learning accuracy; Ant colony algorithm method is initial pheromone scarcity, long-time searching and local best solution; Genetic algorithm is operation complex and different issues need to design different crossover or mutation. So we need to find a simpler and more efficient optimization algorithm to optimize the model parameters. Particle swarm optimization (PSO) is an intuitive and easy to implement algorithm from the swarm intelligence community, and it has been applied to select the proper parameters of SVM [17-19], but the method is easy to trap into local optimum and has a low convergence rate. Focusing on these shortages, the current focus of improvement is mainly focused on: the update formula of velocity and particle position, parameter improvement, hybrid algorithm and so on. Different inertia weight strategies imply different incremental changes in velocity per time step which means exploration of new search areas in pursuit of a better solution. In this paper, an improved inertia weight is proposed. We propose a Tangent Decreasing Inertia Weight PSO (TDIW-PSO) algorithm to get the optimal parameters of SVM.

On the other hand, feature extraction is a crucial step in laser ultrasonic defect classification. In this work, we use sparse representation (SR) theory to analyzing the components of received target echo signals [20-22], and describe the characteristics of the target with the sparse coefficients obtained. In this paper, the goal is to develop a method of TPSO-SVM combined with sparse representation-based feature extraction to effective detection of different defect categories, in which TPSO is used to optimize the parameters of the support vector machine.

The structure of the paper is organized as follows: Section 2 introduces the basic idea of SVM. In Section 3 the basic PSO algorithm and the improved TPSO algorithm based on a tangent decreasing inertia weight strategy are introduced. The optimization procedure to the SVM is presented in Section 4. The classification model for laser ultrasonic defect is presented and the experimental results are reported in Section 5. Finally, the conclusion is presented in Section 6.

## 2 The classification theory of SVM

The support vector machine (SVM) is a machine learning method based on statistical learning theory. This novel learning technique originated as the principle of structure risk minimization, which performs better than empirical risk minimization utilized by traditional neural networks. SVM has been application as a new technique for solving classification, approximation of functions, and time series prediction problems. The aim of SVM is to obtain an optimal hyper plane that can separate the two class samples as well as maximize the margin of the separation beside the optimal hyper plane. In order to describe the principle of SVM, we given a training set $X=\{x_1,x_2,\cdots x_n\}$ , $Y=\{y_1,y_2,\cdots y_n\}$ , where $x_i$ is the input of SVM, $y_i$ is the output of SVM ,then we denote the class $A$ with $x_i\in A$ , $y_i=1$ and class $B$ with $x_i\in B$ *i.e.* $y_i=\begin{cases}1, & x_i\in A\\ -1, & x_i\in B\end{cases}$

In order to get the optimal hyper plane, we can consider an equivalent representation
$$\begin{cases}\omega^T x_i+b\ge 1, & if \quad y_i=1\\ \omega^T x_i+b\le -1, & if \quad y_i=-1\end{cases}$$
Where $\omega$ is the weight vector and $b$ is the constant, the distance between two class is $\frac{2}{\|\omega\|}$, so maximize $\frac{2}{\|\omega\|}$ is equivalent to minimize Euclidean norm of the weight vector $\omega$, **i.e.**to minimize $\frac{1}{2}\|\omega\|^2=\frac{1}{2}\omega^T\omega$. In addition the decision function can be defines as
$$f(x)=\mathrm{sgn}(w^T x_i+b)\,, \tag{1}$$
This decision function is used to solve the linear classification problem. For the nonlinear classification problem, we can find a map that makes the samples $x_i$ from low dimensional space $R$ into a high dimensional feature space $F$ , by nonlinear mapping $x_i\to\phi(x_i)$ , the nonlinear classification problem in the low dimensional space can be solved as a linear classification problem in the high dimensional feature space. In this method, the decision function can be defines as
$$f(x)=\mathrm{sgn}(\omega^T\phi(x_i)+b)\,, \tag{2}$$
Based on the principle of structural risk minimization, the learning process of SVM can be transformed into a convex optimization problem.
$$\begin{aligned}&\min(\frac{1}{2}\|\omega\|^2+C\sum_{i=1}^{n}\xi_i)\\ &s.t.\ \ \omega^T\phi(x_i)+b\le 1-\xi_i\end{aligned}\,, \tag{3}$$
And this constrained optimization problem can be transformed into a dual problem of as follows
$$\begin{aligned}&\max Q(\alpha)=\sum_{i=1}^{n}\alpha_i-\frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}\alpha_i\alpha_j y_i y_j\phi^T(x_i)\phi(x_i)\\ &s.t.\ \sum_{i=1}^{n}\alpha_i y_i=0 \quad and \quad 0\le\alpha_i\le C(i=1,2,\cdots n)\end{aligned}\,, \tag{4}$$
Where $\xi_i$ is slack variables, $C$ is a Penalty parameter and usually it is positive parameter, and $\alpha_i$ is the

