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# An Automated Method for Hemorrhage Detection in Traumatic Pelvic Injuries

Pavani Davuluri, *Student Member*, *IEEE*, Jie Wu, *Student Member*, *IEEE*, Kevin R. Ward, Charles H. Cockrell, Kayvan Najarian, *Senior Member*, *IEEE*, and Rosalyn S. Hobson, *Member*, *IEEE*

*Abstract*— **Hemorrhage is the main cause of deaths that occurs within first 24 hours after a traumatic pelvic injury. Therefore, it is very important to determine hemorrhage quickly. Hemorrhages are detected using a CT scan. However, it is very time consuming for physicians to look for hemorrhage in all CT slices. Therefore, an automated system is needed. This paper proposes an automated hemorrhage detection technique by incorporating anatomical information of pelvic region. The results showed method performs comparably to manual methods. A statistical test is conducted to see if the volume of hemorrhage detected using this technique is significantly different from the volume assessed manually.**

## I. Introduction

HEMORRHAGE is the main cause of mortality in patients with traumatic pelvic fractures. The pelvic fractures may be due to a fall, or motor vehicle accident, and pedestrian hit by the car etc. The mortality rate for pelvic fractures which results in hemorrhagic shock in the emergency department ranges from 8% to 30% [1]–[3]. Patient death caused by hemorrhage usually occurs within first 24 hours. Hence it is very important to quickly and accurately determine a hemorrhage in the pelvic region in order to reduce mortality rates [1], [3].

CT analysis is required in order to detect hemorrhage. Currently, a contrast enhanced CT technique (introducing an enhancer in the blood stream to change the appearance of blood) is used to identify active hemorrhage [1]. Depending on the slice thickness, the number of CT images to be analyzed by the physicians may be large. Hence it is time consuming to analyze manually. Time is a crucial factor in emergency medicine. Thus automated hemorrhage detection will help physicians make faster and accurate decisions.

Identifying active hemorrhage is very challenging due to variation from patient to patient in bleeding contrast, injury severity, presence of several arteries in the pelvic region which may be injured, and variation in size and shape of bone. Since arteries and bones are located in different parts of image, the entire image must be searched adding to the complexity of the problem. To overcome these challenges, anatomical information must be incorporated. Since hemorrhage is usually due to artery injury from a bone fracture or displacement, the active bleeding location is typically close to the arteries or the fractured bone. Bone segmentation, and artery detection may improve the process of detecting hemorrhage.

Several approaches are currently in use for image segmentation. Threshold based methods are simple and fast, but are sensitive to noise and hence are not well suited for segmentation [4], [5]. Deformable model methods such as Active Contour Models or Snakes are able to handle structures with complex topology, but these methods cannot naturally handle topological changes and are sensitive to initial conditions [5], [6].

Tracking artery position is very challenging and is an important problem for identifying hemorrhage. Several object tracking techniques like propagation techniques are currently in use for medical applications [7], [8]. All of these methods require user interaction to some extent. [9] detected hemorrhage automatically. But this method failed to distinguish between slightly contrast enhanced tissue and blood. The method presented in this paper is a fully automated method that uses bone information and arteries information to detect presence of hemorrhage.

The rest of the paper is organized as follows. Section II describes the methods for bone segmentation, artery detection, and hemorrhage detection. Section III presents the results for hemorrhage detection and the discussion of those results. Section V gives conclusion and the future work of the study.

## II. Methodology

This study is continuation to the work done on segmentation of bone in pelvic CT images [10]. Fig. 1 gives the process involved in hemorrhage detection. Each step of the process is described in detail in the following sub sections.

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P. Davuluri is with the Electrical & Computer Engineering Department, Virginia Commonwealth University, Richmond, VA 23284 USA (phone: 804-827-7000; fax: 804-827-7017; email: davulurip@vcu.edu).

J. Wu is with the Computer Science Department, Virginia Commonwealth University, Richmond, VA 23284 USA (email: wuj6@vcu.edu).

