Journal of Food Protection, Vol. 76, No. 11, 2013, Pages 1916–1922
doi:10.4315/0362-028X.JFP-12-161

Assessing the Freshness of Meat by Using Quantum-Behaved Particle Swarm Optimization and Support Vector Machine

XIAO GUAN,[1,2] JING LIU,[3]* QINGRONG HUANG,[4] AND JINGJUN LI[5]

[1]*The State Key Laboratory of Dairy Biotechnology, Shanghai 201103, People's Republic of China;* [2]*School of Medical Instrument and Food Engineering, University of Shanghai for Science and Technology, Shanghai 200093, People's Republic of China;* [3]*College of Information Engineering, Shanghai Maritime University, Shanghai 201306, People's Republic of China;* [4]*Department of Food Science, Rutgers University, New Brunswick, New Jersey 08901, USA; and* [5]*Jiangsu Yurun Food Industry Group Co., Ltd., Nanjing 210041, People's Republic of China*

MS 12-161: Received 4 April 2012/Accepted 7 July 2013

ABSTRACT

To improve the performance of meat freshness identification systems, we present a new identification method based on quantum-behaved particle swarm optimization (QPSO) and the support vector machine (SVM). Fresh pork, beef, mutton, and shrimp samples were stored in a hypobaric chamber for several days, and the conventional indices of meat freshness, including total volatile basic nitrogen content, aerobic plate count, pH value, and sensory scores, were determined to achieve the identification of sample freshness. However, the experiments showed that it was difficult to obtain an ideal freshness assessment by any single physicochemical or sensory property. Therefore, SVM was introduced to use these data to build a freshness model. Furthermore, QPSO was proposed to seek the optimal parameter combination of SVM. The experimental results indicated that the hybrid SVM model with QPSO could be used to predict meat freshness with 100% classification accuracy.

Meat is a highly perishable product due to its biological composition. Freshness is a major contributor to the quality of meat and meat products. A number of factors, including holding temperature, moisture, atmospheric oxygen, and microorganisms, influence the shelf life and freshness of meat *(32)*. Common storage methods, namely, cold storage and controlled atmospheric storage, are usually used to preserve fresh meat *(15, 20)*. However, these methods have some disadvantages, such as uneven environmental temperature and atmospheric compositions. As an emerging preservation technology, hypobaric storage could rapidly remove heat, reduce the oxygen level, and thus effectively inhibit microbial spoilage and minimize other deteriorative changes such as color and oxidative changes *(18)*. Therefore, hypobaric storage could have more optimal results for the storage of meat.

Methods for evaluation of freshness and quality of different meat species are mainly based on the measurements of postmortem changes associated with physicochemical characteristics, microbiological growth, and sensory acceptance *(31)*. The specific freshness indices usually include sensory evaluation, texture analysis, pH, the total volatile basic nitrogen (TVB-N) content, aerobic plate count, etc. *(10, 27)*. In general, the freshness results obtained from different evaluation indices are well correlated. However, sensory evaluation is sometimes subjective, depending on the experience of the sensory panel. On the other hand, chemical methods often have the problems of requiring more procedures and longer time, higher expense, insufficient precision, etc. In fact, meat freshness is a comprehensive description of meat quality. Meat freshness assessment using any single index is not accurate, and it must have more information considered and provided by diverse indices.

Multiple regression models have been previously introduced to evaluate meat quality. However, linear models often fail when nonlinear relationships are present *(2)*. An artificial neural network approximating continuous functions without making any hypothesis about the underlying model was proposed to solve such nonlinear problems. However, the artificial neural network was easily trapped into local optima and required extensive training samples and training time *(11, 12, 17)*. To overcome these disadvantages, support vector machine (SVM), a novel machine-learning method based on statistical learning theory, was proposed and has shown good performance *(29)*. Unlike traditional neural networks based on empirical risk minimization, SVM uses the principle of structure risk minimization to provide high generalization capability, solve nonlinear problems, and avoid overfitting and local optima during the process of model building by training data *(14)*. SVM can also generalize well, especially for small sample sets. These attractive properties make SVM a promising technique in the field of regression forecasting and pattern classification *(29)*. However, the parameter settings of SVM in real applications are complicated combinational optimization problems, which directly affect

* Author for correspondence. Tel: +86 21 38284213; Fax: +86 21 55271117; E-mail: Jingliu@shmtu.edu.cn.

the performance of classification. Therefore, a new algorithm called quantum-behaved particle swarm optimization (QPSO) *(28)* is proposed for parameter selection of SVM and is one of the main contributions of this article. Additionally, this is the first time that SVM has been proposed to assess meat quality (e.g., pork, beef, mutton, or shrimp) based on physicochemical and sensory measurement data.

