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Sound Quality Prediction of Vehicle Interior Noise During Acceleration Using Least Square Support Vector Machine

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Abstract: Based on Least Square Support Vector Machine (LSSVM) algorithm, a Sound Quality Prediction (SQP) model of vehicle interior noise during acceleration is presented in this study. The objective psychoacoustic parameters and subjective annoyance results are used as the input and output of the model, respectively. With correlation analysis, some psychoacoustic parameters, such as loudness, sharpness, roughness, articulation index and tonality, are selected for the modeling. The estimated values of unknown samples with the LSSVM SQP model are highly correlated with the subjective annoyance values, which has a higher accuracy than that with Multiple Linear Regression (MLR) model. Results show that the proposed LSSVM SQP model has good generalization ability and can be applied to the sound quality prediction of vehicle interior noise during acceleration.

Key words: Vehicle interior noise, acceleration, LSSVM algorithm, sound quality prediction, annoyance

INTRODUCTION

With the development of automobile industry, vehicle noise problem has drawn increasing attention all over the world. Correspondingly, sound quality has become an important index to measure the quality of automotive products. Recently, many studies related to Sound Quality Evaluation (SQE) of vehicle noise have been investigated by researchers all over the world, many achievements are acquired. Gonzalez *et al*. (2003) studied the sound quality of car engine noises with a predictive method based on psychoacoustic parameters (loudness, roughness, tonality and sharpness) and subjective method using a jury test. Chen (2005) investigated sound quality preference of vehicle interior noise under stable condition and built a preference prediction model based on psychoacoustic parameters with MLR method. Loudness and sharpness are found to be the most significant factors that affect the preference response for car interior noise in specific experiment condition and the effect of sharpness is stronger. Liu (2007) studied vehicle interior noise in uniform motion with MLR method and described the sound quality objectively with loudness and sharpness. Shen *et al*. (2010) predicted the sound quality of vehicle interior noise at constant speed with three methods: MLR, back propagation neural network and support vector machine, results show that support vector machine is more accurate. Lee (2008) evaluated sound quality of the booming and rumbling sounds in passenger cars during acceleration objectively by using an artificial neural network. Gao *et al*. (2010) researched vehicle interior noise during accelerating and built a mathematical model of sound quality with loudness and roughness using MLR method. Wang *et al*. (2007) predicted sound quality of vehicle interior noise under unstable condition effectively based on wavelet pre-processing neural network.

Vehicle interior noise signal under stable condition is easy to be measured. It changes little with vehicle speed and it's easy to be evaluated. Relatively speaking, unstable vehicle interior noise is complicated and nonlinear. It keeps changing with the vehicle speed and for this reason, how to evaluate the non-stationary signal subjective so that the evaluation results can reflect perception of candidates accurately is a new problem for acoustic engineers. Meanwhile, traditional SQP methods are linear and cannot process non-stationary signal correctly. This influences the SQE of vehicle and the analyzing and controlling of vehicle interior noise. Therefore, it is significant for modern vehicle noise evaluation, analysis and control to build a model which can estimate the vehicle sound quality under unstable condition efficiently and precisely.

Based on the LSSVM algorithm, a SQP model for vehicle interior noise during acceleration is built in this study. With the model established, human auditory

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perception character for vehicle interior noise can be described quantitatively with the model outputs: Subjective annoyance values. Comparison with multiple linear regression method is made by testing with actual samples which haven't been used for the previous modeling process. By comparing the predicted results with the real results, the SQP model shows excellent forecasting accuracy and good generalization ability.

LSSVM ALGORITHM

Support Vector Machine (SVM) is a kind of machine learning methods proposed based on Vapnik-Chervonenkis (VC) dimension and structural risk minimization principle which are both originated from Statistic Learning Theory (SLT). It has been successfully used to process problems related to regression and pattern recognition (Gunn, 1998; Cristianini and Taylor, 2000).

