

Left Ventricle Cavity Segmentation from Cardiac Cine MRI

Marwa M. A. Hadhoud¹, Mohamed I. Eladawy², Ahmed Farag³

¹ Department of Biomedical Engineering, Faculty of Engineering, Helwan University, Cairo, Egypt

² Department of Communication & Electronics, Faculty of Engineering, Helwan University, Cairo, Egypt

³ Department of Biomedical Engineering, Faculty of Engineering, Helwan University, Cairo, Egypt

Abstract

Automatic left ventricle segmentation plays an important role in the evaluation of cardiac function. In this paper, we proposed a method for segmenting the left ventricle cavity by applying pixel classification method. In this method, we used different features (i.e. the output of median filter, the gradient magnitude, the largest eigenvalues, and the gray value), and the principal component analysis (PCA) in building the feature vectors used with the KNN classifier in the segmentation of the LV cavity. We evaluated our method by sensitivity, and specificity, and we achieved good results in the segmentation process reached to 95.61% sensitivity, and 98.9% specificity.

Key Words: Cardiac MRI, Left Ventricle, Pixel Classification, Segmentation.

1. Introduction

According to the World Health Organization [1], the largest diseases leading to death in the world are the cardiovascular diseases, and the early detection of the cardiovascular diseases plays a very important role in the treatment.

The cardiac imaging considered as an important role to evaluate the global and regional cardiac function. This is done by evaluating different parameters like: Ejection Fraction (EF), Left Ventricle Mass (LVM), Left Ventricle Volume, wall thickness, and thickening. Evaluation of these parameters is very helpful in the evaluation of the left ventricle structure which is the first indicator of the diagnosis of the cardiovascular diseases from cardiac images [2].

There are lots of techniques used in cardiac imaging like: Ultrasound, CT, and MRI. In this paper, we concentrated our work on cine MRI images specially the short axis views, because the MRI considered as one of important techniques used in cardiac diagnosis, because of its high resolution and clear tissue contrast without using any contrast agents [3]. Beside these advantages, using the

MRI in calculating the ejection fraction (EF) was validated to be more accurate than echocardiography [4]. The plane of imaging in the short axis view is perpendicular to the long axis (i.e. from apex to base). In this view as shown in fig.1, the blood pools (i.e. of the left and right ventricles) appear brighter than their surrounding structures (i.e. myocardium, lung, and liver). The automatic segmentation of the left ventricle from cardiac images, is considered as a challenging task, and it is the most important step to calculate the left ventricle parameters. There are a lot of techniques for the segmentation of the left ventricle that can be categorized as: image based methods, pixel classification based methods, shape prior based deformable models, active shapes, and appearance models. These techniques, and others are reviewed in [5,6].

In this paper, we focus on the pixel classification method for segmenting the left ventricle cavity. We proposed a set of features (i.e. the gradient magnitude, the largest eigenvalue, and the output of median filter) then we used the PCA for transforming this feature space, and select from its output a specified number of features, that used as inputs to the supervised KNN classifier, to classify the pixel to blood or not.

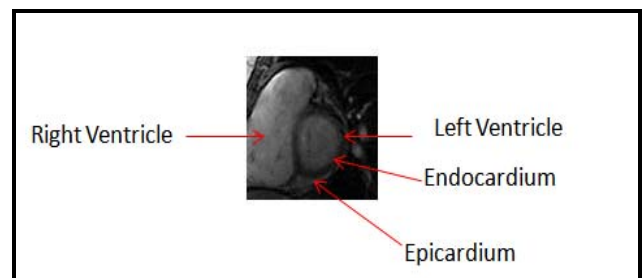


Fig. 1. The short axis view

2. Proposed System

This Paper concentrate in building a fully automatic system to segment the left ventricle cavity from cine MRI images, specially the short axis view. In this view as shown in fig.1, The left ventricle blood pool appears bright, and surrounding it the myocardium, and it is looked as a circular shape.

The proposed system consists of two stages, the first one is the feature extraction stage, and the second one is the classification stage.

Before describing these two stages, we summarize the whole steps of the algorithm as a flow chart shown in fig.2.

