US Image Segmentation Based on Expectation Maximization and Gabor Filter

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***Abstract*—Segmentation of Ultrasound (US) Images is quite challenging as the images are of poor quality, contains strong speckle noise and so are not of that high quality as CT or MRI images. Both supervised and unsupervised segmentation techniques are used for segmentation. Unsupervised segmentation approaches mainly rely on subjective assessment. We propose an unsupervised segmentation technique based on conventional Expectation Maximization (EM) algorithm applied on texture features extracted by a bank of Gabor filters. The approach includes three steps: decomposition of image using Gabor filters, texture feature extraction and segmentation. The segmentation results are compared with the work done using K-means clustering. K-means being a basic technique results in over-segmentation and converges in local minima. EM technique used after texture feature extraction is tested on many US images and results were quite satisfactory.**

***Index Terms*—Expectation maximization, feature extraction, gabor filter, multi-resolution analysis.**

I. INTRODUCTION

Among all the popular image modalities, Ultrasound Imaging (US) is widely used for real-time diagnostic situations. Image segmentation is often the first step for image analysis and is a key basis of many higher-level activities such as visualization, compression, medical diagnosis and other imaging applications. Among all other imaging techniques like Computed Tomography (CT), Magnetic Resonance (MR) imaging Angiography, US imaging is cheap, non-invasive and does not emit radiation. It allows faster and much accurate procedures due to its real time capabilities. But CT and MRI images are taken in well defined planes and the organs in the images are more homogeneous and so are much easy to segment as compared to US image. US images contain strong speckle noise, attenuation artefacts and organs don't appear homogeneous so it is difficult to segment these images. Many challenging methods have been adopted for proper segmentation of US images [1].

Image segmentation is a difficult problem especially in US images. Segmentation algorithms inevitably make mistakes, causing some degradation in performance of any system that uses the segmentation results. It is difficult to classify human body organ tissues using shape or gray level information because the shape of each organ is not consistent throughout all slices of medical images and the gray level intensities overlap considerably for soft tissues. Moreover, the US images are not taken on one fixed plane as in CT and MRI imaging. However, texture information in US images can be used to discriminate among different organ tissues.

Texture can be defined as something consisting of mutually related elements. The process of identifying regions with similar texture and separating regions with different texture is called texture segmentations. Texture analysis has been studied for a long time using various approaches [2]. The first step in texture discrimination is to find some quantitative description of a texture. Usually one chooses a family of texture attributes which account for the main spatial relations between the gray levels of texture. In general, the texture models which underlie the attributes belong to one of the two categories: either structural or statistical. In first case, a texture is characterized by a family of primitives, and by the way according to which they are spatially organized. The second category involves the use of statistical tools and inference: gray level co-occurrence matrices, gray level run-length statistics, and gray level differences. More recently, multi –channel filtering technique namely Gabor filters [3] which constitutes a particular class of windowed Fourier filters have been used in image analysis: image compression, texture image segmentation etc. Gabor filters can extract the information of local spatial frequencies which provide structural features of the image.

Multi-channel filtering is an excellent method for texture segmentation. By processing the image using multiple resolution techniques, it is decomposed into appropriate texture features that can be used to classify the texture accordingly as texture exhibits a sort of periodicity of basic patterns. For feature extraction, fundamental idea behind using Gabor filter is to expand an image into a number of elementary functions that are concentrated in both the time and frequency domain. Gabor filters are efficient for extracting texture features based on localized spatial frequency information [4]. Gabor features are obtained by convolving an image with the Gabor elementary functions. A Gabor elementary function is a 2-D Gaussain modulated by complex sinusoids. The process of texture segmentation using Gabor filters involves proper design of a filter tuned to different spatial frequencies and orientation to cover the spatial frequency space and capture the important information from the image, feature extraction from the image and clustering the pixels in the feature space to produce segmented image. Both supervised and unsupervised approaches are used for texture segmentation. Supervised approaches rely on training methods and

Manuscript received March 29, 2012; revised May 11, 2012.

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reference segmentation for performance assessment, while unsupervised approaches mainly rely on subjective assessment.

