Consonant Recognition of Dysarthria Based on Wavelet Transform and Fuzzy Support Vector Machines

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***Abstract*—Consonant(in Chinese) recognition had important clinical significance in the assessment of dysarthria, while the consonants were so short and unstable that the recognition results of traditional methods were ineffective. The algorithm described in this paper extracted a new feature(DWTMFC-CT) of the consonants employing wavelet transformation, and the difference of similar consonants can be described more accurately by the feature. Then the algorithm classified consonants using multi-class fuzzy support vector machines(FSVM). In order to reduce the computation complexity caused by using the standard fuzzy support vector machines for multi-class classification, this paper proposed a algorithm based on two stages. Experimental results shown that the proposed algorithm could get better classification results while reducing the training time greatly.**

***Index Terms*—wavelets transform, fuzzy theory, support vector machines, consonant recognition**

I. INTRODUCTION

There are a large number of pronunciation-impaired patients in China. It's very important to assess the patient with dysarthria accurately. The methods of traditional dysarthria assessment, including Franchy Dysarthria Assessment and the dysarthria assessment method made by Zhongkang, with great subjectivity, often lead to diagnose inaccurately and incorrectly. Speech analysis is an effective assessment tool. With non-invasive and objective, this method can test a large number of patients in a short time. Speech analysis is often based on some long vowels [1-2], but practice shows that the clinical significance of consonant is more important than the long vowels', and there is almost no objective assessment in dysarthria now. Automatic and accurate identification of the 21 categories of consonant in the Mandarin Language is the key to objective assessment of consonant.

Because of consonant's instability, strong dynamic and short duration, so to identify them is difficult. There are two ways to improve the correct recognition rate: 1) To extract better feature parameters of consonant; 2) To choice a suitable recognition method. Feature parameters of speech are used widely, including Linear Prediction Cepstrum Coefficient (LPCC) and Mel Cepstrum Coefficient (MFCC), etc. They are assumed that speech signal is short-time stationarity, but the consonants are very unstable signal, so these parameter models have poor effect in consonant recognition [3].

It's a good choice to extract the consonant features by employing wavelet transformation, because wavelet transformation has good localize characteristics of time domain and frequency domain. The time-frequency window can adjust according to the signal's shape and multi-resolution analysis, so it can describe non-stable signal more precisely.

HMM technology [4], Gaussian mixture model [5] and neural network [6] are used widely in the field of speech recognition, but all of them have some defects, which are hard to make up. HMM is poor in classification decision-making, and need to priori statistical knowledge first; Gaussian mixture model is also based on statistical theory, and need to a large number of training samples to get good recognition effect; neural network's problems are hard to determine the network structure, local optimization and easy to over learning. Support vector machine is the important theory based on VC-dimensional theory of statistical learning theory and structural risk minimizes principle. It seeks the best compromise between the Modal complexity and learning ability to obtain the best extension according to the limited sample information. It can solve small sample, nonlinear, high dimension and local minimal problems [7].

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This research combines the advantages of wavelet transformation and support vector machine, and puts forward a new two-stage consonant recognition method. The experiments show that this method can make higher accuracy for consonant identification with small samples..

II. FUZZY SUPPORT VECTOR MACHINE

A. *Two-class fuzzy support vector machine*

Standard support vector machine (SVM) is a two-class classifier, if there are k training samples{(x_i, y_i), i=1,2,…,k}. in which $x_i \in R^N$, $y_i \in \{+1,-1\}$ is the corresponding class label. If the training samples are linearly separable, finding separating hyper plane w • xi, + b = 0 to make each sample has: yi [w • xi, + b] -1 ≥ 0. Solving the optimal hyper plane is equivalent to make ‖ w ‖ ^{2}/2 minimize, that is solving the solution of optimal problem:

$$\begin{cases} \min \ \ \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{k}\xi_i \\ s.t. \ \ \ y_i(w\cdot x_i + b) \ge 1-\xi_i, i=1,\cdots,k \end{cases} \quad (1)$$

In which: C is penalty factor, which controls the penalty degree of misclassification; ξ_i is slack variable, which compensates some samples that cannot be correctly classified by hyper plane.

