AN ACCURATE AND AUTOMATIC IDENTIFICATION OF INTRACARDIAC TUMOR AND THROMBI USING ECHOCARDIOGRAPHY

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ABSTRACT

Intracardiac masses identification in echocardiograms is an important task in cardiac disease diagnosis. To improve the diagnostic accuracy, the tumour and thrombi is identified using a automatic classification method based on the sparse representation. A region of interest is cropped to define the mass area. Then, a globally denoising method is employed to remove the speckle and preserve the structures. Subsequently, the contour of the mass and its connected atrial wall are described by our proposed adaptive cosegmentation localized region level set model. These method is used to distinguish intracardiac tumor and thrombi in echocardiography. The adaptive technique, the gradient direction, the shape dissimilarity measure which help to guide the contour evolution and the localization radius is automatically approximated based on the initial contour and the automated selection of localization radius are integrated into an LRLSM. Segmentation of intracardiac tumour in echocardiography videos is an ill-posed problem due to the presence of weak boundaries, intratumoral degeneration and nearby structures and clutter. Our proposed method demonstrates the best performance by achieving an accuracy of more than 96.91%, a sensitivity of 100%, and a specificity of more than 93.02%. Finally, the motion, the boundary as well as the texture features are processed by a sparse representation classifier to distinguish two masses.

Keywords: Echocardiography, Adaptive Co-segmentation localized region-based level set model, sparse representation.

1. INTRODUCTION

Cardiac tumors in general are the tumors can be cancerous or noncancerous [2]. Tumors that begin growing in the heart and stay there are called primary tumors. Tumors that start in another part of the body and move to the heart (metastasize) are called secondary tumors [3]. Most cardiac tumors are benign. But, even benign tumors can cause problems because of their size and location. Sometimes, small pieces of tumor fall into the bloodstream and are carried to distant blood vessels and get in the way of blood flow to vital organs called as embolism. Two main types of intracardiac masses are Tumor and Thrombus. Primary tumors affect only 1 in 1,000 to 1,00,000 people. The most common type of primary cardiac tumor is Myxoma [1]. They are more common in women than men. Most times, the tumor grows in the left upper chamber of the heart (left atrium) at the atrial septum, which divides the two upper chambers of the heart. Myxomas can grow in other areas of the heart or in the heart valves, but such growth is rare. About 10 percent of myxomas are hereditary or develop as a result of other diseases. Malignant primary tumors include pericardial mesothelioma, primary lymphoma and sarcoma. Secondary cardiac tumors are much more common than primary tumors. They do not start in the heart, they move to the heart after developing in another area of the body. Most often, these tumors start in the lungs, breasts, stomach, kidneys, liver or colon. They can also be tumors related to lymphoma, leukemia or melanoma. Intracardiac masses are hazardous in cardiovascular disease. Generally, they are abnormal structures within or immediately adjacent to the heart, which must be distinguished for diagnosis [5]. The tumors need prompt resection, because of the high risk of embolization and sudden death. Thrombi is a fibrinous clot that forms in the blood vessel or that forms in one of the chambers of the heart. Two different types of thrombi can be formed they are Arterial thrombi and venous thrombi. Echocardiography uses probes that emit a sound directed at cardiac structures returning ultrasound signals are received by the probe and the computer in the ultrasound machine uses algorithm to reconstruct the images of the heart. Ultrasound imaging uses high-frequency sound waves to view inside the body. The patient’s heart movements can be seen on a video screen. A videotape or a photograph can be made of the pictures. The test shows the problems with the heart valves and blood clot in the heart. In an ultrasound exam, a transducer probe is placed directly on the skin or inside a body. A thin layer of gel is applied to the skin so that the ultrasound waves are transmitted from the transducer through the gel into the body. The ultrasound images are used for stroke prediction [6]. The processing and analysis can be used to find the diameter, volume and vasculature of a tumor blood and other fluids. The intracardiac tumors shows high degree of mobility, while the thrombi stay motionless. The tumors show continuity with the atrial wall, with a high degree of mobility, as shown in Fig. 1(a) [6]. The contour is well defined, as shown in Fig. 1(b). In clinical applications, the contours of intracardiac tumor and thrombi in echocardiography videos are manually analyzed by the experts. However, manual segmentation is time-consuming, subjective and highly dependent on the experts experience. When masses compress surrounding organs, blurred or missing boundaries may lead to manual errors. The demand for an automatic classification is increasing, it is important to improve the diagnostic accuracy and to find which case should be recommended for a surgery. A fully automatic classification method has not been previously used to distinguish an intracardiac masses in echocardiograms. Strzelecki et al. used a neural network to classify and segment the different intracardiac masses in tumor echocardiograms in a semiautomatic manner [10].
automatic classification method consists of four main parts. These methods involve despiking, segmentation, feature extraction, and classification. To reduce the speckle present in the ultrasound image, the median filter and speckle reducing anisotropic diffusion are used [7]. The active contour model (ACM), the level set method [19], and methods are used for the segmentation of intracardiac tumor and thrombi. The multilayer feed forward artificial neural network (ANN) [8], the back propagation neural network (BPNN) [8], the support vector machine (SVM) [12] are used for computer-aided classification. These type of classifiers require training stages and supervision from experienced cardiologists. Hence, the sparse representation classifier is used. The classifier includes denoising [15], [16], compression [17], regularization in inverse problems [18], and classification [10]. The K-singular value decomposition (K-SVD) is one of the typical methods in the sparse representation, which utilizes overcomplete dictionaries obtained from a preliminary training procedure [9]. The sparse representation provides denoising, image separation and offers better performance. The remaining section of the paper involves the Section 2 describes about K-SVD sparse representation. Section 3 describes about the proposed work. Section 4 explains about the experiments and results. Finally, Section 5 provides the conclusion.