LSSVM is firstly proposed in 1999 (Suykens and Vandewalle, 1999). It is a kind of algorithm based on SVM which replaces traditional SVM with least square linear systems. It solves pattern recognition problems with quadratic programming method. By constructing loss function, the quadratic optimization of original SVM algorithm is transformed into solving linear equations, which reduce the computational complexity efficiently.

The fundamental principle of LSSVM algorithm for a regression problem is presented as the following. The sample set (x_i, y_i) is generated based on a probability distribution P (x, y) which is an objectively existence. The regression equation is:

$$f(x) = w^T\varphi(x)+b \tag{1}$$

where, i = 1, 2, ..., l, $\in x_i \in R^n$ are the input vectors, $y_i \in R$ are the target values, l is the dimension of the samples, w are the weight vectors, b is the offset, φ (x) is the mapping function that maps the n-dimensional input vector x to a high-dimensional feature space. LSSVM can be described as:

$$\min J(w,\xi) = \frac{1}{2}w^T w + \gamma\frac{1}{2}\sum_{i=1}^{l}\xi_i^2 \qquad \text{s.t.}\quad y_i = w^T\varphi(x_i)+b+\xi_i,\ i=1,...,l \tag{2}$$

where, γ is the regularization parameter, ξ_i are the slack variables.

This equation can be solved with Lagrange multiplier method and the augmented matrix can be acquired:

$$L(w,b,\xi,a) = J(w,\xi_i) - \sum_{i=1}^{l} a_i[w^T\varphi(x_i)+b+\xi_i - y_i] \tag{3}$$

where, $\alpha = (\alpha_i, ..., \alpha_l)^T$ is the Lagrange multipliers.

The regression equation can be expressed as the following after introducing the kernel function K (x_i, x_j) which has satisfied the Mercer conditions to replace the original inner product function $\varphi^T(x_i)\,\varphi(x_j)$:

$$f(x)=\sum_{i=1}^{l}\alpha_i K(x,x_i)+b \tag{4}$$

LSSVM SQP MODEL

Road tests and SQE for samples: The vehicle noise signal during accelerating condition used in this study is acquired by vehicle road tests. The test conditions are carefully constructed referring to the measurement method for vehicle interior noise using GB/T 18697-2002 (2002) standard, which has similar settings for the test environment and conditions as the standard ISO 5128-1980 (1980). With the HMS III digital simulation foreman and SQlib II multichannel data acquisition system, 9 kinds of B-class car are tested by accelerating smoothly from 50-120 k h^{-1}or 90% of the rated speed with 3-gear and top gear, the noise signals of co-pilot position throughout the process are recorded 4 times each gear. The best samples of each car under two kinds of gear are picked out. With appropriate interception, 23 noise signal samples are acquired. Sound quality annoyance is divided into 11 grades (Table 1) with annoyance as evaluation index and the jury test is done with 24 volunteers (18 men and 6 women) who are composed of engineers, experts, technicians and drivers. With the ArtemiS™ software, six psychoacoustic parameters: loudness, sharpness, roughness, fluctuation strength, articulation index, tonality and two sound press level: Linear sound pressure level, A-weighted sound pressure level of 23 samples are calculated (Sun, 2011). A-weighted sound pressure level and sound power are usually used to measure the noise but they are not adequate to characterize the impact of vehicle interior noise. In order to determine the sound quality of a product, subjective annoyance or specific index is needed to be defined and it involves both subjective and objective measurements simultaneously (Nor *et al*., 2008; Bodden, 1997). Investigations about the relation between sound pressure levels and loudness is researched and predicted with a neural network. The sound pressure levels are used as inputs to the network and loudness used as outputs of the network. The results show that the relation has almost the same linearity. It means that the loudness closely related to sound pressure levels (Yildirim and Eski, 2008).