The principle between FSVM and standard SVM is similar, the difference is that FSVM weights classification error ξ_i caused by each input point through the fuzzy factor q_i , $q_i\xi_i$ means each input point corresponding classification error. The smaller fuzzy factor q_i , leading to smaller classification error $q_i\xi_i$, which reduces the importance of the wrongly classified samples [8]. The objective function as follows:

$$\begin{cases} \min \ \ \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{k}q_i\xi_i \\ s.t. \ \ \ y_i(w\cdot x_i + b) \ge 1-\xi_i, i=1,\cdots,k \end{cases} \quad (2)$$

To solve the above objective function, it can be transformed into the corresponding dual form. we can get the two classification decisions function:

$$f(x) = sign(\sum_{i=1}^{k} a_i y_i x_i x + b) \quad (3)$$

It transformed the sample points by nonlinear and mapped to high dimensional feature space for the nonlinear problems. It could be realized classification by linear classifier in high-dimension. By the method of introducing the kernel function, it needn't to know the exact mapping function, and could calculate the inner product between the samples. The decision function was:

$$f(x) = sign(\sum_{i=1}^{k} a_i y_i K(x_i \cdot x) + b) \quad (4)$$

The kernel function mainly used in this research was d-order polynomial kernel function:

$$K(x_i, x_j) = (x_i \cdot x_j + 1)^d \quad (5)$$

The choice of penalty factor C and order d of the kernel function can impact the FSVM greatly. There are mainly two methods, including the experience deterministic method and the grid-search method, applied in the current practice. The grid-search method was used in this paper, setting the C value space is {1, 10, 100, 1000, 10000}and d is {1, 1.5, 2, 2.5, 3}, to make the space of C and d divided into grids, which trialed one by one to determine the optimal parameters in each grid point.

B. *multi-class fuzzy support vector machines*

FSVM algorithm was originally designed for two-class classification problems. It needs to be extended to multi-class classifier when dealing with multi-class problems. There are two ways used widely at present: one-to-many and one-to-one. The method of one-to-many makes some class samples classified as one-class in turn when it trains, remaining samples classified as the other one, so k-class samples are constructed to k FSVM. Unknown samples are classified to the class that has the largest classification function value. The practice of one-to-one method is to design a FSVM between any two-class samples, so k-class samples need to design k (k-1) / 2 FSVM. When classifying an unknown sample, the category of the sample is the class that gets most votes by last.

Experiment showed that the one-to-one method could get better classification effect than the one-to-many method [9], however, its time complexity is O (k2). The performance of the algorithm would drop dramatically with the number of categories increases. These FSVM got by one-to-one training method, organized into a directed graph (DirectedGraph, DG) structure with unique root node, then got the fuzzy support vector machine (FDGSVM), shown in Fig. 1. For the k classification problem, FDGSVM required only k-1 dimensions [10], which reduced the time complexity effectively.

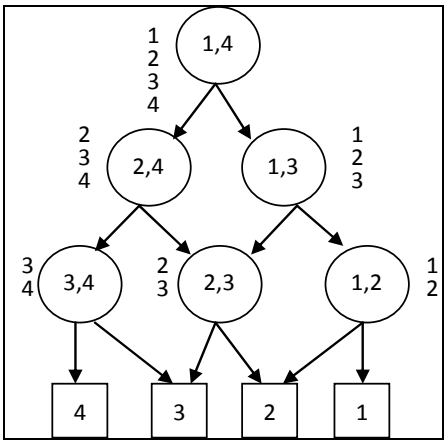

Figure 1. The flow chart of FDGSVM (K=4).

The flow of FDGSVM was as follows: A list was formed by all samples. A test sample was input from the root. First, it was determine that whether it belonged to the first category or the last category in the list. After

removing the category which was not selected, went to the next level node in DG. The new list was made the same treatment until the node was leaf node.

