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Hierarchical Object Recognition in Pelvic CT Images

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Abstract—**This paper introduces a hierarchical method of recognizing bone tissue from regions extracted from Pelvic CT Images. The method allows distinguishing among segmented objects with similar grey level values, such as bone tissue and regions of active hemorrhage. The method addresses the challenge of correctly segmenting and classifying bone as well as assessing presence of active hemorrhage.**

I. Introduction

TRAUMATIC injuries are by far the most common cause of death among patients under 45 years of age. Every year, a total of four million years of potential life are cut short on the U.S territory only [4]. Forty percent of the patients with fatal traumatic injuries die before reaching the emergency room [6]. Motor-vehicle crashes account for 48% to 68% of traumatic injuries. Traumatic Pelvic Injury and associated complications, such as internal hemorrhage, infected hematomas, multi-organ failure and blood clots traveling to the brain, result in a mortality rate ranging from 8.6% to 50% [27]. Even when the injury is not fatal it can be the cause of life long disabilities [3].

For more subtle fractures, such as fractures of the acetabulum, hip displacement or detection of hemorrhage, analysis of Computed Tomography (CT) images is usually required. As the number of CT slices can be quite large, computer aided pre-processing of the data is extremely important, because in general only a small portion of the dataset becomes important in establishing a diagnostic [17].

Segmentation of CT images presents a couple of different challenges. Firstly, the density of cortical bone is very different than that of cancellous bone. For this reason bone density and appearance cannot be uniformly characterized [16]. Secondly, a CT scan usually includes tens of slices in which bones assume different shapes and positions – this further complicates segmentation. A number of these slices include joint regions. In these regions the normal distance between bones is very small which can result in separate bones being merged with each other during segmentation.

There are currently several approaches for image segmentation. Thresholding methods are simple and fast but more suitable for segmenting objects with significantly different grey level values, compared with the grey level values of the background [5]. Such techniques do not incorporate spatial information; hence are sensitive to noise [13]. Partial volume effects and proximity of the bones in the pelvic region result in similar grey level of bone and soft tissue [18] make techniques based solely on thresholding impractical. Deformable Models Methods allow knowledge about adjacent structures to be incorporated in the model and therefore produce more accurate segmentation [8] Such methods cope well with low contrast images and noisy edges [18]. Deformable Model Methods (DMM), such as Active Contour Models or Snakes, are parametric segmentation methods that use closed curves or surfaces that can be deformed under internal and external forces – internal energy defines curvature constraints, external (image) energy attracts the contour towards the edges and other geometric constraints can be applied by incorporating constraint energy factors [11]. Advantages of such methods include directly generating closed curves while the main disadvantages are the lack of convergence towards concave boundaries and sensitivity to initialization. Deformable models that are based on implicit representation rather that explicit parameterization are improved versions of DMM as they are more topologically adaptable [14, 21]

Watershed segmentation techniques are gradient based segmentation methods that segment the image based on its topology: the water is flowing and descending from higher to lower regions in the map, following gradient direction to the nearest local minimum. The image is split into catchment basins and their borders define watersheds that are used for segmentation. [17] Watershed based methods often result in oversegmenation of the image as every local minimum of the image creates its own catchment basin. Region Growing methods [1, 10, 15] are very popular for the segmentation of medical images. In their classic form a region is initialized with a seed point and additional neighboring pixels that satisfy certain similarity constraints are added to the region in an iterative manner. When the current region stops its expansion another seed point, not yet allocated into a region, is used to initialize a new region. The common disadvantage of segmentation methods based on region growing is their dependency on initialization and the challenge to find proper

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similarity constraints. In Region Competition segmentation [20, 24, 26] statistical properties of region growing methods are combined with the geometrical features of deformable models. The quality of final segmentation depends on the initialization and the precision of boundary detection is dependent on the size of the sampling window as well as the signal to noise ratio [26]. Level Set Methods (LSM) define a moving contour as the zero-level set of a time-evolving scalar function defined over a regular grid [19]. The level-set function is regarded as the distance to the contour. Negative values of the function are associated with the points within the contour and the points outside the contour having positive values [19]. The initial curve is deformed according to the solution that is given by a set of partial differential equations (PDEs) [21, 25]. Gaussian Mixture Models (GMM) are parametric models that use a mixture of Gaussians to segment a given image [7, 9, 12]. After initialization, which is usually based on k-means, two GMMs are typically used to segment the image: one to model the ROI and another one to model the background.

