Detection of Tumor and Thrombi in Echocardiography Images by Using Adaptive Co-Segmentation and Sparse Classifier

Sai Baba P[1], Sai Siva Vignesh G[2], Goutham K[3], Latha S[4*], Muthu P[5], Dhanalakshmi S[6]
[1, 2, 3,,4,6] Department of Electronics and Communication Engineering, SRM University, India,
[5] Department of Biomedical Engineering, SRM University, India,
***Corresponding author: E-Mail: latha.su@ktr.srmuniv.ac.in, Phone: +91 9487413951**

ABSTRACT

Identification of intra cardiac masses in echocardiograms is one essential errand in heart ailment determination. To enhance finding exactness, a novel completely programmed arrangement strategy in view of the sparse representation is proposed to recognize intra cardiac tumor and thrombi in echocardiography. Initially, a region of interest is cropped to define the mass area. At that point a unique global denoising technique is utilized to uproot the dot and protect the anatomical structure. Along these lines, the shape of the mass and its connected atrial wall are portrayed by the K-particular quality decay and an altered dynamic form model. Finally the movement, the boundary and the texture features are handled by sparse representation classifier to recognize two masses. Clinical echocardiogram arrangements are gathered to evaluate the adequacy.

KEYWORDS: Automatic identification, Echocardiography, Global denoising technique, Intra cardiac tumor and thrombi, Sparse representation

1. INTRODUCTION

Intra cardiac masses are risky in cardiovascular infection. By and large, they are irregular structures inside or promptly neighboring the heart, which should be recognized for analysis. Two fundamental sorts of intra cardiac masses are tumor and thrombus. Malignant primary cardiac tumors, which often strike a young patient population, have a dismal prognosis: without surgical resection, the survival rate at 9 to 12 months is only 10% Leja, 2011. Echocardiography assumes a key part in building up the conclusion of patients with cardiovascular myxomas and thrombi. The separation between myxomas and thrombi is imperative as a result of the particular treatment procedure Jang, 2010. The echocardiographic IDs of intra cardiac masses impactsly affect the medicinal specialists' choice, since various illnesses are connected with different treatment choices. When all is said in done, the echocardiogram arrangement demonstrates that most intracardiac tumors have a thin stalk and a wide base. The surface might be friable or villous. The inward echoes are heterogeneous. The tumors show congruity with the atrial divider, with a high level of portability. The echocardiographic appearances of the thrombi are still, thick, ovoid, and reverberation reflecting mass with an expansive base of connection to the endocardium. The remainder of the paper is structured as follows It includes the frame decomposition, automatic region of interests (ROI) selection, global despeckling, adaptive co-segmentation, feature extraction and classification.

Pre processing:

Frame decomposition: The cardiologists secure echocardiogram successions when diagnosing the illness. To segment the intracardiac mass and assess its movement, the echocardiographic successions are isolated into consecutive frames heretofore. The average span of an echocardiogram sequence is around 3–4 s. The frame ratio is 39 outlines for each second. Each deteriorated frame is 480 × 640 pixels. Other than the scanned region, an echocardiogram depicts writings labels, containing data about the patient and examining transducer, as appeared in the fig. 1. Compared with the moving heart in two successive frames, these writings and names are static and after subtraction of two successive frames, the static data are all evacuated, while the part examined locale containing moving heart is remained. At that point, the profile of the area filtered locale is distinguished and a rectangle covering the sector is recognized. At long last, the original image is cropped to keep the examined locale for further examination.

Automatic ROI selection: Keeping in mind the end goal to concentrate on the mass range, a ROI containing the mass furthermore, its surrounding tissues are defined. A coarse-to-fine cycle methodology for sub windows clustering is applied to automatically select the ROI. The grouping is executed with a coarse-to-fine methodology. The measure of the initial sub windows is 40 × 40. Each time, a few texture features of sub windows, including the mean, variance, and the grey level co-occurrence matrix (GLCM) are computed and input into a fluffy K-means algorithm to cluster the similar sub windows. The uniform sub windows in a coarse position, which, thus, are sought to get a fine position with half size of sub windows. The cycle closes when all remaining sub windows share the same intensity distribution. In a short axis view echocardiogram, the chamber generally lies close to the cardiac center. So in the fine position, the Euclidian separation between each sub window and the cardiovascular focus is processed to trim off far-away windows and acquire last chamber area. The distance threshold is indicated as 80 pixels by experienced cardiologist