Segmentation is an important component of image understanding and data mining systems for discovering groups and identifying interesting distributions and patterns in input data. In this paper, result of segmentation using EM Algorithm is compared with basic K-means clustering method of image segmentation. K-means is considered one of the major algorithms widely used for clustering. Firstly, K–means clustering (KM) is used for image segmentation of a stack of Gabor filtered multi-channel images as done by Khaled Hammouda and Prof. Ed Jernigan [5]. It's basically hard clustering and converges to local minima. In the second method, in order to segment image automatically, the joint distribution of texture and position features with a mixture of Gaussian is modelled. We use the Expectation Maximization (EM) algorithm [6][7] to estimate the parameters of this model; the resulting pixel-cluster memberships provide a segmentation of the image. EM algorithm is used on Gabor filtered images for segmentation which gives good results.

A. Texture Feature Extraction by Gabor Filters

A Gabor filter is a linear filter whose impulse response is defined by a harmonic function multiplied by a Gaussian function [8]. Because of the multiplication-convolution property (Convolution theorem), the Fourier transform of a Gabor filter's impulse response is the convolution of the Fourier transform of the harmonic function and the Fourier transform of the Gaussian function.

$$g(x,y;\lambda,\theta,\psi,\sigma,\gamma)=\exp(-\frac{x'^2+\gamma^2y'^2}{2\sigma^2})\cos(2\pi\frac{x'}{\lambda}+\psi) \quad (1)$$

where

$$x'=x\cos\theta+y\sin\theta$$

and

$$y'=-x\sin\theta+y\cos\theta$$

In equation (1), λ represents the wavelength of the cosine factor, θ represents the orientation of the normal to the parallel stripes of a Gabor function, ψ is the phase offset, σ is the sigma of the Gaussian envelope and γ is the spatial aspect ratio, and specifies the elliptic nature of the Gabor function.

Gabor filter has the ability to perform multi-resolution decomposition due to its localization both in spatial and spatial-frequency domain. Texture segmentation requires simultaneous measurements in both the spatial and spatial-frequency domains. Filters with smaller bandwidths in the spatial frequency domain are more desirable because they allow us to make finer distinctions among different textures. Gabor filters are well suited for this kind of applications [9].

1) Feature extraction

To extract useful features from the filter output, spatial smoothening, namely Gaussian smoothening function is used given by:

$$g(x,y)=\exp\left\{-\frac{x^2+y^2}{2\sigma^2}\right\}$$

where σ is the standard deviation which determines the (linear) size of the receptive field (window size). σ = 3 σ s was chosen where σ s is the scale parameter of Gabor filter.

B. K-means Clustering

K-means is a fast and simple clustering algorithm, which has been applied to many applications. For a brief review of conventional K-means algorithm, suppose observations are $\{x_i: i=1,\ldots,L\}$. The goal of K-means algorithm is to partition the observations into K groups with means $\overline{x}_1,\overline{x}_2\ldots\ldots\overline{x}_k$ such that

$$D(K)=\sum_{i-1}^{L}\min_{i\le j\le k}(x_i-\overline{x}_j)^2$$

is minimized. K is gradually increased and the algorithm stops when a criterion is met.

K-means clustering algorithm can be easily used in image segmentation [10]. However, the conventional K-means based image segmentation methods only cluster observation vectors in feature space. Considering the spatial constrains are essential attributes of images, combining K-means clustering with spatial constrained region growing to obtain better segmentation.

C. Expectation Maximization Algorithm

The Expectation Maximization (EM) Algorithm is a statistical method developed and employed by several different researchers. Generally, the EM algorithm produces Maximum Likelihood (ML) estimates of parameters when there is a many-to-one mapping to the distribution governing the observation. The EM Algorithm is used widely in the image segmentation field and it produces very good results especially with a limited noise level. The image is considered as a Gaussian mixture model. Each class is represented as a Gaussian model and the pixel intensity is assumed as an observed value of this model. The EM is used for finding the unknown parameters of the mixture model. A set of observed data X = {xi | I =1,2,……..,N} can be modelled as to be generated from a mixture of random processes X1, X2, ……, XK , with joint probability distribution $f(X_1,X_2,\ldots\ldots,X_K)$, where K is the number of classes or distribution functions present in the mixture. It is usually assumed that these processes represent independent identically distributed random variables. Then one can write:

$$f(X_1,X_2,\ldots\ldots,X_K)=\sum_{k=1}^{K}p_kG(x_i\mid\theta_k^{(t)})$$

where $f(x,\theta_k)$ ∀ k=1,2,…….,K is the probability distribution function of the random variable X_k, and θ_k ={ μ_k , σ_k } stands for the parameters that define the distribution k.

