HMRF based Unsupervised Segmentation of Gall Bladder Lesions

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Abstract--- Gallbladder cancer is an uncommon cancer prevalent in some geographical locations such as parts of northern India, Japan, parts of central and Eastern Europe and parts of South America. Detected early patient can be cured by removing portions of liver, lymph nodes and gallbladder. There are no specific symptoms of this disease and the cancer remains undetected till it has spread to adjoining organs. Hence the early detection of gallbladder lesions may save crucial lives. MR image of gallstones may result in early detection of gallbladder lesions. This article proposes to detect gallbladder lesions using artificial intelligence and soft computing techniques. Lesions of Gall-bladder are segmented using Hidden Markov Random Field Model. Expert medical opinion is required to conclude whether the lesions have developed cancer.

Keywords---- Gall Bladder Lessions, Hidden Markov Random Field Model.

I. Introduction

To better understand disease and to quantify its evolution we use Magnetic Resonance imaging. Manual identification of lesion border is a time taking process. It is also prone to observer variability. We require fully automated and reproducible method to correctly segment the lesions and also those should be free of observer variability.

Markov models have shown effective results for a variety of phenomena. The use of these models has increased in the fields of finance, economics, ecology, communications, signal and image processing. Problem of segmentation is effectively solved using Hidden Markov model. The data which models the desired segmented image is hidden and may follow an example of a field, tree or a chain. HMMare also used to treat inverse problems in imaging such as noise removal etc.

We define the segmentation of lesions in Gall bladder as a pixel labelling problem. Hidden Markov Random Field (HMRF) is used to segment the MR image into foreground and background labels. Ising model is used a prior to ensure that the foreground and background components are coherent.

MRI Data Acquisition of Gall Bladder

We have taken STIR FRFSE Resp Trig Fat SAT MR sequences (STIR-Short-T1 Inversion Recovery, Fast Recovery Fast Spin Echo (FRFSE), Respiratory Triggered Fat Saturated). STIR stands for Short-T1 Inversion Recovery and is used to nullify the signals from FAT. There is uniform fat suppression by STIR and independent of magnetic field in-homogeneities. It is better than other fat saturation methods such as "spectral-fat-sat" for abdomen and pelvic areas.

Respiratory Triggering is a type of imaging involving respiratory motion. During expiration MR images are acquired. The scan time is dependent on patient's breathing patterns. Fat Sat saturates fat protons prior to image acquisitions.

We have acquired 22 MR images in this mode of image acquisition using slice thickness of 0.5 mm and resolution of 512×512.

Related Works

The mathematical theory of Markov Process was named after Andrei Markov in the early twentieth century [1]. In 1960's Baum developed the theory of Hidden Markov Models (HMM's)[2].

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Particle Swarm Algorithm was used in combination with Entropy Maximization by [3] for segmenting the MR image of brain .Ref [4] used Grammatical Swarm along with Entropy Maximization for segmenting lesions of human brain. A segmentation and progressive transmission technique based on Hybrid Particle Swarm optimization using Wavelet mutation was proposed by [5] for MR images of brain.

Fusion and segmentation of MR images of brain using the concept of Entropy Maximization was proposed by [6]. Pre-operative staging of enhanced dynamic imaging by gadolinium (Gd-E) and cholangiography of Gall-bladder cancer and un-enhanced imaging as well as biliary MRI were evaluated for performance by [7].In this article we aim to segment the Gall bladder deformity (lesion). The results have to be independently confirmed by other independent tests and doctor consultations.

II. Hidden Markov Random Field Model (HMRF)

Zhang et.al [8] proposed Hidden Markov Model (HMM) to study and model images. Generative sequences can be modelled using HMM. Generative sequences can be explained using an underlying process producing a sequence which can be observed.

HMM has use in number of applications such as speech processing, image processing and computer vision apart from the NLP related tasks e.g. phrase chunking, speech tagging and getting targeted information from given documents.

