J Wood Sci (2017) 63:37–44
DOI 10.1007/s10086-016-1598-8

ORIGINAL ARTICLE

Prediction of Yueqin acoustic quality based on soundboard vibration performance using support vector machine

Yang Yang[1] · **Yixing Liu**[1] · **Zhenbo Liu**[1] · **Sheldon Q. Shi**[2]

Received: 26 July 2016 / Accepted: 2 November 2016 / Published online: 29 November 2016

Abstract As an important material of making instrument resonant component, paulownia has a significant influence on instrument acoustic quality. Using the method of support vector machine (SVM), an evaluation model for predicting the Yueqin acoustic quality was developed based on the wood vibration performance. Generally, the wood selection in the Yueqin manufacture mainly depends on observance weighting by hands, knocking and listening by an instrument technician. The defect in scientific theory impedes the improvement of Yueqin quality. In this study, nine Yueqin were fabricated. Based on the information of their raw materials and Yueqin acoustic quality evaluation, a prediction model was proposed. In the total 180 groups of data, 60 groups of data were randomly selected for the training, 30 groups of data were randomly selected from the unused data for the verification. The radial basis function is used to establish the Yueqin soundboard wood acoustic quality evaluation model and simulate the prediction. The results revealed that the prediction of Yueqin acoustic quality could be achieved based on the soundboard wood vibration performance using the MATLAB simulation. The classification accuracy was 90.00%, indicating that the predicted values were highly consistent with the experimental values. The models are able to be used to precisely predict the Yueqin acoustic quality based on the vibration performance of soundboards.

Keywords Musical instrument quality · Vibration performance · SVM · Kernel function

✉ Zhenbo Liu
zhenboliulinda@gmail.com

1 Key Laboratory of Bio-based Material Science and Technology of National Ministry of Education, Northeast Forestry University, 26 Hexing Rd, Harbin 150040, Heilongjiang, China

2 Department of Mechanical and Energy Engineering, University of North Texas, Denton, TX, USA

Introduction

Due to the good vibration characteristics, wood has been used as an important resonance instrument material over the millennia [1]. The unique and appropriate spectrum of physical properties of wood has made it to be the musical instrument up to now [2, 3]. As a result of the excessive consumption of wood, the cost of the musical instrument increases rapidly. There is a need to look for alternative materials to make traditional musical instrument. Recently, as a wood substitute, some wood-based composites were developed for a violin top plate [1]. However, the performance of the new materials is relatively uncertain. It is therefore desired to develop a model for predicting musical instrument acoustic quality based on soundboard vibration performance of raw materials.

The vibration characteristic of wood plays an important role in affecting the acoustic performance of musical instrument. To demonstrate that wood is ideally suitable for the manufacture of idiophones (xylophone bars and chimes), aerophones (flutes and organs), and chordophones (violins and zithers), Wegst [3] plotted material property charts showing acoustic properties, such as sound velocity, characteristic impedance, sound radiation coefficient and loss coefficient against one another. A new scheme for classifying the woods used in stringed instruments was developed by Yoshikawa [4], which used two regression lines to clearly discriminate the soundboard wood from frame-board wood that were traditionally used for string instruments.

By investigating the vibration characteristic of wood as a soundboard, Norimoto et al. [5], Matsunaga et al. [6] and Kubojima et al. [7–9] found that the wood acoustic vibration characteristics were significantly affected by performance parameters, such as the dynamic elastic modulus E/ρ, elastic modulus and shear modulus ratio E/G, acoustic radiation damping coefficient R, and acoustic impedance ω. Violins were ranked into different grades from the view of acoustic adaptability, esthetic suitability and comprehensive evaluation using a subjective appraisal method by Buksnowitz [10]. In addition, the indexes of material property, including sound velocity, sound damping, resonance frequency, dynamic elastic modulus, rigidity, density, ring width, variable coefficient of tree-ring width, ratio of summer wood, fiber length, dimensional stability, and analyzed the material performance were also measured using multivariate linear regression method. The main acoustic properties of vene wood were determined using a test method of free–free flexural vibration (BING device) by Traore et al. [11].