MATERIALS AND METHODS

Preparation of meat samples. Split pork hind leg meat (Landrace × large Yorkshire pigs, 180 days old), beef *biceps femoris* muscles (Luxi cattle, about 30 months old), and mutton foreleg meat (Shanxi goats, 12 months old) were obtained from a local processing plant (Minhang Livestock Center, Shanghai, China) within 4 h after animals were slaughtered. All samples were cut into pieces of similar size (5.0 by 5.0 cm) with a weight of about 80 g by use of a sterile knife. Live Taiwan shrimp (approximately 35 g each) were chosen as shrimp samples. All samples were stored in a hypobaric chamber under the following conditions: temperature, 2°C; pressure, 600 ± 50 Pa; and relative humidity, 90%. The content of TVB-N, aerobic plate count, pH value, and sensory scores of each type of sample were determined for 3 days until the samples decayed thoroughly.

TVB-N analysis of sample. Water extract of the meat sample was prepared and analyzed for TVB-N levels using the Chinese national standard (GB/T 5009.44-2003) method *(22)*. Briefly, all the meat samples were filleted after the fat was removed, while the shrimp were beheaded and eviscerated. Samples were minced by passage through a meat grinder with 4-mm holes three times. Ten-gram samples were soaked in 100 ml of deionized water for 30 min with occasional shaking. The resulting water-extracted samples were filtered through Whatman no. 1 filter paper (Whatman, GE Healthcare). Next, 5 ml of filtrate was pipetted into a Kjeldahl distillation unit, and then 5 ml of a 10-g/liter MgO solution was added. Steam distillation was performed for 5 min. The distillate was absorbed by 10 ml of 20-g/liter boric acid and then titrated with 0.1 mol of HCl per liter. The TVB-N value was calculated and expressed in milligrams per 100 g.

Measurement of aerobic plate count. The determination of aerobic plate count in different samples was performed according to the Chinese national standard GB 4789.2-2010 method *(25)*. Twenty-five grams of the surface of the sample was removed with a sterilized surgical knife and homogenized with 225 ml of sterile 0.9% saline (NaCl) solution. Decimal dilutions were spread over plates of plate count agar (Sigma-Aldrich, St. Louis, MO) to determine the aerobic plant count. Colonies on the plate were counted after incubation for 48 ± 2 h at 37°C. Duplicate experiments were performed for each specimen.

Determination of pH. The determination of pH was performed using a pH meter equipped with a probe for solids (FC200B, Hanna Instruments, Milano, Italy) according to the Chinese national standard GB/T 9695.5-88 method *(21)*.

Sensory evaluation. Sensory evaluations of the meat samples were performed according to the Carmack et al. *(5)* and Li *(16)* methods with minor modifications. A 10-member trained panel was selected for sensory evaluation. Panel members were recruited from students in the Food Sciences Building at University of Shanghai for Science and Technology. The ages of the panel members ranged from 19 to 28 years. The sensory panel consisted of five males and five females. Panelists were trained in two 1-h sessions to evaluate meat sample color (from 1 for worst color to 10 for normal color), smell (from 1 for extremely spoiled smell to 10 for normal smell), elasticity (from 1 for least elastic to 10 for most elastic), and adhesiveness (from 1 for most adhesive to 10 for least adhesive). The weight coefficients of the above four properties were set to 0.2, 0.2, 0.3, and 0.3, respectively. The final scores of sensory evaluation of meat samples were recorded as the mean scores of panelists. The sensory tests were conducted in the Sensory Testing Laboratory at University of Shanghai for Science and Technology.

Statistical analysis. Each test of TVB-N content, aerobic plate count, pH value, and sensory evaluation was performed for four parallel samples at 3-day intervals, and the results were expressed as the mean values. All data were analyzed by using the SPSS Statistics v18.0 software package.

Modeling meat freshness by SVM. SVM, a novel neural network technique, has gained ground in classification and regression forecasting *(13, 14)*. The basic idea of classification by SVM is to find an optimal separating hyperplane and maximize the margin of separation of two kinds of sample. One of the prominent properties of SVM is to solve a linearly constrained quadratic programming problem, whose solutions turn out to be unique and globally optimal. Another advantage is that the solution to the optimization problem depends only on a subset of the training data called support vectors. Nonlinear problems would turn into linear problems by mapping the original space into a high-dimensional inner product space via kernel function. Therefore, SVM could be applied to classification problems *(14)*. A brief description of the concept of SVM in the framework of classification is given below.

Assuming that the training data with one sample is represented by $(x_1, y_1), \ldots, (x_l, y_l) \in R^n \times \{+1, -1\}$, the separating hyperplane is determined by an orthogonal vector w and bias b, which can be written as follows: $w \cdot x + b = 0$. The margin of separation is $2/|w|$. The hyperplane that optimally separates the data is the one that minimizes equation 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 metaparameter 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 equation 2:

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

under the following constraints,

$$\sum_{i=1}^{n} y_i\alpha_i = 0, 0 \leq \alpha_i \leq C,$$

where $(i = 1, \ldots, n)$.