The HMRF Model is derived from HMM. A stochastic process which is generated by a Markov Chain is called HMM. A sequence of observations of state sequence defines the Markov Chain.

Let us observe a random variable Y_i where $i \epsilon$ S. Hidden Markov Random Fields assume that Y_i is determined by Markov Hidden Random Field X_i, which is unobservable in their nature. We define the neighbours of X_i as N_i. Markov property states that X_i is independent of all other X_j's. The neighbourhood is not defined in one dimension whereas in Random Field X_i is allowed to have more than one neighbours as compared to that of Markov Chain.

HMM's has found use in speech recognition [9] but it cannot be applied to 2-D and 3-D problems. HMM cannot be used for Image segmentation because it is a 3-D model and originally HMM were designed for 1-D problems.

As regards segmentation of 2-D images, Markov Random Field (MRF) can be used instead of Markov Chain. This type of model is known as hidden Markov Random Field (HMRF) model.

Markov Random Field is used to demonstrate its application in image processing techniques. MRF is used together with other already developed algorithms to make inferences about the Magnetic Resonance Image.

The broad steps involved while using MRF in image segmentation.

- MR Images are arranged as an assembly of nodes where each of the nodes may correspond to pixels or a group of pixels.
- Each of the nodes is associated with hidden variables, modelled to explain the intensity values of the grayscale MR image.
- A joint probabilistic model is developed using the hidden variables and the pixel values.
- The statistical dependencies between hidden variables are found by grouping hidden variables which result in edges in a graph.

The choice of graphs is made for image processing tasks because the goal is to establish dependency between the pixels that are nearby or are related to each other. But the proximity of the pixels is of outmost importance.
HMRF X, assuming it has values in a state which is final (L) is given by $\{X_i, i \epsilon S\}$. State X is unobservable.
Emitted Random Field or Observable Random Field Z has a finite state space *D*.

$$Z = \{Z_i, i \epsilon S\} \qquad (1)$$

Given $x \epsilon X$, Every Z_i of the form p (z_i/x_i) is a conditional probability having identical form as $f(y_i, \Theta_{xi})$, where the parameters are denoted as Θ_{xi}.

Conditional Independence for any x ϵ *X,* the random variables Z_i is conditional independent.

$$P\ (z\text{-}x) = \pi_{i\epsilon S}\ P\ (y_i/x_i) \qquad (2)$$

The joint probability of (X, Z) with reference to the above is given as

P (z,x) = P(z/x) P(x)

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$$= P(x)\prod_{i\in S} P\left(\frac{z_i}{x_i}\right) \quad (3)$$

The joint probability of (X_i,Z_i) where the neighbourhood configuration $X_{Ni}$is :

$$P(y_i,x_i/x_{Ni}) = P(y_i/x_i)\ P(x_i/x_{Ni}) \quad (4)$$

Thus depending on the random variable Θ, the marginal probability distribution of $Z_i$is calculated as

$$p(y_i/x_{Ni},\Theta) = \sum_{l\in L} p\left(y_i,\frac{l}{x_{N_i}},\theta\right) \quad (5)$$

where$L$=Land $\Theta = \{\Theta_l, l \in L\}$. This is the Hidden Markov Random Field.

III. Segmentation On A 4-Connected Graph Of Pixels Using HMRF

Hidden Markov Random Field model is used to segment an MR image into foreground and background labels. The MR image is segregated into foreground which is the tumour or lesion and the background is the other healthy tissues. The state space is Boolean in nature $x_i \in \{0,1\}$, where pixel value 0 is the background and 1 is the foreground of the image.

Ising model is used as a prior to encourage the foreground and background components to be coherent as far as possible. This model is named after physicist Ernst Ising. The Ising model was invented by the physicist Wilhelm Lenz. He gave this problem to Ernst Ising and was solved by him in the year 1924. Lars Onsager solved 2-D square lattice Ising model in the year 1944.