Lagrange multiplier.
Here, the decision function can be defines as:

$$f(x)=\mathrm{sgn}(\sum_{i=1}^{n}\alpha_i y_i \phi^T(x_i)\phi(x_i)+b), \quad (5)$$

By defining a $n\times n$ kernel matrix $K$ such that:

$$K(x_i,x_j)=\phi^T(x_i)\phi(x_j)=\phi(x_i)\cdot\phi(x_j), \quad (6)$$

Transform into the following form:

$$\max Q(\alpha)=\sum_{i=1}^{n}\alpha_i-\frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}\alpha_i\alpha_j y_i y_j K(x_i,x_j), \quad (7)$$

The decision function can be expressed as:

$$f(x)=\mathrm{sgn}(\sum_{i=1}^{n}\alpha_i y_i K(x_i,x_j)+\mathrm{b}). \quad (8)$$

And the inner product can be computed by a kernel function in the low dimensional space without knowing the nonlinear mapping explicitly. Any function that meets Mercer's condition (Vapnik 1995) can be used as the kernel function. There are several common types of kernel function:

Linear kernel: $K(x_i,x_j)=x_i^T x_j$;

Polynomial kernel: $K(x_i,x_j)=(x_i^T x_j+1)^d$, where $d$ is a positive integer;

Gaussian kernel: $K(x_i,x_j)=\exp(-\|x_i-x_j\|^2/2\sigma^2)$

where $2\sigma^2$ is the width of the Gaussian kernel.

Research indicates that the Gaussian kernel function shows good performance in nonlinear classification problems. Therefore, we selected it as the kernel function for SVM in this study. In addition, the parameters selection has great influence on the learning and generalization ability of SVM. For SVM with Gaussian kernel function, the parameters include kernel function parameter $\sigma$ and Penalty parameter $C$. The value of $\sigma$ is relevant to the range and width of the input data space, $C$ is the compromise between the structure risk and the samples, and its value is closely related to the tolerated error. As PSO algorithm not only has strong global search ability and but also helps to search for the optimum parameters quickly. Therefore, we use the proposed TDIW-PSO algorithm to optimize parameter $\sigma$ and $C$ in this study, which we call TPSO -SVM.

# 3 Particle swarm optimization algorithm

## 3.1 Canonical particle swarm optimization algorithm

Particle swarm optimization (PSO) developed by Kennedy and Eberhart in 1995 [23], is an evolutionary computation algorithm. In PSO algorithm, each potential solution to the optimization problem is treated as a bird, which is also called a particle. The set of particles, also known as a swarm, are flown through the D-dimensional search space of the optimization problem. Each particle alters its own velocity and position based on the experiences of the particle itself and those of other particles in the swarm. In the searching process, every particle is connected to and able to share information with every other particle in the swarm and the swarm communication topology is known as a global neighborhood described in [24]. This sharing information mechanism keeps the overall consistency to get the global solution for the overall swarm.