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

$$\alpha_i[y_i(w \cdot x_i + b) - 1] = 0, \quad (3)$$

where $i = 1, 2, \ldots n$.

If equation 3 has nonzero Lagrange multipliers, the points x_i satisfy equation 4. These points are termed support vectors:

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

The hyperplane is determined by the support vector, which is a small subset of the training vectors. Therefore, if α_i* is the nonzero optimal solution, the classifier function can be expressed as equation 5:

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

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

$$f(x) = \text{sgn}\{[w^* \cdot \varphi(x)] + b^*\} = \text{sgn}\left[\sum_{i=1}^{n} \alpha_i^* y_i K(x, x_i) + b^*\right] \tag{6}$$

QPSO. PSO is a stochastic population-based optimization algorithm through simulation of simplified social interaction and communication of bird flocking *(14)*. It has become an important tool for optimization problems in academia and the industry mainly because it has fewer control parameters and is easily to implement *(3, 4)*.

In the PSO model, the potential solution is treated as a volumeless particle with the position and velocity of the *i*th particle represented as $x = (x_1, \ldots x_i, \ldots x_n)$ and $v = (v_1, \ldots v_i, \ldots v_n)$. The particles are flown through the problem space by following the personal best position (p_i) of the particle and the global best position of the population (p_g) within a short calculation time to balance their global and local exploration and exploitation abilities. Therefore, the particles in PSO move according to the following equations:

$$v_i = w \cdot v_i + c_1 \cdot \text{rand}(\,) \cdot (\mathrm{p_i} - \mathrm{x_i}) + c_2 \cdot \text{rand}(\,) \cdot (\mathrm{p_g} - \mathrm{x_i}) \tag{7}$$

$$x_i = x_i + v_i \tag{8}$$

where x_i is the location of *i*th particle, v_i is the velocity of the *i*th particle, c_1 and c_2 are acceleration constants; rand( ) represents random values between 0 and 1, and w is the inertia weight to balance the global and local search ability.

Clerc and Kennedy *(7)* further analyzed the trajectory and proved that, whatever model was used in the PSO algorithm, each particle in the PSO system was attracted by the local point p, whose coordinates were defined by the equation $p = (\varphi_1 p_i + \varphi_2 p_g)/(\varphi_1 + \varphi_2)$, where φ_1 and φ_2 were random numbers distributed uniformly on [0, 1]. Inspired from the concept of quantum, a δ potential field centered as point p was built to direct the behavior of particle. Then, in the improved PSO model, which was called ''quantum-behaved particle swarm optimization'' (QPSO), the particles moved according to the following iterative position equation without velocity *(29)*:

$$x = p \pm \beta|\text{mbest} - \mathrm{x}|\ln(1/u) \tag{9}$$

where

$$\begin{aligned}\text{mbest} &= \frac{1}{M}\sum_{i=1}^{M} P_i \\ &= \left(\frac{1}{M}\sum_{i=1}^{M} P_{i1},\quad \frac{1}{M}\sum_{i=1}^{M} P_{i2},\quad \ldots,\quad \frac{1}{M}\sum_{i=1}^{M} P_{id}\right)\end{aligned} \tag{10}$$

which is defined as the mean value of the best position of all particles. β, called the contraction-expansion coefficient, is the only parameter in the QPSO algorithm. Compared with the PSO algorithm, QPSO has better global search ability, faster convergence, and fewer parameters to adjust *(7, 19)*.

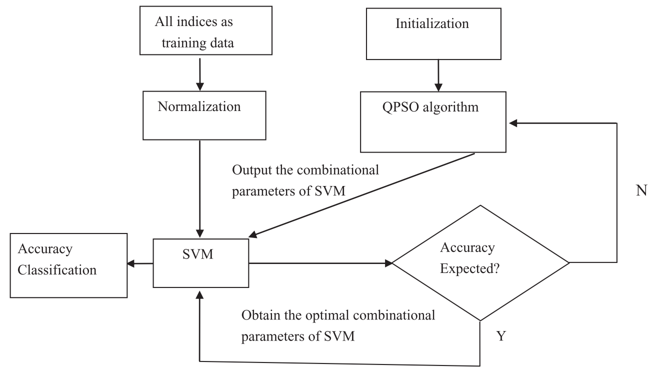

FIGURE 1. *The intelligence identification system.*

The identification system based on QPSO and SVM. The confirmation of unknown parameters (the penalty coefficient and the radial basis function [RBF] kernel parameter) of the SVM is the key step and is a complicated process in SVM, as their combined values determine the boundary complexity and the classification performance. Grid search 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. A large search interval wastes computational resources, while a small search interval might not render an optimal solution. In fact, it is a multivariable optimization problem in a continuous space. To overcome the shortage, a novel metaheuristic algorithm, the QPSO algorithm, was proposed to obtain the global optima without searching all the points in the grid.

The intelligent system of freshness assessment of meat samples based on SVM and QPSO is shown in Figure 1. To evaluate classification capacity of the system, the fitness function of QPSO was designed as accuracy of cross-validation.