K. R. Ward is with the Emergency Medicine Department and Virginia Commonwealth University Reanimation Engineering Science (VCURES), Virginia Commonwealth University, Richmond, VA 23284 USA (email: krward@hsc.vcu.edu).

C. H. Cockrell is with the Radiology Department, Virginia Commonwealth University, Richmond, VA 23284 USA (email: chcockrell@vcu.edu).

K. Najarian is with the Computer Science Department and Virginia Commonwealth University Reanimation Engineering Science (VCURES), Virginia Commonwealth University, Richmond, VA 23284 USA (email: knajarian@vcu.edu).

R. S. Hobson is with the Electrical & Computer Engineering Department, Virginia Commonwealth University, Richmond VA 23284 USA (email: rhobson@vcu.edu).

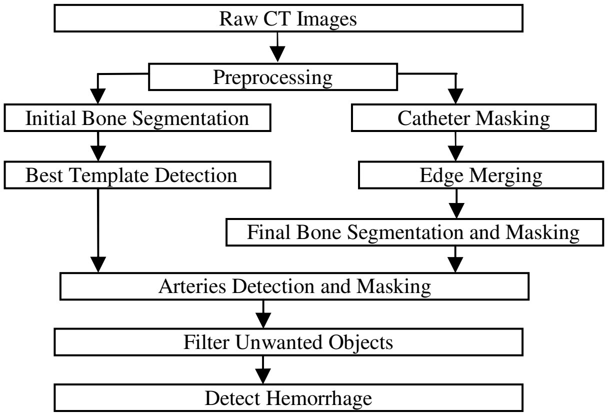


Fig. 1. Setup to detect Hemorrhage

### *A. Preprocessing, Initial Bone Segmentation and Best Template Detection*

The goal of preprocessing is to remove the surrounding artifacts from the images. The preprocessing, initial bone segmentation is done in the same way as in previous work [10]. After initial segmentation, the best template for each image is determined using Shape matching technique given in [9]. Finding best template for each image is needed in determining the iliac (common/external) arteries, explained later.

### *B. Catheter Masking, and Edge Merging*

Since the entire image is searched for the hemorrhage, it is important to mask catheters or any contrast enhanced tissues like bowel etc. Catheter (urinary bladder or intravenous) is a tube inserted into a body cavity for instillation of contrast during CT to assess urinary bladder injury or for fluid infusions. If placed in the femoral vein, it will be visible on pelvic CT scans. Based on experimentation, it is observed that these objects usually have intensity much higher than the intensity of any other objects in an image. Fig. 2 shows the average contrast percentiles for various objects in an image. These percentiles are calculated based on the intensity of the objects in 300 images. Based on these results, the objects with intensities within the range of catheters intensity are set to zero in the images. Bone edges of each preprocessed image are determined using canny edge detection. In some cases, the edges of the bones may not be fully connected. Therefore to ensure better masking of bone, the edges of each bone in the current slice are merged with the respective bone in previous and next slice. Since the study is not focused on fracture detection, slight variation in bone edges will have minimal effect on hemorrhage detection.

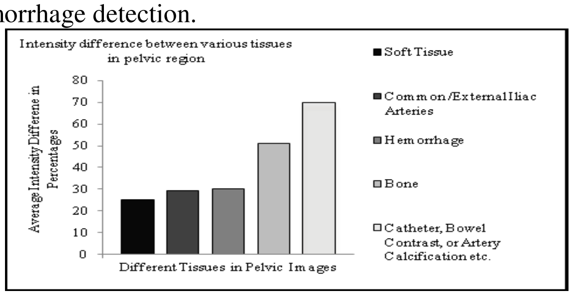


Fig. 2. Average intensity differences in percentages for different objects in an image

### *C. Final Bone Segmentation and Masking*

After edge merging, final bone segmentation is performed using the same automated seed growing technique that is used for initial bone segmentation [10]. The segmented bone pixels are masked by setting their intensity to zero.

### *D. Arteries Detection and Masking*

The main arteries in the pelvic region that cause bleeding are the aorta and its branches. This paper focuses on detecting aorta, common iliac arteries and its branches. Since arteries and bleeding are of similar intensity range (as seen in Fig. 2), the iliac (common/external) artery mean intensity, once calculated, can be used as a threshold to exclude all objects with intensities lower than this threshold.

