A PSO-SVM Method for Parameters and Sensor Array Optimization in Wound Infection Detection based on Electronic Nose

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Abstract—**In this paper a new method based on the support vector machine (SVM) combined with particle swarm optimization (PSO) is proposed to analyze signals of wound infection detection based on electronic nose (enose). Owing to the strong impact of sensor array optimization and SVM parameters selection on the classification accuracy of SVM, PSO is used to realize a synchronization optimization of sensor array and SVM model parameters. The results show that PSO-SVM method combined with sensor array optimization greatly improves the classification accuracy of mice wound infection compared with radical basis function (RBF) network and genetic algorithms (GA) with/without sensor array optimization. Meanwhile, the proposed sensor array optimization method which weights sensor signals by importance factors also obtain better classification accuracy than that of weighting sensor signals by 0 and 1.**

Index Terms—**Electronic nose, Wound infection, Support vector machine, Particle swarm optimization, Sensor array optimization, Parameters optimization**

I. INTRODUCTION

Wounds, which take a heave role of human lives, are a big public hazard in the world. Stretcher cases mainly die in two severe complications, infection and MOF (Multiple Organ Failure). Rapid and timely monitoring of traumatic inflammation, especially identification of type of wound infection and infection levels of bacteria, is conducive to guiding the doctor's diagnosis and treatment.

Traditional method of diagnosing wound infection usually requires a doctor to observe the wound characteristics, and the wound secretion specimen need to smear, gram stain, microscope detect, isolate, culture and distinguish. It is also necessary to take the patient's serum for pathogen antigen detection. The method not only requires specialized equipments, professional technical operation and a long time for detection, but also depends on the doctor's clinical experience. It can not meet the clinical need of rapid and accurate diagnosis and may delay treatment. In fact, the special odor of infected wounds has emerged before the wounds have obvious secretions. Different bacteria, with different bacterial enzymes, have different capacity of decomposition, producing different metabolites. At different growth stages for the same bacteria, the concentrations of its volatile metabolites are different. We can discriminate the types and growth phase of bacteria by detecting the volatile compounds of bacteria broth according to the difference of the compositions and concentrations of metabolites of the bacteria growth phase in wound infection [1].

An enose is a device, which is composed of an array of gas sensors as well as a corresponding pattern recognition algorithm; it is able to imitate the olfaction system of humans and mammals, and is used for the recognition of gas and odor [2]. In recent years, with the development of artificial olfactory simulation technology, there are many works on wound infection detection and identification of bacteria using gas sensor array according to the wound volatile organic compounds (VOCs). Previous works have demonstrated that it is feasible to use enose to detect bacteria including investigation of bacterial volatile organic compounds (VOCs) from cultures and also from swabs taken from wound infected patients [3-8]. So the use of enose technology to achieve a faster and easier detection of wound infection is feasible. Wound infection detection based on enose has its own potential advantages owing to no need of complicated sample processing, low cost, simple operation procedure and suitable for rapid non-invasive detection of wound infection.

Support vector machine (SVM) is a new machine learning method, which is proposed based on statistical learning theory (SLT). Owing to the strong generalization ability, not to converge to local minimum points, and the strong nonlinear processing capacity, etc., SVM becomes

doi:10.4304/jcp.7.11.2663-2670

one of the most active research fields in pattern recognition. Currently, SVM has been widely used in classification of enose signals, especially in some complex odor discrimination [9-11]. Previous works have demonstrated that the SVM has better results than other classification methods not only in qualitative and quantitative analysis of the enose signals but also in other applications. Other classifiers such as artificial neural network (ANN), *etc.* cannot achieve very good classification results in wound detection based on enose [12-14]. It is useful to explore SVM technology in the area of wound infection detection based on enose, with the hope of overcoming some of the shortcomings in ANN and obtaining better performance.

Like other classifiers, the performance of SVM depends on the model parameter setting. Some researchers adopt the genetic algorithm (GA) to optimize model parameter selection for the SVM and achieve a promising result [15-16]. Instead of using GA, this study tries a new technology particle swarm optimization (PSO) which is proposed by Kenndey and Eberhart in 1995 [17] and inspired by social behavior in nature. PSO is a population-based search algorithm which is initialized with a population of random solutions called particles. Each particle in the PSO flies through the search space at a velocity which is dynamically adjusted according to its own and its companion's historical behavior.