The swarm consists of $n$ particles; each particle has a velocity vector $v_i=(v_{i1},v_{i2},\cdots,v_{iD})$ and a position vector $x_i=(x_{i1},x_{i2},\cdots,x_{iD})$, where $i=1,2,\cdots,n$ ;each particle is represented as a potential solution to a problem in a D-dimensional search space, respectively $l_d$ and $u_d$ are the lower and upper bounds of the $d$th dimension of the search space, $x_{id}\in[l_d,u_d]$, $d=1,2,\cdots,D$. During each generation, the particles are accelerated toward the particles previous best position and the global best position. Where, the personal best position of the $i$th particle denotes as $p_i=(p_{i1},p_{i2},\cdots,p_{iD})$, the global best position of the swarm denotes as $p_g=(p_{g1},p_{g2},\cdots,p_{gD})$. The new velocity value is used to calculate the next position of the particle in the search space. This process will keep the iteration until setting the maximum number of iteration or an optimal fitness degree is obtained. The updating of velocity and particle position can be obtained by using the following formula:

$$v_{id}^{t+1}=\omega v_{id}^t+c_1\xi(p_{id}^t-x_{id}^t)+c_2\eta(p_{gd}^t-x_{id}^t), \quad (9)$$

$$x_{id}^{t+1}=x_{id}^t+v_{id}^{t+1}. \quad (10)$$

where $c_1$ and $c_2$ are Learning Factor (also named as the Acceleration Coefficient) and they're positive constants, $\xi$ and $\eta$ are random numbers ranging from 0 to 1, $t$ is the iteration counter, $\omega$ is the inertia weight on the interval keeping the memory of the old velocity vector of the same particle. When $\omega$ is a constant [23], it can lead to a static PSO, and when $\omega$ is varying iteratively, it leads to a dynamic PSO.

## 3.2 Proposed inertia weight variant

As we know, in the operation of the intelligent optimization method, the exploration ability and the exploitation ability of the balanced is very important. In PSO algorithm, the balance of these two kinds of ability is realized by the inertia weight. The larger inertia weight is that the particle has a greater speed in their original direction which can further in the original direction , therefore larger inertia weight is advantageous to find the global best solution as soon as possible in the early iterative steps, but may lead to miss the global best solution easily in later iterative steps. In contrast, the smaller the inertia weight makes the particles inherit a few of the original direction, so as to fly closer, with better exploitation capabilities, so smaller inertia weight means longer time to provide slower updating for fine tuning a local exploration. Appropriate inertia weight is helpful to find the best solution with the least number of iterative steps. Therefore, how to adjust the inertia weight in order to balance the global exploration and local exploitation better has become a problem. To solve this problem, we usually use the following approach: in the early iterative steps, larger inertia weight is needed for coarse global exploration, but in later iterations inertia weight should decrease for fine tuning the local exploration.

A larger inertia weight facilitates global exploration and a smaller inertia weight tends to facilitates local exploration to fine tune the current search area. In order to balance the global exploration and local exploration, we present a new Tangent Decreasing Inertia Weight strategy, hereinafter referred to as TDIW strategy. In this strategy, the inertia weight is with the increase of iterative step $t$ according to tangent decreasing. The proposed inertia weight $\omega$ is determined based on the following equation:

$$\omega(t) = \omega_{start} - (\omega_{start} - \omega_{end}) * \tan\left(\frac{\pi}{4} * \frac{t}{T}\right). \qquad (11)$$

## 4 Optimize the parameters of SVM by PSO

In this paper, the Gaussian kernel function is used to construct SVM classification model, then the width $\sigma$ of the Gaussian kernel and penalization parameter $C$ need to be determined. The proposed TDIW-PSO algorithm is applied to determine the parameters of SVM. The position vector $x$ of each particle is needed to be optimized, which represents the width $\sigma$ of the Gaussian kernel and penalization parameter $C$ .The $k$ -fold cross validation (where $k = 5$) method is used to evaluate fitness in this study, and average classification accuracy (CV) is adopted as the fitness function. The fitness function is denoted by formula:

$$CV = \frac{1}{k}\sum_{j=1}^{k} acc(\mathrm{j}), \qquad (12)$$

$$acc(j) = \frac{n_{jt}}{n_j}(j = 1, 2, \cdots, k). \qquad (13)$$

In $k$ -fold cross validation, the training set is roughly divided into $k$ groups, $train(1)$ , $train(2)$ , $\cdots train(k)$ , $acc(j)$ is the accuracy when $train(j)$ as testing set and other groups as training set. $n_j$ is the sample number of $train(j)$ , $n_{jt}$ is the correct classification number of $train(j)$ .