Detecting pelvic fracture is, beyond any doubt, a very important matter. Current diagnosis methodologies require radiologists and trauma surgeons to examine the series of slices in the CT scan. Diagnostic decisions are extremely time sensitive when dealing with traumatic injuries. A system that could automatically analyze medical images and identify possible locations of fractures and/or hemorrhage will prove very useful in reducing the time of decision making and increasing decision accuracy.

The rest of the paper is organized as follows: Section II describes the proposed technique to recognize bone tissue and identify location of hemorrhage; Section III presents sample test results of the developed methods; Section IV provides a short discussion of the results; Section V is dedicated to conclusions and future work.

II. METHODOLOGY

Although segmentation of Pelvic CT images for bone tissue detection cannot rely solely on grey level information this type of information allows for distinguishing among regions that are candidate to be bone tissue and background. However, anatomical information needs to be included in the segmentation process as other regions might have similar grey level values to bone. A prime example is the case of regions of active hemorrhage, due to the florescence of iodine used to detect hemorrhage. Work that led to the segmentation of bone tissue and can also be used to also detect regions of active hemorrhage was presented in [22] and [23]. The present paper focuses on distinguishing between bone tissue and regions of active hemorrhage.

Fig. 1 presents the outline of the algorithm for object recognition starting from individually segmented regions.

The object recognition method is based on the Matching with Shape Contexts method described by [2]. A brief description of the approach is offered in the following. Starting from two images, one being the segmentation result and the other being the bone template, each of which can consist of multiple objects, the algorithm automatically selects a number of control points in each image. This is achieved by selecting a number of points n on the edges of the objects in the image. It must be specified that n represents a percentage of the total number of points on the edges of the objects and n can have different values for the two images.

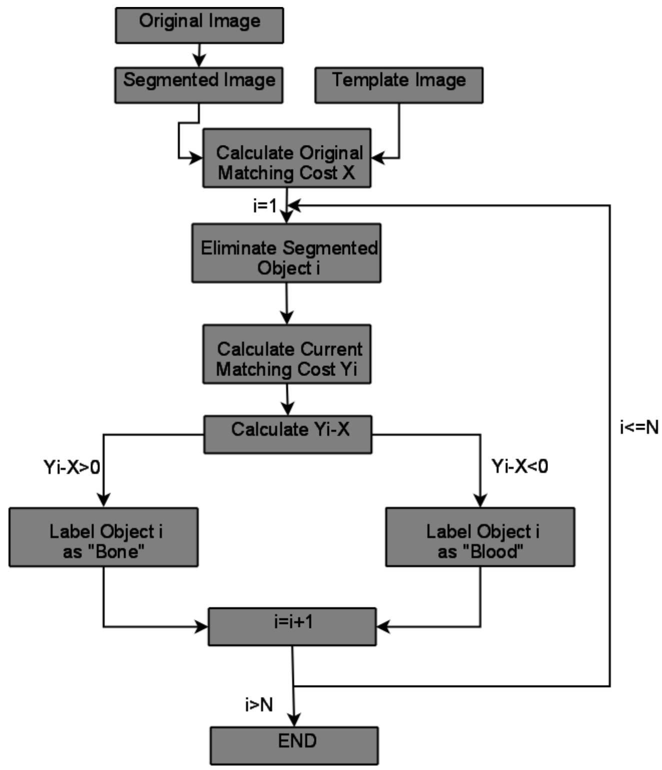

Fig. 1 – Algorithm outline for object recognition. N is the total number of segmented objects

For each of the two shapes for each point among the n control points of the shape a histogram of the relative coordinates of the remaining n-1 points is computed [2]:

$$h_i(k) = cardinality\{q \neq p_i : (q - p_i) \in bin(k)\} \quad (1)$$

where $bin(k)$ defines a region encompassed by two rays and two radii.

The histogram is defined as the shape context of p_i.

The cost of matching a point p_i in the segmented image with a point q_j in the template image is, as defined by [2]:

$$C_{ij} = C(p_i, q_j) = \frac{1}{2}\sum_{k=1}^{K} \frac{[h_i(k) - h_j(k)]^2}{h_i(k) + h_j(k)} \quad (2)$$

where $h_i(k)$ and $h_j(k)$ are the *K-bin* normalized histograms for the two points.

The overall cost of a match between the shape in the segmented image and the shape in the template image is the result of minimizing the sum of all individual point cost matches.

The object recognition algorithm calculates the overall matching cost between the segmented region and a template. In the following step the algorithm sequentially eliminates individual segmented objects and calculates matching costs between the resulted segmentation partitions and the template. Comparing the cost of a partition matching with the cost of the original match a decision can be made regarding the class (“bone” or “blood”) to which the eliminated object pertains. The reasoning behind the decision is as follows: by eliminating a bone region the segmented image is not as a suitable match to the template as the original and therefore the cost of the matching increases, eliminating a region of active bleeding decreases the cost of the match because the similarity between the segmentation result and the bone template increases.

