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A New Hierarchical Method for Multi-level Segmentation of Bone in Pelvic CT Scans

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Abstract— **Pelvic bone segmentation is a vital step in analyzing pelvic CT images and assisting physicians with diagnostic decisions in traumatic pelvic injuries. A new hierarchical segmentation algorithm is proposed using a template-based best shape matching method and Registered Active Shape Model (RASM) to automatically extract pelvic bone tissues from multi-level pelvic CT images. A novel hierarchical initialization process for RASM is proposed. 449 CT images across seven patients are used to test and validate the reliability and robustness of the proposed method. The segmentation results show that the proposed method performs better with higher accuracy than standard ASM method.**

I. Introduction

TRAUMATIC pelvic injuries caused by motor vehicle accidents and falls contribute to a large number of mortalities every year [1]. Information contained in pelvic Computed Tomography (CT) images is very important resource for assessment of severity and prognosis of such injuries. Each pelvic CT scan consists of tens of slices; each slice contains a large amount of data that may not be thoroughly and accurately analyzed via simple visual inspection. As such, a computer-assisted pelvic trauma decision making system is crucial and necessary for physicians to make accurate diagnostic decision and for treatment planning in a shorter time.

Bone segmentation is very important for detecting fractures of patients with pelvic injuries. Bone tissue segmentation by automated CT image processing can significantly reduce the time to examine medical data and improve the accuracy of medical decision making. However, automatic bone tissue segmentation from each CT image using a general method is very challenging due to the complexity of pelvic structures, and variation in bone structure from person to person. In addition, CT images are also susceptible to noise, partial volume effects, and in-homogeneities.

Several methods have been used in the recent years for segmentation of medical images[2]. Some of them are based on thresholding techniques in which the segmentation task is considered as a pixel classification problem [3]. However, it is difficult to characterize the pixels in the segmented region with a single threshold value. Region growing techniques are also used in which an initial set of seeds are chosen and new points are added to the region if they meet a certain similarity criteria[4]. But these techniques are sensitive to initial seed selection. Some other methods include cluster segmentation, in which clusters are created to segment the target image into regions [5]. Calculation of inter- and intra- cluster distances is computationally expensive when the clusters have a large number of pixels. In this paper, a new hierarchical segmentation method is proposed based on shape matching and Registered Active Shape Model (RASM) that can segment the pelvic bones from CT images automatically and accurately. Also, a novel initialization process is proposed for RASM using homogeneity based image registration and extracted pelvic bone features.

II. Methodology

Fig.1 gives the flow chart of the segmentation setup. In the following sections, the setup is explained in detail.

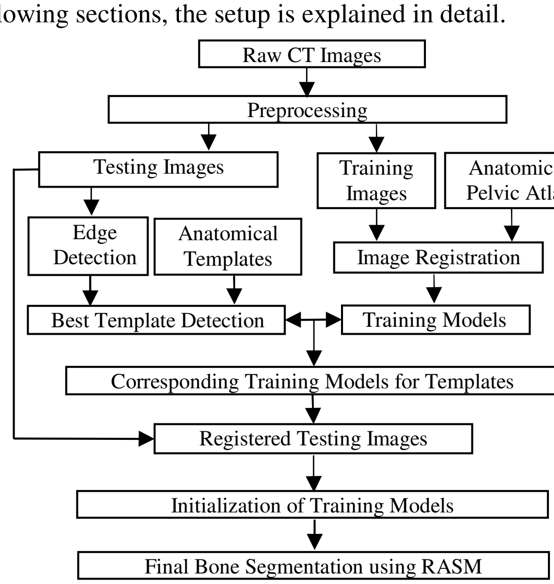

Fig. 1. Segmentation setup

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A. Dataset

The dataset is obtained from the Virginia Commonwealth University Medical Center. The data is collected from twelve traumatic pelvic injury patients. Forty-five to seventy-five images are collected from each patient. Axial CT images with five millimeter slice thickness are used for the study. Images collected from five patients are used for training and the other seven patients' images are used for testing.