Meanwhile, in a specific application problem, not all of the sensors are equally important. Better performance may be achieved by weighting the sensors by their importance factors. Thus, in order to obtain efficient and robust information of sensor array response signals and improve the identification ability of the system, we must eliminate noisy, irrelevant and redundant information, while maintain the discriminating power of the data by sensor array optimization.

In this study, a gas sensor array of fourteen metal oxide sensors and one electrochemical sensor is used to detect the wound odor from mice infected with three common species of pathogens and uninfected. Aim at the optimization problem of the SVM parameters and the sensor array, a SVM model parameters and sensor array synchronization optimization method based on PSO is proposed to analyze the enose signals of detection on wound odor of mice. The performance of this method is remarkable in improving recognition efficiency on discrimination of the infection type of mice.

II. MATERIALS AND EXPERIMENTS

A. *Material and Gas Sensor Array*

Twenty SD (Sprague-Dawley) male rats, 6-8 weeks old and 225-250g weight, were provided by the Experimental Animal Center of Daping Hospital, Third Military Medical University. All rats were randomly divided into four groups (five in each), including one control group and three infection groups by Pseudomonas aeruginosa, Escherichia coli, and Staphylococcus aureus respectively. After the rats were anaesthetised, a small incision (about 1cm long) was made in the hind leg in each rat. Then 100uL bacterial solution (10^9CFU/mL) (Pseudomonas aeruginosa, or Escherichia coli, or Staphylococcus aureus) was infected into the wound described above in respective infection group. Meanwhile, the same volume of physiological saline (0.9% NaCl solution) was added in control group. The rats were used for the further experiment after 72 hours. All experiments were approved by the Animal Care and Ethics Committee of Third Military Medical University.

The metabolites in the reproduction process of the three pathogens are shown in TABLE Ⅰ.

TABLE I
PATHOGENS IN WOUND INFECTION AND THEIR METABOLITES

Pathogens	Metabolites
Pseudomonas aeruginosa	Pyruvate,2-Nonanone, 2-Undecanone, Toluene, 2-Aminoacetophenone, 1-Undecene, Esters, Dimethyldisulfide, 2-Heptanone, Methyl ketones Dimethyltrisulfide, Sulphur compounds, Butanol, 2-Butanone, Isopentanol, Isobutanol, Isopentyl acetate
Escherichia coli	Ethanol ,Decanol, Dodecanol, Methanethiol 1-Propanol,Indole, Methyl ketones, Lactic acid, Succinic acid, Formic acid, Butanediol, Dimethyldisulfide ,Dimethyltrisulfide, Octanol, Acetaldehyde, Hydrogen sulfide, Formaldehyde, Acetic acid, Aminoacetophenone, Pentanols,
Staphylococcu saureus	Isobutanol, Isopentyl acetate, Ethanol, Ammonia, 1-Undecene, Methyl ketones, Acetic acid, 2,5-Dimethylpyrazine isoamylamine, Trimethylamine, 2-Methylamine, Formaldehyde Isopentanol,Aminoacetophenone,

According to the metabolites of pathogens in TABLEⅠ and the sensitive characteristics of gas sensors, we select fourteen metal oxide sensors and one electrochemical sensor to construct sensor array (shown in Fig. 1).The sensitive characteristics of the sensors we used are shown in TABLEⅡ. The gas sensor array is placed in a stainless steel test chamber with the volume of 0.24 liter, which is coated by Teflon. A 32-channel and 14-bit high precision data acquisition system (DAS) is employed for the fifteen gas sensors. Heater voltage of each sensor is 5 ± 0.05 V, and the power supply of amplifying is 5 ± 0.01 V. The response signals of the

Figure 1 The array of sensors.