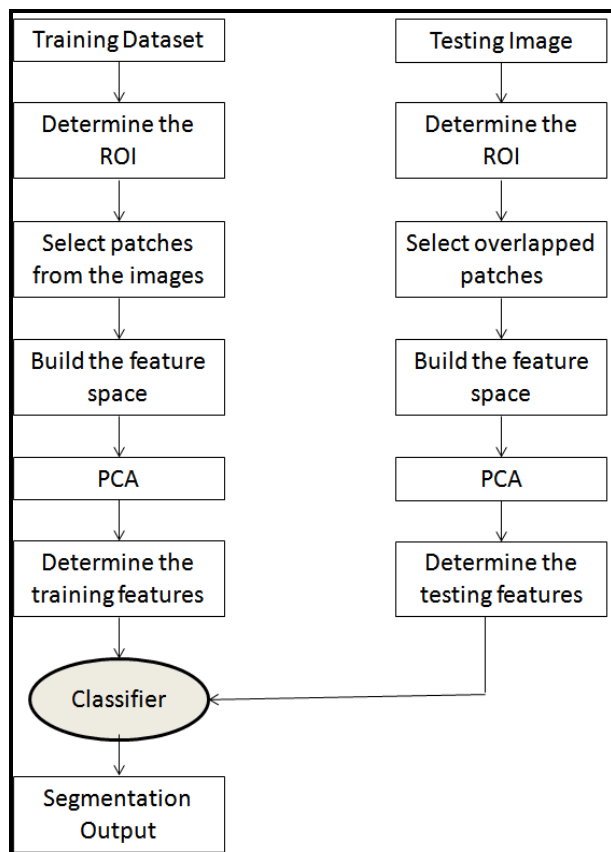


Fig. 2. The Proposed system flow chart

2.1. Feature Extraction

In this work, we used several number of features, then we applied the principal component analysis (PCA) to reduce the dimension of the feature space. When we chose the features that can be used in the classification process, we should understand the nature of the structure that we want to segment it. The Left Ventricle Cavity surrounded by the myocardium, and it appeared brighter than the

myocardium, and it looked as a circular shape in the short axis images that we worked on it. So, the features used in this work are the gradient magnitude, and the largest eigenvalue at different scales, then we take the maximum over all scales, we chose these features to improve edges that surround the LV cavity. Although, the MRI provides good contrast between the myocardium and the blood, but still there is gray value inhomogeneities in the blood pool. So, we take the output of applying the median filter on the image at different scales as a feature in the feature space, beside the gray value itself.

The local maxima of the gradient magnitude and the local maxima of the largest eigenvalue depend on the output of Gaussian derivative filters of up to second order (L_x , L_y , L_{xx} , L_{yy} , L_{xy}) as Eq. (1). at different scales ($s=1,2,4,8,16$).

$$\begin{aligned}
 L_x &= I(x, y) \otimes sG_x \\
 L_y &= I(x, y) \otimes sG_y \\
 L_{xx} &= I(x, y) \otimes s^2G_{xx} \\
 L_{yy} &= I(x, y) \otimes s^2G_{yy} \\
 L_{xy} &= I(x, y) \otimes s^2G_{xy}
 \end{aligned} \tag{1}$$

Where, L_x , L_y , L_{xx} , L_{yy} , and L_{xy} are the first and second derivatives of the image $I(x,y)$ in the x, and y directions, G_x , G_y , G_{xx} , G_{yy} , and G_{xy} are the Gaussian Derivatives in the x, and y directions, and s is the scale parameter.

2.1.1. The gradient Magnitude

The gradient magnitude is calculated as Eq. (2).

$$|\nabla L| = \sqrt{L_x^2 + L_y^2} \tag{2}$$

The local maxima of the gradient magnitude will be calculated from the gradient magnitude at different scale values ($s=1,2,4,8,16$) as Eq. (3).

$$\gamma = \max_s \left[\frac{|\nabla L(s)|}{s} \right] \tag{3}$$

2.1.2. The largest eigenvalue

The large eigenvalue is calculated as Eq. (4).

$$\lambda_+ = \frac{L_{xx} + L_{yy} + \alpha}{2} \tag{4}$$

$$\alpha = \sqrt{(L_{xx} - L_{yy})^2 + 4L_{xy}^2}$$

Where

And the local maxima of the largest eigenvalue will be calculated from the same scale values ($s=1,2,4,8,16$) as Eq. (5).

$$\lambda_{\max} = \max_s \left[\frac{\lambda_+(s)}{s} \right] \quad (5)$$

2.1.3. The median filter

The median filter is normally used to reduce noise in an image, somewhat like the mean filter. However, it often does a better job than the mean filter of preserving useful detail in the image (like: sharp edges).