Global despeckling by non-local means algorithm: All digital images contain some degree of noise. Image denoising algorithms attempt to remove this noise from the image. Ideally, the resulting denoised image will not

contain any noise or added artifacts. Major denoising methods include Gaussian filtering, Wiener filtering, and wavelet thresholding. Many more methods have been developed; however, most methods make assumptions about the image that can lead to blurring. This paper will explain these assumptions and present a new method, the non-local means algorithm that does not make the same assumptions. The non-local means method will then be compared to other denoising methods using several measurements on the output images. One of the measurements used will be the method noise, which is the difference between the image and denoised image Guo, 2011.
Each pixel p of the non-local means denoised image is computed with the following

$$NL(V)(p)=\sum_{q\in V} w(p,q)v(q) \quad (1)$$

where V is the noisy image, and weights w(p,q) meet the following conditions $0\leq w(p,q) \leq 1$
$\sum_q w(p,q)=1$ Each pixel is a weighted average of all the pixels in the image To compute the similarity between two neighbourhoods take the weighted sum of squares difference between the two neighborhoods or as a formula

$$D(p,q)=\left\|V(N_p)-V(N_q)\right\|_{2,F}^2 \quad (2)$$

F is the neighborhood filter applied to the squared difference of the neighborhoods and will be further discussed later in this section. The weights can then be computed using the following formula:

$$W(p,q)=\frac{1}{Z(p)}e^{\frac{-d(p,q)}{h}} \quad (3)$$

Z(p) is the normalizing constant defined as

$$Z(p)=\sum_q e^{\frac{-d(p,q)}{h}} \quad (4)$$

As previously mentioned, F is the neighborhood filter with radius Rsim. The weights of F are computed by the following formula:

$$\frac{1}{R_{sim}}\sum_{i=m}^{R_{sim}} 1/(2 \neq i1)^2 \quad (5)$$

To prevent pixel p from over weighing itself let w(p,p) be equal to the maximum weight of the other pixels, or in more mathematical termsw (p , p) = max w(p , q)|$p \neq q$|

Segmentation: In view of intensity or textural data the job of image segmentation is to partition an image into non-overlapping regions. Image segmentation is a troublesome errand chiefly as a result of a major variability of item shapes, and also distinctive picture quality. Signals and artifacts interfere with the image, what might bring about enormous issues at utilizing of basic systems of segmentation. For identifying the presence of tumor or thrombi in the image, after ROI selection and despeckling, Segmentation of the image based on the ROI is performed.

Active Contour: Active contours or snakes, are utilized widely as a part of computer vision and image preparing applications, especially to find boundaries of objects. After its introduction in 1987, Snakes or active contour or Surfaces or balloons model has become an upcoming research area in the field of image segmentation. They are based on curve evaluation and level set model. They can be either closed or open curve.

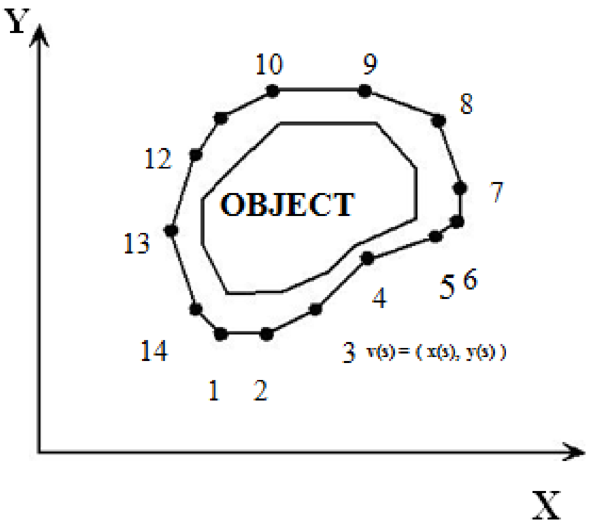

Figure.1.Basic Form of active contour

Parametrically active contour is defined as

$$v(s) = (x(s), y(s)) \quad (6)$$

where s is the control points normalized index, x(s) and y(s) are the x, y coordinates past the contours. Active contour is composed of internal and external energy components. External forces incline the curve towards the borders of the objects. Internal force makes a compact curve and its acuminous deflections are limited. For an elastic energy and a bending energy, the internal energy summation is given by

$$E_{int} = E_{elastic} + E_{bend} = \alpha(s)\left|\frac{dv}{ds}\right|^2 + \beta(s)\left|\frac{d^2v}{ds^2}\right|^2, \quad (7)$$

where α is a continuity specifying adjustable constant and β is an adjustable constant specifying contour curving. The elastic and bending energies are then defined followingly:

$$E_{elastic} = \int_s \alpha\,(v(s) - v(s-1))^2\, ds, \quad (8)$$

$$E_{bend} = \int_s \beta\,(v(s-1) - v(s) + v(s+1))^2\, ds, \quad (9)$$

Reduced energy of functional is given as

$$E^*_{snake} = \int_0^1 E_{snake}\,(v(s))^{as} = \int_0^1 \{E_{int}(v(s)) + E_{image}(v(s)) + E_{con}(v(s))\} ds \quad (10)$$

where E_{int} is the internal energy of the curve, E_{image} is the pictures energy and E_{con} are the external limitations.

$$E_{line} = \text{filter}(I(x,y)) \quad (11)$$

$$E_{edge} = -|\partial I(x,y)|^2 \quad (12)$$

Active contour is a kennel based edge segmentation method which produce continuous boundaries in the sub regions. After the introduction of snakes, it is one of the best connectivity based relaxation technique. In this paper, level set method is combined with integrating edge and region based contour detection. Intensity information of local regions in region based active contour model is implemented. Standard gradient technique is used for energy minimization purpose.

