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Origin Detection of *Illicium Verum* Hook. f. Based on Sensor Array Optimization

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Abstract: To improve the identification ability of electronic nosetostar anise from different areas, this study uses sensor array optimization, Particle Swarm Optimization (PSO), and Support Vector Machine (SVM) to effectively improve the discrimination and prediction ability of electronic nose. Firstly, the initial sensor arrays are selected according to the aroma components of star anise. Based on extracting sensor eigenvalues to form the initial feature matrix, the final sensor arrays are selected by combining variable correlation analysis and coefficient of variation analysis (RSD). Linear Discriminant Analysis (LDA) is applied to the sensor array before and after optimization to increase the group spacing of star anise from different producing areas. Particle swarm Support Vector Machine (PSO-SVM) and Genetic Support Vector Machine (GA-SVM) are used to distinguish the producing areas of star anise samples. The accuracy of the PSO-SVM training set is 99.16%; that of the test set is 93.33%; that of the GA-SVM training set is 99.16% and the accuracy of the test set is 90%. The results show that the PSO-SVM model has high precision and convergence accuracy and it is more feasible to distinguish the origin of star anises.

Keywords: Electronic Nose, Sensor Array Optimization, Particle Swarm Optimization (PSO), Origin Differentiation, Linear Discriminant Analysis (LDA)

Introduction

Illicium verum Hook. f., also known as "star anise" and "Chinese anise", is rich in chemical substances with high edible value and medicinal value. In food processing, star anise (branches, leaves, and fruits) is an important edible spice. In medicine, its nature is pungent and warm and belongs to the liver, kidney, spleen, and stomach meridian with functions of warming Yang, dispersing cold, regulating qi, and relieving pain (Adeoye *et al*., 2014). Modern pharmacological studies show that star anise has antibacterial, analgesic, and antiviral pharmacological effects (Lin *et al*., 2008; Koch *et al*., 2008). In recent years, due to the guidance of the government, the octagonal industry has developed rapidly and is gradually moving to industrialization. Due to the wide variety of star anises on the market, such as different shapes, colors, and flavors, it is difficult for ordinary consumers to accurately distinguish them. The current identification of star anise is still based on sensory evaluation. Therefore, it is of great practical significance to study an effective detection method to realize the identification of star anise origin.

The electronic nose is a kind of bionic olfactory system (Song *et al*., 2020), which is mainly composed of a signal processing system, gas sensor array, and pattern recognition system. Currently, electronic nose technology has been widely used in agricultural production (Yang *et al*., 2020; Du *et al*., 2019; Pang *et al*., 2019), biomedicine (Fitzgerald *et al*., 2017; Yu *et al*., 2011), environmental detection (Szulczyński *et al*., 2017; Tian *et al*., 2016; Peng *et al*., 2015) and food detection Yin *et al*., (2019); (Yin and Zhao, 2019); Vera *et al*., (2011). The gas sensor array is a key part of the electronic nose system and its performance determines the detection effect of the electronic nose. Because the initial sensor array is not independent of each other, the response trend of sensors with a strong correlation to the aroma of star anise is close. If one of them is not removed, the signal information will be redundant. To improve the accuracy of recognition, array optimization is needed to obtain a better sensor array than before (Borowik *et al*., 2020).

Taking individual sensors as the object, common sensor array optimization methods use the search (Bertolazzi *et al*.,

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2016; Jeong *et al.*, 2015) ornon-search feature selection strategy to optimize (Fei *et al.*, 2012; Zhou *et al.*, 2013). In this study, according to the composition of star anise aroma, 14 kinds of metal oxide gas sensors were selected. Firstly, the correlation analysis of 14 kinds of gas sensors was carried out and the gas sensor groups with high similarity were obtained under different detection objects. Combined with the analysis of the variation coefficient, the sensor with a large coefficient of variation in the redundant sensor group is eliminated. For the optimized sensor array, PSO was used to optimize the parameters of the Support Vector Machine (SVM) model and the prediction ability of the optimized sensor array was used to verify the effectiveness of the optimization.