The Ising model with the single parameter ω={γ} is considered which has origins in statistical physics. The state-space consists of Boolean variables$x_i \in$Land$x_i = \{0,1\}$.The energy function is Pseudo-Boolean in nature because the input is Boolean whereas the output is energy which is not boolean.

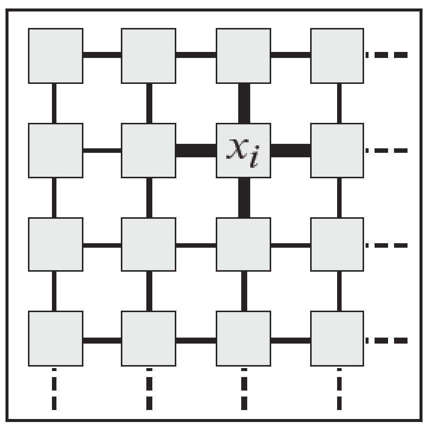

Figure 1: The Cliques of Ising Model

Figure 2: Gall Bladder Image No. 8 From Dataset Fig.7

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Figure 3: Segmentation of Gall Bladder Of Fig.2

Figure 4: Gall Bladder Image No.9 From Dataset Fig.7

Figure 5 : Segmentation of Gall Bladder of Fig.4

Horizontal and vertical edges of the rectangular graph of pixels result in cliques which are maximal in nature depicted in Fig.1.Clique is a subset of vertices of the graph which of undirected nature. Every two distinct vertices

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of the clique are adjacent so the induced sub graph is complete. If one more adjacent vertex is included then the clique is defined as maximal clique and it cannot be extended.

All cliques in this scenario is of size 2, containing two nodes (pixels). The pair-wise potentials are defined as

$$\Psi_{ij}(x_i,x_j) = \gamma|x_i-x_j| \qquad (6)$$

γ is the penalty that increases the energy E whenever x_i and x_j have different values. The ψ in the hidden MRF model are from the Ising prior. Histograms $h_F(z)$ and $h_B(z)$ in foreground and background by avoiding zeros in the gray scale MR image can be used to calculate the Likelihood terms.

$$\Phi_i(z_i)= \log h_F(z_i) - \log h_B(z_i) \qquad (7)$$

The model specifies a posterior which is maximized to segment the lesion. This method of segmentation works effectively and is displayed in Fig.3,5 and 6

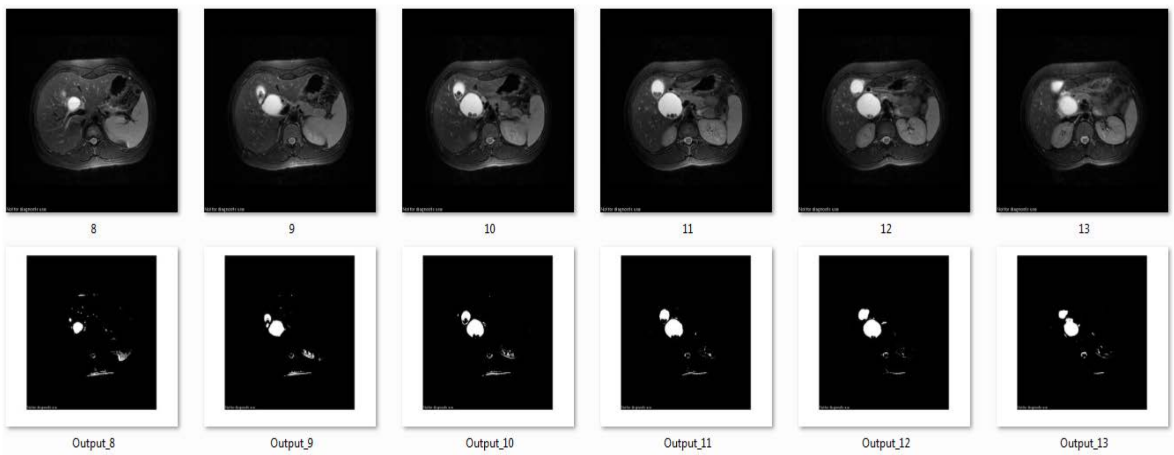

Figure 6 : Gall Bladder Images (Top Row) and Their Corresponding Segmented Results (bottom)