B. Pre-Processing

The first step is to remove surrounding artifacts present in the original image, e.g. CT table, cables, hands, and lower extremities. This is achieved by performing morphological operations on the original image to separate different regions in the image and selection of the region with the largest area. Gaussian filter is used here to remove high frequency speckle noise.

C. Edge Detection of Bone Tissue

The next step is to detect the edges of bone tissue. Initially, the image contrast is enhanced and the edges are detected using Canny edge detection technique. And then, morphological operations are performed to remove spurious edges and to make the bone edges continuous and smooth. Next, the start and end pixels of each sub-edge are detected if there still remain a few disconnected edges. If there are less than three (determined empirically) disconnected pixels between the start and end pixels, they are connected to make the sub-edge continuous. If the number of connected pixels of each sub-edge is less than three, it is considered isolated and those pixels are removed from the image.

D. Shape Matching Algorithm to find Best Matching Template for multi-level Pelvic CT images

This step is designed to make the proposed hierarchical method run automatically. The 100 anatomical bone templates for shape matching are created through manual selection of the bone regions from part of the Visible Human Project dataset [6]. These templates are compared to similar images of patients in order to determine the best matched template using Shape Matching algorithm [7]. Control points on the contour of the objects are selected automatically to allow matching between the images. The overall cost of a match between both images is calculated based upon the minimization of individual point cost matches. This process is repeated for all the bone templates. After the best matched template is found, the corresponding training shape models of each best matched template can be directly applied to the preprocessed image for bone segmentation described in F.

E. Registration of pelvic bone based on homogeneity extraction for training model

Image registration is required in order to get robust training models from different patients with respect to their bone variations (translation, rotation, scaling, etc.). The image registration consists of these steps: enhanced homogeneity feature extraction from each training image [8], correlation coefficient calculation for similarity measure, affine transformation, and Powell algorithm application for optimization [9]. The flowchart of image registration is shown in Fig.2. Homogeneity is defined as a composition of two components: standard deviation describes the contrast within a local region in the image, and discontinuity measures the abrupt changes of gray level [8]. Homogeneity is defined as:

$$Homo(i, j) = 1 - E(i, j) \times S(i, j) \tag{1}$$

where $E(i,j)$ is the normalized discontinuity value, calculated using Sobel operator and use the magnitude of the gradient as the measure, $S(i,j)$ is the normalized standard deviation value for each pixel in the image. In this step, image contrast is enhanced and brightness is adjusted based on extracted homogeneity feature for registration.

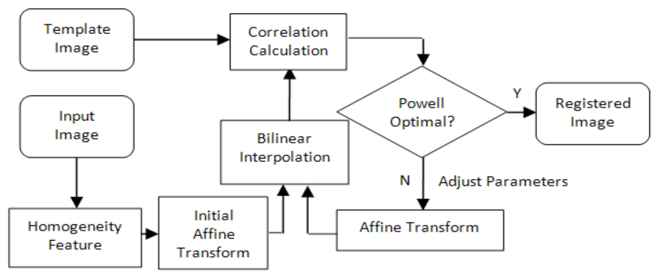


Fig. 2. Image registration algorithm

For each pelvic CT scan, all the training images are registered to their corresponding anatomical bone templates for creating more robust training models. The description for templates is given in subsection D.

F. Segmentation using RASM with proposed initialization

Active Shape Model (ASM) [10] takes a statistical approach that requires a set of labeled training images to determine variations of the desired shape in testing images. Standard ASM has been widely used in recent years. But this method is highly sensitive to initialization. It requires that an initial position must be correctly assigned to the training model in order to detect a target object in the image. Then the algorithm attempts to fit the shape model to the object. If the shape model is not accurately placed, the Standard ASM method may fail to detect the target object.

