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Automatic Segmentation of Echocardiographic Images Using Full Causal Hidden Markov Model

A. Suphalakshmi
Research Scholar, Department of Information Technology, MIT Campus
Anna University Chennai, Chennai-44, India
E-mail: suphaprabhu@gmail.com
Tel: +91 98947 46573, +91 98940 46573

P. Anandhakumar
Asst. Professor, Department of Information Technology, MIT Campus
Anna University Chennai, Chennai-44, India
E-mail: anandh@annuniv.edu
Tel : +91 9841667886

Abstract

Echocardiography with delineated ventricle borders is a principal technique for quantitative assessment of cardiac function. As it is, most of the prevailing segmentation methods suffer in detecting edges at equivocal regions. This paper presents an effective method for tracking Left Ventricle borders in echocardiographic images, using texture features and Hidden Markov Model. We have applied a Full Causal two dimensional Hidden Markov Model (FCHMM) in which the state transition probability depends upon all neighbouring states where causality is preserved. An enhanced 2D Viterbi algorithm is used to decode the proposed model. Experiments over 200 echocardiographic images show that the proposed model ascertains 98% of acceptance level for tracked left ventricle when compared with expert drawn curve.

Keywords: Echocardiography, Hidden Markov Model, Left Ventricle, Viterbi Algorithm, Texture features.

1. Introduction

Echocardiography is the examination of heart using ultrasound, which allows direct visualization of heart in motion. This technique is highly appreciable for its non-invasive nature, relatively inexpensive, less time consumption and easy reproducibility.

Clinical assessment of Left Ventricular (LV) function is essential for evaluating heart function of a patient with known or suspected cardiomyopathy. LV function is normally assessed by two-dimensional cardiac ultrasound imaging (echocardiography). Image sequences of standard cross-sectional views through the heart provide insight in the functional performance of different segments of left ventricular wall. It is widely recognized that quantitative analysis of echocardiograms is preferable over qualitative interpretation, particularly for wall motion and volume estimation. However manual measurements are tedious and time consuming, they require expert knowledge and moreover they suffer from considerable inter-and intra observer variability. (Marleen de Bruijne and Wino J Niessen, 2003)

The major issues with echo cardiac image segmentation are automatic seed point selection and finding the border points of the left ventricle, which separates the tissue (myocardium) and blood pool (J Alison Noble and Djamal Boukerroui, 2006). Effective border detection, based on edges, regions and global thresholding with the combination of probability based techniques was developed for echo cardiac images. Major weakness with these approaches is their inefficiency in detecting the edges present in ambiguous regions. The proposed method addresses this problem by modelling a 2D Hidden Markov Model, to detect edges which lie between the weak and strong edge pixels or regions by assigning probability values to them, which makes the border detection more effective. FCHMM (Suphalakshmi A, Narendran S, and Anandhakumar P, 2009) is used for maximizing the probability of states, which is built based on the observed significance in transition between blood pool and myocardium of echocardiographic images. This transition behaviour based on tissue characterisation can be extracted from texture properties.

2. Related work

HMM has been one of the dominant methods for modelling single dimensional data, which is applied in speech and signal processing (L. R. Rabiner and B. H. Juang, 1986). Turning to the application of image processing, 1D HMM may not be sufficient for handling 2D image data, where as 2D HMM can work efficiently. There are a number of variations available for segmentation of images using 2D HMM. Some of them which are closely related to the present research are discussed. In the method proposed by J. Li, A. Najmi, and R. M. Gray, (2000) a two-dimensional Hidden Markov Model for image classification, where state transition probability for each block is conditioned on the states of nearest neighbouring blocks from horizontal and vertical directions. Bernard Merialdo, Stiphane Marchand- Maillet and Benoit Huct, (2000) has proposed an approximate Viterbi decoding for 2D HMM model. In this model the approximation was done by taking two successive levels of the image and line levels by which it reduced exponential computational growth. However the model failed to incorporate the directional dependency.

