ISSN2394-3777 (Print)
ISSN2394-3785 (Online)
Available online atwww.ijartet.com

International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
Vol. 5, Special Issue 9, March 2018

Automatic Classification of Intracardiac Tumor and Thrombi in Echocardiography Based on Adaptive Neuro Fuzzy Inference System

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***Abstract*-- Nowadays most of the people affected by tumor. According to the location of the tumor, various diagnostic techniques are used. Various image processing techniques are used to automatically classify the intracardiac masses such as tumor and thrombus present in the echocardiography sequences of the heart. The appropriate diagnosis type of intracardiac mass in a living human is a challenge for a cardiologist. So there is a growing interest in automatic classification. Therefore, an automatic classification method is useful for heart diseases diagnosis. However, for the purpose of identifying the tumor, various techniques are there. After identifying the tumor, then the classification process is done. Disease classification is used for the doctor if it is computerized for fast diagnosis and perfect result. First, to identify the mass whether it is present in the heart or not, by using automatic Region of Interest selection.For denoising, the despeckling process is done by Non-Local Mean algorithm and the K-Singular Value Decomposition. After the denoising process noise free image is obtained. For easy way of locating objects and boundaries from images, the segmentation process is used. Then the segmentation process is performed by Active Contour Model, it pointing the exact location of the tumor. In the feature extraction process, particularly for the texture feature analysis Gray Level Co-occurrence Matrix is used. Second, to classify the mass the sparse representation classifier is used to differentiate whether the mass is tumor or thrombus.**

***Keywords*:Segmentation, Feature extraction, Classification, intracardiac masses, sparse representation, tumor, thrombus.**

I. INTRODUCTION

Cardiovascular disorder (CVD) contains more diseases that affect the heart such as angina, congenital heart disease, including stroke and circulation. This is called as a heart and circulatory disease. Intracardiac masses are dangerous in cardiovascular disease (CVD) [1]. Most masses are irregular structures in inside or closely neighboringto the heart that should be differentiated for treatment. Thrombi are communal outcomes in patients with ischemic stroke [2]. Most patients affected by thrombi are treated with heparin and thrombolysis [3]. The two main categories of intracardiac masses are tumor and thrombus. Echocardiography is the type of diagnosis technique of intracardiac masses, which is non-invasive as well as minimum cost. The identification of intracardiac masses at heart using echocardiography depends on seriously the doctor's decision because various treatment options are available for different diseases. The pathology of the intracardiac tumor and thrombus are different, and then they are similar characteristics in echocardiography. Also, masses are misrepresenting frequently. Echocardiography identifications are brought out by cardiologists physically in most hospitals, so the diagnosis takes more time. Identification based on the image quality and methods, as well as the experience of a cardiologist. So, the demand for an automatic identification is gradually

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increasing, that is possible to increase the diagnostic precision and then lead which type of patient should be suggested for surgery.

The analysis based on ultrasound images develops prosperously operating in the computerized analysis for cardiovascular disease, like explain important ultrasound characteristics in initial stroke indicator [4, 5], analysis of coronary artery [6] using fuzzy formula-based evaluation system, then assigning flexible section matching procedure for carotid duct wall and plaque mobility [7]. Yet, identification of intracardiac masses is arousing now

Normally the automated segmentation approach involving first the noise reduction, partitioning, extracting important features and mass classification. Generally, ultrasound image affected by speckle noise that causes due to electronic devices present during the scanning process. To acquire the accurate analysis, it is important to reduce the noise in the images without damaging the picture pixels and spoiling meaningful information. Several strategies can be helpful for reducing the noise in the ultrasound images, for example, mean filter, wavelet-based methods, Noise reduction of anisotropic diffusion filters and median filter. Using these filters, it is possible to minimize the speckle noise, at the same time they discard the important image elements in the echocardiography. Then considering the partition process, methods such as fuzzy-based method, Active Contour Model (ACM), the Active Appearance Model (AAM), the Level set method and Graph-cut method have been examined. Analysis taken from above methods, these can be useful for certain type of images they are unsuitable for intracardiac mass segmentation due to the mobility of cardiac chamber over the cardiac cycle. Atrial wall and the mass region are overlying in the period of systolic phase, the chamber compresses too lower which is occupied with intracardiac mass. Typically classifiers need a training stage and guidance from well-known cardiologists. Hence, there is a growing interest in constant classifier with a high quantity of abstraction with no need of training process.