Inspired from the statistical learning theory, as a powerful classifier, support vector machines (SVMs) have drawn increasing interest lately for pattern classification [12]. One of the attractions of SVM classifier is that it has a solid mathematical foundation using the statistical learning theory. Andersson et al. [13] addressed the issue of automatic wood defect classification and propose a tree structure SVM to classify four types of wood knots using images captured from wood boards. They then put forward the issue of automatic wood defect classification and proposed a tree structure SVM to classify four types of wood knots using images captured from those boards. Using SVM, Hittawe et al. [14] proposed a method for detecting wood defects such as cracks and knots. Turhan et al. [15] utilized SVM for the first time as a predictive method for differentiating species of Salix wood through the biometric analysis of their anatomy using the wood samples taken from basal disks of three species. Zhu et al. [16] developed a method for quantifiably classifying the density of Chinese Fir samples based on the visible/near-infrared (vis–NIR) spectrometry and least squares support vector machine.

Furthermore, SVM is widely used in many other fields, such as geographic information system, and picture processing, which has advantages of solving small sample, nonlinearity and high-dimensional pattern recognition problems [17, 18]. In this study, Kernel function, i.e. radial basis function, was used to map the nonlinear problem in input space to the high-dimension characteristic space. Being built the linear function in high-dimensional space, Yueqin soundboard wood acoustic quality evaluation model is developed. As a result, the Yueqin soundboard wood property can be precisely predicted. This study also discusses methods of selecting Yueqin materials and provides a scientific approach for forecasting the Yueqin soundboard property.

Materials and methods

Materials and data collection

Yueqin (Fig. 1) made from *Paulownia tomentosa* foliage wood was used in this study. Provided by the Tianjin 1st National Musical Instrument Factory, the wood boards were air-dried to a moisture content of below 16%. The specification and dimension of the soundboard wood are shown in Table 1. The dual channel fast Fourier transform analyzer, CF-5220Z, made by Onosokki in Japan was used in the experiment. The sound meter (TES-1350A) and acceleration sensor were used in the test as well. The indexes of dual channel fast Fourier transform analyzer CF-5220Z are listed in Table 2. According to the requirements of the instrument factory, the initial wood material was cut into 36 pieces for making nine Yueqin soundboards.

A flexural vibration test was used to determine the wood acoustic vibration properties in this study. The specimen with longitudinal direction was supported with two foam supports at both ends. The high sensitivity, wide-band, and low-noise microphone was placed at one end of the specimen. With a shaft, a rotating blade strokes the specimen at the other end of the specimen. The sound signals were collected by the microphone, and then amplified, filtered and analyzed using a fast Fourier transform (FFT) analyzer to obtain resonance frequencies. Using the obtained resonance frequencies, the dynamic elastic modulus E/ρ, acoustic radiation damping coefficient R, elastic modulus and shear modulus ratio E/G, acoustic impedance ω were calculated. As a result, the dynamic elastic modulus of the wood E (GPa) was estimated using Eq. (1). The main parameters of wood acoustic vibration property are listed in Table 3.

The dynamic elastic modulus E (GPa) was obtained as Eq. (1)

$$E = \frac{48\pi^2 L^4 \rho f^2}{\beta_n^4 h^2}, \qquad (1)$$

where L is the musical instrument sound board length (m), ρ is the sound board density (kg m^{-3}), f is the sound board resonance frequency (Hz), β_n is the relative constant of wood boundary conditions, h is the sound board thickness (cm).