TABLE Ⅱ
SENSITIVE CHARACTERISTICS OF GAS SENSORS

Sensors	Sensitive characteristics
TGS800	Methane, Carbon monoxide, Isobutane, Hydrogen, Ethanol
TGS813	Methane, Propane, Ethanol, Isobutane, Hydrogen, Carbon monoxide
TGS816	Combustible gases, Methane,Propane, Butane, Carbon monoxide, Hydrogen,Ethanol, Isobutane
TGS822	Organic solvent vapors, Methane, Carbon monoxide, Isobutane, n-Hexane, Benzene, Ethanol, Acetone
TGS825	Hydrogen sulfide
TGS826	Ammonia, Ethanol, Isobutane, Hydrogen
TGS2600	Gaseous air contaminants, Methane, Carbon monoxide, Isobutane, Ethanol, Hydrogen
TGS2602	VOCs, Odorous gases, Ammonia, Hydrogen sulfide, Toluene, Ethanol
TGS2620	Vapors of organic solvents, combustible gases, Methane, Carbon monoxide,Isobutane, Hydrogen, Ethanol
WSP2111	Benzene, Toluene, Ethanol, Hydrogen, Formaldehyde, Acetone
MQ135	Ammonia, Benzene series material, Acetone, Carbon monoxide, Ethanol, Smoke
MQ138	Alcohols, Aldehydes, Ketones, Aromatics
QS-01	VOCs, Hydrogen, Carbon monoxide, Metane, Ethanol, Isobutane, Ammonia
SP3S-AQ2	VOCs, Methane, Isobutane, Carbon monoxide, Hydrogen, Ethanol
AQ	Carbon monoxide, Methanol, Ethanol, Formaldehyde, Isopropanol, Acetaldehyde, Sulfur dioxide, Ethylene, Hydrogen, Hydrogen sulfide, Phenol, Dimethyl ether

sensor array obtained from the mice wound odor are first conditioned through a conditioning circuit and then sampled and saved in a computer via the DAS. The practical electronic nose system is shown in Fig. 2.

B. Measurement

Each mouse is placed in a jar with the volume of 2.8 liter with a rubber stopper. Two holes are made in the rubber stopper with two thin glass tubes inserted, respectively. One glass tube is fixed above the wound as close as possible. The output gases of the tube which contains VOCs of the mouse wound flow out of the bottle through the glass tube, and then flow into the test chamber through a Teflon tube. The clean air flows into the bottle through another glass tube. The experimental system schematic diagram is shown in Fig.3.

The dynamic headspace method is adopted during all the experiments, and the process is as follows. The first stage is the baseline stage, in which the sensors are exposed to clean air for three minutes. The second stage is the response stage, which the gas stream contained VOCs of the wound pass over the sensors for five minutes. The third stage is the recovery stage: the sensors are exposed to clean air again for fifteen minutes. At the end of each experiment, prior to the next experiment, a five minutes purging of the sensor chamber using clean air is performed. The gas flow is controlled by a gas flow rate control system, which contains a rotor flowmeter, a pressure retaining valve, a steady flow valve and a needle valve. The flow rate is kept at 50 ml/min. 20 experiments for each kind of mice in the same conditions are made, and so 80 samples are collected.

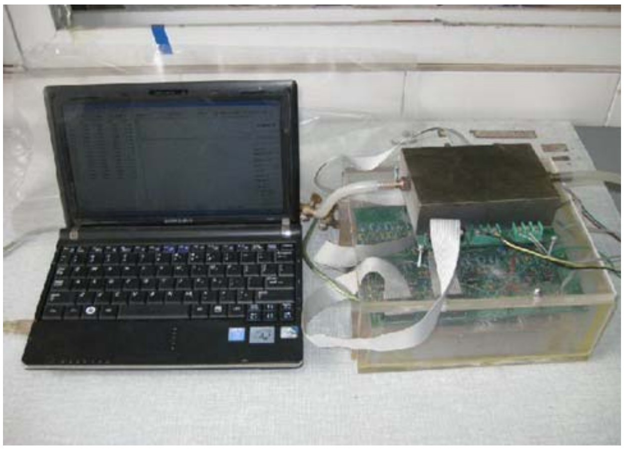

Figure 2 Practical electronic nose system

Ⅲ SUPPORT VECTOR MACHINES

Support vector machine (SVM), which we have applied as the classifier, is known as a very good tool for classification problems. It is a new machine learning method introduced by Vapnik based on the small sample statistical learning theory [18,19]. It adopts structural risk minimization (SRM) principle, and finds the best compromise between the learning ability and the complexity of the model to get the best generalization ability according to the limited sample information. Because of high generalization capability and good ability of dealing with high dimensionality space, SVM has already been widely used in pattern recognition, function regression and density estimation problems in recent years, with excellent performance.

The basic idea of the SVM is to map the n-dimensional input vectors into K-dimensional feature space usually of K> n using a nonlinear transformation $\varphi(\mathbf{x})$ and then construct the optimal separating hyperplane in the feature space.

In Fig.4, linearly separable two classes separating hyperplanes are shown. The rounds and the squares represent positive class and negative class of samples, respectively. H represents the optimal separating hyperplane. H1 and H2 represent the hyperplanes which the nearest samples of the two classes lie in respectively and parallel to the optimal separating hyperplane. The dotted lines are other separating hyperplanes which can classify the two classes correctly, but they are not the optimal separating hyperplane.