Dan Schonfeld and Nidhal Bouaynaya (2006), have proposed an extension of the Viterbi model to semi causal and multidimensional functions. The model has been applied for video processing which takes the diagonal lines and quadrant walls as nearest neighbours. As the method is only semi causal, the contribution of the diagonal neighbour may be suppressed. Man Guo, M. Omair Ahmad, M.N.S. Swamy and Chunyan Wan, (2002) have suggested an adaptive Viterbi algorithm for the strongly connected trellis, where the major concern was improving hardware utilisation. An Image reconstruction algorithm which uses the Viterbi search was proposed by Miller, B. R. Hunt, M. A. Neifeld and M. W. Marcellin, (1997). This model also missed the diagonal element information by taking the vertical neighbourhood pixels. Giuseppe Mastronardi et. al (2007), suggested a pseudo 2D HMM which gave sequence orders that are not constant. An image segmentation algorithm using Markov and Gaussian mixture was given by Kyungsuk (Peter) Pyun et. al (2007), where the authors overcame the difficulty of Gaussian model, by combining it with HMM. A new potential function which involved the pixel intensity and distance values was introduced to MRF by Yimin Hou , Lei Guo and Xiangmin Lun, (2006), but this method used only the traditional MRF without any enhancements.

Combinative effort of MRF with Ant Colony System (ACS) was presented by Xiaodong and Jun zhou (2007). This model presents a second order neighbourhood system where ACS builds the interaction of ants in a neighbourhood of MRF. Even though this method shows effective results, the computation time was a major drawback. Li Huang, George Mathew and Tow Chong Chong, (2005), have proposed a method to reduce computational complexity in 2D Viterbi detector, but at the cost of performance loss. Xiang Ma, Dan Schonfeld and Ashfaq Khokhar, (2007) has suggested 2D HMM which allowed state dependencies as long as causalities were preserved, which enabled the model to capture the dependencies among diagonal states. In this method the dependencies arise from left adjacent diagonal, horizontal and vertical neighbours as shown in the figure 1(a). The paper has also presented a modified Expectation Maximization (EM) algorithm and a Forward Backward algorithm to incorporate the diagonal dependency to the traditional 2D models. Even then, this method failed to capture the complete causality of neighbouring states, as the dependency might arise from the lateral diagonal (Top right) neighbour state.

A full causal model (Suphalakshmi A, Narendran S, and Anandhakumar P, 2009) and enhanced 2D Viterbi decoding algorithm (Suphalakshmi, A., Narendran, S. and Anandhakumar, P, 2008) have been applied for decoding the proposed model. In the following section we brief FCHMM and later with the implementation of it to echo image segmentation.

3. Proposed Work

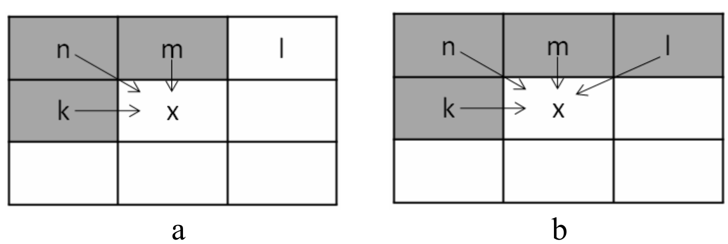
Any image can be assumed as a 2D Trellis of size 'm x n'. For any trellis the following assumptions are made to model FCHMM.

Assumption 1

Transition probabilities of the current state (i, j) of the model depends on all neighbouring states where causality is preserved.

Consider a 2D trellis of size m x n the with P number of states {1,2,...P}, let m denote row and n denote column then we define the current state s(i, j) depends on vertical (i-1,j), horizontal (i,j-1), two lateral neighbours (i-1,j+1) and (i-1,j-1).