III. WAVELET TRANSFORMATION

If $\Psi(t) \in L^2(R)$, the Fourier transform $\hat{\Psi}(\omega)$ meets the permit conditions $C_\Psi = \int_R \left|\hat{\Psi}(\omega)\right|^2 \Big/ |\omega| \, d\omega < \infty$, then $\Psi(t)$ is called a basic wavelet or mother wavelet. It could get wavelet sequence after $\Psi(t)$ expansion and translation:

$$\Psi_{a,b}(t) = |a|^{-1/2} \Psi(\frac{t-b}{a})(a,b \in R, a \neq 0) \quad (6)$$

In which, a is the scale factor and b is translation factor. Set $a = a_0^j$, $b = ka_0^j\tau_0$ (τ_0 is the sampling rate), $j \in Z$, $a_0 \neq 1$, the discrete wavelet sequence is:

$$\Psi_{j,k}(t) = a_0^{-j/2}\Psi(a_0^{-j}t - k\tau_0) \quad (7)$$

In the actual calculation process, the most common method is to binary discrete for scale. That is $a = 2^j$, b is integer. If *f(t)* as the discrete signal, according to orthogonal wavelets in the j (j >=1) layer, then it expands as following:

$$A_{2^{j-1}}[f(t)] = D_{2^j}[f(t)] + A_{2^j}[f(t)] \quad (8)$$

In which, D_{2^j} is the detail coefficient, representing the high-frequency component of the j layer, A_{2^j} is the approximate coefficient, representing the low-frequency component of the j layer, when j = 1, $f(t) = A_{2^0}[f(t)]$.

This research chose db4 wavelet as the mother wavelet, because the db wavelet is the compact orthogonal wavelets, and has a good expansibility. So it could weigh the border problem that brought by increasing the support set length flexibly (to increase the concentrative degree of energy) [11].

IV. ALGORITHM DESCRIPTION

A. *The two-stage recognition algorithm*

To reduce the algorithm's time complexity and ensure its accuracy, the whole algorithm was divided into two stages, shown in Fig. 2.

The first stage is the rough classification stage of consonant. Among a numerous acoustic parameters of consonants, we extracted features such as: length, periodicity, relative energy and zero-crossing rate for the consonant classification [12]. Using FDGSVM, the 21 consonants were divided into 7 rough categories: C1(b,d,g), C2(1,m,n,r), C3(z,zh,j), C4(p,t,k), C5(c,ch,q), C6(f,h) and C7(s,sh,x). The second stage is the fine classification stage of consonants. Because of high similarity between the different consonants in the same rough category, it could be described more accurately by using the wavelet transformation to extract distinguishing features of consonants. And more detailed delineations of 7 categories were done by using FDGSVM again (using a separate fine classifier for each rough category). Finally the purpose of identifying each consonant was achieved.

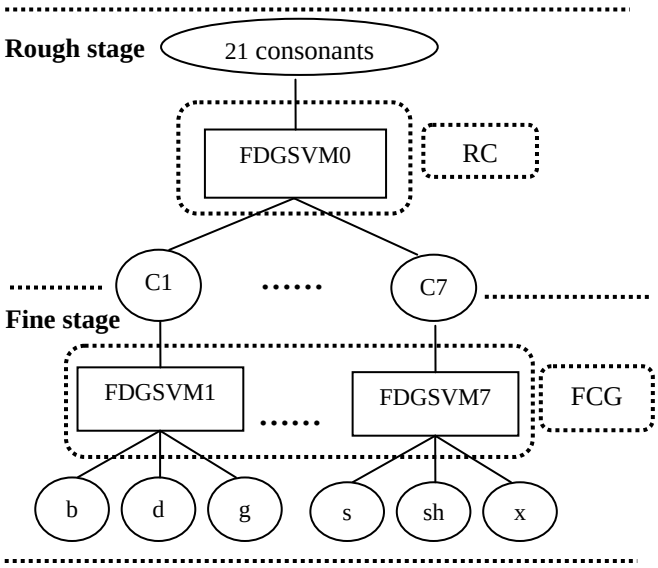

Figure 2. The two-stage recognition algorithm flow (RC=rough classifier, FCG= fine classifier group)..