The first step in arteries detection is to find the region of interest (ROI), i.e. region in which iliac arteries are located. This ROI is determined in the first image. Later, from this ROI, the actual position of arteries is determined. The first image's artery centroid position is used to determine the ROI of next image and so on. ROI for the first image is determined based on the best matched template for that image. A total of 73 bone templates created from a CT scan of a normal case that does not exhibit fractures or bleeding are used. These templates are grouped into 4 categories based on the path of the arteries from the first to the last patient image. Only first $t$ templates are used to detect the first image initial artery position. These are used because the path of arteries from the first template to $t^{th}$ template is in the same direction and since the pelvic CT scans taken in the hospital contain all images of pelvic region, the first image of a patient matches one of these $t$ templates.

### *E. Procedure to determine ROI for first image*

The number of objects (lumbar vertebrae, sacrum, ilium etc.) in the segmented bone image is calculated. Then the centroid and bounding box coordinates of all objects present in each segmented image are determined. If the number of objects is <=2, then by blob analysis, the object with largest area is determined. For that object the centroid ($x_o$, $y_o$), and bounding box coordinates $\mathbf{b}_o=(b_{o1},b_{o2},b_{o3},b_{o4})$ are determined, where, $b_{o1}$, $b_{o3}$ are minimum and maximum horizontal position, and $b_{o2}, b_{o4}$ are minimum and maximum vertical position. This artery position is the position of aorta because aorta has not branched out to common iliac arteries (right/left) at this stage. This artery position is given by (1).

$$\textit{Artery Position} = \left(x_o,\, b_{o2} - 2\times \textit{slice thickness}\right) \tag{1}$$

Let the best matched template for each image be denoted by $j$, and the number of templates in each group by $s$. If the number of objects is > 2, then objects whose $x$ (centroid horizontal coordinate) value lies between the minimum and maximum $x$ values, and whose $b_{i2}$ (minimum horizontal bounding box coordinate of image $i$ ) is minimum is determined. That object is the desired object with centroid ($x_o$, $y_o$), and bounding box coordinates $\mathbf{b}_o$. The distance moved $dm$ by an artery from one image to another image is given in (2) and the arteries position is given in (3).

$$dm = \left(b_{o3} - x_o\right) - \left\{\left(\frac{b_{o3} - x_o}{s}\right)\times\left(s - j\right)\right\} \tag{2}$$

$$Arteries\ Position = \left( x_o \pm d\,m,\ \left(b_{o2} - k\right) \pm \frac{slice\ thickness}{2} \right) \quad (3)$$

where, $k$ is the approximate distance between bone top most tip and the artery. The value of $k$ is chosen as 10 in this study by experimentation. '+/-' in (3) indicates left /right iliac artery position.

The above determined artery positions are the initial position of the arteries. ROI is a 50x50 neighborhood of that position. This size of neighborhood is chosen because a larger window size may sometimes include tissues like bladder etc., and a smaller window may not cover the entire area of the artery. A histogram is used to find minimum intensity required to obtain top 15 percent of the pixels in that ROI excluding the outliers. That intensity is used as a threshold value and blob analysis is used to determine object with largest area. That object is considered an artery and its centroid its actual position. For all the consecutive images, the centroid of artery from previous image is used as initial artery position to determine the current image's artery position by applying the same procedure used to determine the actual artery position of the first image.

### *F. Procedure to determine ROI for first image that has external iliac branches*

The common iliac arteries do not branch out from the first image itself. So, let the original image of a template at which common iliac arteries branches out be $T_d$ and let $T_h$ $(d<h)$ be the image at which they taper off completely. Let $I_f$ be the first image of a patient whose best matched template is $T_c$ $(d<c<h)$. Let $(a_1, b_1)$, and $(a_2, b_2)$ be the left and right external iliac artery positions for image $I_f$.

