INTERNATIONAL RESEARCH JOURNAL IN ADVANCED ENGINEERING AND TECHNOLOGY (IRJAET) E - ISSN: 2454-4752 P - ISSN : 2454-4744
VOL 3 ISSUE 3 (2017) PAGES 2299 - 2305
RECEIVED : 20.04.2017 PUBLISHED : 14.05.2017
May 14, 2017

# ROBUST SPARSE FIELD LEVEL SET BASED IMAGE SEGMENTATION

[1]A.Vijayalakshmi M.E., [2]Dr.M.Suganthi M.E., Ph.D.,
[1]Student, Department of Communication Systems Engg, Mahendra College of Engineering, Salem
[2]Head of the Department, Department of the Electronics and communication engineering,
Mahendra College of Engineering, Salem.

**ABSTRACT**

Due to acoustic interferences and artifacts which are inherent in echocardiography images, automatic segmentation of anatomical structures in cardiac ultrasound images is a real challenge. This paper surveys state of-the-art researches on echocardiography data segmentation methods, concentrating on methods techniques developed for clinical data. We present a classification of methodologies for echocardiography image segmentation. By choosing ten recent papers which have proposed innovative ideas that they proved certain clinical advantages or potential especial role to the echocardiography segmentation task. The contribution of the paper would be serving as a tutorial of the field for both clinicians and technologists, providing large number of segmentation techniques in a comprehensive and systematic manner and critically review recent approaches in terms of their performance and degree of clinical evaluation with respect to the final goal of cardiac functional analysis.

## 1. INTRODUCTION

The echocardiography and cardiac Computed Tomography (CT) are emerging diagnostic tools among modern imaging modalities for visualizing cardiac structure and diagnosing cardiovascular diseases. The echocardiography is real-time, non-invasive imaging modality which is less expensive than CT and Magnetic Resonance imaging (MR). Recently, the problem of automatic detection, segmentation and tracking of heart chambers in radiological imaging, such as ultrasound and CT, have received considerable attentions. Quality of echocardiography images influence directly on segmentation result. There are some artifacts such as attenuation, speckle, shadows and signal dropout which make the segmentation process difficult; because of orientation dependence for acquisition data, result can lead to missing borders. Since the contrast between areas of interest is usually low, segmentation task in ultrasound images turns to a challenging one. Although, recently the quality of information from an ultrasound device has substantially improved, due to recent advances in transducer design, spatial/temporal resolution, digital systems, portability, etc.. Due to these advances use of echocardiography has been increased in many ways; not only the traditional scope of application, CAD and diagnosis, but also new areas like therapy and image guided interventions. Therefore, currently, there is an urge in understanding how to do image segmentation, one of the oldest image processing tasks, to echocardiography data.

Echocardiography images can be used for many different tests: Cardiac structure, heart development, function and also changes in normal physiologic states and pathologic conditions. For example, Left ventricular function can be obtained through 2 dimensional echocardiography images by calculating

INTERNATIONAL RESEARCH JOURNAL IN ADVANCED ENGINEERING AND TECHNOLOGY (IRJAET) E - ISSN: 2454-4752 P - ISSN : 2454-4744
VOL 3 ISSUE 3 (2017) PAGES 2299 - 2305
RECEIVED : 20.04.2017 PUBLISHED : 14.05.2017


the ejection fraction. Depending on where on the chest the user positions the transducer, different views of the heart can be obtained. Some of the most common views are: Long axis view of the left atrium and the left ventricle, short axis views of the heart in planes from the base of the heart to the apex and the four chambers view

## 2. RELATED WORK

Most considerations have been given to tracking the motion of the endocardium, e.g., blood pool or tissue border to allow for approximation of left ventricular volumes or areas and derived measures such as the ejection fraction and for regional wall motion analyzing. Especially, these measures are used in assessment and diagnosis of ischemic heart disease. Most analysis is based on 2D acquisitions in which it is implicitly assumed that the principal component of motion is in the plane of the acquisition slice. Parasternal Short-Axis (SAX) is the standard 2D diagnostic views used for this and apical two-chamber (2C), Four-Chamber (4C) and Three-Chamber (3C) views. The latter three are also sometimes referred to as (apical) Long-Axis (LAX) views.

The quality of data and therefore issues for segmentation, vary regarding to the view due to the anisotropy of ultrasound image acquisition, artifacts like attenuation and shadowing from the lungs which can be severe. Segmentation methods should also have strategies for avoiding the papillary muscles. Reliably finding the pericardial border, i.e., outer wall is more challenging, especially from apical views. Lots of the preliminary works concentrated on one frame segmentation yet; considering maximum expansion or end diastole and maximum contraction or end systole frames to calculate some measurements like EF (the ejection fraction). Although, analysis should be done for the whole cardiac cycle for fully assess heart function. Cardiologists also use a movie of a heart in decision-making as the speckle pattern associated with de-forming tissue can be observed in a movie whereas in a still frame the speckle pattern is not always useful.