Table 1: Ranks of subjective annoyance

Very terrible	Terrible	Very bad	Bad	Dissatisfied	Acceptable	Satisfied	Well	Good	Very good	Excellent
1	2	3	4	5	6	7	8	9	10	11

Table 2: Results of the subjective and objective evaluation of vehicle interior noise during acceleration

Sample labels	Annoyance	Loudness (sone)	Sharpness (acum)	Roughness (asper)	Fluctuation (vacil)	AI index (%)	Tonality (tu)
1	5.55	17.4	0.99	1.25	0.0248	0.818	0.0818
2	4.36	25.9	1.39	2.30	0.0087	0.535	0.0616
3	6.09	17.5	0.97	1.62	0.0465	0.845	0.1300
…	…	…	…	…	…	…	…
22	6.63	17.6	1.14	1.84	0.0158	0.778	0.0352
23	6.35	19.0	1.21	1.95	0.0128	0.734	0.0339

Table 3: Correlation between subjective evaluation values and psychoacoustic parameters

Subjective evaluation values	Loudness	Sharpness	Roughness	Fluctuation	AI index	Tonality
Correlation coefficients	-0.899**	-0.676**	-0.662**	-0.008	0.769**	-0.466*
Two-tailed test	0.000	0.000	0.001	0.972	0.000	0.025

*Indicates two-tailed test level≤0.05, **Indicates two-tailed test level≤0.01

Table 4: KMO and bartlett's test of sphericity

KMO measure of sampling adequacy		0.695
Bartlett's test of sphericity	Approximation chi-square	159.522
	df	15.000
	Sig.	0.000

According to these investigations, we can conclude that sound pressure levels should be excluded and they are not used for the modeling in this study. The subjective and objective evaluation results used in this study are listed in Table 2.

Correlation analysis: For the sake of improving the correlation between estimated values and original values, software SPSS is included to make pearson correlation analysis for the subjective evaluation values and the psychoacoustic parameters. The correlation coefficients are listed in Table 3. Results show that most of the psychoacoustic parameters are closely related to the subjective evaluation values except fluctuation. Therefore, subjective evaluation values and 5 psychoacoustic parameters: Loudness, sharpness, roughness, AI index, tonality are selected for the modeling process.

Significance test: In order to check whether the subjective evaluation values and 5 psychoacoustic parameters are appropriate for factor analysis, Kaiser-Meyer-Olkin measure of sampling adequacy and Bartlett's test of sphericity for the selected arguments are conducted. As can be seen in Table 4, statistic of Bartlett's test is 159.522 and the corresponding significance test value Sig is 0.000, which has reached the significant level. It means that there is a correlation between the original parameters. Meanwhile, the KMO value is 0.695, according to the KMO measurement standard given by Kaiser, it is unsuited but receivable.

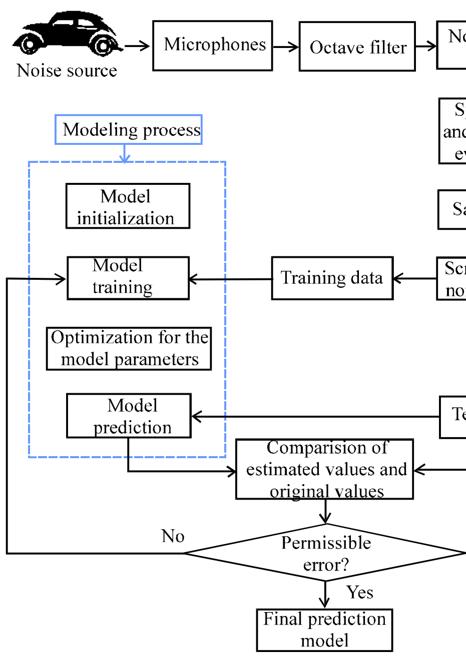

Fig. 1: Construction of LSSVM SQP model

Therefore, the tested parameters can be used for factor analysis and model construction.

Model construction: The LSSVM SQP model is constructed with MATLAB software in this study, the detailed modeling process is represented in Fig. 1. Firstly, noise samples which are obtained by road tests are used for the establishment of vehicle interior noise signal database. Twenty three pairs of interior noise signals are selected as the noise samples.

