K-SVD and Sparse Classification Based algorithm for fast and automatic Identification of Intracardiac Masses in Echocardiography

P. Ganesh Babu[1] G. Deepareddy[2] V. Dhanalakshmi[3] E. Prithima[4]
[1]Assistant Professor [2,3,4]Student
[1,2,3,4]Department of Biomedical Engineering
[1,2,3,4]Adhiyamaan College of Engineering, Hosur – 635109, Tamilnadu

Abstract— The proposed technique helps in automatic identification of intracardiac masses in echocardiograms. This technique aims to help cardiac surgeons to classify tumor and thrombi in patients with cardiac diseases in an easy way thereby improving accuracy and minimizing diagnosis time. It makes use of non-local means algorithm (NLM) for the removal of Rayleigh scattering noise and the despeckled image is processed and segmented with the help of K-singular value decomposition (K-SVD) and sparse representation classifier (SRC) to classify the masses. It aims at better and faster classification results

Key words: Automatic identification, intracardiac masses, NLM, K-SVD, SRC

I. Introduction

Intracardiac masses are abnormal structures found within or adjacent to the heart. These structures lead to severe cardiovascular disorders and require careful diagnosis for prompt resection and treatment. There are two main types of intracardiac masses namely: tumor and thrombi.

Tumors are rare entities and most of them in adults are benign and mainly composed of myxomas [1], [2]. These tumors may cause obstruction to the left ventricular filling which leads to embolization. This leads to cardiac arrest and death if left untreated. Thrombi are commonly found in patients with ischemic stroke. They lead to atrial fibrillation, reduced cardiac outputs and enlarged atrial chamber. Echocardiography is widely used in diagnosis of intracardiac masses for its noninvasive and low cost nature. The internal echoes are heterogeneous. The echocardiography appearances of tumor have a broad base and narrow stalk, as shown in Fig. 1(a). The tumors show continuity with atrial wall and are highly motile. In turn, thrombi are motionless, dense, ovoid, and echo reflecting with a broad base. It has a well-defined contour, as shown in Fig. 1(b).

(a)

(b)

Fig. 1: Examples of echocardiographic images with (a) Intracardiac tumor and (b) Intracardiac thrombus

II. LITERATURE SURVEY

There are various techniques and classifiers which have been reported in literature. It is necessary to classify intracardiac masses so as to find a better treatment solution. Due to the similarity in appearance of the masses in echocardiography, it is very difficult to classify manually. The proposed technique in this paper aims at a fully automatic model with additional features. The algorithm is optimized so as to minimize time-consumption and provide better analysis.

III. METHODS

The workflow diagram of our method is shown in Fig. 2. It involves frame decomposition, selection of region of interests (ROIs), despeckling using NLM and K-SVD, intracardiac mass segmentation, feature extraction and classification using sparse representation classifier.

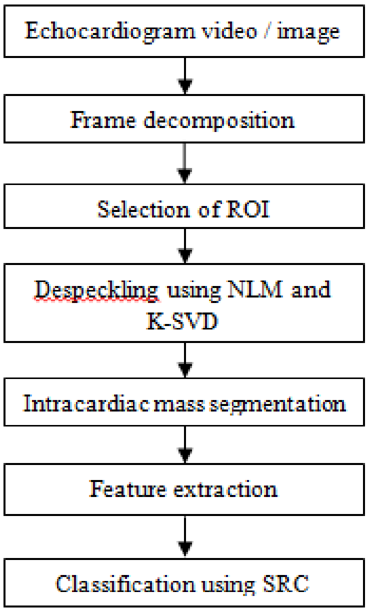

Fig. 2: Workflow diagram

A. *Frame decomposition*

Echocardiogram video is decomposed into frames. One such frame is given as input or the video itself is presented, the algorithm is designed and optimised to work in either way and reduces processing time. The duration of an echocardiogram sequence is usually about 3-4 s. The decomposed frame has a resolution of 480 x 640. Once the input image is read (Fig. 3), it is converted to double and then cropped. Apart from the necessary data (ROI), the image consists of texts and labels (static information). Therefore, it is necessary to eliminate this static data by subtracting two successive frames. This final processed image is used for further analysis.