ϕ = $\{p_1,\ldots\ldots,p_K,\ \mu_1,\ldots\ldots\ldots,\mu_K,\sigma_1,\ldots\ldots\ldots,\sigma_K\}$ called the parameter vector of the mixture, where p_k are the mixing proportions $(0\le p_k\le 1,\forall k=1,\ldots\ldots\ldots,K, and \sum_k p_k=1)$.

The EM algorithm consists of two major steps: an expectation step (E-step), followed by a maximization step (M-step). The expectation step is to estimate a new mapping (pixel-class membership function) with respect to the unknown underlying variables, using the current estimate of the parameters and conditioned upon the observations. The maximization step then provides a new estimate of the parameters.

The EM Algorithm is used in different image segmentation problems, such as medical images, natural scene images, and texture images.

II. Texture Segmentation

The texture segmentation involves the following three steps:

A. Decomposition of input image using filter bank.

B. feature extraction and

C. Segmentation using:

   1. K-means clustering

   2. Expectation Maximization Algorithm

A. Design of Gabor Filter banks

The first step in designing is choosing filter's set of frequency and orientation.

1) Choice of filter parameters:

We have used orientation angle as multiples of 30˚ that is: θ = 0˚, 30˚, 60˚, 90˚, 120˚, 150˚ for finer quantization and values of frequencies were determined by:

FL (i) = 0.25 – 2i-0.5/ N c

FH (i) = 0.25 + 2i-0.5/ N c

where i = 1, 2, ... , log2(Nc/8), Nc is the width of image which is a power of 2. Note that 0 < FL (i) < 0.25 and 0.25 < FH(i) < 0.5. For an image with 256 columns, for example, a total of 60 filters can be used - 6 orientations and (5 + 5) frequencies. The value of the bandwidth b of the Gabor filter is taken as 1 octave.

B. Feature Extraction

To extract useful features from the filter output, spatial smoothening, namely Gaussian smoothening function is used given by:

$$g(x,y)=\exp\left\{-\frac{x^2+y^2}{2\sigma^2}\right\}$$

where σ is the standard deviation which determines the (linear) size of the receptive field (window size). σ = 3 σ s was chosen where σ s is the scale parameter of Gabor filter.

C. Segmentation Techniques Used:

1) K-means clustering

At the end of the feature extraction step, a set of feature extracted images from the filter outputs are achieved. Pixels that belong to the same texture region have the same texture characteristics, and should be closer to each other in the feature space. The final step is to cluster the pixels into a number of clusters representing the texture regions. K-means algorithm has been used for clustering. The steps used for our problem using k-means are as follows:

i. Initialize centroids of K clusters randomly.

ii. Assign each sample to the nearest centroid.

iii. Calculate centroids (means) of K-clusters.

iv. If centroids are unchanged, done. Otherwise, go to step2.

Furthermore, the spatial coordinates of the pixels is included as two additional features to take into account the spatial adjacency information in the clustering process.

D. EM Algorithm

Image segmentation using EM algorithm have been performed on different types of images [11][12]. In our proposed method, EM algorithm is implemented on Gabor filtered US images which helped in removing noise and extracting various features from the image. Initially dimension of space, number of centres and type of mixture models were specified and value of variance was kept unity. With all these parameters, Gaussian mixture model was created and then initialisation of Gaussian mixture model was done. Finally E-step and M-step was performed iteratively until convergence. Mathematically for a given training dataset $\{x_{(1)}, x_{(2)}, \ldots\ldots x_{(m)}\}$ and model p(x, z) where z is the latent variable, we have:

$$\theta := \arg\max_{\theta} \sum_i \sum_{z^{(i)}} Q_i(z^{(i)}) \log \frac{p(x^{(i)}, z^{(i)}; \theta)}{Q_i(z^{(i)})} \tag{2}$$

$$l(\theta) = \sum_{=1}^{m} \log p(x;\theta)$$

$$= \sum_{=1}^{m} \log \sum_{z} p(x,z;\theta)$$

As can be seen from equation (2), the log likelihood is described in terms of x, z and θ. But since z, the latent variable is not known; we use approximations in its place. These approximations take the form of E & M steps mentioned above and formulated mathematically below:

E step, for each i:

$$Q_i(z^{(i)}) := p(z^{(i)} \mid x^{(i)}; \theta)$$

M step, for all z:

$$\theta := \arg\max_{\theta} \sum_i \sum_{z^{(i)}} Q_i(z^{(i)}) \log \frac{p(x^{(i)}, z^{(i)}; \theta)}{Q_i(z^{(i)})}$$

where Q_i is the posterior distribution of $z^{(i)}$'s given the $x^{(i)}$'s.

