AV fistula progress report

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1. Introduction

In this project, the goal is to estimate the blood flow volume in arteriovenous fistula (AVF) to detect stenosis in AVF . Acoustic signal emitted by the artery, vein and vessel in front of artery is recorded to estimate the AVF condition.

2. Literature survey

In the past few years, several research about estimating the AVF condition using acoustic signal was conducted. [1] and [2] use wavelet transform to extract the acoustic feature. [3] and [4] use FFT for feature extraction. [5] and [6] use several commonly used features like MFCC. S-transform and EMD is used in [7] and [8]. Detail about the implementation is shown in Fig.1 .

	Pre-Processing	Feature extraction	Classifier	How to label the data	Samples	Acc
[1]	Segmentation into beat	Wavelet transform	KNN	Ultrasound imaging (6 label)	38	0.81
[2]	Segmentation into beat	Wavelet decomposition	SVM	Not mentioned	8	0.83
[3]	Segmentation into beat	FFT + feature selection algorithm	K-NN	Ultrasound imaging (6 label)	38	0.81
[4]	Segmentation into beat	FFT + feature selection algorithm	K-NN	Ultrasound imaging (6 label)	38	X
[5]	Segmentation into beat	MFCC + normalized cross correlation coefficient + frequency power	SVM	Resistance Index	60	0.553

[6]	STFT	Commonly used features	SVM	Angiography	22	0.843
[7]	Segmentation into beat	S-transform	RBF neural network	Vessel distance	74	0.8784
[8]	Segmentation into beat	Empirical mode decomposition	ANN	Not mentioned	5	0.85

3. MATERIALS AND METHODS

A. Data set and pre-processing

In our work, acoustic signal from 72 patients were collected. The sampling rate is 8k samples /sec. To begin with, segmentation is performed to separate the acoustic signal into single heartbeat. We use homomorphic filtering method based on [9], the block diagram is shown in Fig.I . Homomorphic filtering involved filtering the fast-varying part of signal. Let $\mathrm{x(n)}$ is the energy of input signal. $\mathrm{x(n)} = \mathrm{a(n)} * \mathrm{f(n)}$, $\mathrm{a(n)}$ is the slow varying part, $\mathrm{f(n)}$ is the fast-varying part. By taking the logarithm, $\mathrm{z(n)} = \log(\mathrm{a(n)}) + \log(\mathrm{f(n)})$. With a lowpass filter, $\mathrm{Lowpass(\ z(n)\ )} = \mathrm{Lowpass}(\log(\mathrm{a(n)}) + \mathrm{Lowpass}(\log(\mathrm{f(n)}) \cong \log(\mathrm{a(n)})$. The slow-varying part of signal is thus filtered out. With the slow-varying envelope, segmentation can be done by detecting the local minima. Fig.II is the result of the implementation .

Fig. I , block diagram of segmentation

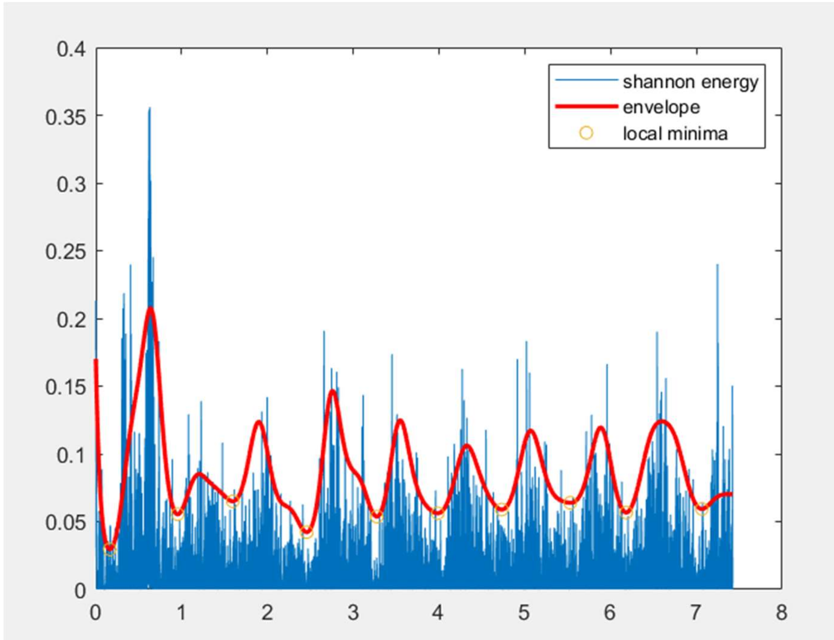

Fig. II result of envelope detection.

B. Feature extraction

In feature extraction, wavelet decomposition and MFCC were test. Since frequency properties is deemed important, wavelet decomposition is taken to extract properties on different frequency range. Daubechies Wavelet is used, and 8 features are extracted. After using principal components analysis (PCA) , two features represent the high and low frequency energy are deemed as important.