## 3. EXISTING SYSTEM

We propose a joint information approach for automatic analysis of 2D echocardiography (echo) data. The approach combines a priori images, their segmentations and patient diagnostic information within a unified framework to determine various clinical parameters, such as cardiac chamber volumes, and cardiac disease labels. The main idea behind the approach is to employ joint Independent Component Analysis of both echo image intensity information and corresponding segmentation labels to generate models that jointly describe the image and label space of echo patients on multiple apical views, instead of independently. These models are then both used for segmentation and volume estimation of cardiac chambers such as the left atrium and for detecting pathological abnormalities such as mitral regurgitation. We validate the approach on a large cohort of echo's obtained from 6,993 studies. We report performance of the proposed approach in estimation of the left- atrium volume and detection of mitral-regurgitation severity. A correlation coefficient of 0.87 was achieved for volume estimation of the left atrium when compared to the clinical report. Moreover, we classified patients that suffer from moderate or severe mitral regurgitation with an average accuracy of 82%

**DISADVANTAGES OF EXISTING SYSTEM:**

1. There is no simple relation between pixel intensity and any physical property of the tissue visualized
2. The limitation of the existing system is unimodal segmentation technique and has less performance.
3. Processing time is high

## 4. PROPOSED SYSTEM

### SYSTEM ARCHITECTURE

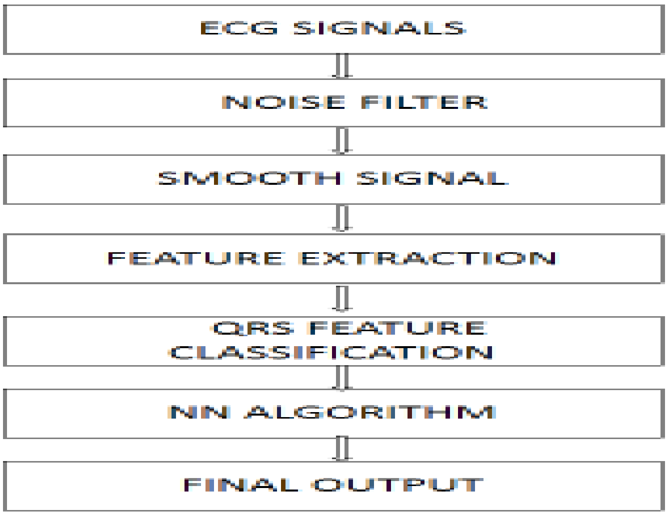


**Figure 1: System Architecture**

Due to acoustic interferences and artifacts which are inherent in echocardiography images, automatic segmentation of anatomical structures in cardiac ultrasound images is a real challenge. This paper surveys state of-the-art researches on echocardiography data segmentation methods, concentrating on methods techniques developed for clinical data. We present a classification of methodologies for echocardiography image segmentation. By choosing ten recent papers which have proposed innovative ideas that they proved certain clinical advantages or potential especial role to the echocardiography segmentation task. The contribution of the paper would be serving as a tutorial of the field for both clinicians and technologists, providing large number of segmentation techniques in a comprehensive and systematic manner and critically review recent approaches in terms of their performance and degree of clinical evaluation with respect to the final goal of cardiac functional analysis.

**ADVANTAGES OF PROPOSED SYSTEM:**

1. The use of this kind of similarity for the performance improvement of medical diagonise identification.

2. Very high accuracy.

INTERNATIONAL RESEARCH JOURNAL IN ADVANCED ENGINEERING AND TECHNOLOGY (IRJAET) E - ISSN: 2454-4752 P - ISSN : 2454-4744
VOL 3 ISSUE 3 (2017) PAGES 2299 - 2305
RECEIVED : 20.04.2017 PUBLISHED : 14.05.2017 May 14, 2017

## ALGORITHM

### PCA ALGORTHIM

Principal component analysis (PCA) is a statistical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. The number of principal components is less than or equal to the number of original variables. This transformation is defined in such a way that the first principal component has the largest possible variance (that is, accounts for as much of the variability in the data as possible), and each succeeding component in turn has the highest variance possible under the constraint that it is orthogonal to the preceding components. The resulting vectors are an uncorrelated orthogonal basis set. PCA is sensitive to the relative scaling of the original variable.