Figure 1: a) General 2D HMM dependency b) Proposed model dependency



Assuming s(i, j) =x , s(i−1, j) = m, s(i−1, j−1) = n, s(i, j−1) = k, s(i-1, j−1) = l then probability of current state is given by

$$P(E) = a_{mnlk} \tag{1}$$

Where m, n, l, k Є {1, 2... P} are actual values of the state.

This assumption guarantees the causal relation of neighbouring states. In the model proposed in Xiang Ma, Dan Schonfeld and Ashfaq Khokhar, (2007), the dependency of state is on vertical horizontal and left diagonal states. But this lacks in capturing the dependency of states in the opposite diagonals which can influence in determining the current state. The figure 2(a) shows the dependency of states in existing method and the figure 2(b) shows the dependency of states in proposed method.

Figure 2: State dependency diagram (a) actual (b) proposed, Shaded blocks denotes dependency for pixel s(i,j)

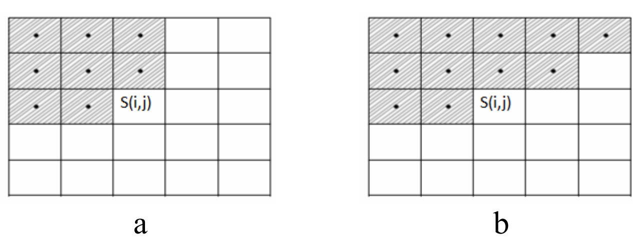
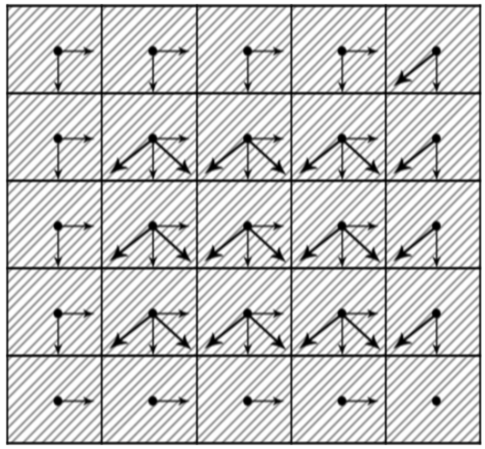


Figure 3: Full causal model



Assumption 2
Given the corresponding states of a feature vector, it is independent of other feature vectors and their corresponding states.

Since any state with an M-component Gaussian mixture can be split into M sub states with single Gaussian distributions (J. Li, A. Najmi, and R. M. Gray, 2000), we define the probability density function of feature vector o(i, j), given its corresponding hidden state s(i,j)= m, as,

$$\delta_m(o(i,j)) = \frac{1}{(2\pi)^{\frac{d}{2}} |\sum m|^{\frac{1}{2}}} e^{\frac{-1}{2(o(i,j)-\mu_m)}} \tag{2}$$

Where d is the dimensionality of feature vector, μ_m and $\sum m$ is the mean vector and covariance matrix of Gaussian distribution corresponding to state m. The proposed model can be seen in Figure 3, which satisfies the above two assumptions.

4. Two Dimensional Hidden Markov Model Evaluation and Decoding

4.1. Expectation-Maximization (EM) algorithm

In the work proposed by Xiang Ma, Dan Schonfeld and Ashfaq Khokhar, (2007), a modified Expectation Maximization algorithm was derived suitable for estimating parameters of general 2D-HMM model. This algorithm has been enhanced to support the proposed model.

Consider a 2D trellis of mxn dimension we define the observed feature vector set O = {o(i, j), i = 1, 2, ...m; j = 1, 2, ...n} and corresponding hidden state set S = {s(i, j), i = 1, 2, ...m; j = 1, 2, ...n}. The model parameters are defined as a set Θ = {Π,A,B}, where Π = {π} is the set of initial probabilities of states; A = {a,m,n,k,l,x} is the set of state transition probabilities, (m, n, k, l,x ε {1, 2, ...,M}); and B is the set of probability density functions (PDFs) of the observed feature vectors given corresponding states. Define F(p)m,n,k,l,x (i, j) as the probability of state corresponding to observation o(i−1, j) is state m, state corresponding to observation o(i−1, j−1) is state n, state corresponding to observation o(i, j−1) is state k and state corresponding to observation o(i, j) is state l, given the observations and model parameters,

