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MEDICAL IMAGING FOR THE SEGMENTATION OF ABDOMINAL ORGANS USING PARALLELIZATION AND ORIENTED ACTIVE APPEARANCE MODELS

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ABSTRACT

Image segmentation plays an important role in medical imaging.Still; several challenges have to be recovered. The major issue deals with segmentation time concerned with each organ. More than five minutes is needed for segmenting each organ while considering multi organ segmentation. The proposed method can be used to segment multiple organs within a less time. The parallelization method can be used to segment the abdominal organs, especially the liver, the kidneys and the spleen .A novel adaptive approach is being used to parallelize, known as the parallel OAAM approach. Here a fast uniform partition is used to partition the graph into a number of regularly-shaped disjoint sub graphs by randomly adding weights and processing them in parallel, and then incrementally merge the sub graphs in an adaptive way to obtain the global optimum. The approach takes only about 53.3% of the time consumed by the sequential OAAM approach.

Keywords: Parallel OAAM, Oriented Active Appearance Model, Live wire

INRTODUCTION

Multiorgan segmentations are normally hybrid image segmentation [6] that combines more than two approaches. The proposed method uses a combination of AAM [1],livewire and parallelization methods. AAM methods use land marks [1] to represent shape and appearance of the organ and use principal component analysis to capture the major modes of variation in shape and appearance observed in the training data sets. Organ can be annoted either using semiautomatic or automatic or manual methods. Manual methods are widely used because of its simplicity, generality, and efficiency and are still use in clinical research. A minimum cost cut known as the max flow problem, that can be used to find the maximum amount of flow that can be sent from source to sink. Max flow algorithms[3]are categorized as augmenting-path based and push-relabel [2][3] based and most practical parallel max flow algorithms[4] are based on push-relabel.This can be done by uniformly partitioning the graph into a number of disjoint rectangular sub graphs denoted as blocks. Next, generate a number of threads to process the partitioned blocks in parallel. Each thread works as follows: A thread visits each segment on its list, and analyzes the heterogeneity increases for each of its neighbor. If at least one of the neighbors does not belong to the tile treated by that thread, the segment is included in the list of frontier segments. Otherwise, the segment is processed normally and marked as visited.

The neighbor that results in the less heterogeneity increase is considered the best neighbor. If this best neighbor is considered, by the fusion factor, as part of the segment, then a merge occurs. This procedure is repeated until the entire list of segments in each thread is covered.

RELATED WORK

The method proposed by Xinjian Chen, Jayaram K. Udupa in medical image segmentation by combining graph cut[2] and oriented active appearance models[1], uses the combination of livewire[4], graph cut and active appearance models[5] known as the IGC-OAAM approach which can be used for multi object segmentation including liver, kidneys and the spleen. But the proposed method takes about five minutes in segmenting each organ. The work done in Parallel Graph-cuts by Adaptive Bottom-up Merging involves minimization of energy function that can be transformed into solving a graph-cuts optimization on a digraph. The method uses parallel version of the BK algorithm and then merge the sub graphs until maximum flow is reached. A drawback of live wire [4] is the computation time for all possible minimum cost paths from each selected point on the boundary to all other points in the image.AAM model [5] deals with optimization problem.Hybrid AAM model [6] need preregistration of the shape templates and leads to inaccurate segmentation.

1. Landmark Specification and Interpolation

Landmark Specification and Interpolation generation can be done during the training phase. Landmarks can be used to represent the shape and appearance of the organ and it uses principal component analysis to capture the major modes of variation in shape and appearance observed in the training data sets. The proposed system uses landmarks for representing the organ as well as the outer region of the organ. Interpolation is the process of determining the values of a function at positions lying between its samples. It achieves this process by fitting a continuous function through the discrete input samples. Interpolation reduces the bandwidth of a signal by applying a low-pass filter to the discrete signal. That is, it reconstructs the signal lost in the sampling process by smoothing the data samples with an interpolation function. The image quality highly depends on the used interpolation technique. The interpolation techniques are divided into two categories, deterministic and statistical interpolation techniques. The difference is that deterministic interpolation techniques assume certain variability between the sample points, such as linearity in case of linear interpolation. Statistical interpolation methods approximate the signal by minimizing the estimation error. This approximation process may result in original sample values not being replicated. Since statistical methods are computationally inefficient, in this article only deterministic techniques will be discussed. A comparison between methods will also be made. Then, linear interpolation is applied to generate the same number of slices for the organ in every training image. This is for establishing anatomical correspondences. The block diagram representation is given in figure