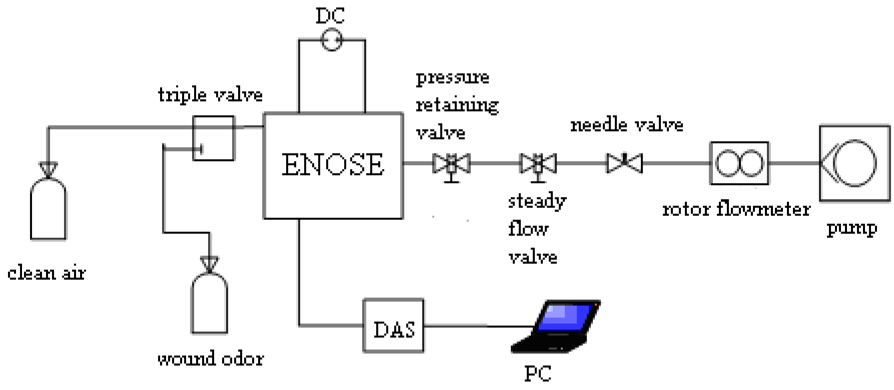

Figure 3 Schematic diagram of the experimental system

For linearly separable two classes data, the optimal separating hyperplane $y = \mathbf{w} \cdot \mathbf{x} + b$ can be found by minimizing the squared norm of the $\mathbf{w}$. The minimization can be formulated as a convex quadratic programming (QP) problem with linear constraints as following eqs. (1), in which the training data are represented as a matrix of inner products between feature vectors.

$$\begin{aligned} &\underset{\mathbf{w},b}{\text{minimize}} \quad \Phi(\mathbf{w}) = \|\mathbf{w}\|^2 = (\mathbf{w}\cdot\mathbf{w}) \\ &\text{s.t.} \qquad y_i((\mathbf{w}\cdot\mathbf{x}_i)+b) \ge 1, i=1,\dots,l \end{aligned} \tag{1}$$

According to duality theory, quadratic programming problem can be equivalent to be solved in its dual space. The original optimization problem is converted into the dual problem, namely:

$$\begin{aligned} &\underset{\alpha}{\text{maxmise}} \quad W(\alpha) = \sum_{i=1}^{l}\alpha_i - \frac{1}{2}\sum_{i,j=1}^{l}\alpha_i\alpha_j y_i y_j (\mathbf{x}_i\cdot\mathbf{x}_j) \\ &\text{s.t.} \qquad \sum_{i=1}^{l}\alpha_i y_i = 0, \quad \alpha_i \ge 0, \ i=1,\dots,l \end{aligned} \tag{2}$$

From Karush-Kuhn-Tucker condition, α_i are not equal to zero only for the points nearest to the hyperplane and α_i corresponding to other points are zero. These points with non-zero α_i are called support vectors because the hyperplane is decided only by them, while the other points with $\alpha_i = 0$ are irrelevant.

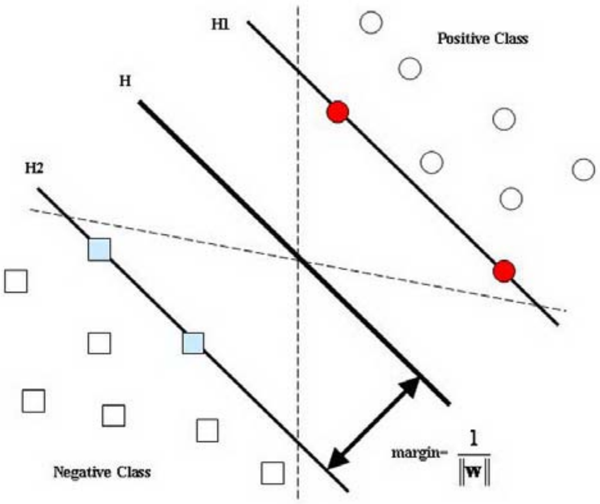

Figure 4 SVM separations of linearly separable two data classes.

The discriminant function of classifying new points $\mathbf{x}$ is given by eq. (3):

$$f(\mathbf{x}) = \mathbf{w}\cdot\mathbf{x} + b = \sum_{i=1}^{l} y_i\alpha_i \cdot (\mathbf{x}_i\cdot\mathbf{x}) + b \tag{3}$$

If the data vector $\mathbf{x}$ fulfils the condition $f(\mathbf{x}) > 0$, it will be classified into one class and when $f(\mathbf{x}) < 0$ it will be in the opposite class. Notice that the class, which the point belongs to, is obtained by calculating the weighted sum of inner products between the point and the support vectors.