Subjective and objective test are conducted to acquire sample data for the SQP model. These data are separated into two groups after relative analyzing and normalization processing. Number 1-17 pairs of sample data are used as training data for the construction of the initial SQP model. The rest samples are used as testing data in order to verify the accuracy of the initial model. After optimizing the model parameters and comparing the estimated values and the original values, the final evaluation model is built within permissible error.

Normalization: Before inputting the sample data to the model, normalization process is conducted in advance. Normalization is to compress the data themselves, for the sake of eliminating characteristics of each parameter and avoiding differences between two sample data with a big difference in absolute value. In this study, the sample data are compressed to (0, 1).

Selection of kernel function: Kernel function directly influences the performance of the model. Some commonly used kernel functions are: Linear kernel function, polynomial kernel function and radial basis kernel function, etc.

By comparison, radial basis kernel function (RBF kernel function) which is the most commonly used and has less average relative error is selected for the LSSVM SQP model, as follows:

$$K(x, x_i) = \exp(\| x-x_i \|^2/2\sigma^2) \quad (5)$$

where, σ is a parameter of the kernel function that indicates the square bandwidth.

Model initialization: With a lssvm toolbox under the environment of MATLAB, an initial LSSVM SQP model can be built using the following codes:

Model = Initlssvm (X, Y, gam, sig. 2, kernel)

where, X and Y represent the objective evaluation values and the subjective evaluation values, respectively, gam is the regular parameter, it depends on the balance between minimizing error of the initial model established with the training data and the generalization ability of the model, its primary election is 100, sig 2 is the RBF kernel function parameter σ^2, its primary election is 10, kernel is the kernel function type, here we choose RBF kernel function.

Optimization methods for model parameters: Many optimization methods are now applied to parameters optimization, such as grid search method, 10-fold cross validation, gradient descent algorithm, ant colony algorithm, Particle Swarm Optimization (PSO) algorithm, etc. In this study, a method for SQP model parameters optimization by combining grid search method and 10-fold cross validation is used. First, the ranges of parameters: Gam and sig 2 are set to (1:10:10000) and (1:10:3000) with grid search method respectively. Model accuracy with different combinations of gam and sig 2 are calculated. Second, further subdivisions for the ranges of parameters are conducted to select parameters with higher accuracy. The ranges of gam and sig 2 are set to (100:0.1:200) and (10:0.1:30). Finally, based on the best parameters, 10-fold cross validation is conducted to verify the corresponding model accuracy. The combination of gam and sig 2 with highest cross validation accuracy is selected as the optimum model parameters. The final model parameters are gam: 153.7 and sig 2: 17.2.

RESULTS AND ANALYSIS

With the optimum model parameters, a LSSVM SQP model for vehicle interior noise during acceleration is established. In order to check the feasibility of the model, the training samples are used make prediction analysis with the optimized model.

The objective evaluation parameters of the training samples such as loudness, sharpness, roughness, AI index and tonality are used as the inputs of the model. The outputs of the model are the estimations of subjective annoyance values. Comparison of estimated values and original values with the training samples is shown in Fig. 2. Further analysis shows that the accuracy of the established prediction model is 90.9% and it meets the accuracy requirement. On this basis, the test samples are used for the prediction of subjective evaluation values. Comparison of estimated values and original values with the testing samples is shown in Fig. 3.

As a comparison, a MLR model is built by SPSS and the obtained MLR equation is:

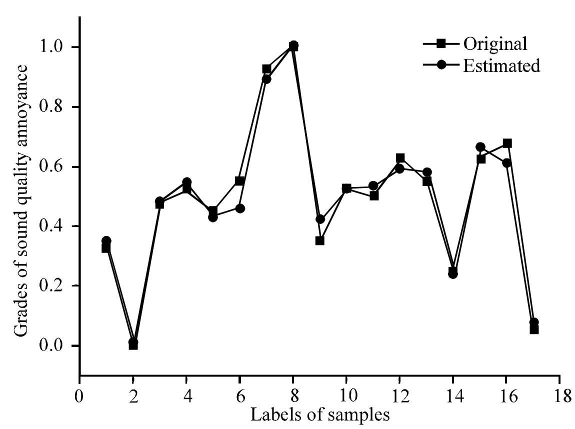

Fig. 2: Comparison of estimated values and original values with the training samples based on LSSVM method

