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Mitral Valve Prolapse Detection Using Landmark Extraction from Echocardiography Sequences

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***Abstract*— the mitral valve is one of the four valves of the heart, whose function is to keep the blood flow in the physiological direction when the heart contracts. There is no satisfactory method allowing an automated assessment for Mitral Valve Prolapse (MVP) detection. In this paper an algorithm is proposed for detecting MVPs automatically from an echocardiography sequence. Our algorithm has two steps; first landmarks are extracted from the echocardiography sequence. Then landmarks are tracked in the whole frames of a sequence. In order to detect MVP and isolate it from a normal mitral motion, we extracted some features (such as maximum deviation of valve angle and spectral power ratio) from the motion pattern of a mitral valve and we gave these features to a SVM classifier. The results show that the mitral motion trajectory may have good discriminative features for detecting MVP (87% specificity and 84% sensitivity).**

I. Introduction

Mitral Valve Prolapse (MVP) is the most common cause of mitral regurgitation (MR) in industrialized countries [1] and yet its etiology and pathophysiology remain unknown. Some investigators have suggested that this condition is inherited as an autosomal dominant trait [2, 3]. The prevalence of MVP in the general population is 2.4% [4] Recent United States census data place the population of the United States at 281,421,906. Thus, currently there are approximately 6,754,125 persons with MVP.

The assessment of patients with mitral valve disease is one of the most challenging and promising clinical applications of echocardiography. Echocardiography has evolved into the most predominant diagnostic imaging technique in Cardiology. Over the last 5 decades the diagnostic capability of echocardiography has increased dramatically from M-mode to two-dimensional (2D) imaging [5].

Every imaging technique in Cardiology aims at a complete visualization and comprehensive assessment of cardiac morphology and pathology, as the heart is a complex geometric structure. Therefore, analysis of the heart in motion in all three or four (including time) dimensions can further facilitate and enhance the diagnostic capabilities of echocardiography [6].

There is an extensive literature describing the application of so-called active contour or snake techniques [7] to cardiac ultrasound [8, 9, and 10]. These methods track the inner (endocardial) and/or outer (epicardial) border of the myocardium by minimizing a combination of internal and external energies of the contour representation.

Active shape models have been applied in echocardiography with partial success [11, 12, and 13]. The major shortcoming of these border-tracing approaches is that they only yield motion information normal to the myocardial boundaries. Motion parallel to the contours, such as longitudinal lengthening and shortening, and deformation of myocardial structures in-between the boundaries cannot be assessed. In this paper we proposed a new algorithm for mitral valve motion for automatic detecting of MVP based on motion pattern of mitral valve.

II. SAMPLING AND IMAGE AQUISITION

The current study was carried out in Alzahara hospital, in Isfahan, Iran. Patients were recruited from those referred to our echocardiography laboratory with symptoms and/or signs consistent with a diagnosis of MVP. We studied 46 patients with non-rheumatic, uncomplicated and isolated mitral anterior leaflet prolapse (14 male and 32 female with a mean age of 26.3± 5.9 years) and 25 healthy control subjects (age and sex matched 9 male and 15 female with a mean age of 25.4 ± 4.3 years). None of the 46 subjects with mitral valve prolapse had a history of ischemic heart disease, other cardiac or systemic disease. Patients were excluded from the study if they showed evidence of inflammatory joint disease or if they had typical features of hereditary disorders of connective tissues.

We analyzed transthoracic ultrasound images acquired using Sequoia® and Aspen™ ultrasound systems manufactured by Accuse Corporation. The image sequences, consisting of standard two- and four-chamber apical views, included both normal and pathological patients and contained frames covering at least one full cardiac cycle.

The measurements were carried out according to the recommendations of the American Society of Echocardiography.

III. Method

In this section, the algorithm is introduced. Proposed algorithm has two steps. First, an image processing algorithm for extracting and tracking landmarks from echocardiography sequences and extracting the mitral valve motion pattern was done. Then signal processing algorithm was used to extracting features and the features were considered to input of classifiers.

