2011 2nd International Conference on Biotechnology and Food Science
IPCBEE vol.7 (2011) © (2011) IACSIT Press, Singapore

Identification of Meat Freshness Based on Particle Swarm Optimization and Support Vector Machine

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Abstract—**This paper presents a new identification model based on support vector machine (SVM) to improve the performance of meat freshness identification systems. To seek the optimal parameter combination of SVM, particle swarm optimization （PSO） is proposed. The results of its application to identification of meat freshness indicate that the method based on PSO and SVM is effective and feasible.**

Keywords-support vector machine, meat freshness, classification, particle swarm optimization

I. INTRODUCTION

Support vector machine (SVM), a new machine learning method proposed by Vapnik on the basis of statistical learning theory (SLT), has drawn much attention in the fields of pattern classification[1]. This algorithm derives from linear classifier, and later finds the optimal hyper-plane to classify the samples set to solve non-linear problem with kernel function. SVMs represent an approximate implementation of the structure risk minimization (RSM) principle as an alternative to the empirical risk minimization (ERM) on the training set to provide high generalization capability and to avoid over-fitting problem. Unlike traditional neural networks, SVM based on RSM theoretical basis could avoid local optima and does not require extensive training samples and training time but rather only support vectors (SVs).

Actually, it is seldom to obtain mass samples from the physicochemical experiments. The ideal method for identifying freshness should be accurate, automated and noninvasive. In the past, two major approaches have been proposed to evaluate the freshness of meat: instrumental and sensory analysis, including TVB-N content, bacterial count, PH, H2S, coarse ammonia content and so on. However, it was difficult to obtain the objective classification accuracy by any single physicochemical or sensory properties, because freshness is a comprehensive character description about quality of meat. Meanwhile, sensory methods are based in subjective information, usually given by a human taste panel.

Under this scenario, the classic approach was introduced based on Multiple Regression (MR) models [2], however, the linear models will fail when nonlinear relationships are presented. Then Artificial Neural Network (ANN), with good predictive knowledge, is proposed to solve such nonlinear problems to assess meat quality [3][4][5]. While ANN are useful black box approaches, capable of approximating any continuous function without assuming any hypothesis about the underlying model, they suffer from the problems of local optima, difficulty in solution interpretation in traditional analytic terms and require extensive training samples and training time.

In this work, SVM was proposed to assess meat quality (e.g. pork, beef, mutton, or shrimp) based on experimental data about instrumental and sensory measurements. The paper was organized as follows. First, a description was given on the datasets in Section 2.1, and the SVM was presented in Section 2.2. And then this paper proposes particle swarm optimization (PSO) to optimize the parameters of SVM in Section 2. The experimental results and analysis were given in Section 3. Section 4 drew the conclusion of this work.

II. MATERIALS AND METHODS

All the meat samples were collected and cut into about 80g within 4h after animals were slaughtered, and live shrimp were chosen as shrimp samples. All samples were stored in decompression room, with the condition set into temperature 2℃, pressure 600±50Pa, and relative humidity 90%. The content of TVB-N and total bacterial count, pH value and sensory scores of each sample were determined for each 72h until the samples decayed thoroughly. And all determination was duplicated for 4 times.

A. Data of Meat

The TVB-N content in meat samples was an important indicator for estimating meat freshness. During the storage, the changes of TVB-N content in four kinds of meat samples were shown in Fig 1. According to the quality standard, it was obvious that samples stored for less than 7 days in decompression room were fresh. After 10 days, the rapid increase of TVB-N content suggested that the quality of all samples depressed significantly.

Fig.2 showed that the changes of total bacterial count of meat samples in the decompression storing period. The bacterial count of each sample was less than 1×104 cfu/g during initial 7 days, which indicated the samples were fresh. During 10-13 days, the bacterial count in beef, pork, and mutton samples were between 1×104 cfu/g and 1×106cfu/g. It showed that these samples could be classified into sub-fresh samples. Beyond 16 days, all samples except mutton sample decayed because the bacterial count was more than 1×106cfu/g.