The iteration process of the improved TPSO-SVM learning algorithm can be described clearly as follows.

*Step1*:Read sample data, and we use sparse representation theory (SR) for feature extraction, then the feature data is divided into two subsets: one subset is training set; the other subset is testing set.

*Step2*: Initialize PSO: Initialize the relative parameters, including the size of swarm, the boundary of velocity $v_{\max}, v_{\min}$ and position $x_{\max}, x_{\min}$ , the acceleration factors $c_1$ and $c_2$ , and max number of iterative $T_{\max}$ . $r_1$ and $r_2$ are the two random numbers with the range from 0 to 1. Initialize $t = 1$; for each particle, select two $D$ -dimensional vectors randomly to initialize the velocity and position of this particle.

*Step3*: Calculate the fitness value of each particle according to formula (12)(13).Set the current position of each particle as the personal best fitness $p_i$ . Then find the maximum fitness value as the global best fitness $p_g$ of the whole swarm.

*Step4*: Update the inertia weight $\omega$ according to formula (11). Modify the particle velocity $v_i$ and position $x_i$ according to formula (9) (10).

*Step5*: Recalculate the fitness values of each particle and modify $p_i$ and $p_g$ .For each particle, if the current fitness value is better than the previous local best, then set the current fitness value to be the local best; or keep the previous local best. For the global swarm, if the best value of all current local best is better than the previous global best, then update the value of global best; or keep the previous global best.

*Step6*: Check stop condition. If $t > T_{\max}$ , then stop the iteration and $p_g$ is the optimal solution which represents the best parameters for SVM, and go to. *Step7*; Otherwise, let $t = t + 1$ go to *Step4*.

*Step8*: Use the optimal SVM to perform classification problem.

Apply the above1- 7 steps until the obtained optimal solution, get the optimized parameters, and then perform classification problem. The flow char is as in Figure 1.

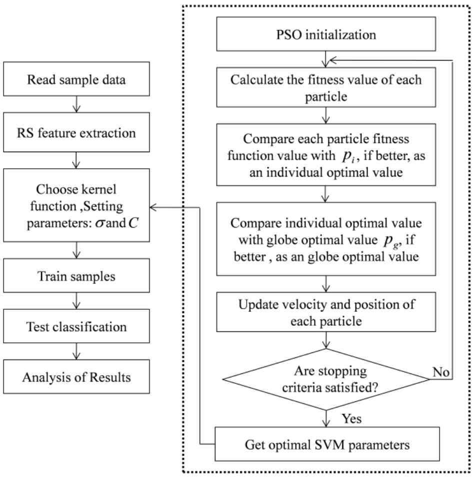
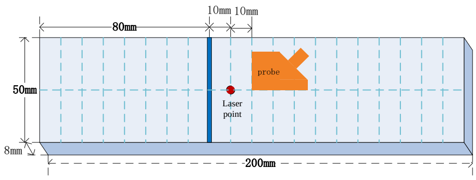



Fig.1. Classification model based on PSO-SVM

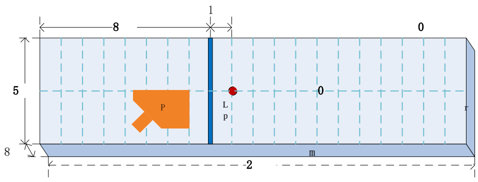
# 5 Example of application

## 5.1 Laser ultrasonic surface acoustic wave defect detection experiment

Laser ultrasonic defect detection technology is based on the theory of sound and light effect. Laser irradiation on the surface of the sample, the ultrasonic signal containing the measured surface information is generated by the thermal elastic effect, and then the defect information is extracted and detected by detecting the ultrasonic signal modulated by the defect.