The median filter is a sliding-window spatial filter, but it replaces the center value in the window with the median of all the pixel values in the window. In our work, we used 3 different sizes of windows (i.e. 3, 5, and 7).

2.1.4. Principal Component Analysis

Principal component analysis (PCA) is considered as an efficient technique for dimensionality reduction in multivariate statistical analysis. So we used PCA to compute the basic components of the feature space, to reduce its dimension. The principal components are calculated as the eigenvectors of the covariance matrix of the data [7].

The selection of the number of PCA coefficients used in the classification is a critical subject. So we used different numbers of principal components as inputs to the classifier and get the accuracy of each of them and we found the highest accuracy occur when we used the first 25 components.

2.2. Classifier

In this paper, we used the supervised KNN classifier because of its simplicity and its ability to model a wide range of complex and non-parametric distributions [9].

The KNN classifier requires the distance measure $d(x_1, x_2)$ between any pair of instances, and each instance is described by number of attributes (i.e. feature vector). It classifies any pixel according to the class of the nearest example in the training data.

The distance between any two pixels, $d(x_1, x_2)$ is calculated as Eq. (6).

$$d(x_1, x_2) = \sqrt{\sum_{i=1}^N (A_i(x_1) - A_i(x_2))^2} \quad (6)$$

Where $A_i(x)$ represents the i th attribute of the pixel x .

3. Experiment

Our experiment was performed on images of 13 different patients [8]. For each patient, we select randomly 20 images for training, and 60 images for testing (i.e. 3 slices, 20 frames in each slice).

The segmented inner contour which is attached with the dataset is used for labeling the left ventricle cavity, and its surrounding border (i.e. endocardium contour), to use it in the training stage, and to use it in the evaluation of our experiment.

In each image, we localize the cardiac structure in the beginning of our work to reduce the time consumed in the segmentation, we applied an algorithm used the variation of the standard deviation over the frames of each slice [10], to detect the Region of Interest (ROI) that contains inside its border the left ventricle structure.

After getting the ROI for all the training dataset, we applied the median filter with different sizes of window (i.e. 3, 5, and 7), and calculated the local maxima of the gradient magnitude, and the largest eigenvalue at different scale values (i.e. 1, 2, 4, 8, 16), beside the gray value of the image itself. All of these features are normalized each one separately.

Although we reduced the size of processing image by localizing the ROI, but still we couldn't work on all pixels in the training dataset because it contains a large number of samples (i.e. 101X101 instances). So, we take from these images un-overlapped patches with size 7X7. In the testing dataset, we took the patches but in this case overlapped to scan all pixels in the image. We chose to take patches for several reasons:

1. To reduce the samples that can be used in the training stage.
2. Because patches are considered as local features which means that they describe properties of the specified region of an image.

Although we used patches to reduce the training instances, but in the same time we increased the feature vector for each instance. Because for 7X7 patch, there are 7^2 components for each feature (i.e. we used 6 features in our experiment). Therefore, the dimensionality reduction of the feature space is necessary, and because of that we applied the PCA on the feature space to reduce its dimension. Then we chose different number of features (i.e. 5, 10, 15,, etc.), then we used the KNN classifier with $K=1$ in our experiment at the different number of features, and measure the performance of each one.

In this work, we measure the performance of the segmentation algorithm by the sensitivity, and specificity [9]. These values are calculated as Eq. (7).

$$S = \frac{TP}{TP + FN} \quad (7)$$

$$SP = \frac{TN}{FP + TN}$$

Where S is the sensitivity, and SP is the specificity. TP is the true positive area (correctly classified as object), FP is the false positive area (classified as object, but in fact it is background), TN is the true negative area (correctly classified as background), and FN is the false negative area (classified as background, but in fact it is object).