This paper addresses this shortcoming by using a hierarchical initialization process which composes of image registration, extracted bone features, as well as prior edge detection results to sequentially place the training models for each individual object. This process avoids the need for manually putting the initial positions. The algorithm is described as follows.

Step1: Each training input image T_n is registered to corresponding anatomical template, as stated in E, where $n = 1, \ldots, N$. N is the total number of training images.

Step2: Let $(X_{p1}, X_{p2}, \ldots, X_{pl}, Y_{p1}, Y_{p2}, \ldots, Y_{pl})$, $p = 1, 2, \ldots, P$ be the coordinates of the mean shape of each piece of bone. P is the number of bones, and l is the number of landmarks for each training model. The mean shapes are obtained using RASM. The landmarks are the points selected by the expert to outline the boundary of bone region in each registered training image. During the training process for creating shape models, the uppermost position of each bone is taken as the starting landmark of the shape model.

Step3: Centroid (C_p, D_p) is determined for all the mean shapes of the bones. All C_p values are sorted from the smallest to the largest.

Step4: Test image E_m is registered to the corresponding template using homogeneity based image registration, where $m = 1, \ldots, M$. M is the number of test images.

Step5: Pre-processing and Edge Detection methods are applied to the test image E_m to get the bone edges. The approximated contour of each piece of pelvic bone is detected.

Step6: Centroid (C_p', D_p') is determined for all approximated contours of each piece of pelvic bone in test images. All C_p' values are sorted from the smallest to the largest.

Step7: The corresponding relationship between these two groups of centroids (C_p, D_p) and (C_p', D_p') is achieved based on their sorted positions, through which the corresponding relationship between different training models and bones in test images is also achieved.

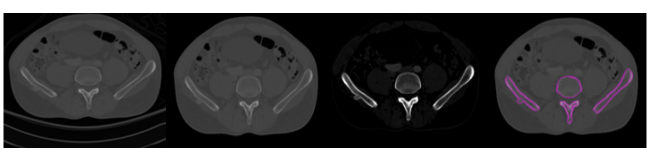
Step8: The bounding box of each bone is determined for the test images.

Step9: In the test images, within each box bounding, the corresponding training model is assigned the initial position with the uppermost position of the bone edge, then each shape model is correctly placed.

III. RESULTS

Results from different stages of the proposed method are presented in this section as follows.

Fig.3. shows pelvic region extraction from the raw CT images and bone edge detection. The results show that edges of bone tissue are clearly defined and these edges accurately represent the location, size, and shape of the bones in the raw image.



(a) (b) (c) (d)

Fig.3. Example results for preprocessing and edge detection. (a) is original pelvic image, (b) is preprocessed image, (c) is brightness enhanced image, and (d) is edge detected image

Fig. 4 shows the result obtained via shape matching algorithm. In Fig.4, the input image - detected bone edge (the upper left image) is compared with all 100 bone templates (template examples on the right side), and the template with minimum matching cost 26.6695 is achieved as the best matching template for the input image.

Evaluation of the matching results are compared with 2-D correlation method and shown in Table 1. The results show that shape matching method proved to get higher matching accuracy than 2-D correlation coefficients method.

TABLE I
EVALUATION OF THE MATCHING RESULTS USING SHAPE MATCHING AND CORRELATION COEFFICIENTS

Similarity Criterion	TOTAL NO. OF IMAGES	Total No. of accurately matched images	Accuracy
Shape Matching	675	548	0.812
2-D Correlation Coefficients	675	440	0.652

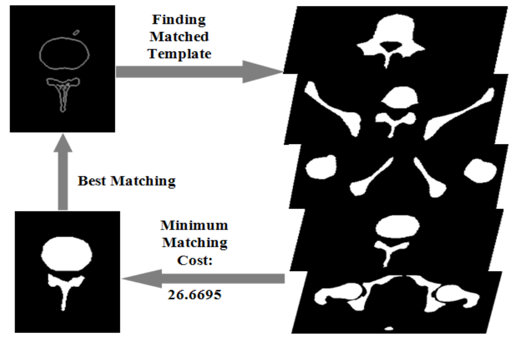
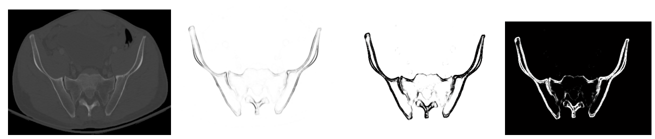


