Classification of Shunt Murmurs for Diagnosis of Arteriovenous Fistula Stenosis

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Abstract—Hemodialysis patients are generally provided with an arteriovenous fistula (AVF), but problems such as stenosis of the blood vessel can occur. Listening to shunt murmurs is an effective way for hemodialysis patients to check their own shunt function. However, manually judging shunt function is difficult and requires correct knowledge and experience. Therefore, a system that can be easily handled by patients and automatically identifies shunt function is required. In this study, we proposed a method for classifying shunt stenosis using the Support Vector Machine (SVM). To record shunt murmurs, we used the electronic stethoscope and the microphone with stethoscope chest piece. We used the resistance index (RI) obtained from the ultrasonic diagnostic equipment as a class label and the normalized cross correlation coefficient, ratio of the frequency power and Mel-frequency cepstral coefficients (MFCC) as the feature. We examined the effectiveness of the proposed method by comparing the accuracy and F-measure. It was found that the classification accuracy of the RI using the SVM was lower than that obtained by human judgment.

I. INTRODUCTION

Some patients, such as those with renal disease, receive hemodialysis to remove waste products and excess water from their blood. For hemodialysis patients, an arteriovenous fistula (AVF) called a shunt, can be created by anastomosing arteries and veins. The problems such as stenosis and occlusion may occur as a result of the age of the hemodialysis patient. If a shunt becomes obstructed, another must be created in a different place to continue receiving hemodialysis. Therefore, patients must check their shunt function in daily life. As one method of checking the shunt function, listening to shunt murmurs can be effective way for patients. However, the analysis of shunt murmurs is difficult because there are individual differences and judging the shunt function requires correct knowledge and experience. In addition, it is possible to confirm shunt function using ultrasonic diagnostic equipment. However, ultrasonic diagnostic equipment is expensive and require specialized knowledge and skills. Therefore, a system that can be easily handled by patients and automatically identifies shunt function is required and it is considered effective to use shunt murmurs for the system.

Previous research has confirmed that shunt murmurs with stenosis or occlusion are characterized by a different frequency from normal shunt murmurs [1]–[7]. These studies used data from patients with stenosis and patients before and after surgery. Since it is not known when and where stenosis will occur, it is thought that it takes a lot of time to collect similar



Fig. 1. Classification method using SVM

data. In Murakami's survey [8], it was confirmed that when the resistance index (RI) was 0.6 or more, there was an increase in the group in which shunt malfunctions tended to occurs. The RI is a scale that indicates the difficulty of blood flow to the distal end and is measured using ultrasonic diagnostic equipment. The RI is easy to measure and vascular function is evaluated by quantifying blood flow with the RI. If the RI can be estimated from shunt murmurs, we thought that shunt function could be evaluated like ultrasound examination.

In this study, we proposed a method to automatically classify shunt stenosis using the Support Vector Machine (SVM) and features obtained from frequency analysis and the RI as the label. To confirm its effectiveness, cross-validation was performed and an evaluation was made based on the accuracy and F-measure.

II. PROPOSED METHODS

We proposed a classification method to create learning data based on the RI. The calculation of the RI is shown in (1).

$$RI = \frac{PSV - EDV}{PSV} \tag{1}$$

where PSV is the peak systolic velocity and EDV is the end diastolic velocity. Fig.1 shows the process of the proposed method. The following is an explanation of the method.

1) Creating training data

To create the training data, the shunt murmurs are first labeled and segmented. When the RI is 0.6 or more, there is an increase in the group in which the shunt malfunctions. Therefore, it is desirable to classify the

TABLE I Frequency characteristic

	frequency response				
AT9903	30-18000 Hz				
ΤΔ-701Τ	20-600 Hz				
1/1-7011	20-000 112				
Electronic StethoScope	Bell: 20-200 Hz				
(Littmann Model3200)	Diaphragm:100-500 Hz				
	Extended Renge:50-500 Hz				



Fig. 2. Microphone with stethoscope chest piece

RI into two groups: values that are less than 0.6 and those that are 0.6 or more. The recorded shunt murmurs are labeled as the class with the RI of less than 0.6 or the class with the value of 0.6 or more. Next, the shunt murmurs of each class are segmented and the data of 0.8 sec are obtained.