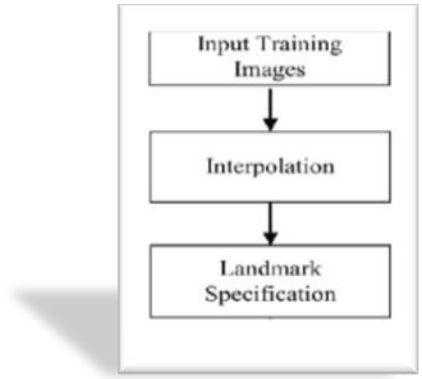

Figure1. Block diagram representation for training phase

2. AAM model construction using Landmark Points

After specifying the landmark points, AAM model can be constructed which is given in fig 3. Landmark points can vary depending upon the size and nature of the organ. The proposed system uses thirteen landmark points for segmenting the liver and uses seven landmarks for segmenting both the kidneys and the spleen which is given in table2. Principle component analysis [1] can then be applied for calculating the live wire cost. Land marking can be done either using automatic methods, semiautomatic methods or using manual land marking methods. Due to its simplicity, manual land marking is still use in clinical research. Since manual landmark needs human effort, segmentation can be done in a more accurate way without preregistering the organ shape or the organ templates. Suppose that M_j represents the AAM model for slice level *j* and the number of slice levels is represented as *n*, then the complete model can be represented as $M=(M_1,M_2,M_3\ldots..M_n)$.

Livewire

The landmark points can be joined using a live wire [4] which is an important tool that can be used for segmentation. It allows user to select regions of interest to be extracted quickly and accurately, using simple mouse clicks. The starting point can be set by clicking on an image's pixel, known as an anchor. Then, move the mouse over other points, the smallest cost path is drawn from the anchor to the pixel where the mouse is over. By simply clicking the image again, path displayed can be chosen. It is based on the lowest cost path algorithm that can be calculated using the equation.

$$c(l) = \frac{\sum_{i=1}^{nf} w_i c_f\left(f_i(l)\right)}{\sum_{i=1}^{nf} w_i}$$

Where w_i a positive is constant indicating the emphasis given to feature, f_i is the function to convert feature values.

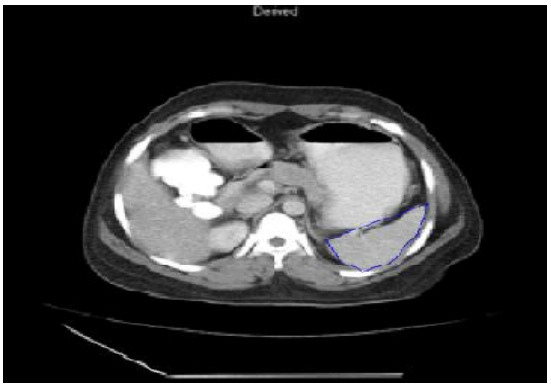

Figure 2: Representation of landmark - points for the spleen

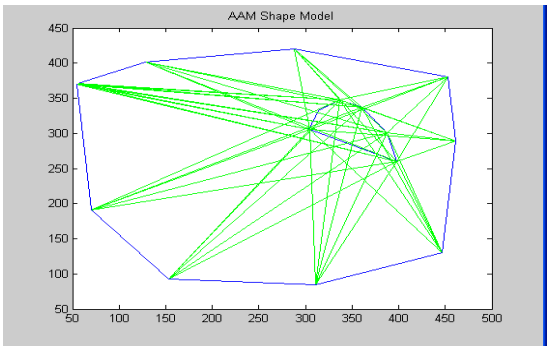

Figure 3: AAM Shape Model for the liver

3. Livewire in refining AAM shape Model

Since the model is already trained for each organ slice, the model can be used for slice localization ie, for the localization of top and bottom slices. CT slice localization method via nearest-neighbor is being employed in the proposed method. For the localization of a top slice in a given image, the top slice model is applied to each slice in the image and the slice corresponding to maximal similarity (minimal distance) is taken as the top slice of the organ. Combination of AAM with the LW method is used. The AAM provides the landmarks to the LW, and in return, LW improves the shape model of the AAM. The conventional AAM searching method is performed once to obtain a rough placement of the model. Then, the refining method is applied to refine the shape model in the AAM. The shape is extracted from the shape model of the AAM, and then the landmarks are updated based on LW using only the shape model and the pose parameters. Subsequently, the refined shape model is transformed back into the AAM.The corresponding AAM shape model is given in figure 3

Table.1 specifying landmark points for the organ

	Number of landmarks in organ	Number of landmarks in skin object
Liver	35	8
Left Kidney	20	8
Right Kidney	20	8
Spleen	26	8