For linearly non-separable case, it is typically addressed by the use of soft margin classifier. We can introduce slack variables $\{\xi\}_{i=1}^{l}$, $\xi_i > 0$ and the generalized optimal separating hyperplane for the non-separable case can be seen as the solution of the following problem:

$$\begin{aligned} &\underset{\mathbf{w},b,\xi}{\text{minimize}} \quad \Phi(\mathbf{w}) = \|\mathbf{w}\|^2 + C\sum_{i=1}^{l}\xi_i \\ &\text{s.t.} \qquad y_i((\mathbf{w}\cdot\mathbf{x}_i)+b) \ge 1-\xi_i, i=1,\dots,l \\ &\qquad\qquad \xi_i \ge 0, i=1,\dots,l \end{aligned} \tag{4}$$

In fact, minimizing the first term is equivalent to maximizing the margin. Moreover, minimizing the second term is equivalent to minimizing the number of misclassified points in training set. The constant C , which can be regarded as regularization constant, is a positive number and determines the balance between accuracy on the training set (i.e. small $\sum_{i=1}^{l}\xi_i$) and margin width (i.e. small $\|\mathbf{w}\|^2$). Increasing C leads to the more complex model structure and giving more importance to the errors on the training set in determining the optimal hyperplane; decreasing C means smaller significance of the learning errors and simpler model structure with larger separation margin.

If the original data are strongly non-linearly separable and more complex separating surfaces are need, the nonlinear SVM first maps the input data into a higher dimensional space called feature space by using a nonlinear transformation φ, where the previous criterion can be implemented. Instead of calculating the inner products between the transformed data in the feature space, the inner products can still be measured in the original space with the introduction of the kernel function.Calculate the optimization problem in the feature space defined by kernel function implicitly, and eq. (4) is transformed into

$$\underset{\alpha}{\text{maxmize}} \quad W(\alpha)=\sum_{i=1}^{l}\alpha_i-\frac{1}{2}\sum_{i,j=1}^{l}\alpha_i\alpha_j y_i y_j \,\mathrm{K}(\mathbf{x}_i\cdot\mathbf{x}_j), \tag{5}$$
$$\text{s.t.} \quad \sum_{i=1}^{l}\alpha_i y_i=0,\quad 0\le\alpha_i\le C,\ i=1,\dots,l$$

where $\mathrm{K}(\mathbf{x}_i,\mathbf{x}_j)=\varphi(\mathbf{x}_i)\cdot\varphi(\mathbf{x}_j)$ is a kernel function which allows the inner products in feature space to be calculated directly in original space, without performing the mapping. Then we can construct optimal separating hyperplane $f(\mathbf{x})=\sum_{i=1}^{l}y_i\alpha_i\,\mathrm{K}(\mathbf{x}_i,\mathbf{x})+b$ in feature space. Because kernel function satisfies the Mercer conditions, the optimization problem is convex. It ensures that maximum interval optimization problem has a unique solution and the unique solution can be found availably. It jumps out of the local minimum problem encountered in neural network training process.

For multi-class classification, we use the "one-against-one" approach in which $k(k-1)/2$ SVM classifiers are constructed and each classifier trains data from two different classes. For training data from the ith and the jth classes, we solve the following two-class classification:

$$\begin{aligned}
&\underset{\mathbf{w}^{ij},b^{ij},\xi^{ij}}{\text{minimize}} && \frac{1}{2}(\mathbf{w}^{ij})^T\mathbf{w}^{ij}+C\sum_t\xi_t^{ij}\\
&\text{subject to} && (\mathbf{w}^{ij})^T\phi(\mathbf{x}_t)+b^{ij}\ge 1-\xi_t^{ij},\ if\ \ y_t=i\\
& && (\mathbf{w}^{ij})^T\phi(\mathbf{x}_t)+b^{ij}\le -1+\xi_t^{ij},\ if\ \ y_t=j\\
& && \xi_t^{ij}\ge 0
\end{aligned} \tag{6}$$

In classification we use a voting strategy: each binary classification is considered to be a voting where votes can be cast for all data points x. In the end the point is designated to be in a class with maximum number of votes. In case that two classes have identical votes, though it may not be a good strategy, now we simply select the one with the smallest index.