The steps of embedded QPSO algorithm are listed below:

Step 1: Initialize the population of particles with random positions in the problem space.
Step 2: Determine the mbest among the particles according to equation 10.
Step 3: Evaluate the fitness of each particle according to the accuracy of cross validation.
Step 4: Compare the fitness of the *i*th particle with its best position p_i and retain the better one as p_i.
Step 5: Compare the fitness of the *i*th particle with global best position p_g and retain the better as p_g.
Step 6: Update the position of particles according to equation 9.
Step 7: If the stopping criterion is satisfied, the search process ends; otherwise, go to step 2.
Step 8: The optimal combinational parameters obtained by QPSO are input into SVM to train the samples and generate the support vectors.

RBF has shown good performance in many actual applications. Unlike the linear kernel function, RBF can classify multidimensional data preferably, and it has fewer parameters to set than the polynomial kernel. Also, RBF has an overall performance similar to that of other kernel functions. Therefore, RBF was used as the kernel function of SVM to classify in this article:

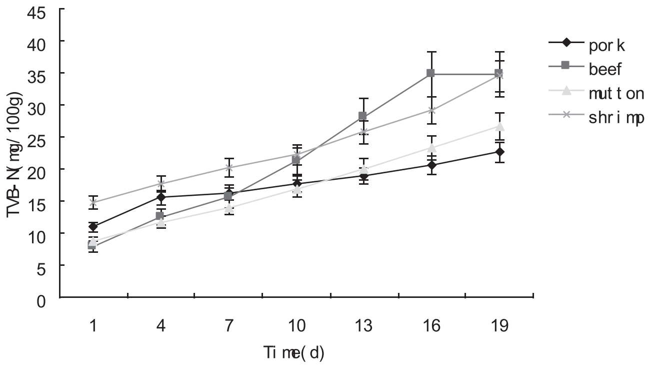

FIGURE 2. *Changes of TVB-N of meat samples in the hypobaric storing period. Data are expressed as mean values of four determinations ± standard deviations.*

$$K(x_i,x_j)=\exp(-g\|x_i-x_j\|^2),g>0 \qquad (11)$$

The steps of freshness assessment of meat samples based on QPSO-SVM are described as follows:

Step 1: Initialize the original data by normalization and then form a training sample set.
Step 2: Based on the RBF kernel function, call the embedded QPSO algorithm and get the optimal parameters. Construct the QP problem (equation 1) of SVM.
Step 3: Solve the optimization problem (equation 2) and compute the classification result according to equation 6.

The identification process of meat freshness based on QPSO and SVM was implemented in the MATLAB (version 2009a) development environment. The experiments were made on a 1.80 GHz Core 2 CPU PC with 1.0 G memory with Microsoft Windows XP Professional.

RESULTS

The TVB-N content in meat samples is a classic indicator for evaluating meat freshness *(30)*. Changes of TVB-N content in four kinds of meat samples during the storage period are shown in Figure 2. According to the livestock meat freshness standard *(23),* meat samples can be classified as ''fresh'' if the TVB-N value is lower than 15 mg/100 g. When the TVB-N value of the sample is between 15 and 25 mg/100 g, the meat may be classified as ''less fresh.'' If the sample TVB-N content is >25 mg/100 g, it is totally spoiled. The shrimp was considered fresh if the TVB-N value was less than 20 mg/100 g and less fresh

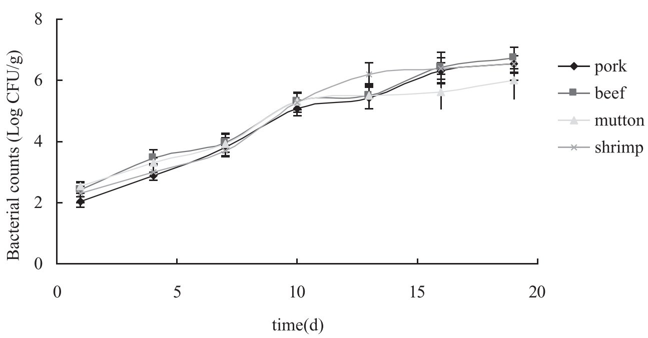

FIGURE 3. *Changes of aerobic plate count of meat samples in the hypobaric storing period. Data are expressed as mean values of four determinations ± standard deviations.*

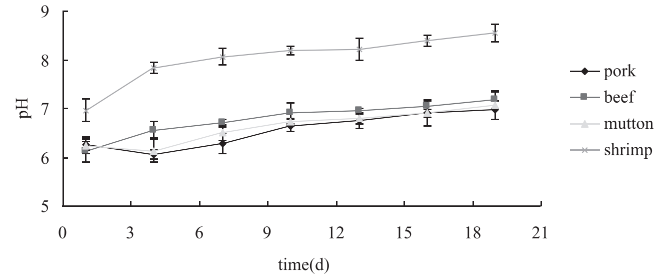

FIGURE 4. *Changes of pH of meat samples in the hypobaric storing period. Data are expressed as mean values of four determinations ± standard deviations.*

between 20 and 30 mg/100 g *(24)*. Most of the samples stored for fewer than 7 days in the hypobaric chamber were fresh. After 10 days, the rapid increase of TVB-N content suggested that the quality of all samples decreased significantly.