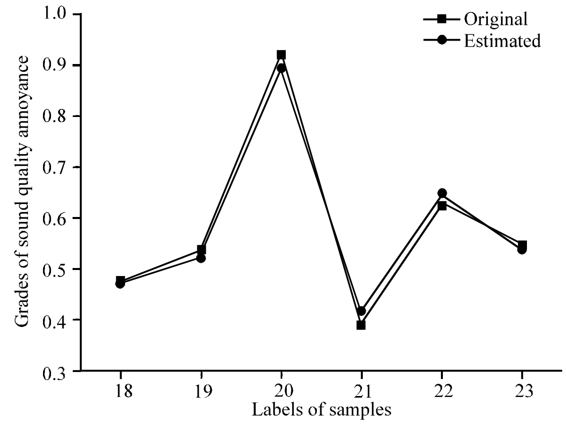

Fig. 3: Comparison of estimated values and original values with the testing samples based on LSSVM method

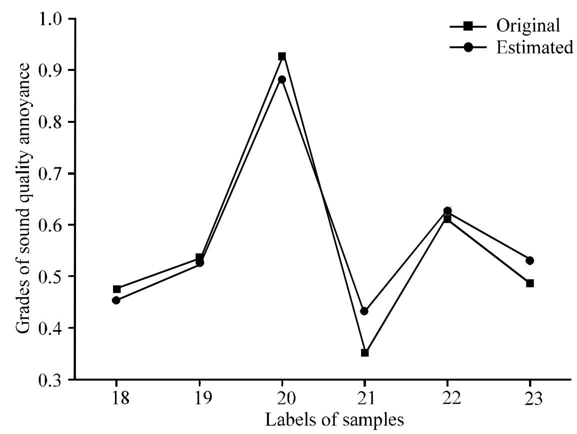

Fig. 4: Comparison of estimated values and original values with the testing samples based on MLR method

Table 5: Error comparison of two SQP models

SQP model	MLR	LSSVM
Average relative error (%)	7.44	3.11
Root mean square error (%)	4.25	1.88

$$SQ = -0.341L - 0.739S + 2.068R + 1.064AI + 2.289T + 8.765 \quad (6)$$

where, SQ is the sound quality annoyance, L is the loudness in sone, S is the sharpness in acum, R is the roughness in asper, AI is the articulation index in % and T is the tonality in tu.

Comparison of estimated values and original values with the testing samples using the MLR model is shown in Fig. 4. By comparing the forecasting accuracy of the two models, conclusion can be drawn that the LSSVM SQP model has higher forecasting accuracy than the MLR model. Comparison results of average relative error and root mean square error of two SQP models are represented in Table 5.

CONCLUSION

In this study, sound quality estimation of vehicle interior noise during acceleration of nine cars have been analyzed with LSSVM and MLR method. By correlation analysis, 5 psychoacoustic parameters which are closely related to subjective evaluations values are selected for modeling. The best model parameters are obtained by using a combination of grid search and 10-fold cross validation method after significance test. With loudness, sharpness, roughness, AI index, tonality used as inputs and subjective annoyance values used as outputs, a LSSVM SQP model is established. The model is examined with unknown noise samples that haven't been used for the previous modeling process. Comparison of average relative error and root mean square error of the LSSVM SQP model and the MLR SQP model clearly indicates that the LSSVM SQP model has smaller error. Prediction results proves that the proposed LSSVM SQP model has a precise prediction performance and good generalization ability in predicting sound quality of vehicle interior noise during acceleration. It is expected to be applied to other non-stationary conditions in the future work.

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