(a)Schematic diagram of reflected wave measurement



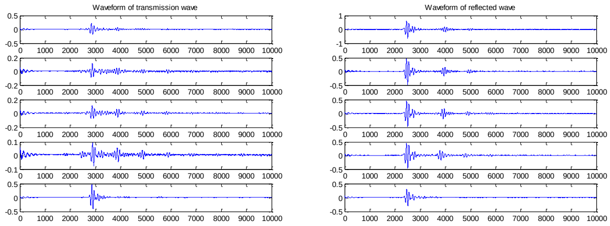
(b) Schematic diagram of transmission wave measurement

Fig.2. Experimental schematic diagram

In the experiment, as shown in Figure 2, test sample is 200*50*8mm aluminum plate, we use 2M ultrasonic probe in the detection distance of laser point 10mm get reflection wave, detection distance of laser point 20mm get transmitted wave, sampling frequency is 200MHz, sampling points is 10000. Five groups of experiments were carried out, each of which was repeated five times. The defect sizes were 0.1*0.3mm, 0.1*0.5mm, 0.1*0.7mm, 0.1*0.9mm and nondestructive. This experiment was done two times, and two groups of transmission wave (tdata1 and data2) and two groups of reflected waves (fdata1 and fdata2) were obtained. The obtained waveforms were as shown in Figure3.

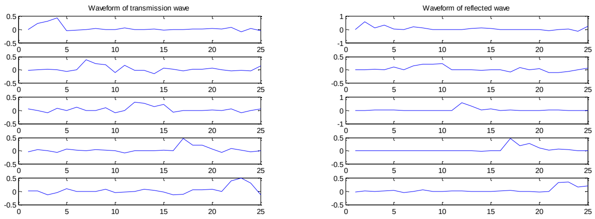
## 5.2 Feature extraction

In the part of the feature extraction, we use the method of sparse representation to extract features which the defect signals obtained from the above experiments. The defect signal waveform after sparse representation was as shown in Figure 4.




(a)Waveform of transmission wave
(b) Waveform of reflection wave

Fig.3. The defect signal waveform




(a)Waveform of transmission wave
(b) Waveform of reflection wave

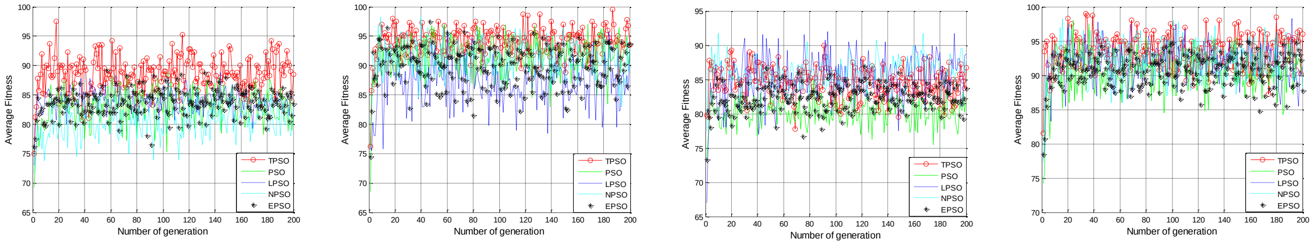
Fig.4. The defect signal waveform after sparse representation

## 5.3 Performance analysis for the proposed model

In this section, we evaluate the performance of the previously proposed method for laser ultrasonic surface acoustic wave defect signal classification. The features of the received signals are extracted based on sparse representation. Then, the sparse representation based features are used as the input of the classifiers. Finally, the proposed TPSO-SVM classifier is used to classify and forecast the target types. We obtained five kinds of defect signals by experiment, with 5 in each group. Therefore, a dataset including 25 samples for all defect types is established. All samples in the dataset are divided into two sets, in which the testing sets including 5 samples (Randomly select 1 sample for each defect types) are used to test the accuracy of the classification for each model, and the train sets including 20 samples are used to train the classification model. To maintain a more realistic investigation of this classification technique, the training and testing sets do not include any overlap in data.

In the context of optimization of the parameters of SVM, in this experiment, we first provide the performance comparison between the TPSO and the classical PSO as well as other improvements PSO (LPSO, NPSO, and EPSO are in the literature [25-27]). The population size N for all is 20, and the maximum evolution generation is set to 200. Figure 5 shows the average fitness curve of TPSO and other PSO for finding the optimal parameters of SVM. From the fitness performances that are shown in Figure 5, it is clearly seen that The average fitness curve of TPSO is better than that of other PSO， It indicates that TPSO is superior to other PSO in SVM parameters optimization.