Figure 3 shows the changes of bacterial populations of meat samples in the hypobaric storage period. The bacterial populations of each sample were <4.0 log CFU/g during the initial 7 days, which indicated that the samples were fresh. During days 10 to 13, the bacterial populations in beef, pork, and mutton samples were between 4.0 and 6.0 log CFU/g, which showed that these samples could be classified as less fresh samples *(16)*. Beyond 16 days, all samples except the mutton sample spoiled, as the bacterial cell populations were >6.0 log CFU/g *(16)*.

The pH of meat samples can also reflect their freshness to some extent. Previous studies suggested that the pH value of fresh meat was <6.2, while that of less-fresh meat was between 6.2 and 6.7 *(15, 16)*. However, for shrimp samples, the pH values were usually higher because there were some alkaline components in shrimp *(8, 26)*. The change of pH for all samples is shown in Figure 4 and demonstrates that an increase of pH corresponds to a decrease of meat freshness.

The sensory quality of all meat samples was evaluated by a sensory panel throughout the storage period. The scores of sensory attributes (olfactory, gustatory, visual, and tactile properties) for all samples with different storage times are shown in Table 1. According to the score standard *(16),* samples scoring higher than 8 could be classified as fresh meat, those scoring 6 to 8 were considered less fresh samples, and those scoring below 6 were classified as spoiled samples. It was evident that all samples stored for the initial 4 days were totally fresh. Starting on day 4, partial samples began to become less fresh, as evidenced by their sensory scores of 6 to 8. After 16 days, all samples scored below 6, which indicated that all of them thoroughly lost the quality required for consumption.

Considering comprehensively the values of TVB-N content, aerobic plate count, pH, and sensory evaluation, it can be deemed approximately that the meat quality was well kept during the initial 7-day storage period and then deteriorated quickly after 10 days, until it was totally spoiled beyond 16 days. However, aiming at any special kind of meat sample, the results of freshness classification were significantly different when a different single index

TABLE 1. *Changes of sensory scores of meat samples in the hypobaric storing period*[a]

Storage time (days)	Sample no.	Mean sensory score ± SD: Pork	Beef	Mutton	Shrimp
1	1	9.9 ± 0.1 A	10.0 ± 0.0 A	9.8 ± 0.2 A	9.9 ± 0.1 A
	2	9.7 ± 0.3 A	9.8 ± 0.2 A	9.9 ± 0.1 A	10.0 ± 0.0 A
	3	9.8 ± 0.2 A	9.9 ± 0.1 A	9.7 ± 0.3 A	10.0 ± 0.0 A
	4	9.9 ± 0. 1 A	9.9 ± 0.1 A	10.0 ± 0.0 A	9.8 ± 0.2 A
4	5	9.1 ± 0.1 AB	8.5 ± 0.3 ABCD	9.1 ± 0.1 ABCD	8.7 ± 0.3 AB
	6	8.5 ± 0.2 ABC	8.0 ± 0.2 DEF	9.5 ± 0.3 AB	8.1 ± 0.2 ABC
	7	8.1 ± 0.1 BCD	8.8 ± 0.1 ABC	8.9 ± 0.2 ABCD	8.5 ± 0.4 AB
	8	9.2 ± 0.3 AB	8.9 ± 0.2 ABC	8.6 ± 0.2 ABCD	8.9 ± 0.1 A
7	9	8.1 ± 0.4 BCD	7.1 ± 0.4 EFG	8.5 ± 0.4 BCD	8.1 ± 0.5 ABC
	10	8.0 ± 0.6 BCDE	7.6 ± 0.5 DEF	7.4 ± 0.2 DEFG	8.6 ± 0.4 AB
	11	7.6 ± 0.2 CDEF	8.2 ± 0.3 BCDE	8.1 ± 0.3 CD	8.1 ± 0.5 ABC
	12	8.6 ± 0.5 ABC	8.1 ± 0.6 CDEF	8.0 ± 0.3 D	7.2 ± 0.2 BCDE
10	13	6.5 ± 0.6 FG	7.1 ± 0.2 EFG	6.3 ± 0.4 FGH	5.5 ± 0.8 EFGH
	14	7.1 ± 0.4 DEF	6.6 ± 0.3 FGH	7.7 ± 0.2 DE	6.2 ± 1.2 CDEF
	15	6.2 ± 0.8 FG	6.2 ± 1.1 GH	6.1 ± 0.0 GH	7.2 ± 0.7 BCDE
	16	6.6 ± 1.2 FG	7.4 ± 0.2 DEF	7.0 ± 0.4 DEFG	7.7 ± 0.1 BCD
13	17	6.2 ± 1.0 FG	6.0 ± 1.3 GHI	6.6 ± 0.1 EFGH	6.0 ± 0.8 DEFG
	18	5.5 ± 1.2 GH	6.2 ± 0.5 GH	5.4 ± 0.9 HI	4.4 ± 1.3 GHIJ
	19	6.6 ± 0.9 FG	6.5 ± 0.2 FGH	6.0 ± 0.6 GH	5.2 ± 0.4 FGHI
	20	6.7 ± 1.4 EFG	6.1 ± 0.7 GHI	6.8 ± 0.2 DEFGH	6.5 ± 0.9 CDEF
16	21	4.7 ± 1.7 HI	2.8 ± 1.2 J	4.5 ± 0.2 IJ	3.6 ± 0.5 IJK
	22	4.3 ± 1.2 HI	5.0 ± 0.2 HI	5.1 ± 0.7 HIJ	2.9 ± 0.3 JK
	23	4.0 ± 0.8 I	4.6 ± 0.7 I	4.6 ± 0.8 IJ	2.5 ± 1.3 K
	24	3.7 ± 1.3 I	5.9 ± 0.4 GHI	3.9 ± 1.2 JK	4.0 ± 0.4 HIJK
19	25	1.9 ± 0.2 J	0.8 ± 0.1 KL	3.1 ± 0.2 KL	0.0 ± 0.0 L
	26	2.4 ± 0.4 J	1.6 ± 0.2 JK	0.0 ± 0.0 M	0.0 ± 0.0 L
	27	1.5 ± 0.1 J	0.0 ± 0.0 L	2.4 ± 0.2 L	2.5 ± 0.2 K
	28	1.9 ± 0.3 J	2.2 ± 0.8 JK	4.1 ± 0.7 IJK	0.0 ± 0.0 L