Adaptive co segmentation: For accurate segmentation of the tumor or thrombi region, adaptive features of different image blocks are learnt and based on that segmentation is performed. It is used as an optimization of the segmentation process. In the original image, by superposition and object detection cue, the image densities are measured and ranked. In our technique, the basic image determination is to streamline object extraction. We can watch that the objects can be effortlessly portioned from the pictures with basic foundation, while it is typically hard to separate the items from the perplexing foundations. Subsequently, we characterize a straightforward image as the picture with homogenous foundation. Actually, an image with muddled foundation is dealt with as complex picture. In this paper, the image complexity is measured by two cues, i.e., the over-segmentation based picture many-sided quality examination and the object recognition based picture intricacy investigation.

1) Create an ellipse and automatically set the localization radii by using

$R^k = \text{round}(\sqrt{s}/2(V_k+1))$ and $V^k = mean_{x_0\in c_0}((\exp(\frac{var_{y_0\in B_0}(y_0)}{(mean_{y_0\in B_0}(y_0))\text{^}2}))$. (13)

Initialize two LSFs φ0 and φ1, corresponding to I0 and I1 respectively.

2) For each image Ik, k∈{0,1}, compute the localized energies from the image pair adaptive to the local contrast ratio by using

$T^k(x) = \frac{|u_x^k - v_x^k|}{M}$ and ω^k=0.5(1-$T^k(x)$), (14)

compute the length term by using Length(φ^k)=$\int_{\Omega_x} g^k.\delta\varphi^k(x)\left|\nabla\varphi^k(x)\right|$dx and

$$g^k = \begin{cases} 1, & -\nabla\varphi^k.\nabla I_G^k \le 0 \\ \text{g}, & -\nabla\varphi^k.\nabla I_G^k > 0 \end{cases} \quad (15)$$

and compute the shape term by using Shape

$(\varphi^k, \varphi^{1-k})$= $\int_{\Omega_x}[H\varphi^k$(x)(1-$H\varphi^{1-k}$(x))+ $H\varphi^{1-k}$ (x)(1-$H\varphi^k$(x))]dx (16)

3) At odd iterations, evolve the LSF φ0 by using the other LSF φ1 as a shape prior, while at even iterations evolve the LSF φ1 by using the other LSF φ0 as a shape prior.

4) Update LSFs φ0 and φ1 by using the evolution equation

$$\frac{\partial\varphi^k}{\partial t} = \delta\varphi^k(\text{x})[\lambda_1^k \text{div}(g^k.\nabla\varphi^k(x)/\left|\nabla\varphi^k(x)\right|) + \lambda_s^k(2\text{H}\varphi^{1-k}(\text{x})-1)) + (1-\omega^k)\nabla_{\varphi^k(y)} f^L(I^k, \varphi^k, r^k) + \omega^k\nabla_{\varphi^k(y)} f^L(I^{1-k}, \varphi^k, r^{1-k}) \quad (17)$$

5) Repeat steps 2)-4) until convergence.

Feature extractions: While distinguishing intra cardiac mass in an echocardiogram succession, for the most part the cardiologists make the judgment based on two guidelines: the motion feature (the mass development) and the boundary (the base length). Although two masses show difference in echo reflections, texture characteristics visually indistinguishable due to the poor image quality. However, texture features, especially the mass internal echo is quite important in the classification. The movement highlight is an primary factor in mass recognition During a cardiac cycle, intra cardiac tumors show high degree of mobility, while the thrombi stay motionless. To quantitatively assess the mass movement, the displacements of every corresponding boundary points in two consecutive frames are calculated. In the earlier segmentation, the extracted contour contains both the mass and the atrial wall, among which only the mass contour is needed. In Fig. 5, the extracted contour is concave, with two inflexions as the division of the mass and the atrial, called "mass–atrial separation points." By computing the coordinates' differences of two consecutive boundary points in the *x*- and *y*-axis, respectively, the mass border can be separated. Then, for each point in the mass border, the block matching algorithm is applied to search their corresponding points in the following frame. The motion feature is defined as the mean displacement of a mass during whole echocardiogram sequence

$$\text{Motion}=\frac{1}{n}\sum_{t=1}^{n}[\frac{1}{m}\sum_{i=1}^{m}|P_t(i)-P_{t+1}(i)|^2 \quad (18)$$