The values of penalty parameter C and parameters of kernel function $\mathrm{K}(\mathbf{x}_i,\mathbf{x}_j)$ have great impact on the performance of the SVM classifier. It is necessary to find the best values of these parameters for high classification rate. So, we propose to use genetic algorithm (GA) to optimize these parameters of SVM to analyze the data of enose on wound infection of mice.

Ⅳ PSO-BASED OPTIMIZATION ALGORITHM

A. Particle Swarm Optimization

PSO is an evolutionary computation technique. Similar to genetic algorithms, PSO is a population-based global optimization evolution algorithm. In PSO each particle is seen as a feasible solution of the optimization problem and moves in the search space of a problem. The population (called swarm) of individuals (called particles) changes searching direction according to the competition and cooperation among individuals and updates from iteration to iteration so as to solving complex optimization problems.

Suppose that a population including M particles flights in the D- dimension space with a certain velocity. A particle is considered as a point in a D- dimension space, and its status is characterized according to its position and velocity. The D- dimensional position for the particle i at iteration t can be represented as $\mathbf{x}_i^t=(x_{i1}^t,x_{i2}^t,\cdots,x_{iD}^t)^{\mathrm{T}},\ i=1,2,\cdots M$. The velocity for particle i at iteration t can be described as $\mathbf{v}_i^t=(v_{i1}^t,v_{i2}^t,\cdots,v_{iD}^t)^{\mathrm{T}}, i=1,2,\cdots M$. By calculating the values of objective function of M particles, we find the optimal position $pbest_i^t$ that particle i has obtained until iteration t and the best position $gbest_i^t$ of the population at iteration t.

To search for the optimal solution, each particle updates its velocity according to eq. (7):

$$\begin{aligned}v_{id}^{t+1}&=\omega v_{id}^t+c_1r_1\left(pbest_{id}^t-x_{id}^t\right)\\&\quad+c_2r_2\left(gbest_{id}^t-x_{id}^t\right),\ d=1,2\ldots,D\end{aligned}, \tag{7}$$

where ω is inertia weight which balances and reconciles the global and local searching capability; c_1 and c_2 are learning factors; r_1 and r_2 are random numbers uniformly distributed in (0,1). Equation (7) is constructed by three parts: the first part is a succession of previous moment velocity of particles, it means the trust on current state of particles, and particles take inertial motion based on their own velocity; the second part is of "self cognition", it indicates the particle's own thinking, that is particles consider their past experience and move close to their own best positions which they have ever found, and it reflects an enhanced learning process; the third part is "social experience", it indicates the sharing of information and mutual cooperation among the particles, and particles move close to the best position which the whole particles have ever found. Each particle then moves to a new potential solution based on eq (8):

$$x_{id}^{t+1}=x_{id}^t+v_{id}^{t+1},\ d=1,2\ldots,D \tag{8}$$

B. Apply PSO to SVM and Sensor Array Optimization

This study applies PSO to synchronization optimization of parameters of SVM with the radial basis kernel function $K\left(\mathbf{x}_i, \mathbf{x}_j\right) = \exp\left(-\gamma \left\|\mathbf{x}_i - \mathbf{x}_j\right\|^2\right)$ and sensor array. Without sensor array optimization, two parameters, penalty parameter C and kernel parameter γ, are required to optimized. For the sensor array optimization, we extract maximum of each sensor response as feature and so we obtain 15 features denoted as $[X_1, X_2, \ldots, X_{15}]$. And then the 15 features are weighted by 15 variables $[a_1, a_2, \ldots, a_{15}]$ ranged between 0 and 1, which is called importance factors of sensors. The weighted features $X_i^{'} = a_i X_i$ are then used as the inputs of SVM classifier. In this study, we use the error classification rate as the objective function, also called fitness function, to calculate the fitness of each particle and the particle with the lowest fitness function value is the optimal solution, and the best C, γ and the importance factors are found.

Fig. 5 illustrates the particle (solution) representation.

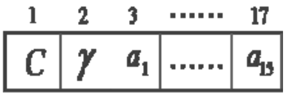

Figure 5 Particle (solution) representation.

Fig. 6 shows the flow chart of the PSO-based synchronization optimization of SVM parameters and sensor array.