2. K-SVD SPARSE REPRESENTATION

The K-SVD algorithm involves the image formulated by using a few linear combinations drawn from a large and redundant dictionary [15]. Here, the original image is decomposed into a sparse coefficients matrix populated primarily with zeros. Only a few nonzero coefficients reveal the nature of the image, greatly reducing the complexity of the original image. Consider an image $Y$ with the size of $M \times N$, $Y \in \mathbb{R}^{M \times N}$, $Y$ is divided into $L$ overlapping image patches of size $b \times b$, $L = (M - b + 1) \times (N - b + 1)$. The patches are ordered as column vectors $y_i \in \mathbb{R}^{b \times b}$. The overcomplete dictionary matrix $D \in \mathbb{R}^{b \times K}$ contains $K$ prototype atoms for columns $(d_j)_{k=1}^{K}$. A sparse approximation of the image $Y$ can be realized by the linear combination of atoms in $D$

$$\min_{x_i} \|y_i - Dx_i\|_2^2 \quad \text{s.t.} \quad \|x_i\|_0 \leq T_0, \quad i = 1, \ldots, L \quad (1)$$

Where $x_i$ is the $i$th vector in the sparse coefficient matrix $X$ corresponding to $y_i$. $\|\|_0$ is the $l^0$ norm, counting nonzero coefficients, $T_0$ is a sparsity threshold, and $\|\|_2$ is the $l^2$ norm. A sparse representation proves to be a nondeterministic polynomial (NP) hard problem. The solution of $l^0$ minimization problem is equivalent to the pursuit problem. The K-SVD optimizes $D$ and $X$ through a number of iterations. Each iteration consists of two steps. The sparsity is measured by the smallest MSE. An orthogonal matching pursuit (OMP) method is used to find the approximation one [20]. The mean square error (MSE) is defined as shown

$$\text{MSE} = \sum_{i=1}^{L} e_i^2 = \sum_{i=1}^{L} \|y_i - Dx_i\|_2^2. \quad (2)$$

In the dictionary updating step, $X$ is fixed, the SVD method is applied to search for a better dictionary $D$. Fixing all other columns in $D$, it updates one column $d_k$ at a time whose coefficient corresponds to the $k$th row in $X$ in the $r$th iteration, called $X_r$. Then, (1) can be rewritten as

$$\left\|Y - \sum_{j=1}^{K} d_j X_j^T \right\|_2^2 = \left\| (Y - \sum_{j \neq k} d_j X_j^T) - d_k X_k^T \right\|_2^2 = \left\| E_k - d_k X_k^T \right\|_2^2 \quad (3)$$