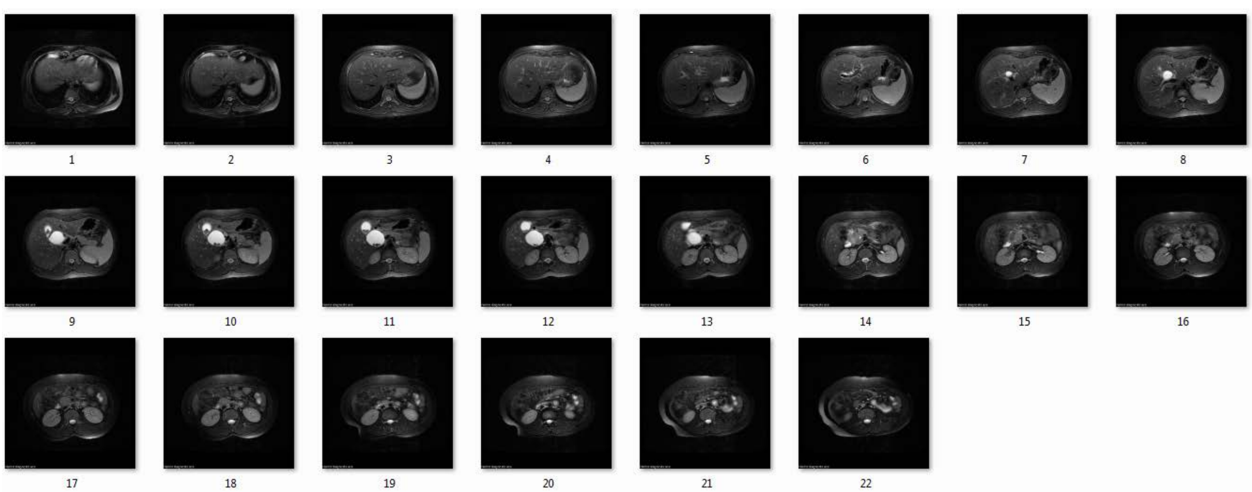

Figure 7: Dataset Of Gall Bladder Images

IV. Results and Discussions

We have performed the segmentation operation for a set of 22 images of Gall bladder as detailed in Fig.7. Fig 6 depicts the segmentation results of a set of 6 images from the Dataset (Fig.7). Fig.3 and Fig.5 also depicts the segmentation results of Fig.2 and Fig.4.

The segmentation accuracy of gall bladder lesions is calculated using Precision and Recall.

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True Positives divided by number of images which are labelled as belonging to the Positive class(including those images wrongly classified as positive class) is called Precision whereas number of True positives divided by the total images that actually belong to the positive class(it does not take into account False positives) is called Recall.

The values for calculating Recall and Precision is given in Table-1.

TN/True Negative: Case was negative and predicted negative.
TP/True Positive: Case was positive and predicted positive.
FN/False Negative: Case was positive but predicted negative.
FP/False Positive: Case was negative but predicted positive.
Precision value of the dataset in Fig.7 is 81.82% and Recall is 75% respectively.

Table: 1

	Expert Knowledge	Total Cases		Predicted Negative	Predicted Positive
Patient Dataset-1	Presence of Lesions in some or all of the MRI's	22	Negative Case	8	2
			Positive Case	3	9

V. Conclusions

The method of Unsupervised Segmentation of Gall Bladder lesions using Hidden Markov Random Field Model results in good segmentation accuracy. This method can be suitably applied for segmentation of lesions of other human organs. The segmentation accuracy can be improved by using suitable optimization techniques.

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