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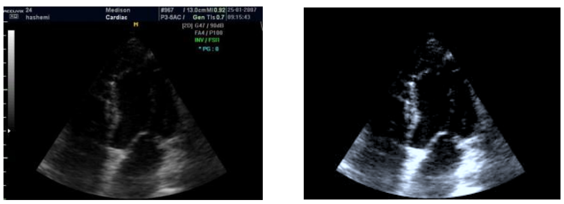
A. *Image processing algorithm*

After obtaining the video file from echocardiography imaging system, all the frames of this video file are extracted. The total number of these frames depends on the frame rate of the echocardiography imaging system. Each frame is considered as an image. In the first step, due to the high level of echocardiography imaging method, a noise removal step seems necessary. For this purpose, the algorithm developed by [14] was used. After this step, for adjusting the contrast and image enhancement algorithm [15] was used. The result of applying these algorithms on a sample of echocardiography image is shown in the following figures.



(a) (b)

Figure 1. (a) Main input image (b)The result of using image enhancement

1) Landmark extraction

For landmark extraction from an echocardiography frame, extended maximum algorithm was used for binarization. Extended maximum [16] finds the regional maxima of an image. It returns the binary image that identifies the locations of the regional maxima in an image (Fig 2 and 3).

10	10	10	10	10	10	10	10	10	10
10	22	22	22	10	10	44	10	10	10
10	22	22	22	10	10	10	45	10	10
10	22	22	22	10	10	10	10	44	10
10	10	10	10	10	10	10	10	10	10
10	10	10	10	10	33	33	33	10	10
10	10	10	10	10	33	33	33	10	10
10	10	10	10	10	33	33	33	10	10
10	10	10	10	10	10	10	10	10	10
10	10	10	10	10	10	10	10	10	10

0	0	0	0	0	0	0	0	0	0
0	1	1	1	0	0	0	0	0	0
0	1	1	1	0	0	0	1	0	0
0	1	1	1	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	1	1	1	0	0
0	0	0	0	0	1	1	1	0	0
0	0	0	0	0	1	1	1	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

Figure 2. Extended max algorithm

A binarized image is the same size as image. In binarized image, pixels that are set to 1 identify regional maxima; all other pixels are set to 0. Regional maxima are connected components of pixels with a constant intensity value, and whose external boundary pixels all have a lower value.

The result of using an extended maximum algorithm on a frame of echocardiography sequence is shown in the following figure.

After this step, a landmark was considered as a maximum of gray level value in each region. This means that the total numbers of landmarks are related to the number of regions.

Figure 3. The result of using extended max algorithm

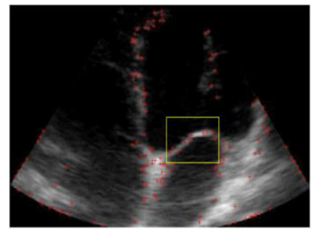


Figure 4. Extracting landmark coresponding to mitral valve

2) Landmark tracking

The landmark extraction step was done for the whole sequence. For mitral valve tracking, the position of landmark should be tracked. For this purpose, the overlap of the regions in the current and previous frame was found. If two regions have overlaps then the related landmarks will be tracked (see fig 5)

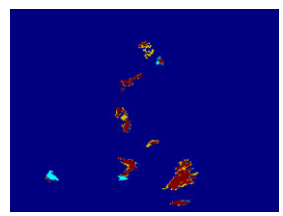


Figure 5. The result of overlap between current and pervious frame

Tracking algorithm was used for the entire of sequence. The landmark related to mitral valve is labeled as 10, and the related landmark in the current frame was labeled as the same as previous frame and this algorithm is repeated through the sequence figure 6 illustrating the result of mitral valve tracking on a two consequent frames.

B. Signal processing algorithm

To extract mitral valve motion pattern, the displacement of landmarks in both x and y coordinates within the whole sequence were plotted.

By extracting the mitral valve pattern (see figure 7) we are able to extract some useful features from the patterns as input of a classifier.