[a] In the same column, values followed by the same letter present no significant difference ($\alpha = 0.05$).

was used as the classification index. For example, the freshness classification of 17 pork samples in a total of 28 samples was correct when a single TVB-N index was used, and the accuracy rate was 60.7%. Especially for the samples stored for 16 days and 19 days, all of the classification results were wrong because these samples were obviously spoiled, although their TVB-N values were <25 mg/100 g. Similarly, the accuracy rate was 67.9% if only pH was used as classification index. When only sensory evaluation was chosen as classification index, there were still two samples (no. 11 and 18) that were wrongly classified, and the accuracy rate was 92.8%. For other kinds of meat samples, there were similar classification results. Therefore, it was not reasonable to evaluate meat freshness by any single physicochemical or sensory property. The freshness of meat samples should be evaluated comprehensively based on TVB-N content, aerobic plate count, pH, and sensory scores.

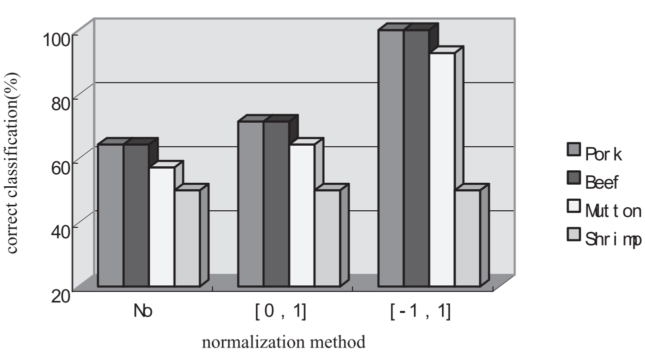

FIGURE 5. *Classification diagram of meat freshness by RBF kernel function.*

Data normalization of the training set and the testing set is essential to the performance of SVM to avoid saturated computation. The min-max normalization method is adopted as the desired range of [0, 1], f_1: $x_{norm} = (x - x_{min})/(x_{max} - x_{min})$, and the range of $[-1, 1]$, f_2: $x_{norm} = 2$ midast; $(x - x_{min})/(x_{max} - x_{min}) + (-1)$, where x_{norm} is the result of normalization, x is the value to be normalized, and x_{max} and x_{min} are the upper and lower bounds, respectively.

The results of RBF kernel function of SVM to classify the meat freshness with default parameters are shown in Figure 5, which indicated that different normalization methods had significant effects on the accuracy of classification.

To improve the model of SVM, RBF kernel parameters were considered to be optimized by the QPSO algorithm. The parameters of the QPSO algorithm were given as follows: the number of particles was 20, max generation was 200, and the contraction-expansion coefficient decreased from 1.2 to 0.4.

TABLE 2. *Correct classification rate by SVM with parameters optimized by QPSO*[a]

Sample	Correct classification (%) with data normalization method			
	[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%

[a] bestc, best penalty coefficient; bestg, best radial basis function kernel parameter.

