



MULTIFRACTAL BASED VENTRICULAR ABNORMALITY DETECTION IN CMR IMAGES

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Abstract

Background: It is important to recognize and diagnose various forms of heart failure that contribute to cardiovascular diseases. One such failure is due to ventricular hypertrophy, characterized by the deformation of ventricular wall. This disorder seriously affects the heart, causing cardiovascular disease. Ventricular hypertrophy is diagnosed using Cardiac Magnetic Resonance (CMR) images which give important information on the function of ventricles and their size. **Objective:** Ventricular analysis needs exact delineation of the ventricles and the current manual clinical practice involves intra and inter-observer variability's. Due to huge amount of data that is to be analyzed, it is a tedious and time consuming process. This paper is an attempt on automated classification of the ventricles based on the multifractal and various other

features of the ventricles extracted from both normal and hypertrophic CMR images. **Methods:** CMR images are preprocessed for intensity in-homogeneity correction and the corrected images are segmented using proposed automated hybrid Spatial Fuzzy C-Means (SFCM) with optimized level set method. The ventricular features are extracted from images using multifractal, intensity and geometric methods. The significant features are selected by dimensionality reduction using principal component analysis and then classified using classifiers such as Naive Bayes Classifier (NBC), Probabilistic Neural Network (PNN) and Support Vector Machine (SVM). **Results:** A maximum efficiency was achieved using SVM compared to other classifiers for classifying the abnormality of the ventricles. **Conclusions:** The results thus obtained shows that using a large set of different features combined with selection of appropriate features allow us to obtain higher classification accuracy.

1 INTRODUCTION

According to the statistics of American Heart Association (AHA), Cardio Vascular Disease (CVD) is one of the common causes of death and about 17.5 million people die each year. Different statistical surveys (Allender et al. 2008, Lloyd-Jones 2010) indicate that CVD is a major health burden and causes mortality in developed as well as developing countries. The main causes of CVD include change in life style of the people, use of tobacco, improper diet, consumption of alcohol and lack of physical exercise. The major risk factors of CVDs are obesity and increase in blood pressure, blood glucose and blood lipids. The statistics of World Health Organization (Alwan 2011) shows that 80% die due to coronary heart disease and cerebrovascular disease. Advanced research is needed from gene level to whole organ function level towards developing more cost effective technologies to prevent this silent killer. Research is also being carried out to significantly provide better diagnostic relevance at early stages to reduce the rate of mortality.

The foremost step in the cardiac ventricular analysis is image

acquisition using various imaging techniques. Echocardiography, Computed Tomography, Positron Emission Tomography and Cardiac Magnetic Resonance (CMR) imaging are the various imaging modalities used in cardiac examinations. CMR is considered as the gold standard for calculating various ventricular indices due to better delineation between the blood pool and myocardium. Local indices such as wall thickness and global indices such as volume and mass of the ventricles at systolic and diastolic phases are obtained using both global and regional myocardial function evaluation.

CMR images are inhomogeneous in nature with low intensity profile and weak wall thickness. There are numerous causes for intensity-inhomogeneity in CMR images, including B1 and B0 field inhomogeneity and patient-specific interactions. Bias field blurs the images by altering the high frequency edges and contour pixels intensity values. The inhomogeneity leads to overlap of intensities between different tissues and often results in misclassification of tissues. Therefore, it is mandatory to use bias field correction, which usually estimates the bias field.

Image segmentation is an important process in many computer vision and image processing applications. It divides an image into a number of discrete regions, such that the pixels have high similarity in each region and high contrast between regions. Properties like gray level, colour, intensity, texture, depth or motion help to recognize similar regions and similarity of such properties is used to construct groups of regions having a specific meaning. There are various methods available in the literature for segmenting LV (Paragios et al. 2002, Jolly et al. 2001). The existing semi-automated and automated methods have various limitations such as i) Faulty convergence of endo and epicardial contours in case of Snakes, Level Set and ii) Inaccurate LV segmentation due to similar intensity distribution among myocardium, papillary muscles, liver and chest. Compared to LV, less attention was given for the delineation of RV that is vital in diagnosing certain cardiovascular diseases like Arrhythmogenic Right Ventricular Dysplasia and hypertension (Goshtasby et al. 1995). RV segmentation is more challenging due to its complex variable shape, motion and uneven borders (punithakumar et al. 2015).