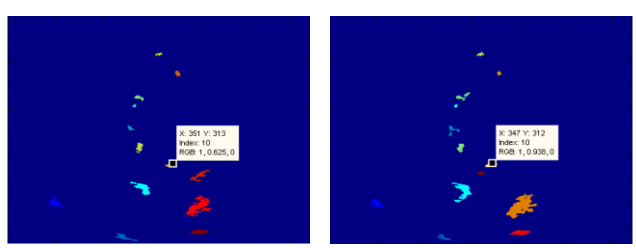


Figure 6. The result of mitral vavle tracking on a two consequent frame

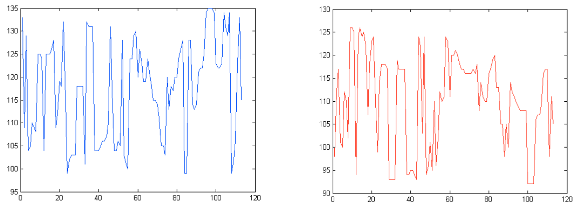


Figure 7. Mitral valve motion pattern in both x and y coordinats

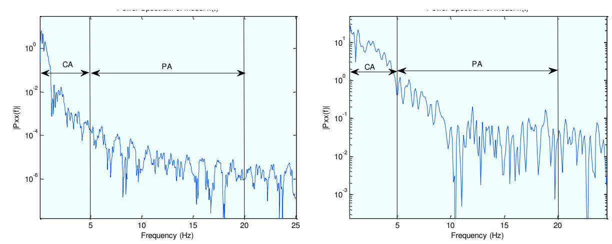


Figure 9. SPR for normal case(left) is less than MVP(right)

1) Preprocessing

Before any process of motion pattern, it should be denoised and baseline wander corrected. A 8th order Butterworth highpass filter with cutoff frequency of 0.2Hz was used to remove wanders produced by low frequency drift of probe. High frequency fluctuations caused by image noise and errors in landmark extraction were eliminated by averaging. Some window sizes of moving average were tested and an optimal window size obtained. We found that a 5 frames window can successfully remove unwanted fluctuations.

2) Feature Extraction

Because the dimensions of mitral valve of studied subjects are different, absolute values of x and y coordinates may be variable among subjects. For solving this problem we used angle of mitral valve defined as $\tan^{-1}(y/x)$.

The origin of coordinates was defined as the position of landmark in the first frame. Figure 8 shows average fluctuation of the angle of mitral valve over one heart beat of two subjects one normal and another with MVP. This trajectory indicates mitral value movements modulated by motion pattern of total heart. One of features can be extracted from such pattern is maximum deviation (*MD*) of mitral valve angle (as shown in figure 8). We found that this parameter is an approximately good discriminative feature.

Another feature that was used for empowering classification is a spectral feature. Averaged Power Spectral Density (PSD) [17] of segmented angle parameter was computed for each subject. With a video frame rate of 25fps frequency span of PSD will be 25Hz. Spectral power ratio (*SPR=CA/PA*) were calculated considering the band 0.2-5Hz as the constant area (*CA*) and the band 5-20Hz as the predictive area (*PA*).