The acoustic impedance ω is expressed mathematically as Eq. (2)

Fig. 1 The Yueqins for the tests

Table 1 Parameters of soundboard wood

Name	Specie	Amount (pieces)	Length (longitudinal) (cm)	Width (tangential) (cm)	Thickness (radial) (cm)	Density (g cm^{-3})	Annual rings
Yueqin	Paulownia	36	36.42–39.47	16.41–19.49	0.95 ± 0.02	0.24–0.29	7.52–12.52

Table 2 CF-5220Z Dual channel FFT (fast Fourier transform) analyzer technical indexes

Index	Parameter
Operation frequency	10 mHz–100 kHz
Microphone frequency	20 Hz–20 kHz
Sampling frequency	2.56 times of measurement range
Sampling node	64–4096 (commonly used as 2048)
Frequency distinguish ability	25, 50, 100, 200, 400, 800, 1600 lpi
Microphone sensibility	−29 dB ± 3 dB (0 dB = 1v/pa)

Table 3 Main parameters of wood acoustic vibration property for Yueqin

	Sample size	E/ρ	E/G	R	$W/10^6$
Average	180	22.75	268.47	18.83	1.21
Standard deviation	180	2.38	55.82	1.09	0.12

E/ρ the dynamic elastic modulus, *R* acoustic radiation damping coefficient, *E/G* elastic modulus and shear modulus ratio, ω acoustic impedance

$$\omega = \rho \upsilon = \sqrt{\rho E}, \tag{2}$$

$$R = \frac{v}{\rho} = \sqrt{\frac{E}{\rho^3}}, \tag{3}$$

where ρ is the density of the sample wood (kg m^{-3}), υ is the surface wave velocity (longitudinal direction) (m/s), E is the dynamic elastic modulus of the wood (GPa).

During the experiments, 36 soundboards were used for the testing with five times determinations for each board. Therefore, a total of 180 groups of data were collected. The acoustic quality (sound loudness, dynamic range, sound length and tone, etc.) of the instrument products was objectively evaluated by dividing them into three grades (grades 1, 2 or 3) by the experienced experts in music and Yueqin performers. In each grade, 20 groups of data were randomly selected for the training, counting to a total of 60 groups (3 grades × 20 groups for each grade) for the training. After the training, there were 120 groups of unused data (180 groups–60 groups) left for the verification. The same as the training process, ten groups of data were randomly selected from the unused data in each grade for the verification. Then we used the 36 boards to make nine Yueqins (two boards for face and two for back for each Yueqin).

Using MATLAB R2010a as the operating environment, the Lenovo ThinkPad S230u Twist (Intel corei7 3517U, CPU basic frequency of 1.9 GHz, internal storage of 8G) was used as a simulation tool. The dynamic elastic modulus E/ρ, elastic modulus and shear modulus ratio E/G, acoustic radiation damping coefficient R, acoustic impedance ω were selected as the inputs, while the three grades of musical instrument were the outputs.

SVM basic design concept

When $f(x)$ is a linear function, it is expressed as

$$f(x) = \langle w, x \rangle + b = \sum_{i=1}^{n} w_i x_i + b, \quad (4)$$

where b is set over, w is callable weight vector quantity. The decision rule is that $\mathrm{sgn}(0) = 1$. $f(x)$ is hyperplane. Hyperplane L from Fig. 2 is defined by $f(x) = 0$, where L divides input space X into two parts.

Training sample is $\{x_i, y_i\}_{i=1}^{l}$, where x_i is the ith sample, $y_i \in \{-1, 1\}$. Hyperplane L in the linear classifier $\langle w, x \rangle + b = 0$, which satisfies

$$\langle w, x \rangle + b \geq 1 \quad y_i = 1, \quad (5)$$

$$\langle w, x \rangle + b \leq -1 \quad y_i = -1. \quad (6)$$

Hyperplane L_1 is defined as $L_1 : \langle w, x \rangle + b = 1$, $y_i = 1$, x_1 is a note on hyperplane L_1; hyperplane L_2 is defined as $L_2 : \langle w, x \rangle + b = -1$, $y_i = -1$, x_2 is a note on hyperplane $L_2 \cdot x_1$ and x_2 satisfy

$$\langle w, x_1 \rangle + b_1 = 1, \quad (7)$$

$$\langle w, x_2 \rangle + b_2 = -1. \quad (8)$$

The distance between hyperplane L_1 and L_2 is d_{dis}, which can be expressed as

$$d_{\mathrm{dis}} = \frac{w}{||w||}(x_1 - x_2). \quad (9)$$

The optimal hyperplane can be formulated into the following expression,

$$\min_{w} \frac{||w||^2}{2}, \quad (10)$$

$$\text{s.t.} \quad y_i(\langle w, x \rangle + b) \geq 1 \quad \forall i = 1, 2, \ldots, N. \quad (11)$$