Conventional hybrid segmentation methods such as Gaussian mixture model with region restricted dynamic programming (Hu et al. 2013) and K-Means clustering with level set (Sreemathy et al. 2012) are in use. There is a scope for improvement of hybrid segmentation methods by overcoming the limitations such as, detecting the small blood pool at the apex and also detecting the periphery slices along the myocardium which are still challenging and time consuming.

The feature analysis relies on appropriate representation of shape and using it for further classification. Based on human interpretation with image information, the parameters such as appearance, shape, spectral, textural and contextual features are considered in various computerized image processing applications. Intensity and geometric features are derived to extract useful characteristics from the segmented ventricular portions. Gray Level Co-occurrence Matrix (GLCM) is a well-known and widely used texture measure, which shows the gray level histogram in the form of a matrix for either a portion of an image or an entire image. The probability density pairs of gray levels that occur in pairs of points are separated by the displacement vector d .

The multifractal analysis uses both local and global features (Stojic et al. 2006) in an image to identify the distribution of dissimilar pixels. Multifractal features obtained from the singularity and generalized dimension spectra are extracted from the segmented ventricular portions. The main features used are apex, width, frequency, right aperture and left aperture.

Feature selection methods select significant features that retain their original physical interpretation based on a criterion function and generate important patterns (Iqbal et al. 2011) for understanding the physical process. In multi-category applications, it is not unusual to encounter problems involving multiple variants of features. Intuitively, it may appear that each feature is useful for discriminations. This large number of features when given as such to a classifier will increase the computational time and inter-class variability (Reyes-AldasoroBhalerao 2003). In order to reduce the computational time, it is necessary to select non-correlated features. In general, if the performance obtained with a given set of features is inadequate, it is natural to consider adding new features. There are a variety of methods such as

spectrum distribution and wavelet transform for evaluating the performance of the extracted features. Feature reduction and feature selection are used to increase the efficiency of the classifier.

Classifiers are widely used in discriminating the normal from its pathological condition. The classification process involves grouping of data into pre-defined classes or finding the class to which a data belongs. This process plays an important role in medical image automation which is part of decision making in medical image analysis. Machine learning based classification techniques provide support in many areas of health care, including prognosis, diagnosis and screening (Luukka 2011). Classifier divides segmented regions into one of the pre-established groups based on the extracted features. Neural network-based classifiers are a part of decision making in medical image analysis and is being widely used in medical image automation. The performance of the classifier with two possible classes is evaluated based on the closeness of the test set result with respect to true positives, false positives, true negatives and false negatives (Kim et al. 2007). These terms describe the clinical efficiency of a classifier. Based on the evaluation criteria, performance of the classifier is measured in terms of statistical quantities such as sensitivity, specificity and accuracy (Makinaci 2005).

The rest of the paper is organized as follows; Section 2 describes materials and methods including feature extraction, feature selection and classification. Section 3 presents the results and discussion followed by conclusion in Section 4.

2 MATERIALS AND METHODS

A. Image Acquisition

CMR short-axis images consisting of both normal and abnormal obtained from 3T MR imaging unit (Magnetom Symphony, Siemens Medical Solutions, Erlangen, Germany) of Rajiv Gandhi Government General Hospital, Park Town, Chennai with 35 data sets are used for the analysis. Using steady state free precession protocol, a stack of 20-30 contiguous short-axis slices of matrix size 174x208 with a slice thickness of 7mm, covering both the ventricles from the base to the apex were acquired for a

repetition time of 3.4ms and echo time of 1.7ms.

Cardiac magnetic resonance images are inhomogeneous due to spatial intensity variations which limits their analysis. Inhomogeneity is mainly caused due to variations in magnetic field intensity and enduring based interfaces. The inhomogeneity leads to overlap of intensities between different tissues and often results in misclassification of tissues. Therefore, it is mandatory to use bias field correction which usually estimates the bias field that interprets the intensity-inhomogeneity.

