Parallelization of the GC-AAM Algorithm with Improved Performance

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Abstract— This paper demonstrates a parallelized 3-D method to segment the medical images efficiently. The method combines the advantage of the three methods: Active Appearance Model (AAM), Livewire (LW) and Graphcut (GC). The model consists of two phases: Training phase and Segmentation phase. During the training phase AAM is generated and estimated the livewire cost and graph cut energy parameters. Segmentation phase consists of AAM optimization, refinement of the recognized shape and object delineation. For object delineation an iterative algorithm is proposed which effectively combines the rich statistical shape information embodied in the AAM with the optimal delineation capability of graph cut method. We demonstrate that only a small number of statistical models are needed to capture the shape and appearance of the image from any angle. For that we have proposed the view based Active appearance model. The view based model (front to parallel) can derive the parameters of the 3-D model, speeding up the matching times and thus reducing the segmentation time. By parallelizing the algorithm we can make the method more practical in clinical applications. We have evaluated the result in a clinical data set.

Index Terms—Active appearance model, Livewire, view based, Graphcut.

I. INTRODUCTION

Medical image processing finds an important application in the clinical radiology. Today most of the work such as recognition, segmentation, and delineation are computerized. This provides greater advantage by increasing the processing speed and performance. In spite of this several challenges still remains in this area. Efficient, robust and automatic segmentation is one such challenge. The segmentation method can be classified as: model based, image based and hybrid based. Model based can be further classified as an active appearance model [1], active contour model [2], active shape model [3]. The image based method includes graph cut [4], live wire [5], level set [6], watershed [7]. The hybrid based method combined the advantage of the above methods.

In this paper, a method is proposed to combine the advantage of graph cut, AAM and live wire. Only a small amount of statistical model is needed to capture the shape and appearance of the image from any view point. For that we have proposed the view based model. The view based model can drive the parameters thereby speeding up the matching times and thus increasing the performance. A parallelized algorithm is used in order to increase the matching speed and thereby reducing the segmentation time. For that we are using parallel computing.

II. PARALLELIZED GC-AAM METHOD

A. Overview

The method consists of two phases: Training and segmentation phases. Figure 1 represents the block diagram of the proposed method. The training phase consists of landmark selection, AAM construction, livewire and graph cut parameter estimation. Segmentation phase consists of slice localization, AAM optimization, recognition of the image and delineation. The entire process will be done iteratively until the AAM has recognized the image.

![Figure 1: Block Diagram of the proposed method](image)

B. Statistical model for appearances

Active appearance model is build into the statistical model of shape and appearances. These are combined to one unified model. There are three steps to handle the shape and appearances in the model: capture, normalization and
statistical analysis[8]. The first step is the data analysis. Then comes a suitable normalization to describe the data in terms of statistical model. Shape is defined in terms of the triangulation mesh and the appearances in terms of the pixels defined by the base mesh. Shape is normalized by aligning the shape with respect to the parameters like scale and position. AAM is constructed by procrustes analysis followed by a principle component analysis. The shape of the organ is represented in terms of vector x and the appearance in terms of vector g. The AAM has a parameter c, controlling the shape and appearance as:

\[ x = x + Q_c c \]
\[ g = g + Q_c c \]  

(1)  
(2)

Where x is the mean shape and g is the mean texture. Qc and Qg are the modes of variation derived from the training image.

C. View based AAM

A set of model is used to track the image through the change in the wide angles [9]. We kept an estimate of current slice orientation and used it to choose the best model to match with the next image. The appearances of the slice changes as the viewing angle changes. By this we can reduce the number of iterations needed to fit a model with the target image thereby increasing the matching time.

D. Tracking through wide angles

The training set consist of a given number of models each valid for a range of angles. To track an image, we locate the image in the first frame and running a global search to match the first frame to one of the models. By taking the model instance from previous frame as the first approximation, an AAM search is carried out to refine the estimation. We estimate the orientation from the search and depending on the orientation the model is changed. We then perform the AAM search to match the new model accurately. When switching to new model, parameter value of the position and scale will be changing. The orientation can be estimated using the following equation[9]:

\[ c = c_0 + c_c \cos(\theta) + c_s \sin(\theta) \]  

(3)

where \( \theta \) is the viewing angle, \( c_c \)-parameter of AAM, \( c_s, c_c, c_s \) are determined from the training set.

E. Live wire cost Estimation

A boundary cost is devised for each organ included in the model. A boundary element BEL is defined as an oriented pixel edge with values 1 and 0. The bel is defined as the ordered pair (p, q) of four adjacent pixels where p is inside the object and q is outside the object[10]. There are different orientation for the pixel (p, q) and we assign different features to these orientations. These features are intended to express the bel belonging to the boundary of a particular object. The cost \( C(l) \) is the combination of the cost associated with its features.

\[ C(l) = \sum_{i=1}^{nf} Wi Cf(f(l)) / \sum_{i=1}^{nf} Wi \]  

(4)

Where \( nf \) is the number of features, \( Wi \) is the positive constant indicating the emphasis given to the feature and \( f \) and \( Cf \) are the functions to convert feature values \( f(l) \) at 1 to cost values \( Cf(f(l)) \) [11].

F. Delineation

The delineation provides the piecewise smoothness of the object shape. The proposed method uses an iterative graph cut algorithm to provide piecewise smoothness. The graph cut method fail in certain cases where there are diffused edges or two similar edges in close proximity to one another [11]. By including the shape prior we can reduce the problem. In order to have an optimal solution we have obtained an energy function that reduces the energy. Let \( p \) be a pixel, \( L \) be the set of all pixel, and \( Ap = 1 \) or 0. Let the cost assigning the label be \( R p, Ap \), and \( B p, q \) varies inversely with the difference of intensities of the pixel. Then the segmentation score is given by [11] as:

\[ E = \sum_{p \in L} Rp Ap + \sum_{p, q \in N} Bp, q \]  

(5)

The proposed shape integrated energy function is defined as follows [11]:

\[ En(f) = \sum_{p \in \Omega} (\alpha Dp(fp) + \beta Sp(fp)) + \sum_{p \in \Omega, q \in \Omega} \gamma Bp, q(fp, fq) \]  

(6)

Where \( \alpha, \beta \) and \( \gamma \) are the weights for the data terms and \( Sp \) is the shape and the boundary term satisfying the equation \( \alpha + \beta + \gamma = 1 \). The graph cut determines the new position of the landmark of the object defined in the initialized shape by moving each point closer to the graph cut boundary such that minimum energy is required.

III. RESULT

The proposed methods were run on the clinical CT data set. The experiment was conducted to evaluate and compare the segmentation using Parallelized GC-AAM method with GC-AAM & LW. We have seen that only a small number of model is required to represent the image slice from a wide range of angle. The figure 1 illustrates the input image to be segmented. In order to segment the liver we have obtained the landmark manually and then statistical model is created. In order to update the AAM we first placed the model above the target image and run an updating process. The figure 2 illustrates the updating window for parallelized method. It took only 2 iteration to remove 87.14% of the total error. The method proposed in [11] needs 20 iterations to remove 99.7% of the total error. The GC-AAM & LW method needs to be updated manually until errors are removed. The method adopted in this does not faces any such problems.
A parallelized method is proposed to segment the medical images. We demonstrated that only a small number of statistical model is needed to capture the shape and appearance of the image from any angle. The model can be used to track the slice from any angle points and it can be used to predict the appearances from new view points. The view based model can drive the parameters of 3-D model, speeding up the matching times and thereby reducing the segmentation time. When compared to the GC-AAM and LW method, the proposed method can obtain better results with minimum iterations.

**REFERENCES**