The pH value of meat samples can also reflect their freshness. The pH value increased with the decrease of meat freshness. In general, pH value of fresh meat was less than 6.2, while sub-fresh meat was between 6.2 and 6.7. The changes of pH value of all samples were shown in Fig. 3. The continuous increase of pH value corresponded to the decrease of meat freshness. Sensory scores of meat samples for different storage time were shown in Table 1, including smell, taste, vision and touch properties. The samples beyond 8 scores could be classified into fresh meat, 6-8 scores sub-fresh samples, and below 6 scores putrid samples.

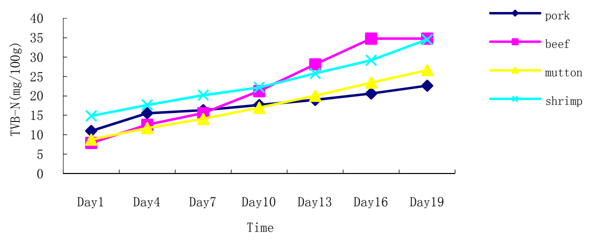

Figure 1. The changes of TVB-N of meat samples in the decompression storing period

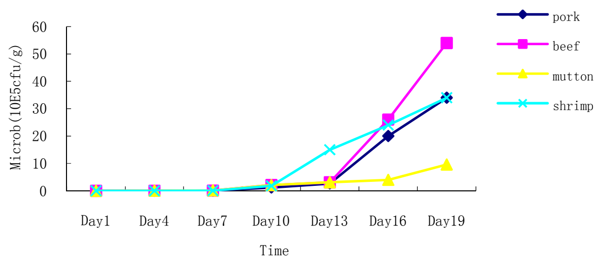

Figure 2. The changes of total bacterial count of meat samples in the decompression storing period

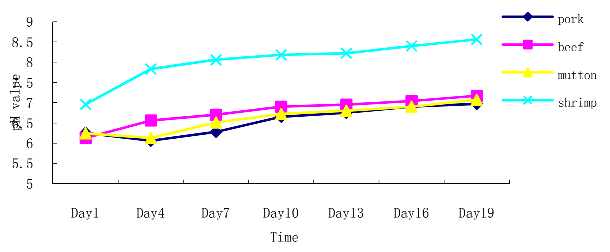

Figure 3. The changes of pH of meat samples in the decompression storing period

TABLE 1 THE CHANGES OF SENSORY SCORES OF MEAT SAMPLES IN THE DECOMPRESSION STORING PERIOD

Store Time	Sample ID	Sensory score			
		Pork	*Beef*	*Mutton*	*Shrimp*
1	1	10	10	10	10
	2	10	10	10	10
	3	10	10	10	10
	4	10	10	10	10
4	5	9	8.5	9	8.5
	6	8.5	8	9.5	8
	7	8	9	9	8.5
	8	9	9	8.5	9
7	9	8	7	8.5	8
	10	8	7.5	7.5	8.5
	11	7.5	8	8	8
	12	8.5	8	8	7
10	13	6.5	7	6.5	5.5
	14	7	6.5	7.5	6
	15	6	6	6	7
	16	6.5	7.5	7	7.5
13	17	6	6	6.5	6
	18	5.5	6	5.5	4.5
	19	6.5	6.5	6	5
	20	6.5	6	7	6.5
16	21	5	3	4.5	3.5
	22	4.5	5	5	3
	23	4	4.5	4.5	2.5
	24	3.5	6	4	4
19	25	2	1	3	0
	26	2.5	1.5	0	0
	27	1.5	0	2.5	2.5
	28	2	2	4	0

According to the different properties to evaluate, significant differences were shown in the respectively classification results. Therefore, it was not wiser to classify meat freshness by any single physicochemical or sensory properties. The freshness of meat samples should be evaluated synthetically based on TVB-N content, bacterial count, pH and sensory scores.