Fig.4. Example result of best shape matching

Fig.5. show the results obtained by homogeneity extraction from original images. The results show that the homogeneity features of bone tissue are clearly detected and actual contours of the bones are precisely represented. Also, other objects like soft tissues are removed.



(a) (b) (c) (d)

Fig.5. Example results for homogeneity extraction, (a) is original pelvic image, (b) is the image based on homogeneity feature extraction, (c) is brightness enhanced image and brightness is adjusted shown in (d).

Fig.6. show the results of homogeneity features based image registration. Visually, the size, location and rotation angle of the registered bone is more closely matched with the reference image rather than the original input image (a). The maximum correlation value of 0.3947 is obtained through registration.

(a) (b) (c)

Fig.6. Example result of image registration, (a) is input image, (b) is reference image, (c) is the registered image.
Affine parameters: translation: 32, 5.25; rotation: 5; scaling: 1.028;

Fig.7. show the segmentation results based on RASM with proposed initialization processing. The results show that the proposed method accurately segment the pelvic bones(lumbar, ilium, sacrum, femur, pubis, ischium). The initial positions of training models are also detected accurately. Results of Standard ASM for segmenting pelvic

bone are shown in Fig.8. The initial positions of training models are not correctly assigned in test images, which may be the main reason of inaccurate bone segmentation.

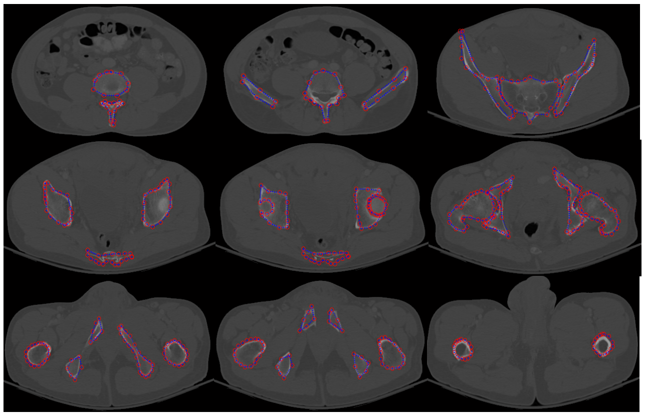


Fig.7. Example results of pelvic bone segmentation via RASM with proposed initialization

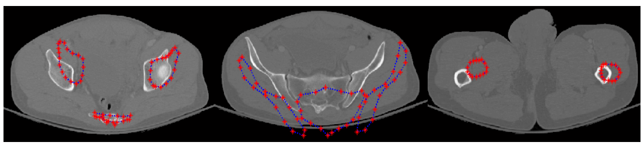


Fig.8. Example results of pelvic bone segmentation via standard ASM without initialization

IV. EVALUATION AND DISCUSSION

Visual inspection is used for evaluating performance of pelvic bone segmentation. The segmented bones are classified into three categories: Good, Acceptable, and Unacceptable. The results are evaluated by a radiologist, who identified the segmentation results as one of these three classes. Among all the segmentation results of 449 testing images across seven patients, 81.96% of them are classified as good, and 13.81% of them are acceptable and 4.23% of them are detected to be unacceptable.

For different pelvic bone structures, the segmentation accuracy results are shown in Fig.9. The ilium, ischium, pubis and femur are almost always detected to be at least acceptable; however, the sacrum and lumbar show a number of unacceptable results. This may be because of the variation in bone shapes, blur edge of the bones, the quality and clarity of the original image is poor, etc. The unacceptable results may be improved by training across a wider dataset or using more landmarks for training the model. Overall, segmentation is rated as good. Segmentation accuracy, including both good and acceptable results of different pelvic bones using proposed method and standard ASM without initialization, are shown in Fig.10. The results show the superiority of the proposed methods with much higher accuracy and more good and acceptable cases.