because of the homogeneous arrival of tumor and thrombus present in the echocardiography and also depends upon the quality of the image while considering noise, inappropriate signals from electronic machines and misplaced curves. Strzelecki*et al.* a partially systematic technique like neural network used for classification and partition of intracardiac masses in echocardiography [8]. Anyhow there is no implementation of differentiating the intracardiac masses with complete automated strategy previously.

Fig.1. Intracardiac Mass

The sparse representation classifier is the transform domain method and also emerging technique in recent years. In this paper, the classification is done by sparse representation method. The novel method gives various helpful innovative ideas for despeckling. For reducing the noise in the images the combination of K-Singular Value Decomposition (K-SVD) and Non-Local Mean (NLM) is used. After reducing the noise in images, then only the segmentation process starts. Here, for segmentation Active Contour Model (ACM) is applied to clarify the tumor and thrombus. After that nine features such as homogeneity, contrast, entropy, autocorrelation, energy, the motion feature, boundary feature, mean intensity and mean sparse coefficients are obtained. Lastly, the sparse representation classifier (SRC) is adapted to estimate the realization classification.

The remaining part of this paper is formulated as follows: In section 2, we present related works. In Section 3, Identification of the problem is presented. In section 4, the objective of the proposed work is presented. In section

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5, the proposed methodology is briefly introduced. In section 6, the results and discussions are presented. Conclusions are reviewed in section 7.

II. Related Work

Chen *et al.* proposed a graph-cut method for medical image segmentation [9]. Graph-Cut Oriented Active Appearance Model (GC-OAAM) contains two parts namely training part and segmenting part [10]. Active Appearance Model, Live Wire, and Graph Cut specifications are predicted. Then the segmentation part contains detection and picture representation. In detection part, a three-dimensional method is selected for estimating the image of organ segment by segment using Multiobject Oriented Active Appearance Model (MOAAM) strategy.

Sérgio Pereira *et al.* proposed convolutional neural network for brain tumor segmentaion [11]. First, the process started from pre-processing, it contains intensity, normalization of patch and bias-field correction. Then in the next stage i.e., while training, the number of training patches are spuriously developed by rotation of training patches, then utilizing the elements of High-Grade Glioma into developing the rare entity of Low-Grade Glioma sets. The convolutional neural network constructed by fully convolutional layers with little 3*3 substances for getting a wide construction.

Nyúl*et al.* proposed while designing the CNN, facing the problem of diversity generated by the acquisition of MRI image from various-site using intensity normalization [12]. It is essential in acquiring a valuable segmentation. The brain tumor is extremely unstable in their geographical localization and structural distribution, so it is essential to examine the utilization of data development to deal with instability. Here the above study gives knowledge about developing training data elements via rolling the patches and also sampling is done by High-Grade Glioma represented in Low-Grade Glioma. The development of data is entirely useful but it is not thoroughly examined in machine learning strategies for brain tumor segmentation. An investigation on deep construction by using little substances and also matching deep Convolutional Neural Network with depthless architecture and higher filters. Even when using more amount of details the depthless architecture produces a smaller performance. From above analysis, Leaky Rectifier Linear unit (LReLU) is essential when compared to Rectifier Linear Unit (ReLU) in Convolutional Neural Network [11].

III. PROBLEM IDENTIFICATION

However our proposed method is done by fully automatic, it has several inconveniences of analyzing the intracardiac tumor. In this paper, considering the analytic proceeding of the tumor, the efficiency and also the minimal usage of patient's were a vital role. The whole analyzing time was more, it is challenging for real-time processing in laboratories. The main issues were the image decomposition; divide each image part into the sparest coefficients. Then another problem in intracardiac mass segmentation, active contour model suffered from two weaknesses: 1) it was sensitive to initial contour; 2) an improper exterior effort might direction to perimeter impression. Further advancement may be used for sharpening and stimulating the process. Additionally, the size of the sample was too small to create a stable outcome. So we have to add more intracardiac masses with various sizes must be combined to demonstrate the capability of our classification method.