V RESULTS AND DISCUSSIONS

In order to evaluate the generalization performance of this method, we use a standard statistical generalization error estimation method—leave-one-out method. In leave-one-out (LOO) method the 80 samples are divides into 80 parts, and all the 80 samples of each class are used for training except one, which is left for testing. 80 distinct classifiers are trained by using 79 samples, cyclically selected among the 80 samples, while the validation of the trained classifier is carried by using the remaining one sample. The LOO method gives an unbiased estimate of the expected generalization error [20]. The used platform is Intel Pentium (R) Dual-Core, 2.2 GHz CPU, 2 GB RAM, Windows XP Professional 2008 operating system. The development environment is MATLAB 2008b. LIBSVM toolbox is used to implement our SVM classifier.

Through initial experiment, the parameter values of the proposed PSO-SVM method are set as follows. The inertia weight ω decreases from 0.9 to 0.4. Both the c_1 and c_2 are set to 2. The number of particles and generations are set to be 20 and 200. The searching range of parameter C of SVM is between 1000 and 1000000, while the searching range of parameter γ of SVM is between 0.0001 and 1. The 15 importance factors $[a_1, a_2, \ldots, a_{15}]$ range between [0,1]. For GA, a population size of twenty individuals is used with randomly generated initial genomes. Two elite children are selected and retained for the next generation; coding method is double vector; crossover method is intermediate recombination; mutation method is uniform mutation. The crossover and mutation rates are set to p_c=0.8 and p_m=0.1, respectively.

The result of the proposed PSO-SVM method is compared with PSO-SVM method without sensor array optimization and GA-SVM method with/without sensor array optimization. TABLE Ⅲ shows the results of these methods.

The classification rate of the proposed method is better than those of the other three methods obtained. The PSO-SVM method with sensor array optimization finds the more appropriate C, γ and importance factors values, and gives the highest classification rate for wound odor of mice. We also can notice that the methods with sensor array optimization obtain better results than those of without sensor array optimization. GA-SVM and PSO-SVM methods with sensor array optimization obtain 95% and 97.5% classification rate respectively, while 91.25% for the methods without sensor array optimization. It means that each sensor has different importance in pattern classification. Sensor array optimization is useful to enhance the recognition ability of enose system.

TABLE Ⅲ
CLASSIFICATION RATE OF THE PSO-SVM AND GA-SVM METHODS

	without sensor array optimization		with sensor array optimization	
Methods	GA-SVM	PSO-SVM	GA-SVM	PSO-SVM
Optimal parameters	C=371390 γ=0.0803	C=515760 γ=0.0612	C=695650 γ=0.4737	C=620440 γ=0.3594
Classification rate	91.25%	91.25%	95.00%	97.50%

To demonstrate the validity of the proposed method, RBF network classifier is used as contrast. GA and PSO are used to optimize the spread coefficient σ, the criterion of convergence (g) and sensor array. The results of the GA-RBF and PSO-RBF methods with/without sensor array optimization are shown in TABLE Ⅳ

From TABLES Ⅲ and Ⅳ, we can see that the classification rates with SVM classifier are better than those of RBF neural network classifier in the classification of enose signals of wound infection of mice. The proposed method can obtain 97.5% classification rate, which is much higher than those of RBF classifier methods, even though we use GA or PSO optimize the model parameters and sensor array.

TABLE Ⅳ
CLASSIFICATION RATE OF THE PSO-RBF AND GA-RBF METHODS

	without sensor array optimization		with sensor array optimization	
Methods	GA-RBF	PSO-RBF	GA-RBF	PSO-RBF
Optimal parameters	σ=5.7362 g=0.0426	σ=1.6224 g=0.0385	σ=15.4488 g=0.0381	σ=14.1036 g=0.0425
Classification rate	85.00%	86.25%	86.25%	87.50%