In the optimized SVM, penalty parameter $C$ and the width of RBF kernel function $\sigma$ are optimized by the proposed TPSO and classical PSO and other improvements PSO, the adjusted parameters with maximal classification accuracy rate are selected as the most appropriate parameters. Then, the optimal parameters are utilized to train SVM model. In the canonical SVM model, the parameter $C$ and $\sigma$ are randomly selected to construct the classification model. Then, all the samples gained from experimental measurements are adopted to verify the superior classification performance of the proposed method compared with that of PSO-optimized support vector machine model (PSO-SVM), canonical SVM model, the back propagation neural networks (BPNN) model. Each experiment is carried out 1000 times. The experimental results are showed in Tables 1 and 2




(a) tdata1 (b) tdata2 (c) fdata1 (d) fdata2

Fig.5. Fitness performance for the proposed TPSO and others PSO

Table1: Classification results comparison of four sets data

| data | Average classification accuracy rate (%) | | | | | | |
|---|---|---|---|---|---|---|---|
| | TPSO-SVM | PSO-SVM | LPSO-SVM | NPSO-SVM | EPSO-SVM | SVM | BPNN |
| tdata1 | **99.06** | 98.84 | 98.90 | 99.04 | 99.14 | 75.3 | 76.7 |
| tdata2 | **100** | 100 | 99.98 | 99.96 | 99.98 | 73.56 | 82.40 |
| fdata1 | **100** | 100 | 100 | 99.98 | 100 | 61.86 | 28.98 |
| fdata2 | **94.54** | 94.58 | 94.86 | 94.72 | 94.44 | 79.76 | 69.84 |

Table2: Classification average computing time comparison of four sets data

| data | Average computing time(s) | | | | | | |
|---|---|---|---|---|---|---|---|
| | TPSO-SVM | PSO-SVM | LPSO-SVM | NPSO-SVM | EPSO-SVM | SVM | BPNN |
| tdata1 | **3.0966** | 2.9791 | 3.1337 | 3.1075 | 3.1220 | 0.0028 | 0.1941 |
| tdata2 | **3.0081** | 3.0028 | 3.1380 | 3.1274 | 3.1398 | 0.0023 | 0.1926 |
| fdata1 | **3.0142** | 3.0207 | 3.1410 | 3.1228 | 3.1361 | 0.0023 | 0.1905 |
| fdata2 | **2.9204** | 3.0375 | 3.0276 | 3.0375 | 3.0066 | 0.0027 | 0.1931 |

From Tables 1 and 2, we can see that, the PSO-optimized support vector machine model has higher average classification accuracy rate than canonical SVM and BPNN classification algorithmic to laser ultrasonic surface acoustic wave defect signal classification. The average classification accuracy rate of the improvement SVM by PSO is more than 98.9%. Among the several PSO-SVM models mentioned in this paper, we proposed that TPSO-SVM model not only has higher classification accuracy, but also the computational complexity is not increased .Therefore, the proposed method has more excellent classification performance than these traditional classification algorithmic to laser ultrasonic surface acoustic wave defect signal classification.

## 6 Conclusion

In this paper, an improved support vector machine (SVM) based on particle swarm optimization algorithm is used as classifier for laser ultrasonic surface acoustic wave defect signal classification. And the classification performance of this model is demonstrated on four group defect signals.

In the presented method, a new Tangent Decreasing Inertia Weight strategy particle swarm optimization (TPSO) algorithm is proposed to determine the optimal parameters of SVM, and sparse representation is used to extract the target features from the real target echo waveform in experiment. The experimental data sets are used to evaluate its feasibility and performance in the classification of defect. Experimental results show that the proposed TPSO-SVM has more excellent classification compared to the commonly PSO-SVM, classical SVM and BP neural network (BPNN) in the laser ultrasonic defect signals classification. In future research, the proposed method will be made toward a higher efficient model beyond current level, and more attention should paid to investigate the classification performance of models on large size of training sets once enough samples are obtained.

## Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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