Segmentation is a vital step in image analysis for object identification or delineation in medical images. Even though there are different segmentation methods available in the literature, choice of appropriate segmentation algorithm for computerized diagnosis make it still a challenging task. CMR short axis images are widely used to analyse the functionality of the ventricles by ventricular segmentation. The conventional ventricular segmentation methods are classified as manual, semi-automatic, automatic and hybrid segmentation methods. Manual segmentation is the current clinical practice that leads to intra and inter-observer variability. It is a complex and time consuming process, as large set of data has to be analysed. Conventional semi-automatic and automatic methods are limited by user interaction and inaccurate delineation. Hence, there is a need for hybrid segmentation for accurate delineation of the ventricles.

B. SFCM Method

In SFCM method, initially bias correction is done using Spatial fuzzy C means algorithm. FCM is an unsupervised iterative clustering algorithm in which the observed MRI signal is modeled as a product of true signal and a spatially varying parameter called the gain field

$$Y_k = X_k G_k \quad \forall k \in \{1, 2, \dots, N\} \quad (1)$$

where G_k is the gain field at the k th pixel, the values X_k, Y_k are true and observed intensities respectively and total number of pixels in the image is N . The transformation of the MRI intensities allows the gain artifact to be estimated by a Bayesian approach as

$$y_k = x_k + \beta_k \quad \forall k \in \{1, 2, \dots, N\} \quad (2)$$

where x_k, y_k are the true and resultant log-transformed intensities at the k th pixel respectively and β_k is the bias field at the k th pixel. Thus the BCFCM objective function J_m that is to be minimized is represented as

$$J_m = \sum_{i=1}^c \sum_{k=1}^N u_{ik}^f \|y_i - \beta\|^2 + \sum_{i=1}^c \sum_{k=1}^N u_{ik}^f \left(\sum_{r \in N_k} w(y_i, y_r) \|y_r - \beta\|^2 \right) \quad (3)$$

The minimization of objective function is achieved by the first derivative of J_m with respect to u_{ik} -membership estimator, v_i - vector of c clusters and β_k - bias estimation terms, i.e the objective function is minimized by lowering the membership values if the pixel values are far from the centroid and vice versa, if the pixel values are near to the centroid.

Bias-field estimation β_k^* is represented as

$$\beta_k^* = y_k - \frac{\sum_{i=1}^c v_i \left(u_{ik}^f + \sum_{r \in N_k} w(y_i, y_r) u_{ir}^f \right)}{\sum_{i=1}^c \left(u_{ik}^f + \sum_{r \in N_k} w(y_i, y_r) u_{ir}^f \right)} \quad (4)$$

The fuzziness is determined by parameter f which is a weighting exponent and $w(y_k, y_r)$ is a weighting function satisfying the following condition

$$\sum_{y_r \in N_k} w(y_k, y_r) = \alpha, 0 \leq \alpha < 1, \forall k \in \{1, 2, \dots, N\} \text{ especially, when } w(y_k, y_r) = \frac{\alpha}{N_R}$$

N_R is the cardinality of N_k that represents the set of neighbors that exist in a window around x_k and the effect of neighbors will be controlled by the parameter α .

C. Proposed Method

Split-Bregman (Tom et al 2010) method is applied to the modified CV in order to optimize the combined energy function c1 and c2. The complex energy function can be reduced to a sequence of problems in the form,

$$\min_{0 \leq \phi \leq 1} |\nabla \phi + \mu \langle \phi, r \rangle| \text{ where}$$

$$r = \delta_z(\phi) \left(I_0(x, y) - \frac{c_1(p_1) + c_2(p_1)}{2} \right)$$

To convert the constrained into unconstrained problem, apply the auxiliary variable $d \rightarrow \nabla \phi$, employ the Bregman iteration to the problem and add a quadratic penalty function for equality constraint. The final unconstrained problem is written as

$$(\phi^{k+1}, d^{k+1}) = \arg \min_{\phi \in [0,1], d} |d| + \mu \langle \phi, r \rangle + \frac{\lambda_p}{2} \|d - \nabla \phi - b^k\|^2 \quad (5)$$

$$b^{k+1} = b^k + \nabla \phi^{k+1} - d^{k+1} \quad (6)$$

The constrained problem is globally minimized, if the solution to this equation lies inside the interval $[0, 1]$. If the solution lies outside the interval $[0, 1]$, the energy is strictly monotonic as the energy is quadratic and the minimizer lies at the endpoint closest to the unconstrained minimizer. Following are the element-wise minimization formula:

$$\alpha_{i,j} = d_{i-1,j}^x - d_{i,j}^x + b_{i,j}^x + d_{i,j-1}^y - d_{i,j}^y - b_{i,j-1}^y + b_{i,j}^y \quad (7)$$

$$\beta_{i,j} = u_{i-1,j} + u_{i+1,j} + u_{i,j-1} + u_{i,j+1} - \frac{\mu}{\lambda_p} r + \alpha_{i,j} \quad (8)$$

$$\phi_{i,j} = \max \{ \min \{ \beta_{i,j}, 1 \}, 0 \} \quad (9)$$

Equation (9) is minimized for fixed level set function ϕ with respect to d and obtained

$$d^{k+1} = \text{shrink}_{\frac{\lambda_p}{2}}(b^k + \nabla \phi^{k+1}, \lambda_p) \quad (10)$$

In this algorithm, Gauss-Siedel (Bresson et al 2007) function $(r^k, d^k, b^k, \lambda_p)$ is updated by Equations (7) - (9).

D. Feature Extraction and Classification

Feature extraction refers to the process that aims at computing abstractions of image information. The left ventricle is ellipsoidal in shape and right ventricle is crescent shaped and there is a change in the shape of the ventricles from the base to the apex (Farrar et al. 2016). Due to the ventricular shape variation, this information

is important for extraction of different type of features and the classification scheme.

Classifiers are widely used in discriminating the normal from its pathological condition. The classification process involves grouping of data into pre-defined classes or finding the class to which a data belongs. This process plays an important role in medical image automation which is part of decision making in medical image analysis. Machine learning based classification techniques provide support in many areas of health care, including prognosis, diagnosis and screening (Luukka 2011). Classifier divides segmented regions into one of the pre-established groups based on the extracted features. Neural network-based classifiers are a part of decision making in medical image analysis and is being widely used in medical image automation.

3 RESULTS AND DISCUSSION

The short axis CMR images consisting of both normal and abnormal with steady state free precession protocol stack of 20-30 contiguous short-axis slices obtained from 3T MR imaging unit of Rajiv Gandhi Government General Hospital, Park Town, Chennai are considered in the analysis. The CMR images are usually corrupted with in-homogeneity due to non-uniform magnetic fields produced by RF coils as well as disparities due to patient artifacts. In case of hypertrophic images, in-homogeneity is high because of similarity in the intensity values of uneven thickening of left ventricular walls. Thus to enhance the delineation of the ventricles for further analysis, it is necessary to perform in-homogeneity correction. The ventricular cavities are structures filled with blood and have a homogeneous dark region. In order to consider all these issues while segmenting, a new automatic hybrid Spatial Fuzzy C-Means (SFCM) with optimized level set method is proposed.

The proposed SFCM with Split-Bregman method is applied to segment the inhomogeneous cardiac MRI images and its performance is compared with SFCM and FCM methods. The initialization of the contour in SFCM with Split-Bregman method starts at the finest level of intensity in the image. The

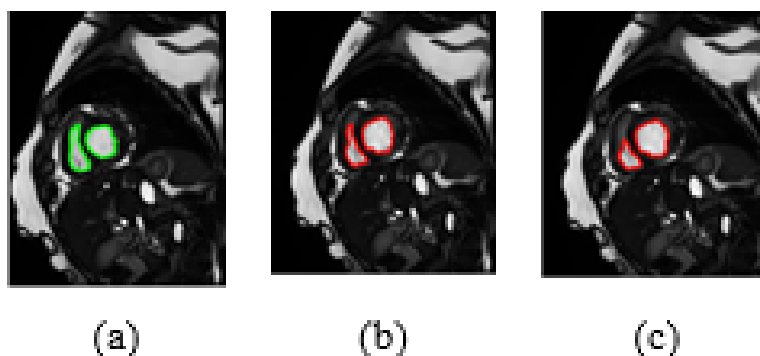


Figure 1: Segmentation using proposed method and conventional methods (a) Proposed method output (b) SFCM method output and (c) FCM method output.

segmentation starts by determining the mean inside and outside intensity of the contour. Depending on the change in the mean intensities the segmentation becomes coarse and finally, the Split-Bregman method slows down the computation. This effect is due to the fact that the Gauss-Seidel iteration converges more slowly for small values of the fidelity parameter.