4. Results and discussion

After building the training feature space, we label the LV cavity with its surrounding contour as 1, and its surrounding structure as 0. Then we used them with the KNN classifier for classifying the feature space of each image in the testing dataset. As shown in fig.3, the output of the KNN classifier didn't give us just the LV blood pool, but also the RV blood pool. So, we will need to do some post-processing steps to determine the object of the LV blood pool, and get its boundary contour.

The output of the KNN classifier contain holes inside the object boundary, and some isolated pixels. So, in the post-processing stage, we fill the holes inside the connected components, then removing the small connected objects. After getting the output of the post-processing stage that is shown in fig.3, we calculated the circularity of the remaining objects as Eq. (8):

$$C = \frac{4 * \Pi * A}{P^2} \quad (8)$$

Where A is the area, and P is the perimeter of the object. The most circular object considered as the LV blood pool, then we take the convex hull of this object and determine its boundary that represent the endocardium contour as shown in fig.4.

After determining the boundary of the left ventricle cavity, we calculate the sensitivity, and specificity between our results and the manual output. As shown in Table 1, the difference between the results of using 20 features, or 25 features from the PCA is very small. The 25 features gave us the highest sensitivity 95.61%, and specificity 98.90%, where the 20 features gives 94.89% sensitivity, and 98.86% specificity. In the same time the 40 features gave us sensitivity 95.14%, and specificity 98.75%, but there is an important factor that must be considered in determining the number of features that should be used in the classification, which is the

processing time, because if the size of the feature vector, increased the processing time will be increased too.

Table 1: Sensitivity and specificity of different number of features for the output of the KNN classifier, and after post-processing

No. of Features	KNN output		After post-processing	
	Sensitivity %	Specificity %	Sensitivity %	Specificity %
5	63.5	84.93	83.87	98.06
10	71.9	84.54	91.66	98.63
15	74.01	84.69	92.78	98.70
20	75.23	84.56	94.89	98.86
25	75.55	84.55	95.61	98.90
30	76.15	84.43	93.54	98.70
35	76.44	84.39	92.95	98.55
40	76.62	84.36	95.14	98.75

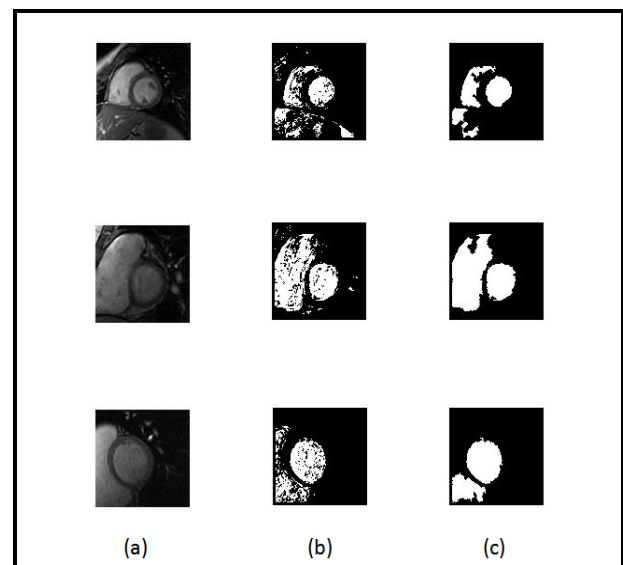


Fig. 3. (a) Cardiac MRI image (Region of Interest) for 3 different patients, (b) The output of KNN classifier, and (c) The output after post-processing .



Fig. 4. Final results of the proposed algorithm for 3 different patients, where the red contour represent the endocardium contour.

5. Conclusion

We have proposed in this paper a new technique for segmenting the left ventricle cavity by using pixel classification method. This method built feature space that consists of different features (i.e. output of median filter with different windows, the local maxima of gradient magnitude, the local maxima of the largest eigenvalue, and the gray value) then applied PCA for reducing the dimension of the feature space. The output of the PCA used with the KNN classifier to classify the pixels of the cine MRI images to segment the left ventricle cavity. The results show the availability of the proposed method for fast and reliable segmentation of the left ventricle cavity.

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