B. Support Vector Machine

The SVM stresses to study statistical learning rules under small samples. The basic idea of classification algorithm is to find an optimal separating hyper-plane and maximize the margin of separation of two kinds of sample. A brief description of the concept of SVM in the framework of classification will be given below.

Assuming that the training data with l number of samples is represented by $(x_1, y_1), \cdots, (x_l, y_l) \in R^n \times \{+1, -1\}$, the separating hyper-plane is determined by an orthogonal vector w and a bias b, which can be written as follows: $w \cdot x + b = 0$. And the margin of separating is $2/\|w\|$. The hyper-plane that optimally separates the data is the one that minimizes Eq.(1) with constraint:

$$\begin{cases} \min\left(\frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}\xi_i\right) \\ \xi_i + y_i[(w \cdot x) + b] - 1 \geq 0, \xi_i \geq 0 \end{cases} \quad (1)$$

The parameter C is a regularization meta-parameter that balances the penalization of errors. The minimization procedure uses Lagrange multipliers and quadratic programming optimization methods and the transformed dual problem is given by:

$$\max_{\alpha}\left[\sum_{i=1}^{n}\alpha_i-\frac{1}{2}\sum_{i,j=1}^{n}\alpha_i\alpha_j y_i y_j(x_i\cdot x_j)\right] \tag{2}$$

under constraints $\sum_{i=1}^{n} y_i\alpha_i=0$, $0\le\alpha_i\le C$ (i=1,…,n) .

According to the Kuhn Tucker theorem of optimization theory, the optimal solution of the dual problem satisfies:

$$\alpha_i\left[y_i(w\cdot x_i+b)-1\right]=0,\quad i=1,2,\cdots n \tag{3}$$

If Eq.(3) has non-zero Lagrange multipliers, the points x_i satisfy Eq.(4). These points are termed support vector:

$$y_i(w\cdot x+b)=1 \tag{4}$$

The hyper-plane is determined by the support vector, which is a small subset of the training vectors. Therefore, if α_i^* is the non-zero optimal solution, the classifier function can be expressed as:

$$f(x)=\operatorname{sgn}\{(w^*\cdot x)+b^*\}=\operatorname{sgn}(\sum_{i=1}^{n}\alpha_i^* y_i(x\cdot x_i)+b^*) \tag{5}$$

For training samples that are not linearly separable, the data need to be transferred onto a space of higher dimensionality feature space through non-linear mapping ϕ so that a reliable linear separation can be computed. $K(x_i,x_j)=(\phi(x_i)\cdot\phi(x_j))$ is the kernel function performing the non-linear mapping into feature space. Then the classifier function Eq.(5)can be written as:

$$f(x)=\operatorname{sgn}\{(w^*\cdot\phi(x))+b^*\}=\operatorname{sgn}(\sum_{i=1}^{n}\alpha_i^* y_i K(x,x_i)+b^*) \tag{6}$$

The most frequently used kernel function is radial basis function (RBF). Unlike the linear kernel function, RBF can classify multi-dimensional data better. And RBF has fewer parameters to set than the polynomial kernel. Also RBF has similar overall performance with other kernel functions. Therefore, RBF was used as kernel function in SVM to classify in this paper:

$$K(x_i,x_j)=\exp(-g\left\|x_i-x_j\right\|^2),\gamma>0 \tag{7}$$

C. The identification system based on PSO and SVM

The confirmation of unknown parameters (regularization parameter and RBF kernel parameter) of the SVM is the key step and complicated process in SVM as their combined values determine the boundary complexity and the classification performance. Grid search [6] is the most common method to determine the values of parameters by setting appropriate values for the upper and lower bounds with the appropriate search step. However, the search interval setting is a problem, which a large search interval wastes computational resource, while a small might not render an optimal solution. In fact, it is a multivariable optimization problem in a continuous space. And meta-heuristic algorithm could obtain the global optima without searching all the point in the grid. Therefore PSO is considered in this paper as an excellent technique to solve the combinatorial optimization problems.