Where $E_k$ stands for the error for all column when the $k$th atom is removed, and $\omega_k$ is the group of indices to $y_i$, which uses the atom $d_k$

$$\omega_k = \{ i \mid 1 \leq i \leq K, X_k(i) \neq 0 \}. \quad (4)$$

Then, (3) is rewritten as

$$\left\| E_k \Omega_k - d_k X_k^T \Omega_k \right\|_2^2 = \left\| E_k^R - d_k X_k^T \right\|_2^2, \quad (5)$$

The SVD decomposes $R_{K_0} \times N$ into $U \Sigma V^T$, where $U$ is left singular vectors, $V$ is right singular vectors, and $\Sigma$ is the transpose of $V$. $d_{k}$ is replaced by the first output basis vector of $U$. After several iterations, the algorithm stops when there is no change in the MSE. All atoms are updated and a better dictionaries found. The K-SVD is originally designed for Gaussian noise removal. It cannot be directly applied to ultrasound images with the Rayleigh distribution noises. Here, the K-SVD is modified in our processing steps.

3. PROPOSED WORK

The proposed method is applied to the intracardiac tumor and thrombi co-segmentation in echocardiography images. Fig 2 shows the work flow of proposed method. co-segmentation level set formulation analyze global image information that was more robust against poor initialization than local methods. However, it was prone to boundary leakage in the cases with weak boundaries. The proposed work is shown in Fig 1. It consists
of converting the video into frame, automatic selection of region of interest (ROI), despeckling, intracardiac mass segmentation, feature extraction, and classification. Segmentation is used to locate object and boundaries in tumor and thrombi images.

A. Converting Videos Into Frame

The video means multiple frames. The captured video is converted into frames using matlab codes as it act as a video to frame converter. The cardiologists acquire echocardiogram sequences when diagnosing the disease. To segment the intracardiac mass and evaluate its movement, the echocardiographic sequences are divided into consecutive frames. The typical duration of an echocardiogram sequence is about 3-4s. The frame rate is 39 frames per second. Each decomposed frame is 480 × 640 pixels. Besides the scanned region, an echocardiogram assigns texts and labels, containing information about the patient and scanning transducer. Compared with moving heart in two successive frames, these texts and labels are static.

B. Preprocessing

Preprocessing involves automatic selection of Region Of Interest (ROI) and despeckling. A ROI containing the mass and its surrounding tissues are defined. The ROI is used to identify the boundaries of a tumor defined on an image. It is used for the purpose of measuring the size of tumor and thrombi. The ROI is used to crop only the particular of the image with tumor and thrombi. A coarse-to-fine iteration strategy for sub windows clustering is applied to automatically select the ROI [11]. The size of the initial sub windows is 40 × 40. Several texture features of sub windows, which involves the mean, the variance, and the gray level co-occurrence matrix (GLCM) are calculated and input into a fuzzy K-means algorithm to cluster the similar sub windows. Despeckling involves removing noise from the image. Here, the non local means (NLM) algorithm is used. The NLM extends the neighbourhood to the whole image, especially in the edge preservation. To identify the globally despeckling in the whole image and to decrease the computational complexity, a new non local means helps to compress the original image and to estimate the patches similarities much faster.

C. Mass Segmentation

Mass segmentation is important for the basics of feature extraction. Extracting the boundary of the mass is important. Hence, the intracardiac mass has a base connected with the atrial wall, the mass and the atrial wall should be segmented together. The mass segmentation involves initial contour and refining the boundaries using adaptive co-segmentation localized region level set model. Refining the boundaries using CoLRLSM provides an aclear border of the two different masses.

D. Feature Extraction

The motion feature, the boundary feature and the texture features are extracted from feature extraction [1]. The motion feature is a primary factor in mass recognition. The two masses show differences in echo reflections, texture characteristics are visually indistinguishable due to the poor image quality. They are always omitted clinically. Essential boundary feature is the base length.
An intracardiac tumor has a narrow stalk connected to the atrial Wall, and the 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. 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 segmented

![Fig. 5. Intracardiac mass segmentation.](image)

The motionfeature is defined as the mean displacement of a mass during whole echocardiogram sequence (6).

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

(6)

where $P(i)$ is the mass border, $m$ is the length of $P$, and $n$ is the frame number of the whole sequence. The base length of a thrombus is much longer than that of a tumor. Three kinds of texture features are extracted. The GLCM is a common method for the texture feature analysis. Five features are derived from the GLCM. They are contrast, entropy, autocorrelation, energy and homogeneity are computed. The mass movement, the base length, five GLCM features, the mean intensity and the mean sparse coefficient are calculated for the further classification.