The results of optimal parameters and correct classification by RBF of four different meat models are shown in Table 2. The experimental results showed that the classification accuracy would be greatly improved after optimizing the parameters by QPSO as shown in Figure 6, and the identification accuracy could reach 100% because the QPSO algorithm could search the parameter combination in a wider range.

DISCUSSION

Accurate meat freshness assessment is crucial for the problem of food quality. In general, meat freshness cannot be assessed accurately by any single conventional index because every index reflects only partial characteristics of a meat sample. Sometimes the results obtained from different indices are inconsistent. Therefore, a freshness assessment with greater accuracy should depend on more-comprehensive indices. In this article, due to the experimental limitation, only four typical indices, namely, sensory evaluation, pH, the TVB-N content, and aerobic plate count of meat samples, were chosen to identify the meat freshness independently or comprehensively.

This study introduced a novel freshness assessment technique based on SVM and further investigated its feasibility in assessing meat freshness. SVM, as a very promising statistical-learning method, is especially suitable for solving small-sample-size problems and has already been successfully used for classification *(1, 6, 9)*. To obtain better performance, the selection of parameters of SVM is crucial and is usually realized by an optimization algorithm. In recent years, some optimization algorithms such as genetic algorithm, PSO, QPSO, etc., have been developed. These algorithms show different superiority characteristics in different application ranges. However, compared with other optimization algorithms, the main advantage of the QPSO algorithm consists of fewer parameters to control and faster global search ability. Therefore, QPSO was introduced to select the optimal combination parameters of SVM in this study.

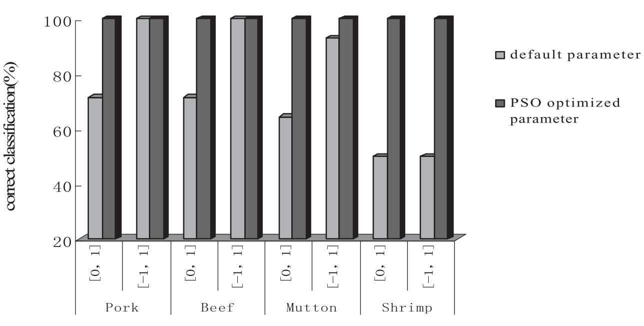

FIGURE 6. *Comparison diagram of classification under default and optimal parameters.*

In this article, TVB-N content, total bacterial count, pH value, and sensory scores of meat samples as input of a hybrid model based on SVM and QPSO yielded freshness classification results that were more comprehensive and accurate. The reason is that SVM performed structural risk minimization rather than minimization of the training errors, which improves the generalization performance compared to the regression model. Moreover, QPSO was used to determine suitable parameters to identify meat freshness, which avoided overfitting or underfitting of the SVM model. The empirical results demonstrated that the proposed model offered a valid alternative for application in a meat freshness identification system.

ACKNOWLEDGMENTS

This work has been financially supported by the National Natural Science Foundation of China (Grant no. 31101348 and 31000780) and the Open Foundation of the State Key Laboratory of Dairy Biotechnology.

REFERENCES

1. Akay, M. F. 2009. Support vector machines combined with feature selection for breast cancer diagnosis. *Expert Syst. Appl.* 36:3240–3247.
2. Arvanitoyannis, I., and M. Houwelingen-Koukaliaroglou. 2003. Implementation of chemometrics for quality control and authentication of meat and meat products. *Crit. Rev. Food Sci. Nutr.* 43:173–218.
3. Banks, A., J. Vincent, and C. Anyakoha. 2007. A review of particle swarm optimization. Part I. Background and development. *Nat. Comput.* 6:467–484.
4. Banks, A., J. Vincent, and C. Anyakoha. 2008. A review of particle swarm optimization. Part II. Hybridization, combinatorial, multi-criteria and constrained optimization, and indicative applications. *Nat. Comput.* 7:109–124.