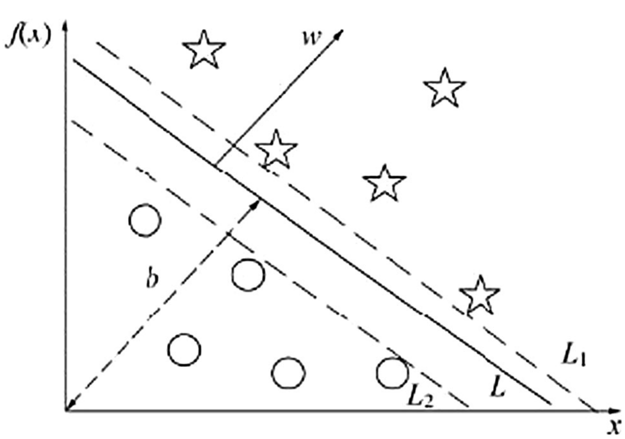


Fig. 2 Classification hyper plane on two-dimensional training set (*circles* represent the first class of sample data predicted by the analysis, *stars* represent the second class of sample data predicted by the analysis)

Lagrange multiplier method is used to solve the stated quadratic programming problem, the Lagrange function is,

$$J(w, b, a) = \frac{1}{2} w^T w - \sum_{i=1}^{l} a_i [y_i(\langle w, x_i \rangle + b) - 1], \quad (12)$$

where a_i is Lagrange multiplier.

Lagrange function is employed to calculate the minimum value of w, b and the maximum value of a_i. w_0, b_0, a_0 on saddle point of the function satisfy

$$\sum_{i=1}^{l} a_{0i} y_i = 0, \; a_{0i} \geq 0 \quad i = 1, 2, \ldots, l, \quad (13)$$

$$w_0 = \sum_{i=1}^{l} y_i a_{0i} x_i, \; a_{0i} \geq 0 \quad i = 1, 2, \ldots, l. \quad (14)$$

Substitute (13) into (12), and use Eq. (14) to solve dual problem of the original optimization problem. The dual problem is

$$\max_{a} -\frac{1}{2} \sum_{i=1}^{l} \sum_{j=1}^{l} y_i y_j a_i a_j \langle x_i, x_j \rangle + \sum_{j=1}^{l} a_j, \quad (15)$$

$$\sum_{i=1}^{l} y_i a_i = 0, \quad (16)$$

$$a_i \geq 0 \quad i = 1, 2, \ldots, l. \quad (17)$$

Classification rule based on optimal hyperplane is

$$f(x) = \mathrm{sgn}\left(\sum_{i=1}^{l} y_i a_i^* \langle x_i, x \rangle - b_0 \right). \quad (18)$$

Results and discussion

SVM model establishment

Index selection and establishment of the relevant standard were based on the important part of instrument product grade prediction. To appraise the predicted grade of Yueqin, two professors from Chinese Conservatory of Music who are practiced instrument lists of national musical instrument were invited to carry out the evaluation. Based on the Chinese national standard GB/T16463-1996 [19] (broadcasting program sound quality subjective evaluation method and technical index), subjective assessment and grade standard adopted by Chinese national quality and CSBTS (Chinese State Bureau of Quality Technology Supervision) and statistical approach in Chinese national standard GB/T16463-1996 [19], the nine Yueqin products were ranked into 1–9 grades, in which grades 1–3 were the first grade, grades 4–6 were the second grade, and grades 7–9 were the third grade. According to the most significant factors influencing the acoustic quality of Yueqin, the dynamic modulus of elasticity E/ρ, elasticity modulus and shear modulus ratio E/G, acoustic damping coefficient R, and acoustic impedance ω, four evaluation indexes and three grades were used to evaluate the Yueqin soundboard wood vibration performance.