The detail steps of the algorithm were as follows:

Step 1 Set the training sample set was $S=\{S_1, S_2, \ldots, S_7\}$, in which $S_i(i=1,\ldots,7)$ was sample set of the *ith* rough category. The training samples were extracted consonant's length(L), periodicity(P), relative energy(E) and zero-crossing rate (including the mean zero-crossing rate(MZ), the last zero-crossing rate(LZ) and phonetic rhyme transition zero-crossing rate(TZ)) to form the characteristic parameters(F = (L, P, E, MZ, LZ, TZ)) of rough category.

Step 2 Set a sample point $SP_{i,j} \in S_i$ (j=1,…, N_i, N_i is the number of samples in S_i). Rough category feature with different units and orders, were normalized first, and then calculated the average of each feature, composed the center of feature vector F of S_i: $F_i = (\overline{L_i}, \overline{P_i}, \overline{E_i}, \overline{MZ_i}, \overline{LZ_i}, \overline{TZ_i})$ (in which $\overline{L_i} = \sum L_{i,j} \big/ N_i$, other features were treated similarly).

The calculation method of each sample fuzzy factor $q_{i,j}$ was: $q_{i,j} = 1 - d_{i,j} \big/ \max\{d_{i,1}, \cdots, d_{i,Ni}\}$. In which, $d_{i,j\ I}$ is Euclidean distance between the sample point $SP_{i,j}$ feature vector and the feature vector center F_i.

Step 3 The algorithm trained 21 FSVM by using the training sample S, then organized these trained FSVM into a fuzzy directed graph support vector machines: FDGSVM0 for rough classification.

Step 4 New consonant feature vectors (DWTMFC-CT) were extracted based on discrete wavelet transform (see section B), as the fine feature vectors in the second phase.

Step 5 Based on parameters DWTMFC-CT, similar to the method of step 2, the algorithm then calculated the fuzzy factor for each sample (7 rough classification sample sets were calculated independently), The

algorithm trained the K_i*(K_i-1)/2 FSVM used for subdividing rough category C_i by using the training sample S_i, (K_i is the number of class of consonants in C_i), then organized them into fine classifier group: FDGSVMi (i = 1, ..., 7).

Step 6 The algorithm extracted test samples feature parameters F and DWTMFC-CT, and input feature parameter F to the rough classifier FDGSVM0, the most appropriate fine classifier would be selected from the fine classifier group, and then determined test samples belong to different categories according the parameters DWTMFC-CT.

B. *feature parameters DWTMFC-CT extraction*

Some speech features had be extracted using wavelet transform by some researchers, such as MWBC [13], DWT-MFC [14]. The method of DWT-MFC was improved appropriately in this paper as it could adapt the features of consonant recognition. The extraction method of the new consonant feature vector DWTMFC-CT was as follows:

Step 1 Enflame: According to the different length of consonant, the consonant signal was split up into several frames on average, as shown in TABLE I.

Step 2 Wavelet transformation: Using db4 as mother wavelet, the consonant signals were decomposed to 3 layers, then 3 groups of detail coefficients: D_2^1, D_2^2, D_2^3 and a group of similar coefficients: A_2^3 were extracted.

TABLE I.
THE NUMBER OF FRAMES

rough category	C1	C2	C3	C4	C5	C6	C7
number	1	2	2	3	3	4	4

Step 3 Spectrum combined: The 4 groups of wavelet coefficients were done by Fast Fourier Transform (FFT), the wavelet coefficients spectrum were translated from the time domain into the frequency domain, then all of the wavelet coefficients will combined into a full spectrum.

Step 4 Calculation cepstrum coefficient: The full spectrum above were done by M-order Mel filter, and got Mel spectrum, furthermore, translated by discrete cosine transformation to obtain cepstral vector coefficient d_h= ($d_{h,1}$, $d_{h,2}$,…,$d_{h,M}$) of the *hth* frame, in which h=1,…, *Nci*, *NCi* is the number of the frames.

Step 5 Cepstrum coefficient splice: Each frame was processed by the method above, and cepstrum coefficients of all frames were spliced, then could get *NCi***M*-dimension feature vectors DWTMFC-CT=(d_1, d_2,…,d_{NCi}).