Materials and Methods

Material Selection

The samples of star anise used in the experiment are produced in Zunyi of Guizhou, Funing of Yunnan, and white star anise in Guangxi. Before the experiment, these star anises should be sealed and stored at 25°C.

Instruments and Equipment

Data processing software and SPSS26.0 Data analysis software. The experimental electronic nose olfactory system developed by our group is composed of a power supply unit, sensor unit, gas circuit unit, and data acquisition unit. The structure of the electronic nose system is shown in Fig. 1.

There are many complex aroma components in star anise and different aroma components are very similar and slightly different. Therefore, it is necessary to select a gas sensor that is sensitive to the aroma of star anise from a variety of gas sensors. The sensor arrays initially selected in this study are shown in Table 1 (Liu and Liu, 2017).

Test Method

The samples of star anises from Guizhou, Yunnan, and Guangxi were evenly divided into 50 parts and 10 g each. The dynamic headspace sampling method was used in the test. Before the test, the response signal of the electronic nose was cleaned to the reference value with air and the cleaning time was 3 min. The octagonal sample was put into the sampling bottle for data acquisition. After the 40s, the value of the sensor tended to be stable. The average value of the relatively stable state of a sensor at 60-80s was taken as the characteristic value. Each group of the octagonal sample contains 14 data parameters.

Optimization Method of Sensor Array

The 14 selected gas sensors were not independent of each other. The response trend of the sensors with a strong correlation to star anise aroma is close. If one of them is not eliminated, signal redundancy will be caused and the results would be affected. By investigating the correlation characteristics of the sensors in the initial array, the sensor combinations with high similarity under different detection objects can be obtained. Combined with the coefficient of variation, the value with a large coefficient of variation in the combination of redundant sensors is eliminated to complete the elimination of sensors.

Sensor Correlation Analysis

Correlation analysis was first proposed by statistician Karl Pearson, which can be used to describe the correlation between variables. Therefore, only the correlation coefficient between the two gas sensors is needed to calculate. The larger the correlation coefficient of the two sensors, the better the correlation of the two sensors and the closer the obtained signal information. The two sensors can replace each other and one of them can be eliminated. The calculation formula of a correlation coefficient is as follows:

$$|R_{xy}| = \left| \frac{\sum_{I=1}^{N}\left(x_i - \bar{x}\right)\left(y_i - y\right)}{\sqrt{\sum_{I=1}^{N}\left(x_i - \bar{x}\right)^2\left(y_i - y\right)^2}} \right| i = 1, 2, \ldots, N \tag{1}$$

where x and y are two different gas sensors; $\bar{x}$ is the average value of x gas sensor in test acquisition time; $\bar{y}$ is the average value of the gas sensor in test acquisition time; $|R_{xy}|$ is the absolute value of the correlation coefficient of the measurement results of x gas sensor and y gas sensor. x_i is the i^{-th} measurement value of *the x* gas sensor and y_i is the i^{-th} measurement value of the y gas sensor. When the absolute value of the correlation coefficient is greater than 0.8, it means that the two sensors are very similar and can replace each other and one of them needs to be deleted.

In table 2, a list of sensors with a correlation coefficient greater than 0.8 is given. Correlation analysis provides a theoretical basis for eliminating similar sensors. The method of calculating the correlation coefficient cannot completely determine the sensor selection, but also need to combine the coefficient of variation analysis.

Redundant Sensor Elimination Based on Correlation Analysis and Coefficient of Variation

The coefficient of variation is often used to compare the dispersion of two indexes with different population means or dimensions. If the RSD value of a sensor is larger, the test result is more discrete, that is, it is not stable and needs to be eliminated. As shown in Table 2, the sensor detects the variation coefficient of different kinds of star anise aroma.

The calculation formula of coefficient of variation (RSD) is shown in Eq. 2:

$$RSD = \frac{\sqrt{\frac{1}{n}\sum_{1=1}^{n}\left(x_i - \bar{x}\right)^2}}{\bar{x}} \tag{2}$$

where x_i is the i-th test value of gas sensor; $\bar{x}$ is the average value of x gas sensor in the test acquisition time and n is the total number of tests.