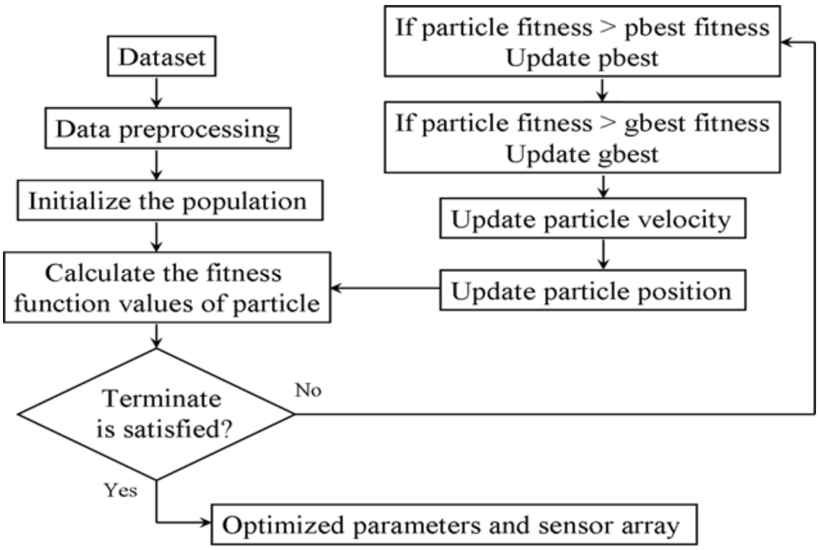

Figure 6 The flow chart of the PSO-based synchronization optimization of SVM parameters and sensor array.

The traditional sensor array optimization method weights the multidimensional sensor signals by 0 and 1. The values of weighting coefficients range between [0,1]. If the value is less than 0.5, then the weighting coefficient is set to be 0 and its corresponding sensor signal is not chosen to use as the input of classifier. Conversely, if the value is greater than or equal to 0.5, the weighting coefficient is set to be 1 and then its corresponding sensor signal is chosen. TABLE Ⅴ shows the classification results of the PSO-SVM with the traditional sensor array optimization method and the proposed method.

From TABLE Ⅴ, we can see that the classification result of PSO-SVM method combined with weighting sensor array by importance factors is better than that of weighting sensor array by 0 or 1, which obtains 92.5% classification rate. The optimal importance factors for 15 sensors is [0.2540 0.1821 0.0785 0.2617 0.6581 0.3104 0.6847 0.4917 0.9434 0.1026 0.5583 0.1372 0.6492 0.5788 0.7801] respectively. And the optimal weight coefficients of the traditional sensor array optimization method is [1 1 1 1 1 1 0 1 1 1 1 0 1 1 1]. The traditional sensor array optimization method simply removes or retains gas sensors with redundancy or correlation and is not conducive to full performance of the role of differences in gas sensors. The method we proposed calculated importance factor of each sensor according to the generalization error of SVM classifier enhance or decrease the sensor responses based on the importance factor of each sensor and better optimize the sensor array.

TABLE Ⅴ
CLASSIFICATION RATE OF THE PSO-SVM WITH DIFFERENT SENSOR ARRAY OPTIMIZATION METHODS

	Weight with 0 or 1	Weight with importance factors
Optimal parameters	C=574280 γ =0.1012	C=620440 γ =0.3594
Classification rate	92.50%	97.50%

Ⅵ CONCLUSIONS

In this paper, a new method based on SVM and PSO is proposed analyze the enose signals of the detection on wound odor of mice infected with three common species of pathogen or uninfected. PSO is used to find optimal SVM model parameters and importance factors of sensors and realize the model parameters and sensor array synchronization optimization. The proposed method achieves a classification rate of 97.5% for discriminate the enose signals of mice wound infection detection. This result is better than that of the GA-SVM method with sensor array optimization, which is at 95% classification rate. Without sensor array optimization, GA-SVM and PSO-SVM methods both obtain only 91.25% classification rate. We also use RBF network classifier as contrast and obtain 85% and 86.25% classification rates using GA-RBF and PSO-RBF methods without sensor array optimization, and 86.25% and 87.5% classification rates with sensor array optimization, which are much lower than the proposed method. Finally, we compare the differences in the classification rates of PSO-SVM method with different sensor array optimization methods. The results show that weighting sensor array signals by 0 and 1 obtain 92.5% classification rate, which is worse than proposed method weighting sensor array signals by importance factors of sensors. In summary, this method is a useful tool for classifier model parameters and sensor array synchronization optimization, classification enose signals of mice wound infection detection and an increasingly accessible technology for accurate and fast detection of wound infection.

ACKNOWLEDGMENT

This work is supported by the Natural Science Foundation Project of CQ CSTC, 2009, P.R. China(CSTC, 2009BA2021), China Postdoctoral Science Foundation funded project (20090461445), Chongqing

University Postgraduates' Science and Innovation Fund, Project Number: 200911B1A0100326, Chongqing University Postgraduates' Innovation Team Building Project, Team Number:200909C1016 and the Fundamental Research Funds for the Central Universities (No. CDJXS10160001).

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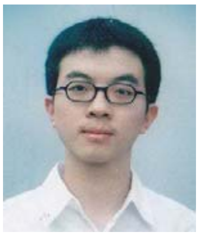

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