V. EXPERIMENTS

Speech samples were collected in a quiet environment, recorded by Cool Edit software. The number of recording channel was one, its frequency was 16000Hz and precision was 16bit. The distance from microphone to people's mouth is form 10 cm to 20 cm. 10 females and 10 males (healthy and speech Mandarin)

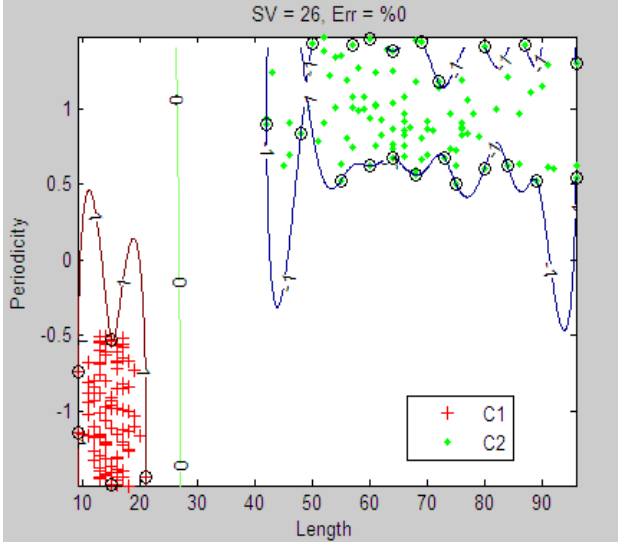

Figure 3. A graph describing the result of FSVM(C1-C2).

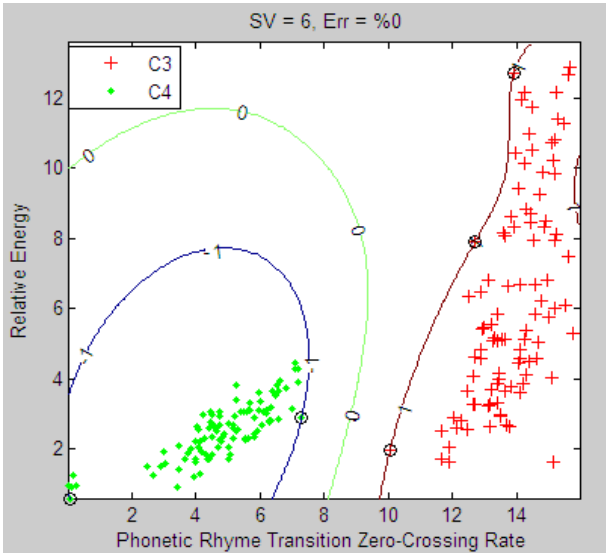

Figure 4. A graph describing the result of FSVM(C3-C4).

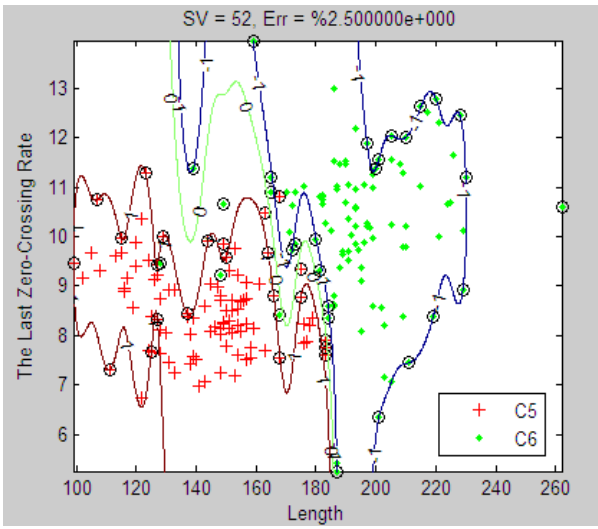

Figure 5. A graph describing the result of FSVM(C5-C6).

were called to do experiments. Each consonant was read 5 times, then all of the samples were front-end processed and segmented the vowel parts and consonant parts of consonants by usual. Finally each consonant had 100 samples.

The aim of the first experiment was to determine whether the feature parameter vector F (including length (L), periodicity (P), relative energy (E) and zero-crossing rate(Z)) was useful in the first stage of consonant recognition. 100 samples in each rough category set were selected randomly. Two-class fuzzy support vector machine was used as classifier. For example, three pictures of results were shown in three rough category pairs (C1-C2 (Fig. 3), C3-C4 (Fig. 4), and C5-C6 (Fig. 5)). We can see that, there were significant differences among the rough categories with the feature parameter vector F.