2) Feature extraction from training data

The features are extracted using the training data of 0.8 sec. At this time, the normalized cross correlation coefficient, ratio of the frequency power and MFCC, is used as the feature.

3) Learning using SVM

The extracted features are used for learning using the SVM. The SVM [9] is an algorithm that can find a hyperplane that passes through the middle of a set of classes by maximizing the distance from each class. To find a hyperplane, the maximum margin region where data are not contained is found. The test data is categorized into classes using the hyperplane obtained from the training data. The SVM is intuitive and supported by the learning theory.

4) Creating test data

To create the test data, the shunt murmurs are segmented. Unlike creating the training data, labeling is not performed here. The test data is classified by the SVM instead of labeling. At this time, the shunt murmurs are segmented using the same method as used for the training data.

5) Feature extraction from test data

The features are extracted using the test data of 0.8 sec. At this time, the features are extracted from the test data using the same method as used for the training data.



TABLE II

Fig. 3. Example of segmentation of shunt murmurs

6) Classification

Using the model obtained by the SVM and the features extracted from the test data, the test data is categorized as the class with the RI of less than 0.6 or the class with the value of 0.6 or more.

III. COLLECTION OF SHUNT MURMURS

To collect the shunt murmurs, we used an electronic stethoscope (3M Littmann electronic stethoscope model 3200) and a microphone with stethoscope chest piece connected to an AT9903 microphone from Audio-Technica and an FC-200 stethoscope chest piece from FOCAL CORPORATION. The microphone with stethoscope chest piece is shown in Fig.2. These microphones were used because the recording equipment used in the previous research had a narrow frequency range, and it was thought that the features of stenosed shunt murmurs were not sufficiently obtained. Therefore, an improvement in the classification accuracy was expected from using recording equipment with a wider frequency range. A comparison of the recording equipment is shown in Table I. In addition to the microphone with stethoscope chest piece to record shunt murmurs, a DR-05 IC recorder from TAS-CAM was used. The settings of the DR-05 are shown in Table II. Using these instruments, the shunt murmurs from the anastomotic area of AVF patients before hemodialysis were recorded. The shunt murmurs were recorded before hemodialysis because the state after hemodialysis was different from everyday condition. Therefore, we chose to record the condition before hemodialysis, which was thought to be closer to the condition of the shunt during daily life. During the recording, the patients were asked to sit in a chair with their arm on a desk. Immediately after recording the shunt murmurs, the RI was measured using the ultrasonic diagnostic equipment. At this time, measurements were taken in the same position as where shunt murmurs were recorded.



Fig. 4. Process for finding ratio of the frequency power

IV. SEGMENTATION OF SHUNT MURMURS

When extracting the features from the shunt murmurs, we segmented the data of before and after the peak of the shunt murmurs and used the data of 0.8 sec. To obtain the data of 0.8 sec from the recorded shunt murmurs, smoothing was performed first for finding the signal peak by eliminating information of low importance such as noise. Peaks were calculated from the smoothed signals and the data of before and after each peak were segmented. The process is shown in Fig.3.

V. FEATURE EXTRACTION

This section describes the methods for extracting features from the data of 0.8 sec.

A. Ratio of The Frequency Power

The features of stenosis shunt murmurs appear in the frequency. Therefore, we attempted to extract these features using the Fourier transform. The Fourier transform is one of the methods used in the frequency analysis of signals, and the frequency spectrum can be obtained by Fourier transforming the time signal. First, the frequency spectrum was obtained by Fourier transforming the shunt murmur signal. Next, a range of 1-2000 Hz was divided into four bands, and the frequency power for each band was calculated.