PCA is mostly used as a tool in exploratory data analysis and for making predictive models. PCA can be done by eigen value decomposition of a data covariance (or correlation) matrix or singular value decomposition of a data matrix, usually after mean centering (and normalizing or using Z-scores) the data matrix for each attribute.[4] The results of a PCA are usually discussed in terms of component scores, sometimes called factor scores (the transformed variable values corresponding to a particular data point), and loadings (the weight by which each standardized original variable should be multiplied to get the component score).[5]

PCA is the simplest of the true eigenvector-based multivariate analyses. Often, its operation can be thought of as revealing the internal structure of the data in a way that best explains the variance in the data. If a multivariate dataset is visualized as a set of coordinates in a high-dimensional data space (1 axis per variable), PCA can supply the user with a lower-dimensional picture, a projection or "shadow" of this object when viewed from its (in some sense; see below) most informative viewpoint. This is done by using only the first few principal components so that the dimensionality of the transformed data is reduced. PCA is closely related to factor analysis. Factor analysis typically incorporates more domain specific assumptions about the underlying structure and solves eigenvectors of a slightly different matrix.

PCA is also related to canonical correlation analysis (CCA). CCA defines coordinate systems that optimally describe the cross-covariance between two datasets while PCA defines a new orthogonal coordinate system that optimally describes variance in a single dataset

### ADAPTIVE MODEL SHAPING

Adpative shape models (ASMs) are statistical models of the shape of objects which iteratively deform to fit to an example of the object in a new image, developed by Tim Cootes and Chris Taylor in 1995. The shapes are constrained by the PDM (point distribution model) Statistical Shape Model to vary only in ways seen in a training set of labelled examples. The shape of an object is represented by a set of points (controlled by the shape model). The ASM algorithm aims to match the model to a new image.

INTERNATIONAL RESEARCH JOURNAL IN ADVANCED ENGINEERING AND TECHNOLOGY (IRJAET) E - ISSN: 2454-4752 P - ISSN : 2454-4744
VOL 3 ISSUE 3 (2017) PAGES 2299 - 2305
RECEIVED : 20.04.2017 PUBLISHED : 14.05.2017



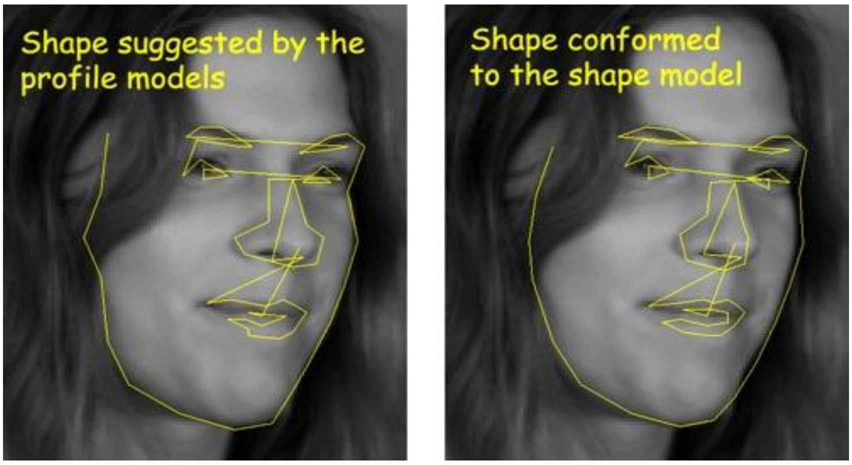


**Figure 2: Adaptive Model Shaping**

**The ASM works by alternating the following steps**

1. Generate a suggested shape by looking in the image around each point for a better position for the point. This is commonly done using what is called a "profile model", which looks for strong edges or uses the Mahalanobis distance to match a model template for the point.
2. Conform the suggested shape to the point distribution model, commonly called a "shape model" in this context.
3. The technique has been widely used to analyse images of faces, mechanical assemblies and medical images (in 2D and 3D). It is closely related to the adpative appearance model. It is also known as a "Smart Snakes method, since it is an analog to an adpative contour model which would respect explicit shape constraints

**GAUSSIAN SCALE**

Gaussian filtering is used to remove noise and detail. It is not particularly effective at removing salt and pepper noise. Compare the results below with those achieved by the median filter.