In the second stage of consonant recognition, in order to test the effectiveness of the 7 fine classifiers, 10 experiments were done. In each experiment, 60 samples in each consonant sample set were selected randomly as the training samples, the remaining 40 samples as the test samples. That is, the *ith* fine classification had $60*K_i$ training samples and $40*K_i$ test samples. The Mel cepstrum coefficients (MFCC) and DWTMFC-CT of consonant samples were extracted (the number of FFT points was min {512,the number of sample points}, Mel filter order was 24). SVM and FSVM were also used for comparative experiments. The recognition results of 7 classes were shown in TABLE II and TABLE III. The results of TABLE II and TABLE III were the average of 10 experiments.

We can see that: compared with the speech feature classification by using the MFCC directly, the DWTMFC-CT based on wavelet transformation could reduce a large number of support vectors and improve the correct rate, particularly in rough categories with similar pronunciation: C3 (z similar to zh), C5 (c similar to ch), C7 (s similar to sh), and the effectiveness of C1 (with the strongest instability and the shortest length) was also significant. It showed that unstable consonants can be described more accurately by the multi-scale wavelet analysis. When chosen the same DWTMFC-CT feature vectors, compared with SVM, the recognition correct rates of FSVM were better, while the difference of support vectors number was small. It showed that FSVM

TABLE III.
THE RECOGNITION RESULTS OF 7 CLASSES

category title		SVM(MFCC)		SVM(DWTMFCC-CT)		FSVM(DWTMFCC-CT)	
		Accuracy(%)	number of support vectors	Accuracy(%)	number of support vectors	Accuracy(%)	number of support vectors
C1	[b,d,g]	84.33	63.4	89.83	47.2	91.58	46.8
C2	[l,m,n,r]	93.75	88.8	97.13	47.5	98.38	50.6
C3	[z,zh,j]	85.75	61	90.92	49.5	92.17	54.4
C4	[p,t,k]	85.67	68.7	89.33	51.5	91.67	50.2
C5	[c,ch,q]	82.58	68.7	88.17	41.8	90.83	44.2
C6	[f,h]	95.50	10.1	98.25	7.3	99.25	8.4
C7	[s,sh,x]	86.42	75.9	95.50	23.5	96.58	24.8
Average		87.71	61.34	92.73	38.33	94.35	39.91

TABLE II.
COMPARISON AMONG SVM(DWTMFCC), SVM(MFCC) AND FSVM(DWTMFCC-CT)

category title		SVM(MFCC) VS SVM(DWTMFCC-CT)		SVM(DWTMFCC-CT) VS FSVM(DWTMFCC-CT)		SVM(MFCC) VS FSVM(DWTMFCC-CT)	
		Difference of Accuracy(%)	Difference of the number of support vectors(%)	Difference of Accuracy(%)	Difference of the number of support vectors(%)	Difference of Accuracy(%)	Difference of the number of support vectors(%)
C1	[b,d,g]	6.52	-25.55	1.95	0.85	8.60	-26.18
C2	[l,m,n,r]	3.60	-46.51	1.29	-6.53	4.93	-43.02
C3	[z,zh,j]	6.03	-18.85	1.37	-9.90	7.48	-10.82
C4	[p,t,k]	4.28	-25.04	2.61	2.52	7.01	-26.93
C5	[c,ch,q]	6.76	-32.03	3.02	-5.74	9.99	-28.13
C6	[f,h]	2.88	-27.72	1.02	-15.07	3.93	-16.83
C7	[s,sh,x]	10.51	-69.04	1.13	-5.53	11.76	-67.33
Average		5.80	-60.04	1.77	-3.97	7.67	-53.69