Table 1: Computational evaluation

Method	No. of Iterations	Execution time (sec)
FCM	25	16.8
SFCM	20	12.1
Proposed	12	7.67

The proposed method is evaluated in terms of computation time by comparing it with conventional methods of FCM and SFCM. It is inferred from Table 1 that the proposed hybrid method, due to the Split-Bregman optimization, the speed of execution is high.

The feature analysis relies on appropriate representation of shape and presenting it for further classification. Based on human interpretation with image information, the parameters such as appearance, shape, spectral, textural and contextual features are considered in various computerized image processing applications.

Intensity and geometric features are derived to extract useful characteristics from the segmented ventricular portions.

Feature selection methods select significant features that retain their original physical interpretation based on a criterion function and generate important patterns (Iqbal et al. 2011) for understanding the physical process. To improve the classification accuracy, relevant features are selected from the extracted features and used for automatic recognition of different types of pathological conditions in ventricles.

Principal component analysis uses an orthogonal transformation to convert a set of observations of linear correlated variables into a set of values of uncorrelated variables called principal components. This is performed by analysing the Eigenvalues of the correlation matrix. The Eigenvectors then become the principal components and are selected in order depending on their eigenvalue. The largest eigenvalue is associated with the first component and the smallest with the least. PCA is based on the statistical representation of a random variable. The images are then classified with NBC, SVM and PNN. SVM classifier classifies normal and hypertrophic with an accuracy of 56% before feature selection and 82% after selection using PCA. 35 samples were randomly split into 60% (20 samples) for training and the remaining 40% (15) for testing.

Table 2: Classifier performance measures

Classifier	Performance estimators for different type of features			
	Sensitivity	Specificity	Accuracy	F-measure
NBC	0.75	0.73	0.78	0.81
PNN	0.78	0.72	0.71	0.8
SVM	0.89	0.75	0.82	0.87

The performance of three classifiers such as SVM, PNN and NBC are evaluated with sensitivity, specificity, accuracy and F-measure metrics as shown in Table 2. It is inferred from Table 2 that SVM gives better classification compared to PNN and NBC.

The classifiers performance is then evaluated with different parameters. SVM classifier performance estimation is given in Table 3 and Table 4 gives the performance estimation of PNN classifier. It can be observed from Tables 3, 4 and 5 that multifractal features gives better performance estimation when compared to other features as it has higher values of accuracy.

Table 3: SVM Classifier performance estimation

S.No	FEATURE	ACCURACY	SENSITIVITY	SPECIFICITY	F-SCORE
1	Multifractal	0.95	1	0.8	0.88
2	Flusser	0.58	1	0	0
3	Hu	0.56	1	0	0
4	Tamura	0.83	1	0	0
5	GLCM	0.68	1	0.39	0.56

Table 4: PNN Classifier performance estimation

S.No	FEATURE	ACCURACY	SENSITIVITY	SPECIFICITY	F-SCORE
1	Multifractal	0.91	0	1	0
2	Flusser	0.6	0.93	0	0.93
3	Hu	0.67	1	0	1
4	Tamura	0.57	1	0	1
5	GLCM	0.82	1	0	1

Table 5: NBC Classifier performance estimation

S.No	FEATURE	ACCURACY	SENSITIVITY	SPECIFICITY	F-SCORE
1	Multifractal	0.79	0	1	0
2	Flusser	0.54	0.83	0	0.86
3	Hu	0.57	1	0	1
4	Tamura	0.47	1	0	1
5	GLCM	0.78	1	0	1

4 CONCLUSION

This paper, proposes a new approach based on NBC, PNN and SVM for classification of ventricular abnormalities. The proposed algorithm employs an improved bias correction based spatial FCM with optimized level set method for ventricle segmentation of a cardiac MRI image. The results delineated in the earlier section show that using a very large number of features combined with a feature selection approach allow us to achieve high classification rates. The SVM training scheme achieves maximum efficiency compared to existing methods.

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