4. Parallelization using new BK algorithm for the refined AAM model

The goal of parallelization is to find the minimum path by separating the sink and the source known as the MaxFlow algorithm. Maxflow algorithm can be push relabel or pull relabel algorithm. Commonly used ones are push relabel algorithms. Augmenting path will involve number of nodes from source to sink for sending the flow. To speed up the process, consider the augmenting flow on the paths as short as possible. This will give better results.Parallelization is usually followed by a partitioning step. Partitioning involves subdividing the graph into a number of disjoint rectangular sub graphs denoted as blocks. Each block will be including a boundary segment and involves number of threads. A thread visits a single block at a time; process the blocks and then move to the next block after completing. Each thread work as follows. A thread visits each segment on its list, and analyzes the heterogeneity increases for each of its neighbor. If at least one of the neighbors does not belong to the tile treated by that thread, the segment is included in the list of frontier segments. Otherwise, the segment is processed normally and marked as visited. The neighbor that results in the less heterogeneity increase is considered the best neighbor. If this best neighbor is considered, by the fusion factor, as part of the segment, then a merge occurs. This procedure is repeated until the entire list of segments in each thread is covered.To the refined AAM shape model, BK algorithm using parallelization is applied.

5. Parallel merging of blocks

After the thread visits each block and move to the next block, parallel merging of boundary segments can be done. Merging refers to uniting two isolated blocks into one and exhausting all augmenting paths within the new block.Adaptive merging can be performed by incrementally removing the boundary segments to form larger

blocks.Once a boundary segment is removed, new augmenting paths can be used for sending the flow from source to sink. After finishing the BK algorithm, the thread marks the block as unlocked, and returns to the scanning list. A thread exits when it can no longer find a boundary segment to merge

6. Parallelization using OAAM Approach

The goal of parallelization is to find the minimum path by separating the sink and the source known as the Max Flow algorithm. Max flow algorithm can be push relabel or pull relabel algorithm. Commonly used ones are push relabel algorithms. Augmenting path will involve number of nodes from source to sink for sending the flow. To speed up the process, consider the augmenting flow on the paths as short as possible. This will give better results. Sequential OAAM approach is done by adjusting the weights in a random manner to each landmark points. This is much time consuming as a single weight can be adjusted to each landmark point at a time. The proposed method provides adjusting the weights in a parallel manner i.e., more than two weight factors can be added to each landmark point at a time and the refinement can be done in a better way .This reduces the segmentation time nearly half.

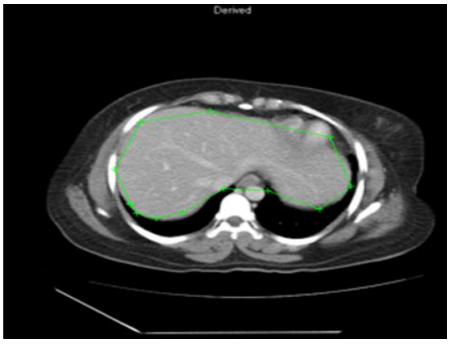

Figure 4: Segmentation using parallel OAAM Approach

7. Conclusion and Discussions

In this paper, a semiautomatic anatomy segmentation method has been proposed. The method effectively combines the AAM, LW, and parallel OAAM to perform segmentation in a limited time. The method was tested on a clinical CT data set from 20 patients for segmenting the liver and kidneys. The experimental results suggested that segmentation time can be reduced to nearly half compared to sequential OAAM Through novel uniform partitioning and adaptive merging operations; the proposed algorithm achieves near-linear speedup for common vision problems. The algorithm is cache-friendly, keeps balanced workloads, and causes little overhead. These features make the algorithm a practical and attractive replacement for the sequential OAAM. It can be found that there are usually some pixels not belonging to the target organ but still inside the shape, such as urine inside the kidney that can be excluded by the proposed OAAM method. While considering sequential OAAM algorithm, the proposed method takes only about 53.3% of the time consumed. In future, the approach can be used for diagnosing lymph node in an organ and can segment out the infected portion alone.Time required for segmenting liver usinp parallel OAAM with sequential OAAM is represented in figure 5

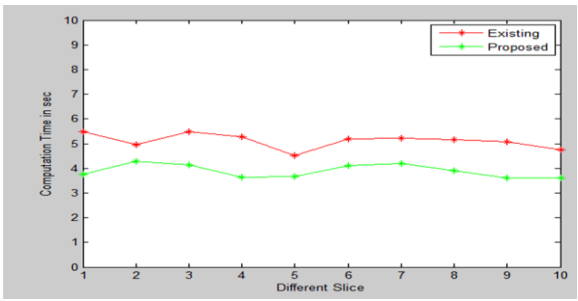

Figure 5: Computation time of parallel OAAM approach with sequential OAAM for liver.

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