IV. OBJECTIVE OF PROPOSED WORK

The main objective of the proposed work is to save the patient's life. For that treatment is the key stage to safeguard the patients from dangerous. In previous, the identification of tumor is manually by the experienced cardiologist. Here, the identification process is automated by using image processing techniques. To identify the tumor present in the human's heart using automatic Region of Interest (ROI) selection. An acquisition of the image from MRI source, speckle noise present in an image. Noise reduction is going to do by Non-Local Mean Algorithm (NLM) and K-Singular Value Decomposition (K-SVD). After noise reduction process the intracardiac mass segmentation process is very easy. Then all the image features are extracted by feature extraction process. Finally, the mass is classified into tumor or thrombus. After the classification process, the treatment process is started.

V. PROPOSED METHODOLOGY

The proposed methodology has two stages of processing: 1) Pre-processing. 2) Post-processing.

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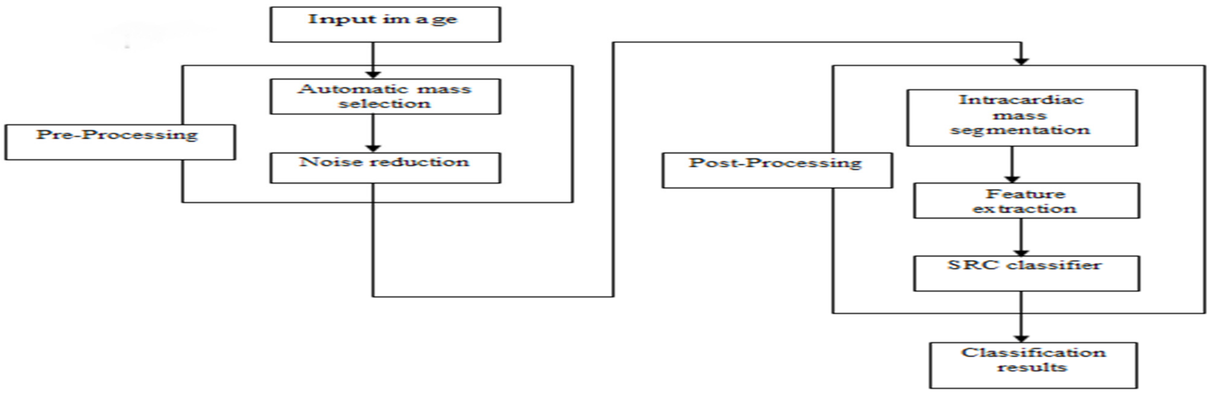

Fig.2. Flow diagram for proposed method

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1) PRE-PROCESSING

a) Automatic Region Of Interest selection

In the pre-processing stage, the input image is given to the automatic Region of Interest (ROI) selection. It selects the exact position of the mass area i.e., the ROI containing the tumor or thrombus part. Generally, ROI is used for medical image processing, for example, the particular section of a two dimensional, three-dimensional or four-dimensional image that is important while during analyzing. When the mobility of the organ having an ROI, the doctor needs to diagnose how the organ structure moves in a particular time duration.

Fig.4 represents that the extraction of ROI containing the mass. Extraction ROI by applying the binary mask on input image the same size. To differentiate the ROI from the input image, the pixels that denote the ROI are fixed to 1 and all other pixels fixed to 0. By using this method can differentiate one or more ROI in an image. The nature of the region is geographic, such as a shape that enclosed through continuous pixels or describes by intensity ranges. In the final case, the pixels are not essentially continuous.

b) Noise reduction by Non-Local Mean and the K-Singular Value Decomposition algorithm