$$F^{(p)}_{m,n,k,l,x}(i,j) = P(m = s(i-1, j), n = s(i-1, j-1), k = s(i, j-1), l = s(i-1, j-1), x=s(i,j) \mid O,\Theta(p)) \tag{3}$$

and define $G^{(p)}m(i,j)$ as the probability of the state corresponding to observation O(i, j) is state m, then

$$G^{(p)}m(i,j) = P(s(i,j) = m \mid O, \Theta(p)) \tag{4}$$

We can get the iterative updating formulas of parameters of the proposed model,

$$\pi_m^{p+1} = P\left(G^{(p)}m(1,1) \middle| O, \theta^{(p)}\right) \tag{5}$$

$$a^{(p+1)}_{m,n,h,l,x} = \frac{\sum_i^m \sum_j^n F^{(p)}_{m,n,h,l,x}(i,j)}{\sum_{x=1}^{M} \sum_i^m \sum_j^n F^{(p)}_{m,n,h,l,x}(i,j)} \tag{6}$$

$$\mu_m^{(p+1)} = \frac{\sum_i^m \sum_j^n G^{(p)}m(i,j)O(i,j)}{\sum_i^m \sum_j^n G^{(p)}m(i,j)O(i,j)} \tag{7}$$

$$\sum_m^{p+1} \square = \frac{\sum_i^m \sum_j^n G^{(p)}m(i,j)\left(O(i,j) - \mu_m^{(p+1)}\right)^{T+1}}{\sum_i^m \sum_j^n G^{(p)}m(i,j)} \tag{8}$$

In eqns. (3)-(8), p is the iteration step number. $F^{(p)}_{m,n,h,l,x}$, and $G^{(p)}m(i,j)$ are computed using Forward-Backward (GFB) algorithm, (Bernard Merialdo, Stiphane Marchand- Maillet and Benoit Huct, 2000), (L. R. Rabiner and B. H. Juang, 1986), Xiang Ma, Dan Schonfeld and Ashfaq Khokhar, (2007).

4.2. Enhanced 2D Viterbi Algorithm

We propose an enhanced 2D Viterbi algorithm which can decode the states of the proposed model. Consider a trellis of size m x n, transition matrix ‘a’ and observation matrix ‘b’.

The proposed algorithm uses Viterbi algorithm (1D) for probability maximization of states in first row and first column,

Probability maximization for first row,

$$\delta_{x=1,y}(i) = max_j\left[\delta_{x=1,y-1}a_{ji}b_{ik_{x=i,y}}\right] \tag{9}$$

Probability maximization for first column,

$$\delta_{x,y=1}(i) = max_j\left[\delta_{x-1,y=1}(i)a_{ji}b_{ik_{x,y=1}}\right] \tag{10}$$

Where

$$\delta_{x=1,y=1}(i) = \pi(i)b_{ik_{x=i,y=1}} \tag{11}$$

To find the maximum likelihood of successive states, an auxiliary variable $\delta_{x,y}(i)$ is defined

$$\delta_1(x,y)(i) = \max_j 1/3\ [\,(\delta_1(x-1,y)(j)\, a_j|i\, b_1(ik_1(x,y)) + @[\delta]_1(x-1,y-1)(j)\, a_j|i\, b_1(ik_1(x,y)) + @\delta_1(x,y-1)(j)\, a_j|i\, b_1(ik_1(x,y)) + @\delta_1(x-1,y+1)(j)\, a_j|i\, b_1(ik_1(x,y)))] \tag{12}$$