Sample establishment and training

SVM uses nonlinear transformation defined by inner product function to transform input space into higher space. The classification function of SVM is similar to neural network, taking linear combination of intermediate node as input; every support vector gets the corresponding intermediate node as shown in Fig. 3. Based on the chosen kernel function, the corresponding SVM model is obtained and formula (18) is employed to classify the samples. The diagrams of the Yueqin soundboard wood forecasting grade classification training and classification training error are shown in Figs. 4 and 5.

The main structure of Yueqin soundboard wood vibration performance predicting model is consisted of dynamic modulus of elasticity E/ρ, elasticity modulus and shear modulus ratio E/G, acoustic damping coefficient R, and acoustic impedance ω.

Forecasting grade assessment and verification analysis

Using Lisbsvm toolbox, the parameters were set to: penalty factor $C = 100$, radical basic function parameter $r = 15$, insensitive parameter $e = 0.02$. The 180-group experimental data were calculated by the svmtrain tool. The 20-group data of each grade were used to train the

Fig. 3 SVM designing principle

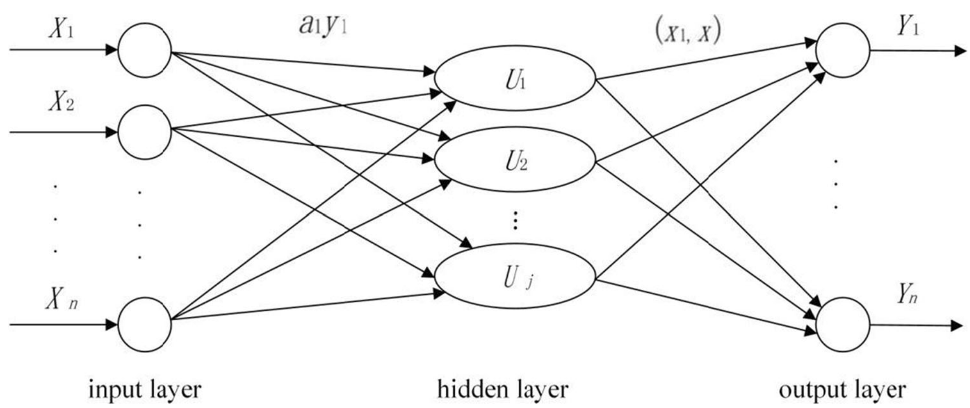
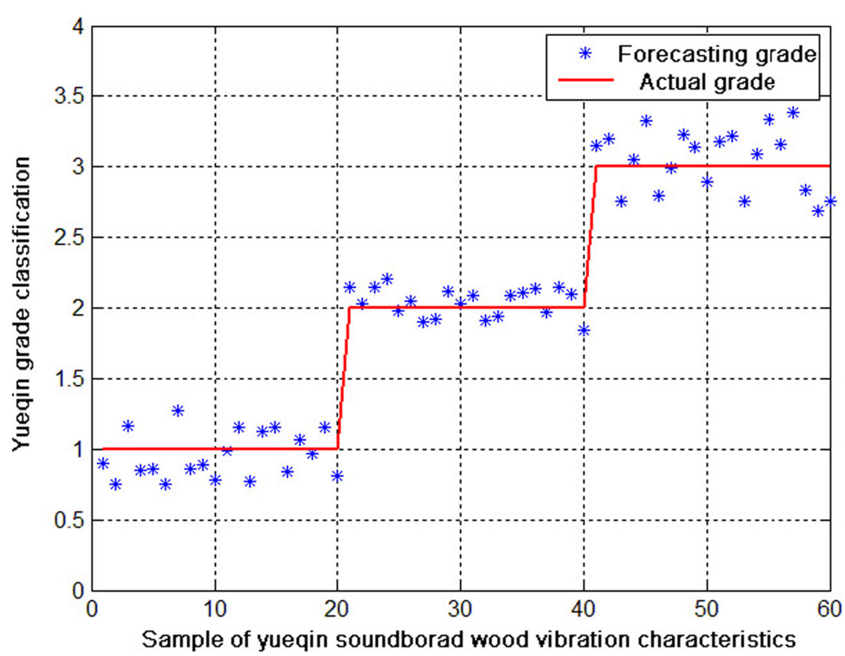