Then the left/right iliac branch initial position is given in (4) and (5).

$$Left\ iliac\ branch\ (l_0, l_1) = (a_1 + 2 \times p, b_1 + 2 \times p) \quad (4)$$

$$Right\ iliac\ branch\ (r_0, r_1) = (a_2 - 2 \times p, b_2 + 2 \times p) \quad (5)$$

where: $p = c - d + 1$.

Once the initial position of internal iliac branches of the image $I_f$ is determined, the following image internal iliac arteries initial position is determined from the first image arteries position and is given in (6) and (7).

$$Left\ iliac\ branch = \left( l_0 + 1, l_1 + \frac{slice\ thickness}{2} \right) \quad (6)$$

$$Right\ iliac\ branch = \left( r_0 - 1, r_1 + \frac{slice\ thickness}{2} \right) \quad (7)$$

This positions $(l_0, l_1)$, and $(r_0, r_1)$ of internal iliac arteries are used for the following image. This process is repeated iteratively for all the images whose best matched template number is less than or equal to $h$. Similar to common/external iliac arteries, ROI is chosen with same size of neighborhood and internal iliac arteries position in the ROI is determined in the same way as that of common/external iliac arteries but instead of finding one large object, all objects whose size is smaller than the external iliac arteries and with similar intensity are considered internal iliac arteries. Finally, after detecting the arteries, the mean and maximum intensity of the common/external iliac arteries pixels are determined for each image and all the arteries are masked.

### *G. Filter unwanted objects*

After masking the catheter, bones and arteries, each image is searched for finding the objects that fall within the mean and maximum artery intensities. Every pixel whose intensity is below mean value or above maximum value is eliminated. Hence the image will be left with hemorrhage and/or some bone pixels that are not masked due to fracture in patient and fall within these limits, or isolated artery pixels. These pixels are filtered in 4 steps. The first step is morphologic operations. This eliminates any isolated pixels. The second step checks if the current object is present in previous or next slices through sliding. If not present in previous or next slice then it is eliminated. This removes any unwanted pixels whose intensity is similar to that of arteries. The third step is to remove any unwanted residue bone pixels. This is done by comparing the detected unwanted object pixels to all previous scans to see if any of those regions are masked in those slices. If masked, then that object is eliminated. The final step is to eliminate any artery pixels that are missed during detection. This is done by using a 2x2 neighborhood of each pixel detected. If any pixel's intensity in that neighborhood is zero then the current pixel is the unwanted pixel and hence it is eliminated. Therefore, all the unwanted pixels are eliminated.

### *H. Detect Hemorrhage*

After the filtration of unwanted objects, if the image has any objects present, then it is considered as hemorrhage else there is no hemorrhage. In order to measure the severity of hemorrhage, volume of the hemorrhage should be determined. To do this, the area of hemorrhage must be determined. This is done using a region growing technique, with the centroid of detected hemorrhage as initial seed point and its intensity as region mean and with a 8-connected neighborhood. The region is iteratively grown by comparing the neighboring pixels that are unallocated to the region. The difference between the pixel's intensity and the region's mean is used as a measure of similarity. The pixel with the smallest distance is added to the region. This is repeated until the difference between the region mean and new pixel is larger than a certain threshold. The difference between the mean intensity and minimum intensity of common/external iliac arteries is chosen as the threshold. The volume of hemorrhage for each patient is determined by viewing the images that have hemorrhage as a pyramid and calculating the area in each image and slice thickness. The total area of hemorrhage is the area of hemorrhage present in all the images. Slice thickness is considered as height of the pyramid.

### *I. Statistical Analysis*

Statistical analysis is used in the study to determine if there is a significant difference in volume of hemorrhage detected by the proposed method and manual method. This analysis is conducted using a t-test with 95% confidence. A $p$-value less than 0.05 indicate a significant difference in the hemorrhage volume detected using automated versus manual technique.