Where 1< i < m;

$$\varphi_{x-1,y} = \mathrm{argmax}_j[\delta_{x-1,y}(j)\, a_{ji}] \tag{13}$$

$$\varphi_{x,y-1} = [\mathrm{argmax}_j[\delta_{x,y-1}(j)\, a_{ji}] \tag{14}$$

$$\varphi_{x-1,y-1} = \mathrm{argmax}_j[\delta_{x-1,y-1}(j)\, a_{ji}] \tag{15}$$

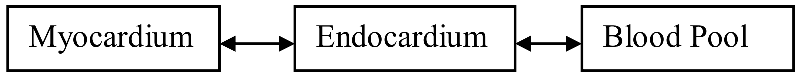
$$\varphi_{x-1,y+1} = \mathrm{argmax}_j\left[\delta_{x-1,y+1}(j)a_{ji}b_{ik_{x,y}}\right] \tag{16}$$

The equations (13), (14),(15) and (16) are the back pointers used to reduce the computational complexity of the algorithm which are very similar to the back pointers in Viterbi decoding algorithm (L. R. Rabiner and B. H. Juang, 1986).

5. Modelling FCHMM for Echocardiographic Image Segmentation

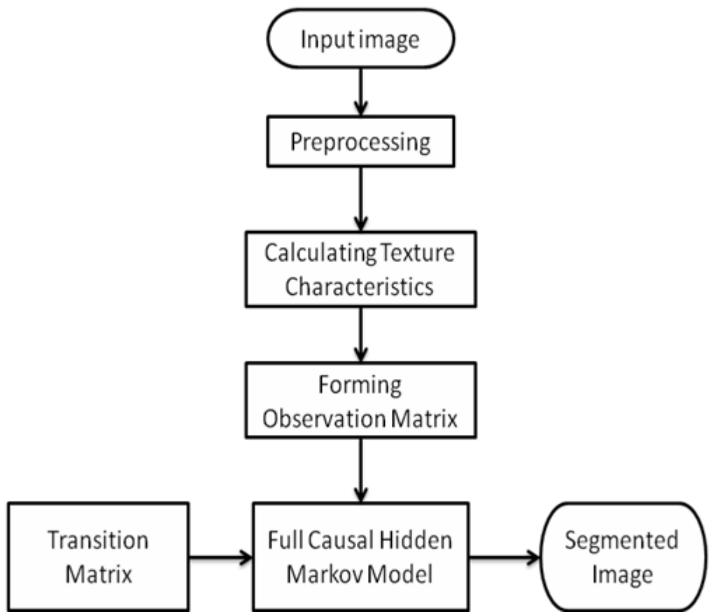
Segmentation of echocardiographic images with FCHMM produces output states as edge and not edge condition over observation states myocardium, endocardium and blood pool. However there are no specific values to represent these three observation states. Value of observation states can be calculated with the help of the structure of heart. In any echocardiographic image, three possible elements are Myocardium (the thick muscular layer) followed by Endocardium (the thin inner layer) followed by the blood pool. This transition remains the same at various views and can be expressed theoretically as follows,

Figure 4: Transition behaviour



During a raster scan, values that follow first transition (T1) are called myocardium, and those that follow second transition (T2) are called endocardium, finally pixels can be grouped as blood pool following transition three (T3). As texture components show significant variation between two different elements located closely on an image. Aforementioned transition behaviour can be accurately calculated over texture components.

Figure 5: Flow diagram of proposed method



Texture properties are calculated using gray level co-occurrence matrix at desired direction. The gray-level co-occurrence matrix P[i, j] is defined by first specifying a displacement vector d = (dx, dy) and counting all pairs of pixels separated by d having gray levels i and j in the direction θ. Any texture properties like energy, homogeneity, Entropy, Contrast (Haralick R.M., Shanmugan K. and I. Dinstein, 1973) can be used for segmentation. Figure 5, depicts the flow diagram of the proposed method. Probability of an observation state that can yield an output state is calculated using a normal curve.