Fig. 4 Diagram of Yueqin soundboard wood forecasting grade classification training



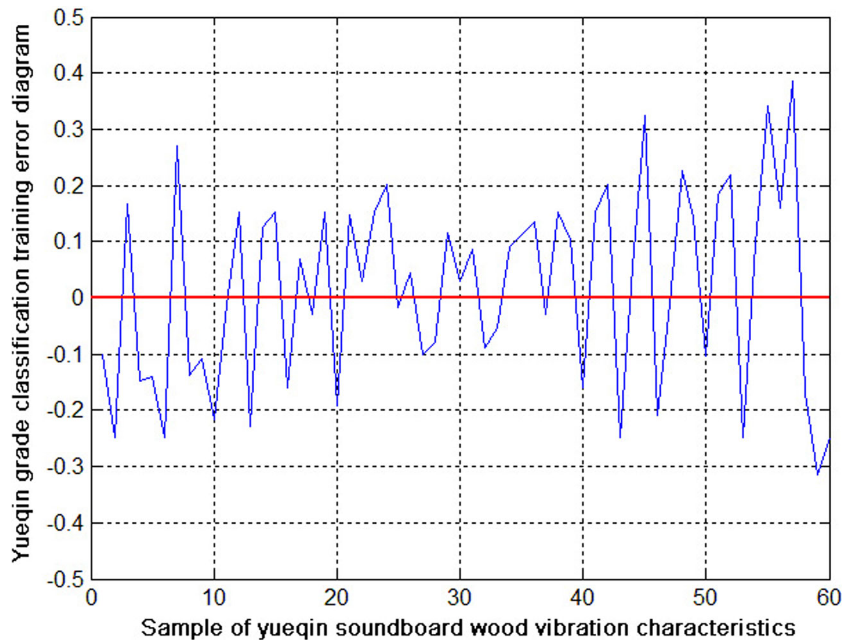


Fig. 5 Diagram of Yueqin soundboard wood forecasting grade classification training error

Table 4 Yueqin classification forecast actual grade of incorrect forecasting sample, forecasting grade and error

Incorrect sample number	25	28	29
Forecasting grade	3.3345	3.3263	3.4426
Actual grade	3	3	3
Error	−0.3345	−0.3263	−0.4426

model, while the 10-group data of each grade from the rest 120 groups were used to verify the model (90 groups were selected from the total 180 groups, 60 groups were used to train model, 30 groups were used to verify the classification).

Table 4 presents the number of incorrect samples by the comparisons of predicted grade and actual grade, which is classified as false when the error is greater than ±0.3. Figure 4 shows the diagram of grade classification training predicted by Yueqin soundboards, which indicates four samples from the 60 Yueqin soundboard wood samples are false, counting the accuracy of grade classification training predicted by Yueqin soundboard wood is 93.33%. Figure 5 illustrates the diagram of grade