Currently, a set of 44 bone templates is created from a CT scan of a normal case that does not exhibit fractures or bleeding. The suitable template to compare to a segmentation result is selected by calculating the matching cost between the segmented image and all the available templates and choosing the one with minimum matching cost. We are currently exploring the selection of the best template by using a another automated approach: identifying the initial appearance of the iliac crests and the initial occurrence of the femoral heads in the sequence on segmented CT images and finding a mapping between the segmented image sequence and the template sequence, using these occurrences as reference points. To ensure better correspondence, a total of eleven template sections would be explored in order to find the best match to the segmented image: the template the image is mapped to, five templates preceding the corresponding template and five templates that are succeeding it.

III. RESULTS

This section focuses on presenting the results obtained by applying the proposed method to a series of test images.

In Fig. 2, the image in the upper corner represents an original CT image from a patient scan. It can be observed that, apart from the brighter region of bone which occupies the center of the image, a bright region which represents active bleeding is present in the upper left part. In the upper right hand corner of Fig. 2 results based on the segmentation method described in [22] and [23] are provided. The images at the bottom of Fig. 2 represent the segmentation results out of which the large region of active bleeding was eliminated and the chosen template, respectively.

The initial matching cost between the segmentation result and the template was 51.0062. The cost decreased to 39.5937 after eliminating the region of active bleeding and increased to 62.2254 when eliminating the bone region. As the cost decreases in the first case and increases in the second case, compared to the original matching cost, the algorithm labels the first region as bleeding and the second region as bone.

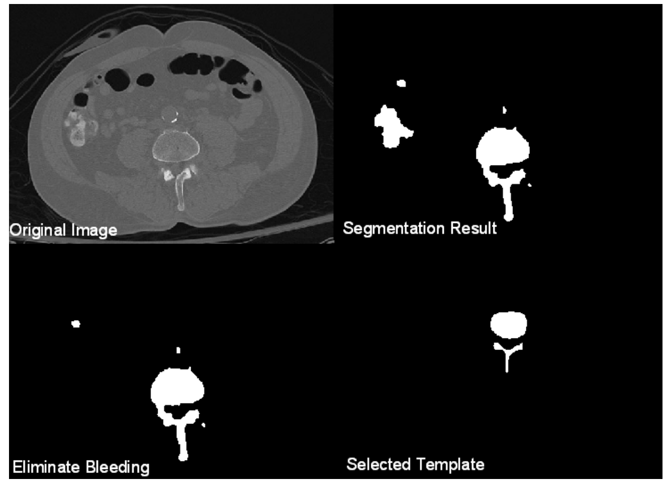

Fig. 2 – Examples of images used in the algorithm

In Fig. 3, on the left hand side, the grey region was labeled as bleeding. On the right hand side a graphic display of the algorithm results is provided. This result was obtained by intersecting the labeled bleeding region with the unprocessed segmentation results. By unprocessed segmentation results we refer to segmentation results obtained by following the method described in [22] and [23]. For the object recognition algorithm presented by this paper, segmentation results were further processed by applying morphological operations, in order to ensure better object connectivity and decrease the number of iterations in the object recognition algorithm.

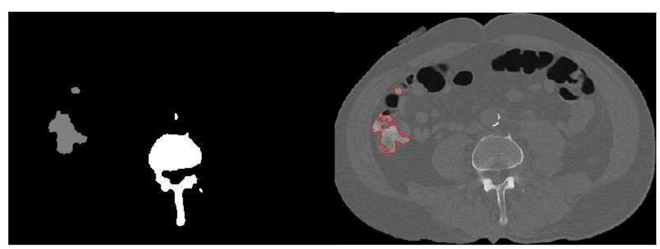

Fig. 3 – Example results of the algorithm

The algorithm was tested on a series of 36 CT images. A larger dataset of images in which active hemorrhage is present is now available and further testing will be performed. On the tested images the algorithm performed successfully and proved to be robust in distinguishing between regions of active bleeding and bone tissue. Cases in which the algorithm had a poor performance were cases in which initial segmentation was very poor. Poor segmentation is usually the result poor quality of the original CT image.

IV. DISCUSSION AND CONCLUSIONS

As it can be observed from examining the sample image presented in Results section, the method is capable of distinguishing between bone and active hemorrhage regions. This is a challenging task as the average grey level of these objects is similar.

Future work will include improving results of segmentation, detecting regions of inactive bleeding, and assessing the severity of hemorrhage by estimating the volume of accumulated blood.

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