Figure 7, illustrates normal curves of three observation states (Myocardium, Endocardium, Blood pool) whose, mean (μ) are T1, T2 and T3 respectively. The standard deviation (σ) of the curves is same as that of the image. Since endocardium is the region of interest, area of the curve which lies inside normal curve of endocardium is the probability of being edge and the rest is the probability of being not edge. Figure shows the probability calculation of observation states for an echo image shown at Fig 6.

Figure 6: Sample image

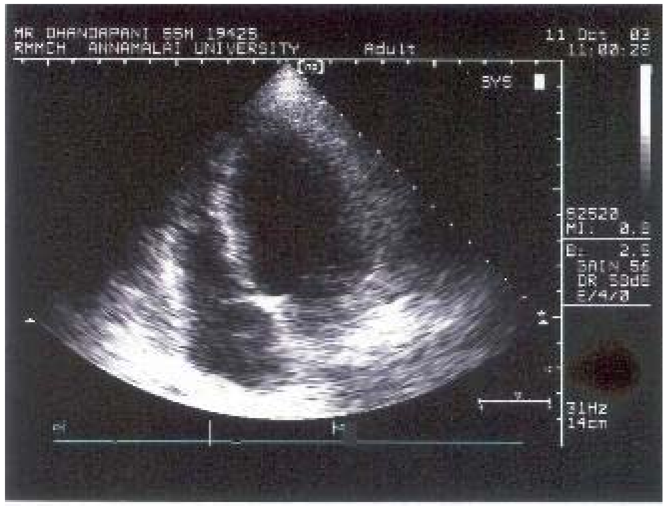
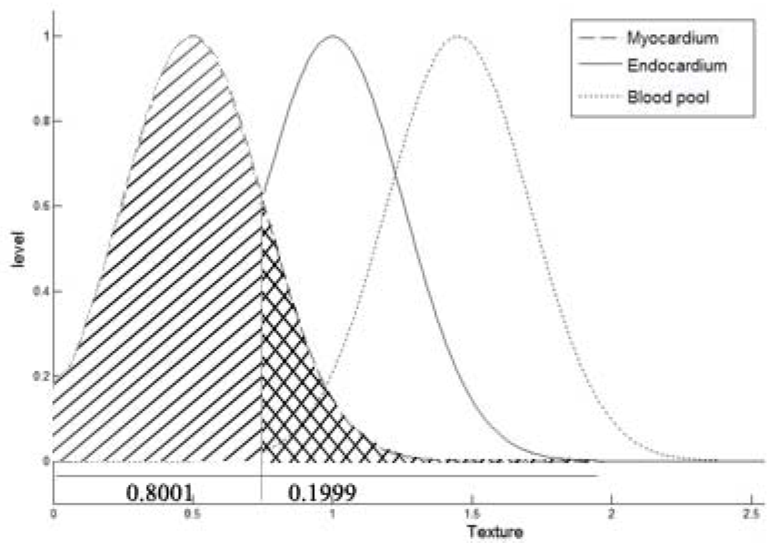


Figure 7: Gaussian plot for a sample image



Observation matrix thus formed is shown below,

$$\begin{array}{l} \\ \text{Myocardium} \\ \text{Endocardium} \\ \text{Blood pool} \end{array} \begin{array}{c} \begin{array}{cc} \text{Edge} & \text{Non-Edge} \end{array} \\ \begin{bmatrix} 0.1999 & 0.8001 \\ 0.1967 & 0.8033 \\ 0.0032 & 0.9968 \end{bmatrix} \end{array}$$

Transition matrix is formed by computing state transition over expert segmented curve. These probabilities remain same for any echo image and it is shown below,

$$\begin{array}{l} \\ \text{Edge} \\ \text{Non-Edge} \end{array} \begin{array}{c} \begin{array}{cc} \text{Edge} & \text{Non-Edge} \end{array} \\ \begin{bmatrix} 0.2363 & 0.241 \\ 0.1482 & 0.3745 \end{bmatrix} \end{array}$$

6. Results and Discussions

The proposed method is tested with more than 200 Echocardiographic images. Opinions from three experts were obtained and Error is calculated by taking the Euclidean distance between the expert marked curve and segmented curve by the proposed model. Table 1 shows the acceptance level of segmented LV by various algorithms compared with expert opinion. ‘A’ denotes Acceptance criterion and ‘CA’ denotes Conditional Acceptance criterion. Figure 8 shows the segmented output for various methods and the proposed method.