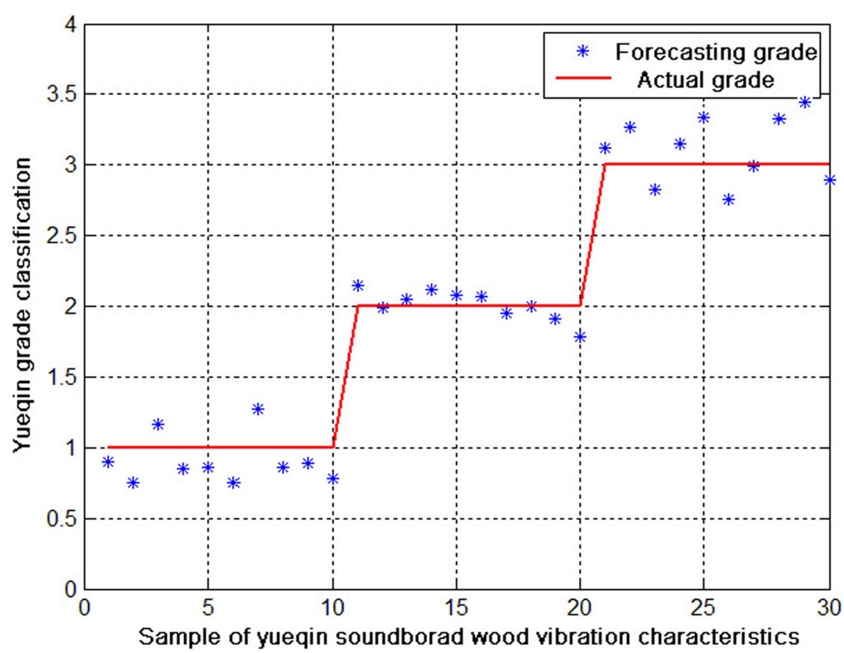


Fig. 6 Diagram of Yueqin soundboard wood forecasting grade classification verification

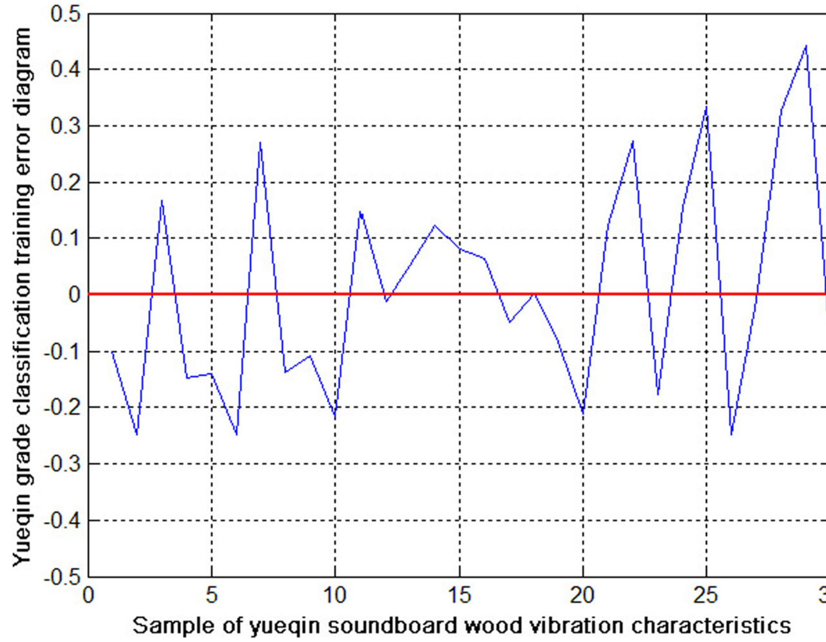


Fig. 7 Diagram of Yueqin soundboard wood forecasting grade classification verification error

classification training error predicted by Yueqin soundboard wood, which shows that the errors of Yueqin soundboard wood sample fluctuate between ±0.5 and most errors are between ±0.2. It is confirmed that the Yueqin grade classification training error is tolerant and the classification is precise. Figure 6 presents the diagram of grade classification verification predicted by Yueqin soundboard wood, which shows three samples from the 60 Yueqin soundboard wood samples are false and the accuracy of grade classification verification is 90.00%. Figure 7 illustrates the diagram of grade classification verification error predicted by Yueqin soundboard wood, which shows errors of Yueqin soundboard wood sample fluctuate between ±0.5 and most errors are between ±0.2. It is indicated that the Yueqin grade classification verification error is tolerant. The classification result demonstrates the strong generalization ability of the model, which can be used to predict the grade of Yueqin.

In Figs. 4, 5, 6 and 7, the simulation results show that the grade classification predicted by Yueqin soundboard wood matches the actual values well, which proves that it is feasible and reliable to use SVM algorithm predicting Yueqin quality.