In the detection of star anise in Guizhou, the correlation coefficients of TGS832, TGS2620 and MQ7 are greater than 0.8, thus only those with a small coefficient of variation are retained. It can be seen from Table 3 that the coefficient of variation of TGS832 is 8.0, that of MQ 7 is 12.5 and that of TGS 2620 is 46.9. Therefore, redundant sensors MQ7 and TGS2620 are omitted. In the same way, different sensors of star anise aroma can be obtained, Table 4.

Due to the contingency of detection, if the sensor is discarded in two or more groups, it will not be retained. Gas sensor MQ7 was abandoned in the detection of star anise from Guizhou and Guangxi and gas sensor TGS2600 was abandoned in the detection of star anise from Guangxi and Yunnan. The final result was MQ135, MQ5, MQ2, TGS2611, TGS2610, TGS2602, TGS822, TGS2620, TGS832, MQ3, MQ8, and MQ6.

Verify the Prediction Ability of the Optimized Sensor Array

LDA is used to identify and analyze the characteristic matrix of the sensor array before and after optimization and the results are shown in Fig. 2 and 3. Through LDA dimensionality reduction, the initial sensor array of star anise from Guizhou and Guangxi overlaps. However, through the optimization of the initial sensor array, the spacing between groups of star anise from different areas is relatively increased and there is no overlap. The star anise from three different areas can be preliminarily distinguished.

Table 1: Response characteristics of gas sensor

Serial number	Sensor type	Main sensitivity
1	MQ135	Ammonia, sulfide, benzene vapor
2	MQ5	Liquefied gas, natural gas, and more
3	MQ2	Smoke gas sensor
4	TGS2611	Alkanes, methane
5	TGS2610	Alkanes, propane, butanes
6	TGS2602	Benzenes
7	TGS822	Acetone, ethanol, benzene, ethane
8	TGS2620	Organic solvent
9	TGS832	Sensitive to chlorinated hydrocarbon and alcohol
10	MQ3	Ethanol vapor
11	MQ8	Ethyl ether
12	MQ6	2-4 carbon alkanes, olefins
13	TGS2600	Hydrogen sulfide gas
14	MQ7	Carbon monoxide

Table 2: List of gas sensors with strong correlation

		Star anise from Yunnan		Star anise from Guangxi	
Sensor type	$\lvert R_{xy}\rvert$	Sensor model	$\lvert R_{xy}\rvert$	Sensor model	$\lvert R_{xy}\rvert$
TGS822/MQ7	0.81	TGS2600/TGS2610	0.80	MQ2/TGS2600	0.81
TGS2620/TGS832	0.85	TGS822/TGS832	0.83	TGS2611/TGS2610	0.81
TGS2620/MQ7	0.82	TGS822/MQ3	0.84	TGS822/MQ3	0.85
MQ7/TGS832	0.80			MQ3/MQ7	0.85

Table 3: Variable coefficient of different kinds of star anise aroma detected by a sensor

	Guizhou		Yunnan		Guangxi	
Sensor type	RSD	Rank	RSD	Rank	RSD	Rank
MQ135	37.2	2	29.6	1	11.4	6
MQ5	19.8	3	12.4	8	15.2	4
MQ2	12.3	8	16.4	4	10.4	10
TGS2611	7.1	14	7.0	14	7.8	12
TGS2600	13.4	6	16.7	3	10.6	8
TGS2610	9.2	10	11.4	11	6.9	13
TGS2602	17.7	5	14.9	6	10.5	9
TGS822	7.3	13	10.9	13	10.6	8
TGS2620	46.9	1	27.3	2	51.7	1
TGS832	8.0	12	11.6	9	8.7	11
MQ3	8.5	11	11.5	10	10.7	7
MQ7	12.5	7	11.2	12	14.3	5
MQ8	19.7	4	12.5	7	16.5	3
MQ6	12.1	9	15.2	5	18.5	2