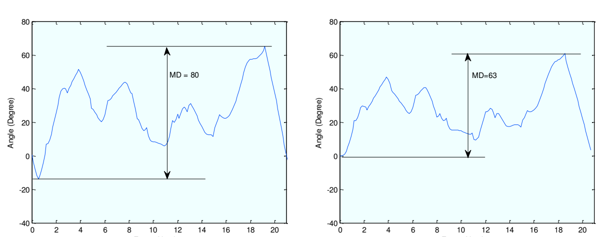


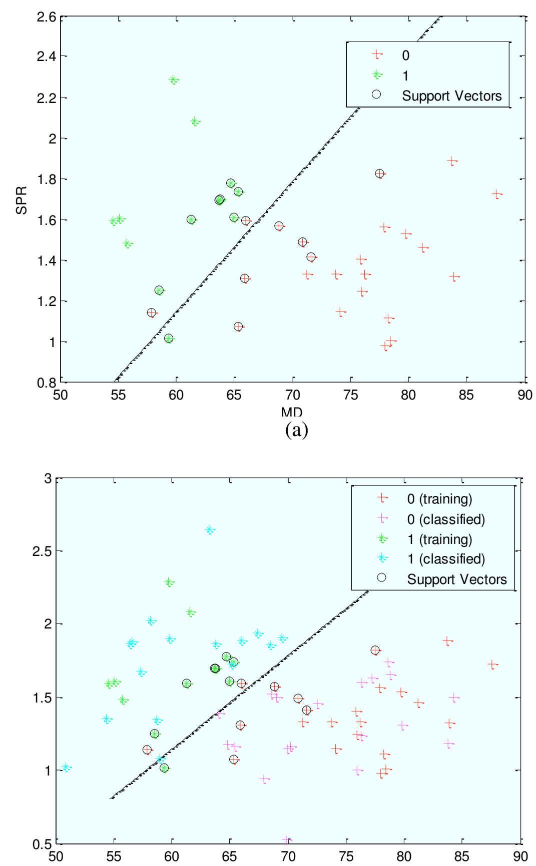
Figure 8. Maximum deviation of angle trajectory of mitral valve in normal(right) and MVP (left)

Figure 9 shows averaged PSD of normal/MVP subjects and *SPR* of each spectrum. We found that the energy of signal for MVP cases is spread over span and the spectral power ratio will be less than normal cases.

3) Classification

After calculating feature vector [MD_i , SPR_i] for each subject i, and defining two classes Normal (N) and MVP a classification problem was defined.

However results for Linear Discriminant Analysis (LDA) [18] seemed acceptable in first approach, we achieved an optimum classifier using Support Vector Machine (SVM) classifier [19] of Bio-informatics Toolbox of MATLAB software. The function was set to randomly select train and test set (50%) among total number of subjects (46 patient + 25 normal = 71). Figure 10 shows training and final classification result.



(a)

(b)

Figure 10. Classifier trainig (a) and validation (b) results.

IV. RESULT AND DISCUSSION

As shown in figure 10 the classification result is approximately acceptable. Table 1 shows summary of results. False positive detection rate of MVP is 1/25 or on the other word specificity of method is 96%. The test sensitivity as the other measure of accuracy is 44/46=95%.

Table 1. Classification result summary

	Normal	MVP
Normal detected	24	2
MVP detected	1	44

We tried to measure the accuracy of method against changing selected landmark. If the classifier designed with the pattern extracted from one landmark is used for another landmark of same subjects, the results may be different a little. As shown in tables 2,3 the sensitivity drops to 21/25=84% and specificity to 40/46=87%. This result indicates we need to find an optimum landmark for each subject or combine extracted features with some features of another heart signal (such as ECG) to have a better classifier.

Table 2. Classification result using another landmark

	Normal	MVP
Normal detected	21	6
MVP detected	4	40

Table 3. Classification accuracy results

	same landmark	Another landmark
Sensitivity %	95	84
Specificity %	96	87

Using 5 landmarks for each subject and analyzing results, we found that best results would be achieved from such landmark that has larger MD of mitral valve. Thus if an analyst visually chooses one landmark among several detected landmarks that has maximum deviation in its fluctuations, it may be the optimum landmark for classification.

V. CONCLUSION

Cardiac diseases are a major health concern world-wide. In particular, useful information about the cardiac function can be extracted by analyzing of echocardiography sequences. However, echocardiographic images are difficult to analyze. The images contain a high level of multiplicative speckle noise. The active shape models (as the best algorithm for cardiac motion analysis) need a pre-segmentation step. Besides, since ultrasound images are typically noisy and of low quality, the inner and, especially, outer borders are usually not clearly defined, limiting the applicability of standard border detection algorithms significantly.

In this paper a novel algorithm was proposed for detecting mitral valve and extracting its motion pattern. In the next step the person with normal mitral valve pattern from the person who has MVP was acceptably isolated.

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