$$p_1 = \sum_{f=1}^{500} \{20 \log 10(abs(X(f)))\}$$
(2)

$$p_2 = \sum_{f=500}^{1000} \left\{ 20 \log 10 (abs(X(f))) \right\}$$
(3)

$$p_3 = \sum_{f=1000}^{1500} \left\{ 20 log 10(abs(X(f))) \right\}$$
(4)

$$p_4 = \sum_{f=1500}^{2000} \left\{ 20 \log 10(abs(X(f))) \right\}$$
(5)

Next, the sum of the frequency power values for the entire range of 1-2000 Hz was calculated by adding the values obtained from (2) to (5).

$$P_{total} = p_1 + p_2 + p_3 + p_4 \tag{6}$$

Finally, the ratio of each band was calculated using the sum calculated by (6).

$$P_{1} = \frac{p_{1}}{P_{total}}, P_{2} = \frac{p_{2}}{P_{total}}, P_{3} = \frac{p_{3}}{P_{total}}, P_{4} = \frac{p_{4}}{P_{total}}$$
(7)

This process is shown in Fig.4.

B. MFCC

The Mel-frequency cepstral coefficients (MFCC) is lowdimensional spectrum information defined in the quefrency region. To obtain the MFCC, we defined a filter object called the Mel filter bank and obtained the general form of the spectrum by multiplying the amplitude spectrum by the Mel filter bank. The Mel filter bank was a filter whose operation was fine in the low-frequency band and rough in the highfrequency band on the Mel scale. The Mel scale [10] is shown in (8).

$$Mel(f) = 2595 \log 10(1 + \frac{f}{700})$$
(8)

The quefrency region is obtained by transforming the general form of the spectrum using discrete cosine transforms. The low-dimensional features of this obtained quefrency region were called the MFCC. We used 16 dimensions of the MFCC as a feature.

C. Normalized Cross-Correlation Coefficient

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The normalized cross-correlation coefficient [5] is obtained using normalized cross-correlation analysis and shows the correlation between two images or the similarity between systems. Normalized cross-correlation analysis is an effective means to investigate the correlation and similarity. The normalized cross-correlation coefficient is obtained by treating the results of a wavelet transform as an image. Wavelet transform [11] is a method of time-frequency analysis that estimates a signal by shifting and scaling a small wave called a wavelet. The function $\psi(t)$ that exists around the origin t = 0 with an average value of 0 is an example of a wavelet. By shifting and scaling this $\psi(t)$ on the t-axis, a basis $\psi_{a,b}(t)$ is generated.

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi(\frac{t-b}{a}) \tag{9}$$

where a is a scaling parameter and b is a shift parameter. The inner product of $\psi_{a,b}(t)$ and signal f(t) is the wavelet transform. In this study, the normalized cross-correlation coefficients were obtained for the shunt murmurs of two patients. Their RI values were low. The normalized cross-correlation coefficient is shown in (10).

$$R = \frac{\sum_{x} \sum_{y} \left\{ (g(x,y) - \overline{g(x,y)}) \times (h(x,y) - \overline{h(x,y)}) \right\}}{\sqrt{\sum_{x} \sum_{y} (g(x,y) - \overline{g(x,y)})^2} \times \sum_{x} \sum_{y} (h(x,y) - \overline{h(x,y)})^2}$$
(10)

where g(x, y) and h(x, y) are the average values. g(x, y) and h(x, y) are calculated by (11).

$$W(b,a) = \frac{1}{\sqrt{a}} \int f(t) \overline{\psi(\frac{t-b}{a})} dt$$
(11)

where $\psi(-)$ is the complex conjugate of $\psi(-)$.

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TABLE III					
EXPERIMENTAL CONDITION					
Sampling frequency	iency 48 kHz (microphone)				
	4 kHz (Electronic Stethoscope)				
Data length	0.8 sec				
Number of test data	60				
Number of traning data	240				
	MFCC				
Feature	Ratio of frequency power				
	Normalized cross correlation coefficient				
TABLE IV					
RELATIONSHIP BETWEEN STAFF'S JUDGMENT AND RI					

		Staff Judge			
		No doubt of stenosis	Doubt of stenosis		
Measure of	less than 0.6	28	4		
ultrasonic	more than 0.6	21	8		

VI. EXPERIMENTS

This section outlines how the effectiveness of the proposed method was confirmed by comparing the accuracy of the SVM classification to that of a human judge.