MFCC is also used in feature extraction. The window size is 256 and overlap is 128. Three features are deemed as important by PCA . Around 400 samples are generated. The block diagram is shown in Fig. III

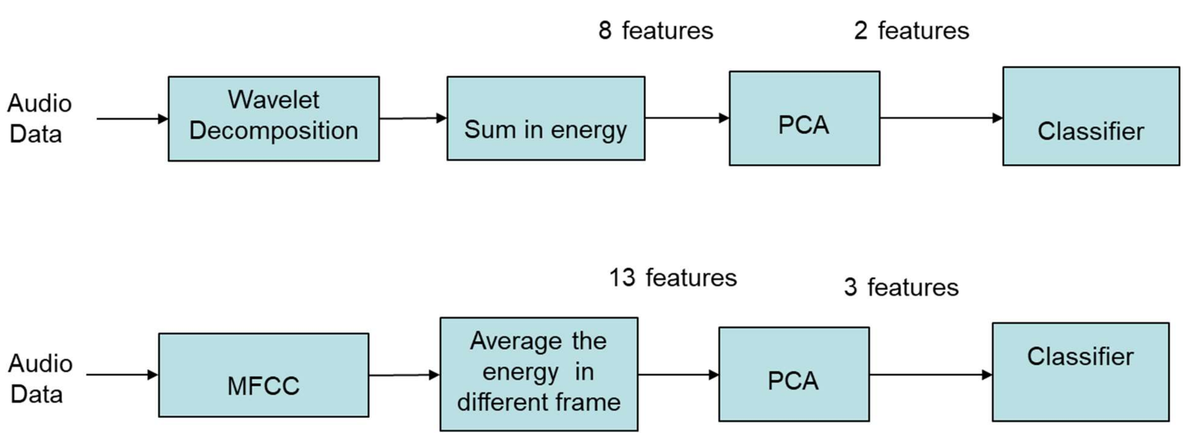

Fig. III, block diagram of feature extraction

C. Label

In our work, we label our data as good or bad based on the median of data. Samples with blood flow volume larger than median of blood flow volume will be labeled as good, vice versa. Vessel width is also taken into consideration with the same labeling manner.

D. Classifier

Based on the survey, SVM and KNN are used with the help of Sklearn module. Five fold cross validation is used. Table II ,Table III and Fig. IV show the result of classification.

Table II classification result of blood flow volume

Flow	SVM	KNN
Wavelet1	0.61	0.52
Wavelet2	0.6	0.48
Wavelet3	0.528	0.51
MFCC1	0.597	0.457
MFCC2	0.627	0.506
MFCC3	0.528	0.459

Table III classification result of vessel width

Width	SVM	KNN
Wavelet1	0.573	0.513
Wavelet2	0.642	0.608
Wavelet3	0.666	0.609
MFCC1	0.51	0.526
MFCC2	0.647	0.647
MFCC3	0.686	0.642

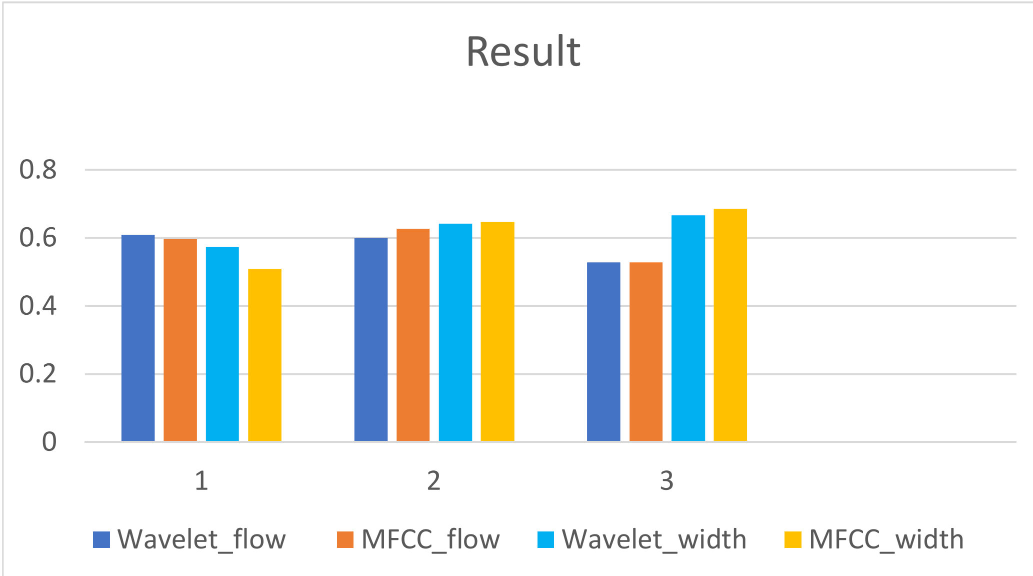

Fig. IV Classification result with three part of acoustic signals.

4. Conclusion and Discussion

With the result so far, it seems that there is not a strong connection between acoustic feature and blood flow volume. In the literature survey, acoustic feature is recorded from the AVF directly. However, we only have acoustic signal recorded from related artery and vein. This might be a reason that blood flow volume is not strongly related to acoustic feature since the turbulent sound cause by stenosis is not recorded.

As for the vessel width, there seems to be a connection in artery and vein. However, research about the acoustic feature and vessel width is not found in the literature survey, more experiment is needed in this case.

5. Reference

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