where $P(\cdot)$ is the mass border, m is the length of P, and n is the frame number of the whole sequence. Another essential boundary feature is the base length. An intracardiac tumor has a narrow stalk connected to the atrial wall, whereas a thrombus lies entirely on the wall. The overlap length of these two masses with the atrial wall is different. Here, the base length is the Euclidian distance between two mass–atrial separation points. The base length of a thrombus is much longer than that of a tumor. In addition, texture characteristics derived within the mass are also considered. Three kinds of texture features are extracted. The GLCM is a common method for the texture feature analysis. Five features derived from the GLCM (contrast, entropy, autocorrelation, energy and homogeneity) are computed at $\theta = 0^\circ$, 45° 90° and 135° and $d = 1$. Furthermore, the mean sparse coefficient is introduced as a new texture feature for a better classification. The sparse coefficients represent the integrative information of the local statistics in a mass. A total of nine features: the mass movement, the base length, five GLCM features, the mean intensity and the mean sparse coefficient are calculated for the further classification.

Sparse classifier: A sparse representation-based classifier (SRC) is used to identify an intracardiac mass. In this Instead of using the generic dictionaries we represent the test sample in an over complete dictionary whose base elements are the training samples themselves. The main idea is that the sparse nonzero coefficients should concentrate on the training samples with the same class label as the test sample.Given sufficient training samples of the ith object class Wright , 2009

$$A_i=[v_{i,1}, v_{i,2},\ldots\ldots\ldots\ldots v_{i,ni}]\in IR^{m*ni}, \quad (19)$$

any new (test) sample y$\in IR^m$ from the same class will approximately lie in the linear span of the training samples associated with object i:

$$Y=\propto_{i,1} v_{i,1} +\propto_{i,2} v_{i,2} +\ldots\ldots\ldots\ldots\ldots+\propto_{i,ni} v_{i,ni} \quad (20)$$

Since the membership i of the test sample is initially unknown, we define a new matrix A for the entire training set as the concatenation of the n training samples of all k object classes A=$[A_1, A_2, \ldots\ldots A_k]$=$[v_{1,1}, v_{1,2}, \ldots\ldots, v_{k,nk}]$ Then, the linear representation of y can be rewritten in terms of all training samples as y=A$x_0 \in IR^m$,where $x_0 = [0,\ldots.,0,\propto_{i,1},\propto_{i,2} \ldots\ldots\ldots \propto_{i,n}, 0,\ldots\ldots 0]^T$is a coefficient vector whose entries are zero except those associated with the ith class y=A$x_0 + z$,where z$\in IR^m$is a noise term with bounded energy $\|z\|_2$<E. The sparse solution x_0 can still be approximately recovered by solving the following stable l^1-minimization problem:

(l_s^1): $\hat{x_1}$=arg min$\|x\|_1$ subject to $\|Ax - y\|_2 \le e$.

(l^2): $\hat{x_2}$=arg min$\|x\|_2$

$$min_i\ r_i(\text{Y})= \left\|y - A\delta_i(\hat{x_1})\right\|_2 \quad (21)$$

Algorithm 1 summarizes the complete recognition procedure using (SRC)

1. Input: a matrix of training sample $A_i=[v_{i,1}, v_{i,2},\ldots\ldots\ldots\ldots v_{i,ni}]\in IR^{m*ni}$ for k classes, a test sample y$\in IR^m$

2: Normalize the columns of A to have unit l^2-norm

3: Solve the l^1minimization problem: $\hat{x_1}$=arg min$\|x\|_1$ subject to Ax=y or alternatively, solve $\hat{x_1}$=arg min$\|x\|_1$ subject to $\|Ax - y\|_2 \le e$

4: Compute the residuals $min_i\ r_i(\text{Y})= \left\|y - A\delta_i(\hat{x_1})\right\|_2$

5: OUTPUT: identity (y)= $min_i\ r_i$(Y)

2. CONCLUSION

In this paper, another strategy is proposed for the order of intracardiac tumor and thrombi in the echocardiograms. The entire technique depends on the sparse representation. The mass zone in ROI is programmed characterized by a coarse-to-fine technique. A novel all around denoising approach brushing the K-SVD and the NLM is utilized to take out the dot. The despeckling calculation yields better clamor constriction and edge improvement, without pulverizing the vital cardiovascular structures. Sub regions with continuous boundaries were detected by active contour and adaptive co segmentation methods. Use of level set theory has made a flexible segmentation method for the image where ROI containing Tumor or thrombi region is present. Local minimum problem exists and it has to be addressed. Energy minimization techniques were applied. The better precision and basic usage make the proposed strategy valuable to offer the cardiologists some assistance with making an analysis before the surgery, providing a practical execution benchmark for further research endeavors.

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