Table 4: The gas sensor for different star anise aroma retention

Test object	Gas sensor type				
Star anise from Guizhou	MQ135	MQ5	MQ2	TGS2611	TGS2600	TGS2610
	TGS2602	TGS822	TGS832	MQ3	MQ8	MQ6
Star anise from Yunnan	MQ135	MQ5	MQ2	TGS2611	TGS2620	TGS2610
	TGS2602	TGS822	MQ7	MQ8	MQ6	
Star anise from Guangxi	MQ135	MQ5	MQ2	TGS2620	TGS2610	TGS2602
	TGS822	TGS832	MQ3	MQ8	MQ6	

Table 5: Comparison of two optimization algorithms

Classification model	Optimal value		Average classification accuracy /%	Test set classification accuracy /%
	Penalty factorc	Kernel functiong		
PSO-SVM	39.95	9.7656e-04	99.16	93.33
GA-SVM	6.03	0.014	99.16	90

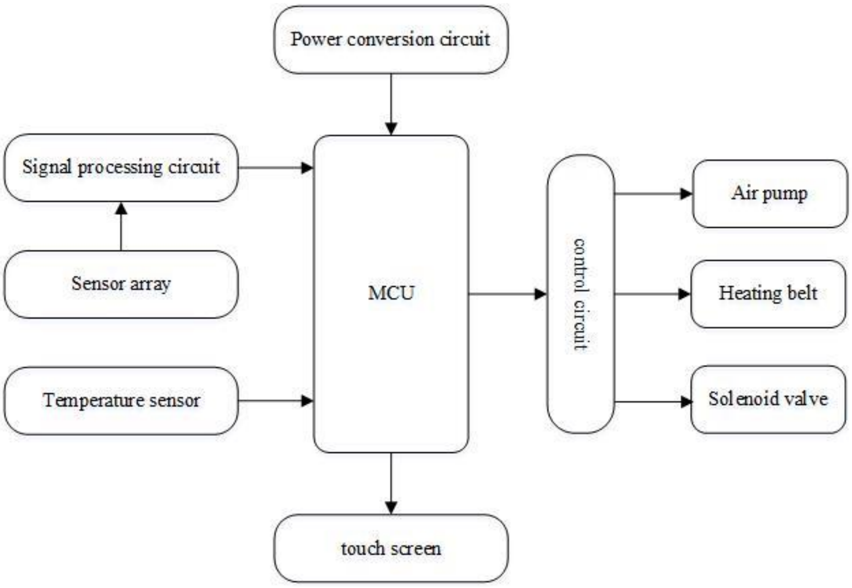

Fig. 1: System hardware structure

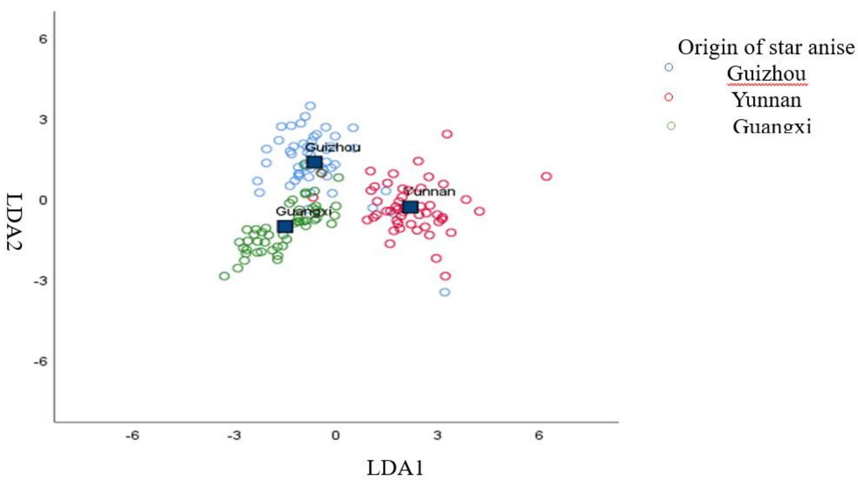

Fig. 2: Raw data

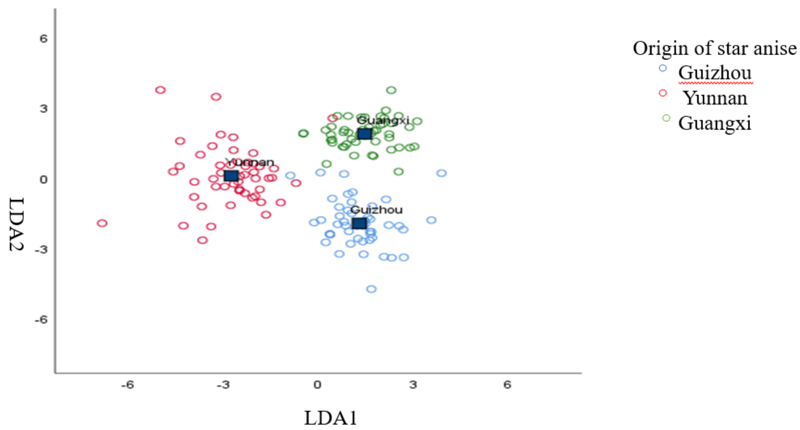

Fig. 3: After optimization analysis

Test Results and Analysis

PSO-SVM Parameter Optimization

Particle Swarm Optimization (PSO) is an intelligent search method based on swarm optimization. Firstly, the initial population is generated. Each particle moves in the feasible space as the solution and the fitness value is determined by the objective function. The speed of particles determines their flight direction and distance. In general, due to the special memory ability of particles, they can follow the optimal particles to search in the space. In each iteration, particles will pass through two paths, one is the local optimal solution Pid and the other is the global optimal solution Pgd.

Suppose the particle swarm searches in an N-dimensional solution space and the population is denoted as:

$$X = \left\{X_1, X_2, ..., X_m\right\} \tag{3}$$

The number of particles is m and the position of each particle is recorded as:

$$X_i = \left\{x_{i1}, x_{i2}, ... x_{in}\right\} \tag{4}$$

$$V_i = \left\{v_{i1}, v_{i2}, ... v_{in}\right\} \tag{5}$$

$$P_i = \left\{p_{i1}, p_{i2}, ... p_{i3}\right\} \tag{6}$$

When the two optimal solutions are found, each particle updates its velocity according to the following formula:

$$v_{id}^{t+1} = wv_{id}^{t} + c_1 r_1 \left(p_{id}^{t} - x_{id}^{t}\right) + c_1 r_2 \left(p_{id}^{t} - x_{id}^{t}\right) \tag{7}$$

$$x_{id}^{t+1} = x_{id}^{t} + v_{id}^{t+1}, i = 1, ..., m \tag{8}$$

where w is the inertia weight and r_1 and r_2 are random numbers between 0 and 1. c_1 is the learning factor and c_2 is the social factor. When the learning factor is greater than the social factor, the particle is easy to falls into local search. When the social factor is greater than the learning factor, it is helpful for the particle to search for the global optimum. Thus, $c_1 = 1.5$ and $c_2 = 1.5$. Ware was taken as the inertia weight to adjust the global and local optimization. There are many ways to choose the weight and the time-varying weight can be dynamically adjusted with iterations. Moreover, to make the particles have optimal searchability in the early stage and good development ability in the later stage of flight, the time-varying weight is selected in [$w_{\max}$, $w_{\min}$]. The maximum number of iterations is iter max. The formula is as follows:

$$w_i = w_{\max} - \frac{w_{\max} - w_{\min}}{iter - \max} \times i \tag{9}$$

To avoid excessive particle velocity, the upper limit $v_{\max}$ and lower limit $v_{\min}$ are set:

$$\begin{cases} v_{\max} = \left(X_{\max} - X_{\min}\right)/2 \\ v_{\min} = -\left(X_{\max} - X_{\min}\right)/2 \end{cases} \tag{10}$$

Because the kernel function selected in this study is a polynomial kernel function, when particle swarm optimization is applied to the parameter optimization of a multi-classification support vector machine, the particles are the penalty parameters c and g. The purpose of PSO parameter adjustment is to maximize the classification accuracy of SVM. Therefore, the maximum classification accuracy after cross-validation is taken as the fitness function of particle swarm optimization. The parameter flow of SVM based on particle swarm optimization is Fig. 4.