PSO, initially proposed by Kennedy and Eberhart, is a stochastic global optimization technique through simulation of simplified social behavior of bird flocking [7]. PSO has become an important tool for optimization problem in academia and the industry mainly because of its fewer control parameter and its ease of implementation [8][9].

In PSO model, the potential solution is treated as a volume-less particle in the D-dimensional space with the position and velocity of ith particle represented as $x_i=(x_{i1},...,x_{id},...,x_{iD})$ and $v_i=(v_{i1},...,v_{id},...,v_{iD})$. The particles are flown through the problem space by following the personal best position (pi) of the particle and the global best position of the population (pg) within a short calculation time to balance their global and the local exploration and exploitation abilities. Therefore the particles in PSO move according to the following iterative Equations:

$$v_{id}=w\cdot v_{id}+c_1\cdot rand()\cdot(p_{id}-x_{id})+c_2\cdot rand()\cdot(p_{gd}-x_{id}) \tag{8}$$

$$x_{id}=x_{id}+v_{id} \tag{9}$$

where x_{id} is the dth dimension location for ith particle, also v_{id} is the dth dimension velocity for ith particle, c1 and c2 are acceleration constants; rand() are random values between 0 and 1; and w is the inertia weight to balance the global and local search ability. The position of particle is updated using its velocity vector as shown in Eq.(9). Clerc and Kennedy further analyzed the trajectory and proved that, whichever model is employed in the PSO algorithm, each particle in the PSO system converges to its local point p, whose coordinates are $p=(\varphi_1 p_i+\varphi_2 p_g)/(\varphi_1+\varphi_2)$ so that the best previous position of all particles will converge to an exclusive global position at $t\to\infty$, where φ_1, φ_2 are random numbers distributed uniformly on [0,1].

The basic scheme of PSO algorithm can be expressed in the following steps:

Step1: Initialize the population, randomly generating the position and velocity;

Step2: Evaluate the fitness of each particle according to the objective function;

Step3: Compare the fitness of the ith particle with its best position p_i and retain the better as p_i;

Step4: Compare the fitness of the ith particle with global best position p_g and retain the better as p_g;

Step5: Update the velocity and position of particle according to Eq. (8) and Eq. (9);

Step6: If the stopping criteria is satisfied, the algorithm ends; otherwise goto Step2.

The intelligence identification system based on SVM and PSO are shown in Fig.4. To evaluate identifying capacity of the system, the fitness function of PSO is designed as accuracy of cross validation.

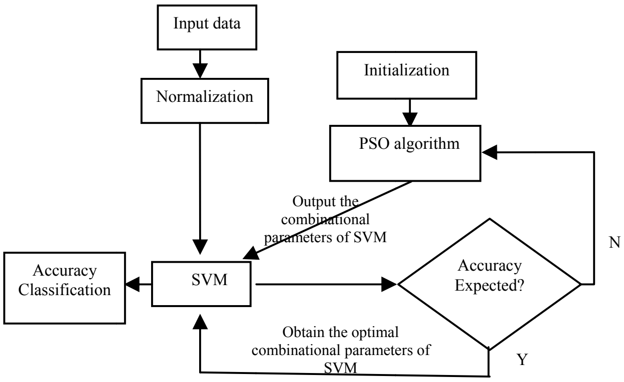

Figure 4. The intelligence identification system

III. RESULTS

The identification process of meat freshness based on particle swarm optimization and support vector machine was implemented in MATLAB (2009a) development environment. The experiments are made on a 1.80 GHz Core(TM) 2 CPU PC with 1.0G memory under Microsoft Windows xp professional.

The results of RBF kernel function SVM to classify the meat freshness with default parameters were shown in Fig.5 and Table 2, which indicated that different normalization methods had effects on the accuracy of classification.