B. Selection of ROI

The region of interest (ROI) containing the mass and its surrounding tissues is selected in order to focus on the mass area, fig. 4. This is done by applying coarse-to-fine iteration strategy that makes use of sub windows clustering [1]. The size of the sub windows is 40 x 40. At each iteration, several texture features of sub windows like mean, variance, and gray level co-occurrence matrix (GLCM) are calculated and input into a fuzzy K-means algorithm to cluster the similar sub windows. The iteration stops till a coarse-to-fine, (i.e., when all the sub windows share the same intensity distribution) is obtained.

(a)

(b)

Fig. 3:(a) Input image and (b) Resized image

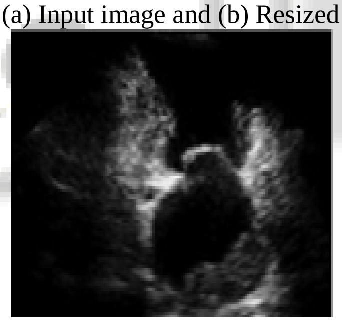

Fig. 4: Automatic ROI selection

C. Despeckling using NLM and K-SVD

Echo images possess noise in the form of speckle which occurs as a result of multiple reflections known as Rayleigh noise. Various methods have been used previously like wavelet method, median filter, speckle reducing anisotropic diffusion (SRAD) [3]. This noise degrades the resolution of the mass area and limits the detectability of small lesions. The image of ROI is despeckled using the non-local means algorithm. NLM is an image processing algorithm that takes a mean of all pixels in the image, weighted by how similar these pixels are to the target pixel. It results in greater clarity and less loss of detail in the image.

The weighting function sets up a normal distribution with a mean, $\mu = B(p)$ and a variable standard deviation:

$$f(p,q) = e-(|B(q) - B(p)|^2) / h^2 \quad (1)$$

where h is the filtering parameter (standard deviation) and B (p) is the local mean value of the image point values surrounding p.

K-SVD makes use of a overcomplete dictionary D, through which the original image is decomposed into a sparse coefficients matrix [4]. The dictionary contains two kinds of atoms with different sparse coefficients where the texture area (intracardiac mass and atrial wall) consists of small number of non zero coefficients and the homogenous area (cardiac chamber) coefficients are all zeroes. This identifies the initial mass contour at a proper location.

D. Intracardiac mass segmentation

For the analysis of masses, it is necessary to extract the boundary of the mass. The base of the intracardiac mass is attached to the atrial wall and therefore both are segmented together. The original image is converted into a binary image to avoid misclassification. This binary image is eroded and dilated with a structuring element of size 3 x 3 to choose eight-connectedness sub-regions. And calculate the Euclidean distance between each sub-region and the centre of ROI to trim off those far away ones. The initial rough contour is obtained by canny edge detector where the sigma of Gaussian filter (SoG) and the gradient threshold are set to 1.

The resultant boundary is segmented using a modified active contour model which is based on curve evolution and minimization of energy function. This is done by altering the dictionary. The segmentation is based on complementary local radius and local statistics technique.

E. Feature extraction

Apart from the motion and boundary feature, it is necessary to take into account the texture feature in order to identify the intracardiac mass. The texture feature is based on the internal echo.

Motion feature: intracardiac tumor possesses high motility, whereas thrombi are non-motile [2].

Boundary feature: intracardiac tumor has a narrow stalk which is connected to the atrial wall, whereas a thrombus lies entirely on the wall and has longer base length than that of a tumor.

Texture feature: Gray level co-occurrence matrix (GLCM) is used to extract five features: contrast, entropy, energy, autocorrelation and homogeneity. These are computed at various values of $\Theta = 0°, 45°, 90°, 135°$ and $d = 1$.

Along with these 5 GLCM features, mean intensity and the mean sparse coefficient, motion of mass and the base length are calculated for further classification.

F. Classification using SRC

The final mass is classified using sparse representation-based classifier (SRC). It is a non-parametric learning method. It does not require training process but only need the training data. It is based on the fact that the test sample can be represented as a linear combination of the training sample [4]. For each sample, the error is calculated. The test sample is classified with the class having minimal residual error. SRC has good generalization ability.