Verify the Prediction Ability of the Optimized Sensor Array

To verify the fast convergence speed and high accuracy of the Particle Swarm Optimization Support Vector Machine (PSO-SVM), it is compared with the Genetic Optimization Support Vector Machine (GA-SVM) and the feature matrix of the optimized sensor array is input into PSO-SVM and GA-SVM respectively for training and testing. The process of basic parameter optimization of GA and PSO algorithm is shown in Fig. 5. When the termination algebra and population number are the same, the convergence speed of PSO-SVM is fast.

It can be seen from Table 5 that the average classification accuracy of the two algorithms under cross-validation can reach 99.16%, while the classification accuracy of PSO-SVM is slightly higher than that of GA-SVM on the test set.

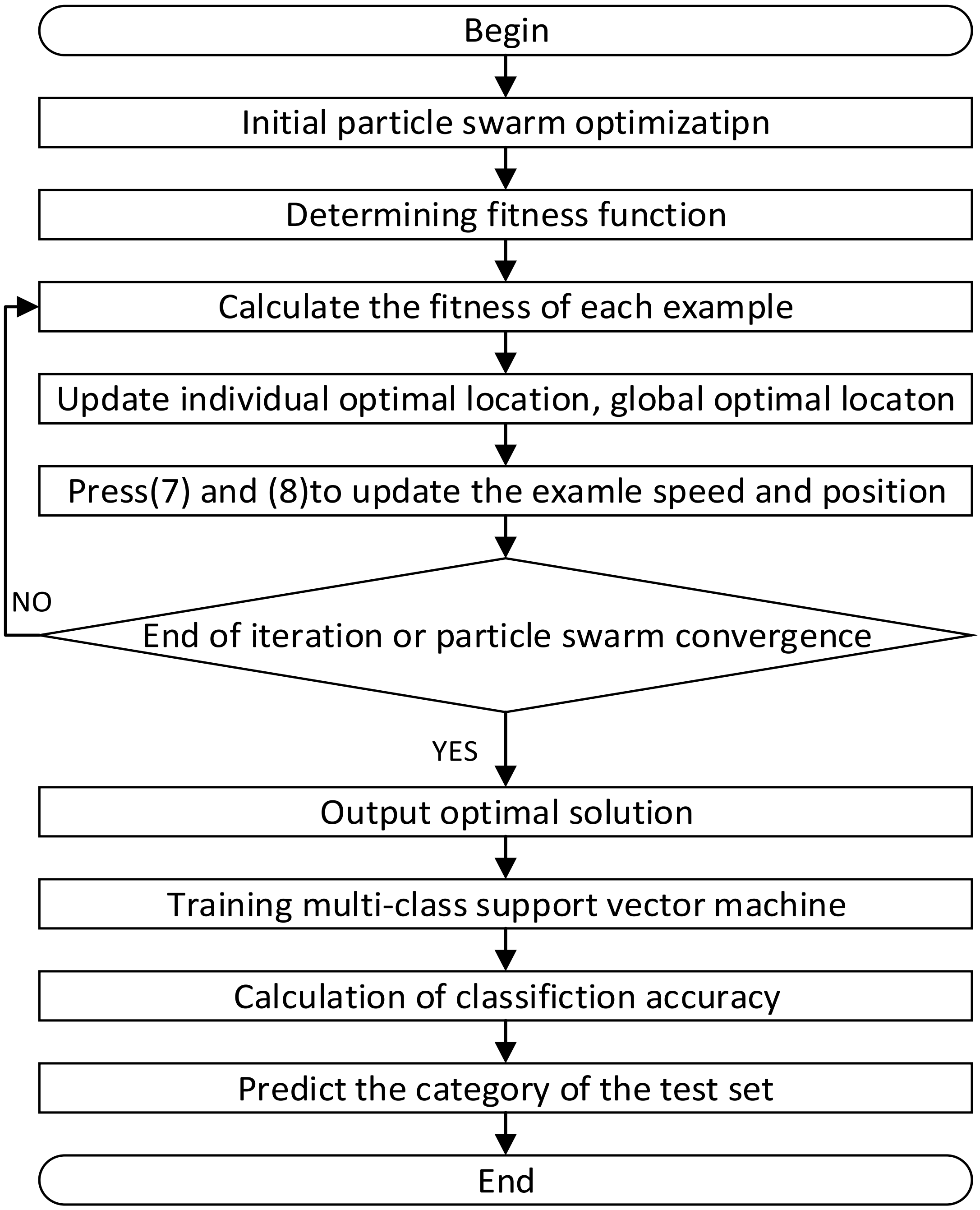

Fig. 4: PSO-SVM flow chart

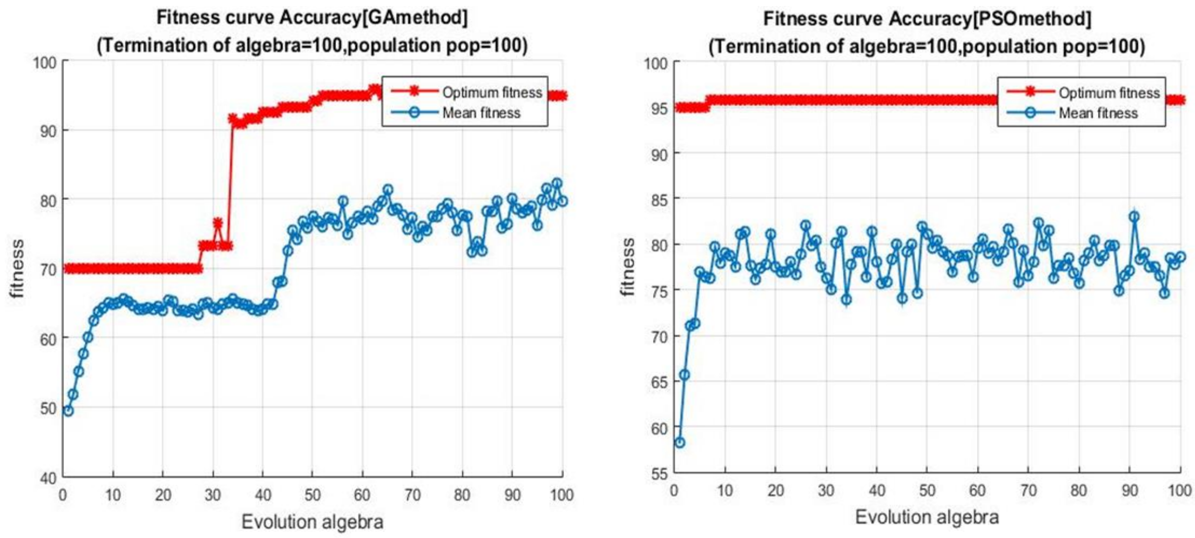

Fig. 5: Iterative evolution process diagram

Conclusion

In this study, the average value of the relatively stable state of the sensor is taken as the object to optimize the sensor array. The self-designed embedded electronic nose is used to detect star anise samples from different areas (Guizhou, Yunnan, Guangxi). The sensor array is optimized based on the correlation and coefficient of variation. After optimization, the support vector machine model is established by feature matrix and the parameters of the support vector machine model are optimized by particle swarm optimization. Experiments show that the effect of sensor array optimization based on correlation analysis and coefficient of variation analysis is optimal. It can be seen from Table 5 that the most effective parameter $c = 39.95$ and the optimal parameter $g = 9.7656e\text{-}04$ are found by the particle swarm optimization algorithm and the accuracy of the test set is 93.3%. It is proved that the proposed optimization method can effectively optimize the sensor array. The results show that the classification accuracy of the support vector machine optimized by PSO is high, which can provide an idea for the development of a specific electronic nose.

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Author's Contributions

Pang Tao: Designed and performed the experiments.
Pang Tao and Lv Lu: Wrote the paper.
Chen Xiaoyan and Ma Jingchen: Participated to collect the materials related to the experiment.
Liu Xiaozheng: Revised the manuscript.

Ethics

The authors declare their responsibility for any ethical issues that may arise after the publication of this manuscript.

Conflict of Interest

The authors declare that they have no competing interests. The corresponding author affirms that all of the authors have read and approved the manuscript.

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