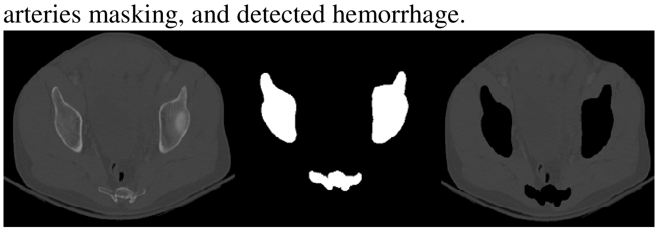
## III. Results and Discussion

### A. Data

The data is collected from Virginia Commonwealth University Medical Center. The images used in this study are axial CT images of 5mm thickness and are obtained from 12 pelvic trauma injury patients with a total of 515 images.

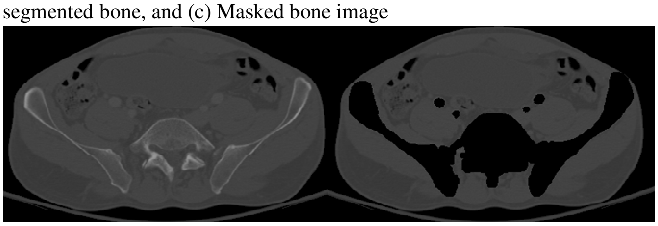
### B. Results and Discussion

The proposed method was tested on 12 patients consisting of a total of 515 images to detect hemorrhage. The proposed method is able to detect hemorrhage with an accuracy of 85.71%. "No hemorrhage" detection accuracy is 88.91%. This detection of false positives is important for this application as it reduces the chance of missing the hemorrhage. The ground truth for assessment of these images was the read made by the participating radiologist who analyzed the same images. The proposed method is also able to detect hemorrhage in those images in which the radiologists were unable to detect when read for the first time. Figures 3 to 5 show sample results of final bone segmentation, bone masking, external and internal iliac arteries masking, and detected hemorrhage.



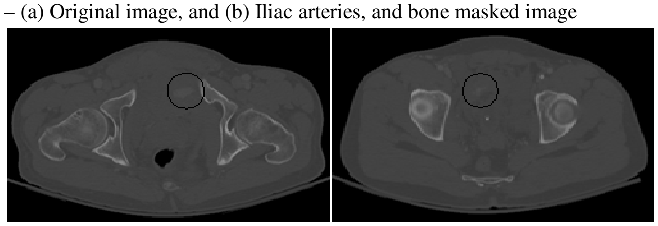
(a) (b) (c)

Fig. 3. Sample result for bone masking – (a) Original image, (b) Final segmented bone, and (c) Masked bone image



(a) (b)

Fig. 4. Sample result with external/internal iliac arteries, and bone masked – (a) Original image, and (b) Iliac arteries, and bone masked image



(a) (b)

Fig. 5. Sample results for the hemorrhage detection (circle on the image denotes the hemorrhage region detected)

The volume of the hemorrhage is detected for all those cases that are detected with the hemorrhage. The volume detected with the automated method is compared with the volume detected manually to determine if there is a significant difference using a t- test. The obtained *p*-value using t-test is 0.8753(>0.05). This shows that the volume of the hemorrhage detected using an automated method is not significantly different from that of volume detected manually. The algorithm for arteries detection is also able to detect iliac veins along with the external iliac arteries when the scans are in veinal phase (i.e. delay in scanning pelvic region after injecting contrast enhancer). It is to be observed that in that phase, the veins and arteries are all of similar contrast. But in arterial phase (i.e. scanning pelvic region immediately after injecting contrast enhancer), there is a significant contrast difference between iliac arteries and veins, and the algorithm determined only the arteries. Bleeding from arteries depends on the severity of injury, how fast the blood is pumping through in the patient etc. The method also detected the hemorrhage in cases that has a very low contrast difference between the hemorrhage and the soft tissues other than vessels.

## IV. Conclusion and Future Work

An automated method for detecting hemorrhage in traumatic pelvic injuries is proposed in this study. Hemorrhage is detected by masking arteries, bone and catheter etc. by following a series of steps. The results showed that the performance of the method is acceptable. In the future, the proposed method's performance will be tested on a larger data set. Also, the extracted hemorrhage will be combined with other features like fracture and patient's medical records to make recommendations to physicians.

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