### E. Sparse Representation Classifier

A sparse representation-based classifier (SRC) is used to identify an intracardiac mass. It involves the test sample can be represented as a linear combination of the training sample [10]. Different from other classifiers, the SRC is a nonparametric learning method which does not need a training process but only need the training data. Suppose $A$ is a training matrix for the entire training set with/without samples of $p$ classes

$$A = [A_1, A_2, \ldots, A_p] = [v_{11}, v_{12}, \ldots, v_{p1}, \ldots, v_{pL}]$$

(7)

where $A_i$ is the $i$th training sample and $v_{iq}$ is its $q$th feature. A new test sample $y$ is the linear representation of the training matrix $A$

$$y = Ax_0$$

(8)

Where

$$x_0 = [0, \ldots, 0, \alpha_{i,1}, \alpha_{i,2}, \ldots, \alpha_{i,L}, 0, \ldots, 0]^T$$

(9)

is a coefficient vector, whose coefficients are remarkable for the class the test sample which belongs to, for the other class, the coefficients are all zeros. $x_0$ is obtained by solving the linear equation (8), which is underdetermined. Where,

$$\hat{x}_0 = \arg \min \|x\|_0 \quad \text{subject to } Ax = y.$$  

(10)

Unlike the K-SVD, the SRC approximates the $l^p$ norm coefficients by $l^1$ minimization problem [42]. If the test sample $y$ belongs to a certain class, the coefficients in the estimated $\hat{x}_0$ not within this class should all be zeros. But when there is a noise and the modeling error, there are small nonzero entries associated with multiple object classes. The noisy model is modified as

$$y = Ax_0 + \varepsilon$$

(11)

Where $\varepsilon$ is the noise level. Then, (10) is converted into

$$\hat{x}_1 = \arg \min \|x\|_1 \quad \text{subject to } ||Ax - y||_2 \leq \varepsilon.$$  

(12)

We consider using the residual error to classify $y$. After estimating $\hat{x}_1$, the given test sample $y$ is approximated as

$$\hat{y}_i = A\delta_i(\hat{x}_1)$$

(13)

where $\delta_i(x_i)$ is a new vector whose only nonzero entries in $x_i$ are associated with the class $i$. The residual error $r_i(y)$ is

$$r_i(y) = y_i - A\delta_i(\hat{x}_1).$$

(14)

The test sample $y$ is classified with the class having the minimal residual error.

### F. Classification Result

A sparse representation-based classifier (SRC) is used to identify an intracardiac mass. The SRC is a nonparametric learning method which does not need a training process but only need the training data. The test sample $y$ is classified with the class having the minimal residual error. The SRC algorithm can generalize well in the face recognition with insufficient training samples. It is also quite suited for our application because it is not only computationally simple, but also has good generalization ability.

### 4. EXPERIMENTS AND RESULTS

#### A. Data Description And Method Implementation

The whole classification method was applied on the sequences after they were recorded and stored by the cardiologists. All patients were submitted to surgery. A total of 97 clinical echocardiogram video sequences were collected. The sequences were saved in AVI format. Our proposed classification method
was implemented on echocardiogram sequences. The collected video sequences were processed from frame decomposition, automatic ROI selection, globally despeckling, intracardiac mass segmentation, and nine GLCM feature extraction. Fig. 6 depicts the output for an intracardiac tumor. The coarse-to-fine strategy helped to automatically select the ROI in an echocardiogram [11]. The globally despeckling is mainly used to eliminate the noise while preserving important anatomical features. The sparse representation is used to identify the initial contour of the mass. The proposed adaptive cosegmentation localized region level set model for mass segmentation guides the deformable contour in a desired manner and eliminating the ambiguity and converging to the true boundary better than the conventional single image based segmentation [13] and cosegmentation algorithms [14].

B. SRC Sparsity Evaluation

The main aim of this experiment was to evaluate the sparsity and residual of the SRC. The sparsity was defined as the average ratio of zero coefficients number to the training sample at each test sample. The residual was the mean of all residual errors. Sparsity was related not only with the training or testing data set, but also with the noise level $\varepsilon$ in (9). The noise $\varepsilon$ was varied in the set $\{10^{-4}, 2 \times 10^{-4}, 10^{-3}, 2 \times 10^{-3}, 10^{-2}, 2 \times 10^{-2}, 10^{-1}\}$. A leave-one-out trial was employed in the SRC to distinguish these two masses. The single remaining case was tested and compared with its labeled class. This process has been repeated until all samples were tested.