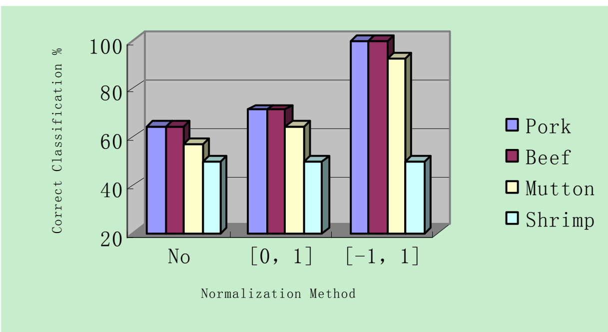

Figure 5. The classification diagram by RBF kernel function

TABLE 2. THE CORRECT CLASSIFICATION RATE BY RBF KERNEL FUNCTION UNDER DEFAULT PARAMETERS

Correct Classification %	[0，1]	[-1，1]
Pork	71.4286	100
Beef	71.4286	100
Mutton	64.2857	92.8571
Shrimp	50	50

To improve the model of SVM with RBF kernel parameters were considered to be optimized by PSO algorithm. The parameters of PSO algorithm were given as follows: acceleration constants c_1 =1.5, c_2=1.7; number of particles was 20; max generation was 200.

The results of optimal parameters and correct classification by RBF of four different meat models were shown in Table 3. The experimental results showed that the classification accuracy would be greatly improved after optimizing the parameters by PSO as shown in Fig.6 and the identification accuracy could reach 100% because PSO algorithm could search the parameter combination in a wider range.

TABLE 3 THE CORRECT CLASSIFICATION RATE BY SVM WITH PARAMETERS OPTIMIZED BY PSO

Correct Classification %	[0，1]		[-1，1]	
Pork	bestc=1.13205 bestg= 4.76453	100	bestc= 1.46853 bestg= 7.0792	100
Beef	bestc= 1.07869 bestg= 12.8625	100	bestc= 1.67132 bestg= 3.26328	100
Mutton	bestc= 1.09113; bestg= 15.2678	100	bestc= 1.11208; bestg= 1.74695	100
Shrimp	bestc= 1.00158; bestg= 23.1094	100	bestc= 0.981812; bestg= 1.94095	100

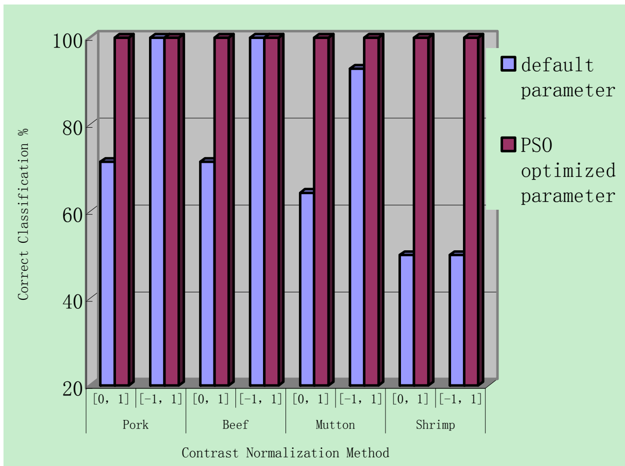

Figure.7 The comparison diagram of classification under default and optimal parameters

IV. CONCLUSIONS

In this work, several fresh agricultural products, including pork, beef, mutton and shrimp samples, were stored in decompression storeroom, and the TVB-N content, total bacterial count, pH value and sensory scores of these samples in different time were determined to achieve the correct classification of freshness. And SVM was applied to train these samples and predict the classification of meat freshness. Simulation results demonstrated that the identification system based on SVM is effective and feasible. Moreover, it was shown that the particle swarm optimization algorithm is available for SVM to seek optimized parameters to improve the performance greatly.

ACKNOWLEDGMENT

This work has been financially supported by "Chen Guang" project by Shanghai Municipal Education Commission and Shanghai Education Development Foundation (Grant No. 2008CG055, No.2009CG50).

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