IV. Results And Discussion

This model aims at minimization of the time taken to process by optimizing the algorithm that can read either video or an image. The ROI cropped is despeckled using NLM and K-SVD. The despeckled image D is shown in fig. 5. The despeckled image is further cropped and resized for further analysis, Fig. 6. This resized image D1 is converted to a binary image format S and its complementary is obtained (T). Edge detection is used to obtain the initial boundary. Using a mask, localized segmentation is done to obtain the final contour. A sparse representation based classifier identifies the intracardiac masses.

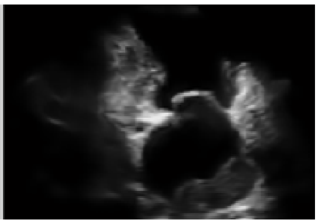

Fig. 5: Despeckled image D

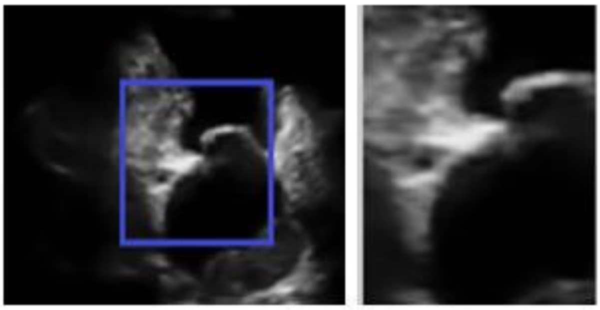

Fig. 6: Further cropping of ROI

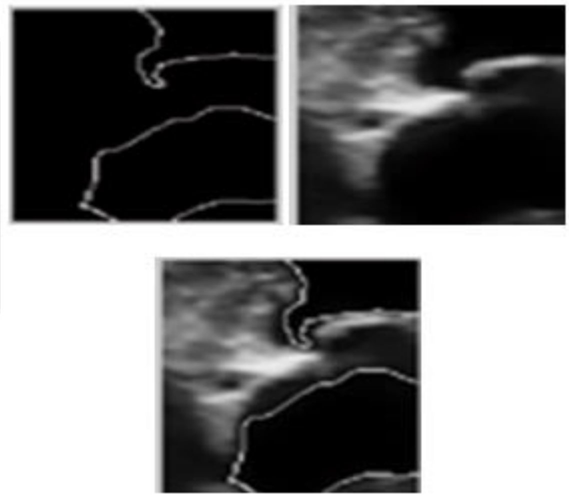

Fig. 7: Initial boundary (edge detection)

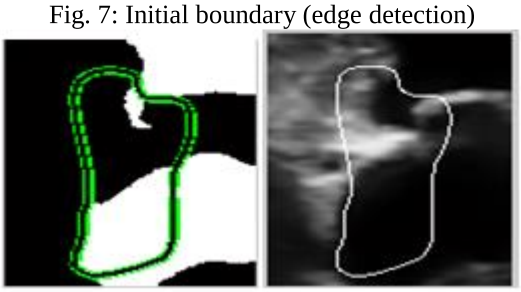

Fig. 8: (a) Localized segmentation and (b) Final contour

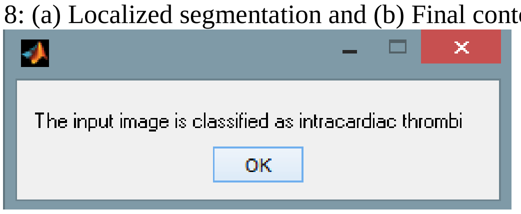

Fig. 9: Classification result

V. CONCLUSION

In this paper, a new approach for automatic classification of intracardiac masses has been presented. Initially, input is fed and the ROI is cropped. The ROI is defined automatically by a coarse-to-fine strategy. Then the Rayleigh noise is eliminated by the combined use of K-SVD and NLM. The image is despeckled while retaining the important cardiac structures. Then, image segmentation is carried out using a modified ACM. The features are extracted using GLCM approach. The mass is classified using SRC. Thus, intracardiac masses are classified automatically.

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