5. Carmack, C. F., C. L. Kastner, M. E. Dikeman, J. R. Schwenke, and C. M. Garcia Zepeda. 1995. Sensory evaluation of beef-flavor-intensity, tenderness, and juiciness among major muscles. *Meat Sci.* 39:143–147.
6. Chandaka, S., A. Chatterjee, and S. Munshi. 2009. Cross-correlation aided support vector machine classifier for classification of EEG signals. *Expert Syst. Appl.* 36:1329–1336.
7. Clerc, M., and J. Kennedy. 2002. The particle swarm-explosion, stability, and convergence in a multidimensional complex space. *IEEE Trans. Evolut. Comput.* 6:58–73.
8. Elliott, R. P. 1947. Evaluation of surface pH as a freshness index for fish fillets. *J. Food Sci.* 12:87–98.
9. Elmasry, G., M. Kamruzzaman, D. W. Sun, and P. Allen. 2012. Principles and applications of hyper spectral imaging in quality evaluation of agro-food products: a review. *Crit. Rev. Food Sci. Nutr.* 52:999–1023.
10. Funazaki, N., A. Hemmi, S. Ito, Y. Asano, Y. Yano, N. Miura, and N. Yamazoe. 1995. Application of semiconductor gas sensor to quality control of meat freshness in food industry. *Sensor. Actuat. B-Chem.* 24–25:797–800.
11. Guo, P. Y., S. H. Qu, Y. Chen, and Y. Fu. 2006. Study on intellectual detection techniques to freshness of pork. *Trans. Chin. Soc. Agric. Machinery* 37:78–81.
12. Hill, B., R. Jones, and W. Robertson. 2000. Neural network modeling of carcass measurements to predict beef tenderness. *Can. J. Anim. Sci.* 80:311–318.
13. Hsu, C. W., and C. J. Lin. 2002. A comparison of methods for multiclass support vector machines. *IEEE Trans. Neural Netw.* 13: 415–425.
14. Kennedy, J., and R. C. Eberhart. 2001. Swarm intelligence. Academic Press, Waltham, MA.
15. Lawrie, R. A., and D. A. Ledward (ed.). 2006. Lawrie's meat science. Woodhead Publishing Ltd., Cambridge, England.
16. Li, B. 2007. Examination of raw pork's fresh degree and appraisal of raw pork's storage quality. *J. Shangluo Univ.* 21:57–59.
17. Li, J., J. Tan, F. Martz, and H. Heyann. 1999. Image texture features as indicators of beef tenderness. *Meat Sci.* 53:17–22.
18. Li, W. X., M. Zhang, and Y. Han-qing. 2006. Study on hypobaric storage of green asparagus. *J. Food Eng.* 73:225–230.
19. Liu, J., W. Xu, and J. Sun. 2005. Quantum-behaved particle swarm optimization with mutation operator, p. 237–240. Proceedings of the 17th IEEE International Conference on Tools with Artificial Intelligence. IEEE Computer Society, Washington, DC.
20. McMillin, K. W. 2008. Where is MAP going? A review and future potential of modified atmosphere packaging for meat. *Meat Sci.* 80: 43–65.
21. Ministry of Health of the People's Republic of China. 1988. National Standards of the People's Republic of China GB/T 9695.5-88 (25 February 1988) on the meat and meat products—method for measurement of pH. Ministry of Health of the People's Republic of China, Beijing.
22. Ministry of Health of the People's Republic of China. 2003. National Standards of the People's Republic of China GB/T 5009.44-2003 (11 August 2003) on the method for analysis of hygienic standard of meat and meat products. Ministry of Health of the People's Republic of China, Beijing.
23. Ministry of Health of the People's Republic of China. 2005. National Standards of the People's Republic of China GB 2707-2005 (25 January 2005) on the hygienic standard for fresh (frozen) meat of livestock. Ministry of Health of the People's Republic of China, Beijing.
24. Ministry of Health of the People's Republic of China. 2005. National Standards of the People's Republic of China GB 2733-2005 (25 January 2005) on the hygienic standard for fresh and frozen marine products of animal origin. Ministry of Health of the People's Republic of China, Beijing.
25. Ministry of Health of the People's Republic of China. 2010. National Food Safety Standard of the People's Republic of China GB 4789.2-2010 (26 March 2010) on the food microbiological examination: aerobic plate count. Ministry of Health of the People's Republic of China, Beijing.
26. Ocaño-Higuera, V. M., A. N. Maeda-Martínez, E. Marquez-Ríos, D. F. Canizales-Rodriguez, F. J. Castillo-Yáñez, E. Ruíz-Bustos, A. Z. Graciano-Verdugo, and M. Plascencia-Jatomea. 2011. Freshness assessment of ray fish stored in ice by biochemical, chemical and physical methods. *Food Chem.* 125:49–54.
27. Oury, M. P., B. Picard, M. Briand, J. P. Blanquet, and R. Dumont. 2009. Interrelationships between meat quality traits, texture measurements and physicochemical characteristics of M. *rectus abdominis* from Charolais heifers. *Meat Sci.* 83:293–301.
28. Sun, J., W. Xu, and B. Feng. 2004. A global search strategy of quantum-behaved particle swarm optimization, p. 111–116. 2004 IEEE Conference on Cybernetics and Intelligent Systems, Singapore, vol. 1. doi:10.1109/ICCIS.2004.1460396.
29. Vapnik, V. 1998. Statistical learning theory. Wiley, New York.
30. Vinci, G., and M. L. Antonelli. 2002. Biogenic amines: quality index of freshness in red and white meat. *Food Control* 13:519–524.
31. Yano, Y., M. Numata, H. Hachiya, S. Ito, T. Masadome, S. Ohkubo, Y. Asano, and T. Imato. 2001. Application of a microbial sensor to the quality control of meat freshness. *Talanta* 54:255–262.
32. Zhou, G. H., X. L. Xu, and Y. Liu. 2010. Preservation technologies for fresh meat. *Meat Sci.* 86:119–128.