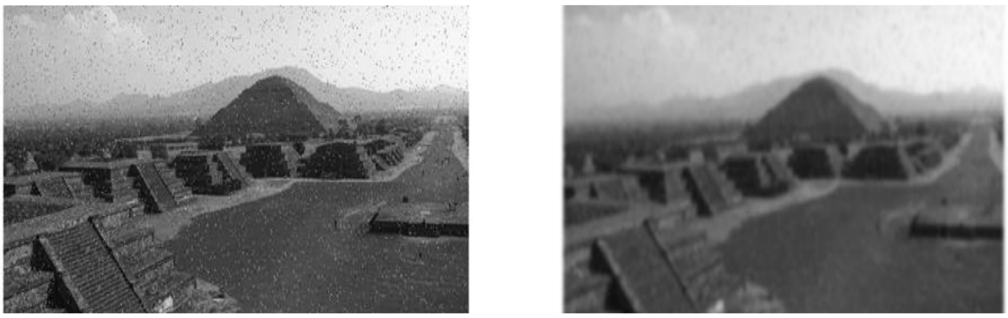

**Figure 3: Gaussian Scale**

Gaussian filtering is more effective at smoothing images. It has its basis in the human visual perception system. It has been found that neurons create a similar filter when processing visual images. The halftone image at left has been smoothed with a Gaussian filter and is displayed to the right.

**Figure 4: Gaussian Filtering**

This is a common first step in edge detection. The images below have been processed with a Sobel filter commonly used in edge detection applications. The image to the right has had a Gaussian filter applied prior to processing.

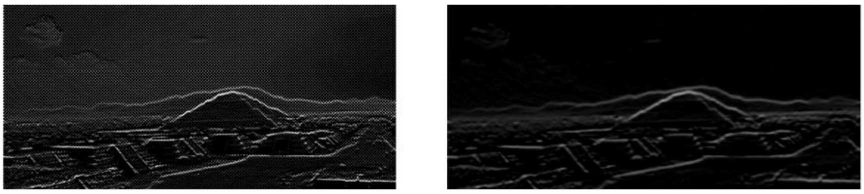

**Figure 5: Edgedetection**

## APPLICATION

- GSM since it applies GMSK modulation
- The Gaussian filter is also used in GFSK.
- Canny Edge Detector used in image processing.

## CONCLUSION

Usually, for examining medical image segmentation techniques in a quantitative way, we can use animal model studies, phantom studies, simulation and manual delineation. One modality as a “reference” or “gold standard”, or some relation between clinical results. Mostly, clinical info is utilized in evaluation. However, there is some literature on echocardiography segmentation techniques shows that some phantom and simulation studies also have been done. We have made comparison between methods which proposed by research groups, since there is no standard database to compare results. Lacking of a standard dataset is confusing, since quality of echocardiography images varies a lot, in compare with other clinical imaging such as CT or MRI.

**REFERENCES**

[1] W. P. Abhayaratna, J. B. Seward, C. P. Appleton, P. S. Douglas, J. K. Oh, A. J. Tajik, And T. S. M. Tsang, “Left Atrial Size: Physiologic Determinants And Clinical Applications

[2] D. Agarwal, K. S. Shriram, And N. Subramanian, “Automatic View Clas Sification Of Echocardiograms Using Histogram Of Oriented Gradien

[3] E. E. Apostolakis And N. G. Baikoussis, “Methods Of Estimation Of Mitral Valve Regurgitation For The Cardiac Surgeon

[4 ]E. Aune, M. Baekkevar, J. Roislien, O. Rodevand, And J. E. Otterstad, “Normal Reference Ranges For Left And Right Atrial Volume Indexes And Ejection Fractions Obtained With Real-Time Three-Dimensional Echocardiograph

[5] M. E. Barnes, Y. Miyasaka, J. B. Seward, B. J. Gersh, A. G. Rosales, K. R. Bailey, G. W. Petty, D. O. Wiebers, And T. S. M. Tsang, “Left Atrial Volume In The Prediction Of First Ischemic Stroke In An Elderly

[6] J. Bell And T. J. Sejnowski, “An Information-Maximization Approach To Blind Separation And Blind Deconvolution,” Neural Computation

[7] O. Bernard, B. Touil, A. Gelas, R. Prost, And D. Friboulet, “Segmentation Of Myocardial Regions In Echocardiography Using The Statistics Of The Radio-Frequency Signal

[8] J. G. Bosch, S. C. Mitchell, B. P. F. Lelieveldt, F. Nijland, O. Kamp, M. Sonka, And J. H. C. Reiber, “Automatic Segmentation Of Echocardiographic Sequences By Active Appearance Motion Model

[9] Y. Cao, P. Mcneillie, And T. Syeda-Mahmood, “Segmentation Of Anatomical Structures In Four-Chamber View Echocardiogram Images

[10] B. A. Carabello, “Mitral Valve Repair In The Treatment Of Mitral Regurgitation