The non-local mean algorithm is used in image processing for reducing the noise in an image. Not at all like local mean filters, which take the average value of a group of pixels encompassing a target pixel to smoothing the image, the non-local mean filtering takes an average value of all pixels in an image, weighted by how identical these pixels are to the target pixel. When comparative analysis taken from local mean algorithms, above result gives high post-filtering brightness and low harm of information in the picture. If the analysis is taken from other well-known denoising methods, the non-local mean algorithm adds the “method noise” such as the error in the denoising process which exactly looks like a white noise, which is suitable since it is generally less troubling in the denoised product[13, 14]. The main application of K-SVD is in an image processing, processing of audio, analyzing of document, and biology. K-SVD is an algorithm for dictionary learning, to create a dictionary for sparse representations through a singular value decomposition method. K-SVD is an establishment of the K-means clustering approach, it works through continuously varying in the middle of sparse coding the input data based on the present dictionary, and revising the atoms in the dictionary to greater apt the data. K-SVD produce the overall dictionary including two types of atoms with various sparse constants. For that texture area having a low amount of non-zeros, all zeros denoting the constants of the homogeneous areas.

2) POST-PROCESSING

a) Intracardiac mass segmentation

Segmentation of mass is important for the further analysis of extracting a feature from the denoised image. segmentation is the initial stage for extracting information from an image.

i) Initial contour of mass

The mass and atrial wall are varying in image intensities. The whole dictionary of K-SVD can segregate the above areas by two sorts of atoms, interrelated to the texture area and chamber of cardiac i.e., homogeneous area. For differentiating two areas by transferring the original image into a binary image, the intensities of the homogeneous areas are 1. Due to intensity inhomogeneity in echocardiogram, misclassification is done in few regions of the image. The binary image is processed by dilation and erosion with a square structuring mask which is used to choose 8-connectedness subregions and then evaluate the distance between each subregion afterthat center of the mass to trim off those faraway ones. To denote the correct initial contour of the mass region, the Canny edge detection operator is used. The value of sigma is set to 1 for both Gaussian filter and gradient threshold in canny edge operator.

ii) Active contour model

ACM is a well-known technique in the segmentation of an image [15]. Here, the segmentation depends on minimization of energy and spline evolution, moving in response to two segments: the external and the internal forces. The internal force enforces the suppression on within the contour, while the external force impacts the contour against image features.

$$E_{\text{int}} = \frac{1}{2}(\beta(s)\left\|\frac{d\bar{v}}{ds}(s)\right\|^2 + \gamma(s)\left\|\frac{d^2\bar{v}}{ds^2}(s)\right\|^2)...(1)$$

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Where $\frac{d\overline{v}}{ds}$ and $\frac{d^2\overline{v}}{ds^2}$ incorporate the internal force. These are the 1st and 2nd derivative of the boundary spline, β and γ are constant weights, respective to a measure of flexibility and rigidity. Typically, the external energy considers the high gradient edges for attracting the image features.

The ACM has two disadvantages: i) it is more precise to the initial contour; ii) an improper external energy may lead to perimeter hole.According to the first issue, when the initial contour of the mass located faraway from the object, it will be tough for Active Contour Model to concentrate the correct segmentation.

For the second issue, typically, the gradient and gradient vector flow (GVF) is used as the exterior energy [16]. These are sensitive to the image noises, mainly challenging in echocardiograms with poor image quality and inhomogeneous intensities. So, here for taking as a new external energy, K-SVD is the best method. K-SVD contains local characteristics of each image patch, picture intensity, texture features, variances, most powerful than the conventional gradient.

b) Extracting features from segmented image

When locating the mass in an echocardiogram sequence, typically the doctor's judgment depends on two rules: the motion feature and the boundary feature. Even if two masses present the variation in sound reflections, texture features are visibly non-identical because of low image quality. Poor image features are neglected while processing. But for the classification process texture features, specifically, the mass internal echo is very important [17].