A. Experimental Condition

The shunt murmurs used for classification were recorded using the electronic stethoscope and the microphone with stethoscope chest piece. The shunt murmurs at the anastomosis of 60 AVF patients (30 patients with the RI of less than 0.6 and 30 patients with the RI of 0.6 or more) were used for classification. We extracted five data sets from each participant, using the recorded shunt murmurs. Thus, a total of 300 sets of data were used. As a method of evaluation, fifth-order cross-validation was performed, and we evaluated the data based on the accuracy and F-measure. When doing a crossvalidation, 80% of the total data was used for training and the remaining 20% was used for testing. In this study, the data from different people were used as the training and test data. The normalized cross-correlation coefficient, ratio of the frequency power, and MFCC were used as the features. The experimental conditions are shown in Table III. Among the 62 patients used at this time (2 patients were used to calculate the normalized cross-correlation coefficient and 60 patients were used for the experiment), 32 patients had the RI of less than 0.6 and 30 patients had the RI of 0.6 or more. The relationship between the judgments of the medical staff for 61 people (excluding one who was not judged by the staff) and the RI is shown in Table IV. If the RI was less than 0.6 and the judgment of the staff was undoubted, or if the RI was 0.6 or more and the judgment of the staff was doubted, a decision was regarded as correct. In this survey, the accuracy of the staff judgment was 59%. This was used as a performance indicator of human judgment.

B. Results and Discussion

The classification results of the experiment are shown in Table V. Fig.5 shows the results of calculating the accuracy and F-measure from Table V. In the classification using the shunt murmurs recorded by the electronic stethoscope, the accuracy was 0.483 and the F-measure was 0.478. In the classification

TABLE V Shunt murmur classification results

					Measure of ultrasonic				
					less th	an 0.6	mor	e than (0.6
Classi	Classification of SVM Microphone		less than 0.6 more than 0.6		83		67		
Ν					67		83		
Classi	Classification of SVM		less than 0.6		71		76		
Electro	onic Stethos	cope -	more	than 0.6	7	9		74	
0.8							0 601		
0.7							0.051		
0.6		0.553	0.59			0.553			
0.5	0.483				0.478				
0.5									
0.4			-						
0.3			-		-				
0.2			-						
0.1			-		_				
0									
Accuracy F-measure									
Electronic Stethoscope Microphone with stethoscope chest piece Staff Judge									

Fig. 5. Comparison of accuracy and F-measure

using the shunt murmurs recorded by the microphone with stethoscope chest piece, the accuracy was 0.553 and the Fmeasure was 0.553. The accuracy and F-measure when using the microphone with stethoscope chest piece were observed to be better than those when using the electronic stethoscope. However, the accuracy and F-measure when using the SVM were lower than the staff's judgment. Because the staff made judgments comprehensively (in addition to sound, the staff could check the blood vessel for confirmation, see the state of the blood vessel, check blood flow during dialysis, etc.), their classification accuracy increased. In addition to the RI, the classification accuracy could be expected to be improved by using another feature of the patient. The features used for the SVM learning did not effectively reflect the characteristics for classifying the RI. Therefore, it is necessary to investigate the relationship between the RI and shunt murmurs in the future.

VII. CONCLUSION

Some patients, such as those with renal disease, check their own shunt function by listening to shunt murmurs. However, the analysis of shunt murmurs is difficult because there are individual differences and judging shunt function requires correct knowledge and experience. A system that can be easily handled by patients and automatically identifies shunt function is required. In this study, we proposed the method for classifying shunt stenosis using the SVM. An experiment confirmed that classification based on the SVM was less accurate than the judgment of trained human staff. The observed classification accuracy was insufficient to realize the system. In the future, it is necessary to investigate the relationship between the RI and shunt murmurs to obtain significant features.

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