Figure 8: a) Long axis view end systole, b) long axis view end diastole, c) Parasternal short axis view end diastole, SCHMM – Semi Causal Hidden Markov Model, 2DHMM – Hidden Markov Model, FCHMM – Proposed Full causal Hidden Markov model.

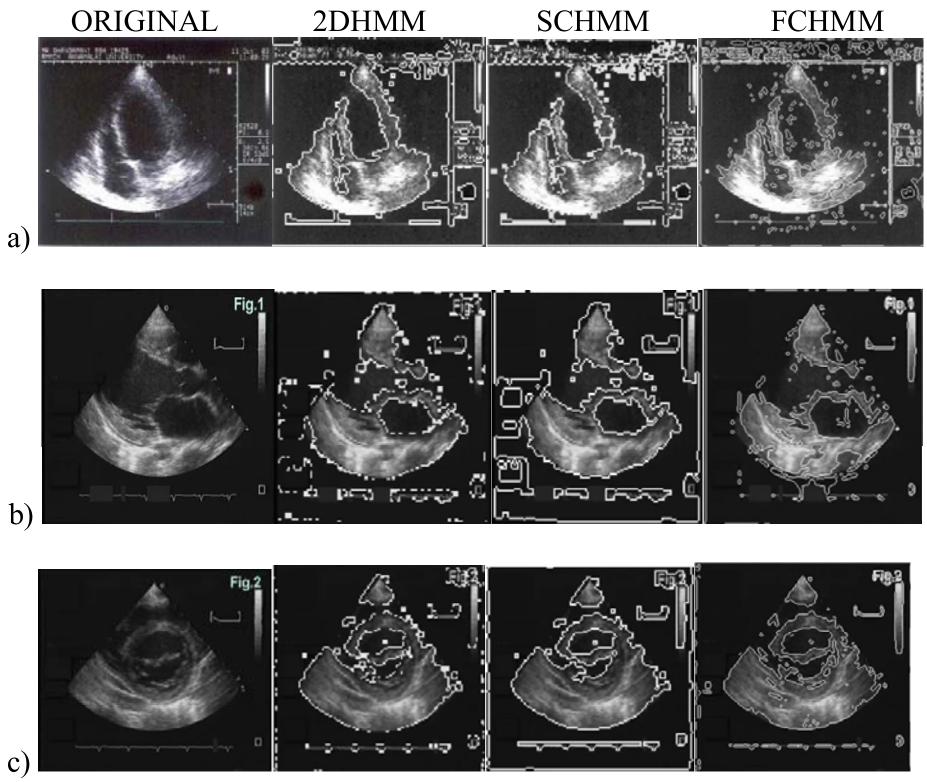


Table 1: Comparison of proposed algorithm and other methods with expert opinion

Method	A<2 Average Pixel Difference	CA<2-2.5 Average Pixel Difference	A+CA	Rejectable >2.5 Average Pixel Difference
FCHMM	95.1%	3.3%	98.4%	1.6%
SCHMM	91.6%	3.2%	94.8%	5.2%
2DHMM	88.8%	2.8%	91.6%	8.4%

7. Conclusion

In this paper an effective method for the segmentation of left ventricle is proposed by integrating both texture properties and 2D full causal Hidden Markov model. The enhanced 2D Viterbi algorithm serves the purpose of detecting edges at ambiguous regions. When compared with other traditional edge detection methods the proposed algorithm produces an appreciable acceptance level of 98% which is appreciated by the experts concerned.

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