C. Comparison Of Features Subsets And Classifier

A total of nine features were calculated for the further classification. The four subsets were selected which includes feature descriptors, the traditional texture features. The cardiologist’s feature descriptors included the mass movement and the base length. The traditional texture features were five GLCM features and the mean intensity. The accuracy and effectiveness of each feature subsets were evaluated using five performance indices based on the true positive (TP), the true negative (TN), the false positive (FP) and the false negative (FN), the overall accuracy (ACC), the sensitivity (SEN), the specificity (SPE), the positive predicative value (PPV), and the negative predicative value (NPV) [21]. Table I shows the performance of our method with different feature sets. The overall classification accuracy ranged from 74.23% to more than 96.91%. The highest classification rate was achieved when all nine features were employed as expected.

\[
\begin{align*}
\text{ACC} &= \frac{TP + TN}{TP + FN + FP + TN} \\
\text{SEN} &= \frac{TP}{TP + FN} \\
\text{SPE} &= \frac{TN}{FP + TN} \\
\text{PPV} &= \frac{TP}{TP + FP} \\
\text{NPV} &= \frac{TN}{TN + FN}.
\end{align*}
\]

<table>
<thead>
<tr>
<th>Feature Subset</th>
<th>ACC (TP/FN)</th>
<th>SEN (TP/FN)</th>
<th>SPE (TP/FN)</th>
<th>PPV (TP/FN)</th>
<th>NPV (TP/FN)</th>
</tr>
</thead>
<tbody>
<tr>
<td>All nine features</td>
<td>&gt;96.91% (94/97)</td>
<td>94.85% (92/97)</td>
<td>74.23% (72/97)</td>
<td>86.69% (87/97)</td>
<td></td>
</tr>
<tr>
<td>Only the cardiologist’s feature subset</td>
<td>94.44% (51/54)</td>
<td>94.44% (51/54)</td>
<td>93.02% (40/43)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Only the traditional texture features</td>
<td>74.23% (72/97)</td>
<td>95.35% (21/43)</td>
<td>93.02% (40/43)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Only the new texture features</td>
<td>69.86% (51/73)</td>
<td>94.00% (47/50)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table I: Performance of the Proposed Classification Method on Different Feature Subsets
TABLE III
Runtime For Different Steps Of The Proposed Classification Method.

<table>
<thead>
<tr>
<th>Method</th>
<th>Run time (s)</th>
<th>selection</th>
<th>true positive</th>
<th>true negative</th>
</tr>
</thead>
<tbody>
<tr>
<td>SVM</td>
<td>1.768</td>
<td>6.912</td>
<td>&lt;269.8</td>
<td>&lt;105.8</td>
</tr>
<tr>
<td>Adaboost</td>
<td>1.132</td>
<td></td>
<td>0.715</td>
<td></td>
</tr>
</tbody>
</table>

5. CONCLUSION

The paper proposed a new method of novel adaptive CoLRLSM based method for the co-segmentation in echocardiography image for the classification of intracardiac tumor and thrombi. The whole method is based on the sparse representation. The mass area in ROI is automatic defined by a novel globally denoising approach. A novel globally denoising approach provides a new NLM is employed to remove the speckle. The algorithm yields better noise attenuation and edge enhancement. The CoLRLSM is applied to segment the mass. Gradient direction, shape dissimilarity measure and automated localization radius selection are integrated to further facilitate the segmentation. Our detected contours closely approximate the manually traced ones. Nine features, including the cardiologist’s original selected features and new texture characteristics are then extracted. Finally, all features are implemented to the SRC. The simple classifier is able to identify the intracardiac mass with an overall accuracy of more than 96.91% and a sensitivity of 100%. It can detect all intracardiac tumors. The improved accuracy and very simple implementation make the proposed method to help the cardiologists make a diagnosis before the surgery.

REFERENCES

Thrombi in Echocardiography Based on Sparse Representation", IEEE Journal Of Biomedical and Health Informatics, Vol. 19, No. 2.