Conclusions

This study tested the vibration performance of the Yueqin soundboard and extracted the main indexes of wood acoustic property. Using SVM, based on the soundboard selection, the forecasting model of the Yueqin soundboard acoustic quality was developed. It was implemented a partial prediction of Yueqin acoustic quality and conducted the classification of Yueqin products quality before the manufacture process. Classification training and forecasting precision were 93.33% and 90.00%, respectively, which confirmed that the forecasting values were comparable with the actual values. The developed model can be used as a practical guideline for estimating instrument quality.

Acknowledgements This work was financially supported by the Natural Science Foundation of China (NSFC) through grant number 30972300, the Fundamental Research Funds for the Central Universities 2572014CB02 and supported by China Scholarship Council.

References

1. Damodaran A, Lessard L, Babu AS (2015) An overview of fibre-reinforced composites for musical instrument soundboards. Acoust Aust 43:117–122
2. Fletcher NH, Rossing TD (1998) Classical continuum physics. The physics of musical instruments. Springer, New York, p 756
3. Wegst UGK (2006) Wood for sound. Am J Bot 93:1439–1448
4. Yoshikawa S (2007) Acoustical classification of woods for string instruments. Acoust Soc Am 122:573
5. Norimoto M, Tanaka F, Ohgama T, Ikimune R (1986) Specific dynamic Young's modulus and internal friction of wood in the longitudinal direction (in Japanese). Mokuzai Gakkaishi 22:53–65
6. Matsunaga M, Sugiyama M, Minato K, Norimoto M (1996) Physical and mechanical properties required for violin bow materials. Holzforschung 50:511–517
7. Kubojima Y, Yoshihara H, Ohta M, Okano T (1997) Accuracy of the shear modulus of wood obtained by Timoshenko's theory of bending (in Japanese). Mokuzai Gakkaishi 43:439–443

8. Kubojima Y, Yoshihara H, Ohta M (1997) Effect of annual ring widths on structural and vibrational properties of wood (in Japanese). Mokuzai Gakkaishi 43:634–641
9. Kubojima Y, Okano T, Ohta M (1998) Vibrational properties of sitka spruce heat-treated in nitrogen gas. J Wood Sci 44:73–77
10. Buksnowitz C (2007) Resonance wood [*Piceaabies* (L.) Karst.]—evaluation and prediction of violin makers' quality-grading. J Acoust Soc Am 121:2384–2395
11. Traore B, Brancheriau L, Perre P, Stevanovic T, Diouf P (2010) Acoustic quality of vene wood (*Pterocarpus erinaceus* Poir.) for xylophone instrument manufacture in Mali. Ann For Sci 67:815
12. Cristianini N, Shawe-Taylor J (2000) An introduction to support vector machines and other kernel-based learning methods. Cambridge University Press, Cambridge, p 325
13. Andersson H (2010) Wood defect classification based on image analysis and support vector machines. Wood Sci Technol 44:693–704
14. Hittawe MM, Muddamsetty MS, Sidibe D, Meriaudeau F (2015) Multiple features extraction for timber defects detection and classification using SVM. In: International Conference on Quality Control by Artificial Vision, Quebec City, QC, Canada
15. Turhan K, Serdar B (2013) Support vector machines in wood identification: the case of three Salix species from Turkey. J Agric For 37:249–256
16. Zhu X, Shan Y, Huang A, Zhang Z (2009) Prediction of wood property in Chinese Fir based on visible/near-infrared spectroscopy and least square-support vector machine. Spectrochimica Acta Part A 74:344–348
17. Konstantinidis K, Gasteratos A, Andreadis I (2005) Image retrieval based on fuzzy color histogram processing. Opt Commun 248:375–386
18. Martínez JC, Medina JM (2007) Retrieving images in fuzzy object relational databases using dominant color descriptors. Fuzzy Sets Syst 158:312–324
19. GB/T 16463–1996 (1996) The method of subjective assessment of the sound quality for broadcast programmes and the technical parameters requirements. Chinese national standard, Beijing, p 8