III. Experimental Results and Conclusion

Texture segmentation using Gabor filter and K-means clustering was done by Khaled Hammouda and Prof. Ed Jernigan. In this paper, result of their segmentation method is compared with segmentation using EM Algorithm on texture feature extracted US image. In order to test performance of our proposed method, we have applied it on different ultrasound images collected from well established medical clinic. By carefully designing a Gabor filter bank covering the spatial frequency domain we can decompose an image into multi-resolutions that correspond to different texture characteristics based on orientation separation of filters of 30˚.

We have applied the proposed methodology on US image of liver and cystic kidney as shown in fig 1(a). Original image in Fig 1(a) shows background, liver, kidney, cyst in the kidney and posterior enhancement below liver and kidney. Fig.1(b) shows one of the Gabor filtered image. In the experiment, we preset the number of classes to 5. Fig 1(c) is the segmented result of K-means clustering which shows cyst and posterior portion but merges the background with the liver. Segmented result using EM Algorithm is illustrated in Fig 1(d) which is able to partition the background clearly. Portion of the liver, posterior portion and cyst is visible clearly and results in much better segmentation than the earlier method.

Another test is performed on US image of liver containing cyst as shown in Fig 2(a). The results of K-means clustering (Fig 2(c)) is compared with EM segmented result shown in Fig 2(d). The boundary of the image is well defined and the proposed methodology is able to detect the liver and cyst quite well. The result of this approach is much satisfactory than the K-means clustering method. Unsupervised segmentation based on multi- channel filtering is a natural approach to the problem. Our major novelty of the paper is that we have proposed EM Algorithm combined with texture features extracted using Gabor filters. The performance of this approach in segmenting image gives better results than basic K-means clustering. Also, the method is general and can be applied to other images.

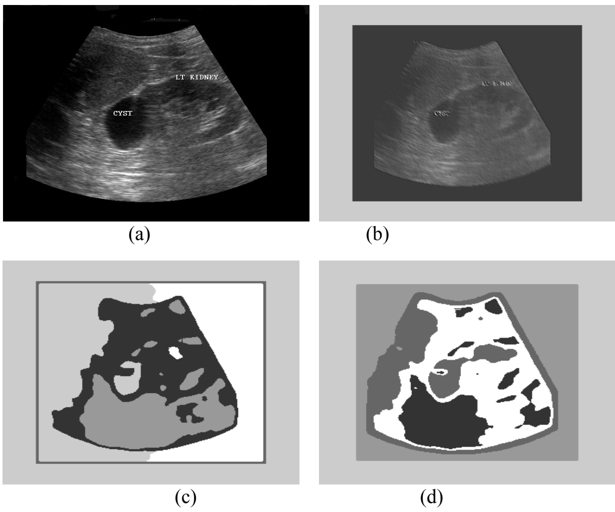

Fig. 1(a). Original image (b): one of the gabor filtered image (c): result using K-means clustering (d): segmentation result using EM algorithm

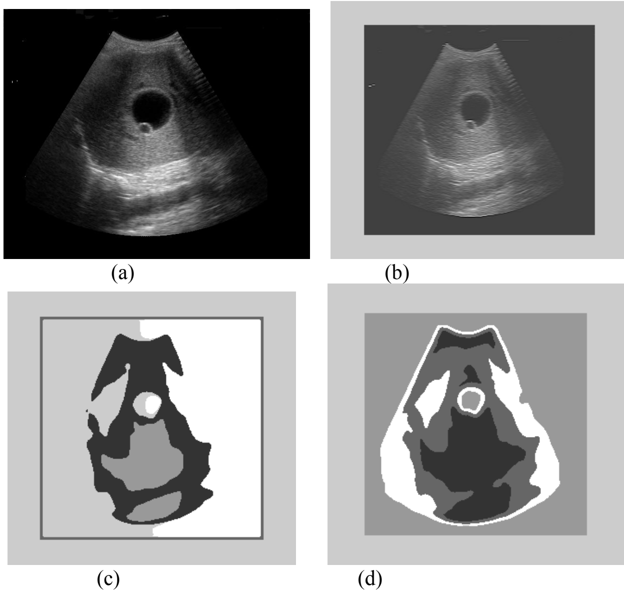

Fig. 2(a). Original image (b): one of the gabor filtered image (c): segmentation result using K-means clustering (d): segmentation result using EM algorithm.

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