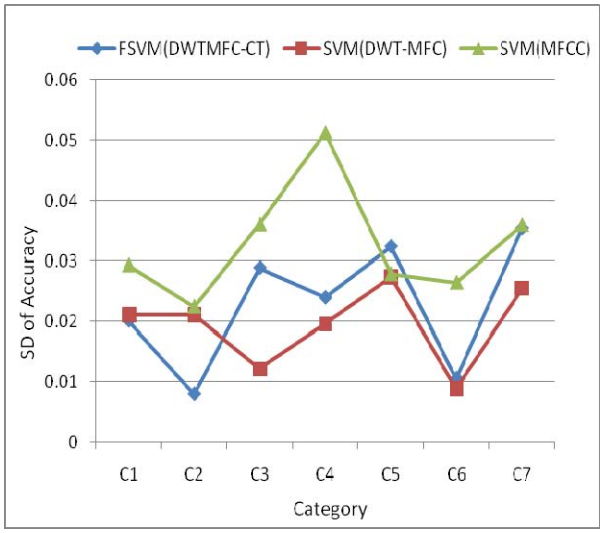

Figure 6. The Standard Deviation of accuracy of each category.

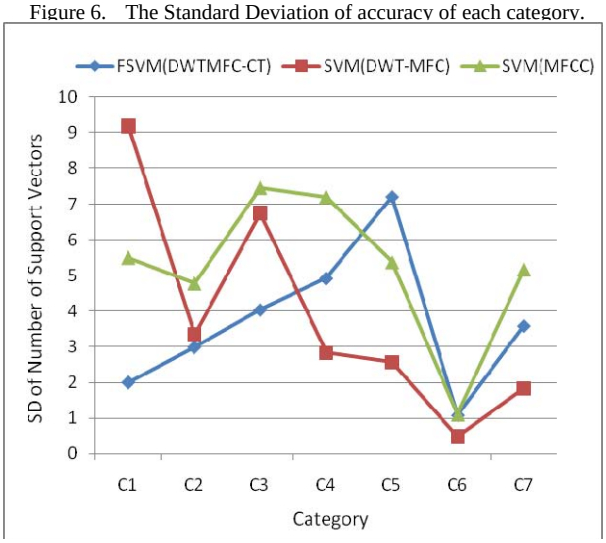

Figure 7. The Standard Deviation of the support vector number of each category.

with introducing fuzzy membership could describe the importance of each training sample to classification result. So it could optimize SVM classification face and improve recognition accuracy (Fig. 6, Fig. 7).

At last the efficiency of algorithm (CFDCT) mentioned in this paper was further validated by comparing with the BP neural network (three structures, hidden nodes is 49, the maximum training number is 500 and error goal<0.005). The training samples and test samples were obtained by the method mentioned above. Consonants feature vectors F and DWTMFC-CT of the sample were extracted, and then trained rough classifier in the first stage and 7 fine classifiers in second stage respectively. The performances of BP and CFDCT were given in TABLE IV.

TABLE IV.
PERFORMANCES OF BP AND CFDCT

	Training time (min)	Accuracy (%)
BP	28.7	83.7
CFDCT	11.5	90.8

The experimental result showed that the algorithm in this paper was superior to BP neural network. Because there is no correlation between each frame in consonants (except for voiced consonants), it needed to splice consonant feature of every frame, so the feature vector DWTMFC-CT were high-dimensional. FSVM could solve high-dimension through nonlinear transformation and nuclear function skillfully, making the algorithm complexity unrelated to the dimensions of the sample features. At the same time, two-stage method was used and accelerated the training speed further. It also trained each classifier pertinently, so each classifier had a higher recognition rate in the particular samples, avoiding interference by the irrelevant consonant samples. FSVM could also overcome local minima and over-learning of neural network with utilizing distribution characteristics of small samples.

VI. CONCLUSION

A consonant recognition method based on wavelet transform and FSVM was proposed in this paper, which could identify the various consonant effectively in small samples. Two-stage strategy was adopted and minimized the algorithm's complexity.

The samples used in this paper were limited, so it will need to collect more samples to verify the reliability of the algorithm. We also need to focus on studying more effective feature vector to improve the recognition rate in the further.

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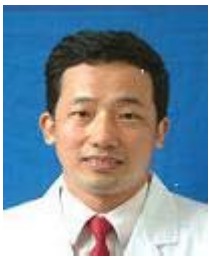

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