V. CONCLUSION AND FUTURE WORK

Pelvic CT scans of twelve patients are processed and bone structures from seven patients are accurately and automatically segmented using the proposed hierarchical approach which incorporates preprocessing, edge detection, Shape Matching, homogeneity based image registration and RASM with novel initialization. Segmentation results are evaluated by a

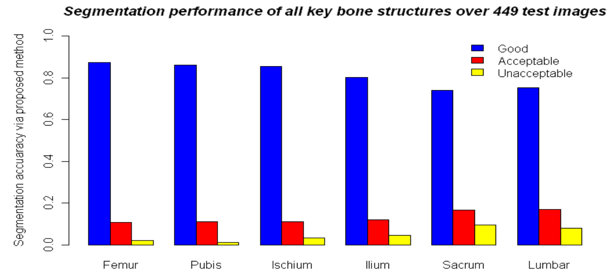


Fig.9. Segmentation accuracy results using proposed method of different pelvic bone structures

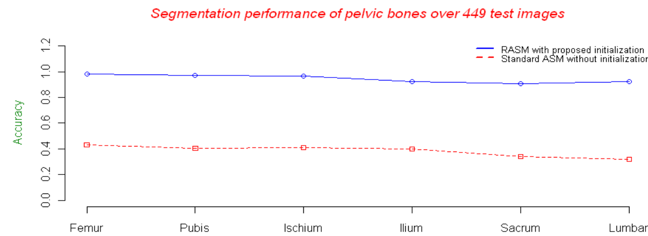


Fig.10. Segmentation accuracy including both Good and Acceptable results of different pelvic bones using proposed method and standard ASM

radiologist and comparison results show the proposed method performs better with higher segmentation accuracy than standard ASM. Additionally, computation time taken by this method is less than manual segmentation, making it practically applicable in the real time. Future work will focus on a larger database, with higher resolution CT images to improve the performance of the algorithm for detecting the bone fracture.

REFERENCES

[1] Fracture of the Pelvis, http://orthoinfo.aaos.org/topic.cfm? topic =a00223

[2] D.L. Pham, C. Xu, and J.L. Prince. "Current methods in medical image segmentation," *Annual Review of Biomedical Engineering*, 2(1), 2000.

[3] M. Sezgin. "Survey over image thresholding techniques and quantitative performance evaluation," *Journal of Electronic Imaging*, 2004.

[4] Z. Peter, V. Bousson, C. Bergot, and F. Peyrin. "A constrained region growing approach based on watershed for the segmentation of low contrast structures in bone micro-ct images," *Pattern Recognition*, 41(7), 2008.

[5] J. Yao, M. Miller, M. Franaszek, and R.M. Summers. "Colonic plyp segmentations in ct colonography-based on fuzzy clustering and deformable models," *IEEE Transactions on Medical Imaging*, 23(11), November 2004.

[6] http://www.nlm.nih.gov/research/visible/visible_human.html

[7] S. Belongie, J. Malik, and J. Puzicha. "Shape matching and object recognition using shape Contexts," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 24(4), 2002.

[8] Heng-Da Cheng and Ying Sun. "A Hierarchical Approach to Color Image Segmentation Using Homogeneity," *IEEE Transactions on image processing*, 9(12), 2000.

[9] F. Maes, D. Vandermeulen and P. Suetens, "Comparative evaluation of multiresolution optimization strategies for multimodality image registration by maximization of mutual information", Medical image analysis, 3(4), pp. 373-386, 1999

[10] T.F. Cootes and C.J. Taylor and D.H. Cooper and J. Graham (1995). "Active shape models - their training and application," *Computer Vision and Image Understanding* (61): 38-59.