Here Gray-Level Co-occurrence Matrix (GLCM) is a general method for analyzing texture features. There are five features obtain from GLCM such as Autocorrelation, homogeneity, entropy, contrast, and energy. The mean intensity and mean sparse coefficients are also calculated for further analysis of the texture features. Finally, the whole of nine features is the mass movement, the base length, five GLCM features, the mean intensity and mean sparse coefficient are calculated for classification.

c) Sparse Representation Classifier

Identification of intracardiac mass is done by sparse representation classifier. Here the test sample can be described as a linear sequence of training sample. Compared to other classifiers, SRC is a nonparametric learning method, it doesn't need a training process but only need a training data [18]. In face recognition process, the SRC can establish well with insufficient training samples. It is suitable for identification of tumor because of simplicity and good generalization ability.

VI. RESULTS AND DISCUSSION

The classification method is based on the representation of sparse elements, by using four novel methods. Initially, coarse-to-fine iteration method is used to automatically select the ROI. Then denoising process is done by the combination of NLM and K-SVD. After that modified Active Contour Model is employed for separating the intracardiac mass from the image. SRC is very sensitive to identify tumor from an input image.

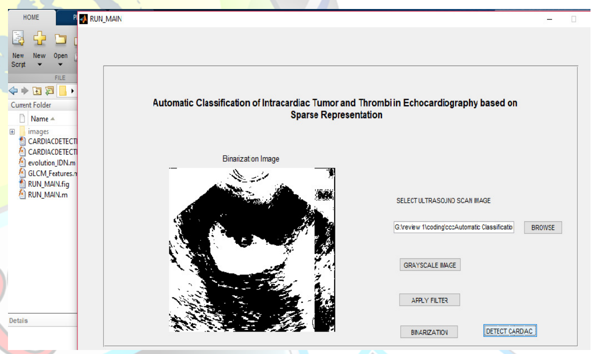

Fig.3. Automatic Region of Interest selection

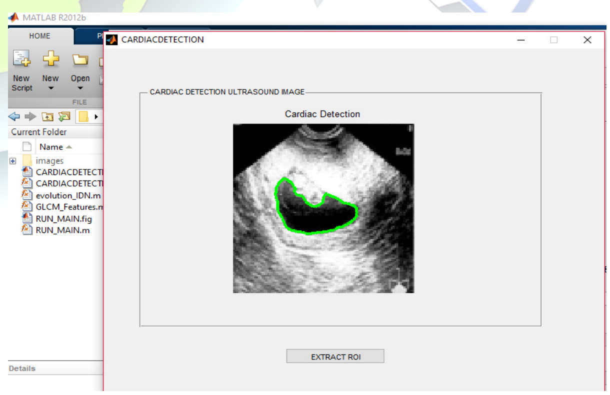

Fig.4. Intracardiac tumor detection

TABLE I
Evaluation of the various classifiers

	Ada boost(%)	ANN(%)	SVM(%)	SRC(%)

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SEN	96.29	96.30	96.29	100
ACC	94.84	90.72	95.87	96.91
SPE	93.02	83.72	95.34	93.02
PPV	94.54	88.14	96.29	94.74
NPV	95.23	94.74	95.34	100
Run time(s)	80.55	60.66	6.835	0.715
Training is need or not	Yes	Yes	Yes	No

The above table shows the evaluation of the various classifiers such as Adaboost, Artificial Neural Network [19], Support Vector Machine and Sparse Representation Classifier. The evaluation using performance indicator based on the sensitivity (SEN), the accuracy (ACC), the specificity (SPE), the positive predictive value (PPV) and the negative predictive value (NPV) [20].

VII. CONCLUSION

In this paper, the novel strategy is introduced for classification of intracardiac tumor and thrombi in the echocardiogram sequences. Here the entire strategy is based on sparse representation. The Region of Interest is considered as a mass area described by coarse-to-fine strategy. A novel noise reducing method with the combination of K-SVD and NLM is employed to reducing the speckle. The noise reducing algorithm produces better noise reduction and image enhancement, without disturbing the cardiac structures. The K-SVD and improvement of ACM with an extra exterior energy are employed to extract the mass. Simulation results show that the detected contours nearly denote the manually traced ones. After, that nine feature extraction and cardiologist's original selected features are extracted. These are the abilities to show the differences between two masses. All the extracted features are established in Sparse Representation Classifier (SRC). The simple classifier is applied to diagnose the mass with high efficiency and low computational time.

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