2014 X International Symposium on Telecommunications (BIHTEL)
October 27-29, 2014, Sarajevo, Bosnia and Herzegovina

Alignment of X-ray Bone Images

Mario Mustra, Mislav Grgic, Branka Zovko-Cihlar
University of Zagreb, Faculty of Electrical Engineering and Computing, Unska 3, 10000 Zagreb, Croatia
mario.mustra@fer.hr

***Abstract*—Switching to digital technology from analog brought many changes, especially in storage of digital X-ray images. In cases of multiple fractures or need for imaging of a large area it is necessary to make more than one X-ray image for the observed part of body. This is often the case with spine, legs and arms. Radiologists use dedicated workstations to view X-ray results and need to manually switch between different images to be able to complete the examination of longer bone segments. Dedicated software gives some possibility of automatic or semiautomatic image stitching which allows combining of multiple images into one. In this paper we propose a method for automatic detection of bone position in X-ray images of arms and legs and their automatic alignment with one of image's borders.**

Keywords—X-ray; bone images; segmentation; alignment; registration.

I. INTRODUCTION

Some medical imaging modalities and especially X-ray imaging of large bones require combination multiple images in order to capture all the required regions for the examination process. Development of image storage in digital formats and fully digital X-ray devices originate from the mid 1990's. Since then digital imaging techniques have rapidly developed, mostly because of huge increase in computation power of computers and workstations used for those purposes. Computed radiography (CR) imaging presents the mostly used segment of X-ray techniques for bone imaging in cases of fractures and dislocations. Many different papers from the last 20 years address alignment of multiple CR images. Althof et al. [1] presented an automatic image registration algorithm which is used on CR images in order to register them and to avoid severe edge artifacts which can occur in combined images. There are many different approaches to image registration and they can be sum up into ones which are non-invasive or invasive in terms of influencing on the location of each pixel to its neighboring pixel and ones which uses markers or landmarks to achieve registration as detailed described in [2]. Accurate segmentation in CR images and generally in all X-ray medical imaging modalities is rather difficult because of varying conditions among different patients and inside individual images as well. Therefore segmentation cannot be simply threshold based because that approach would not give highly accurate results. Segmentation needs to be object based and intensity properties of the desired object need to be known before the automatic method is applied. Pettersson et al. [3] proposed a method for automatic segmentation of bones from CT data using the local deformation model to fit the prototype to the target structures. Ding et al. [4] proposed a method for automatic segmentation of femur bones for detection of fractures. Their idea relies on alignment of each bone from the atlas to the actual image which is being segmented to provide good region of interest identification which should help in later segmentation. Hand bone segmentation requires accurate segmentation of each individual small bone in the hand and that is a rather challenging task because it involves high accuracy to allow good segmentation in the area of joints. Sotoca et al. [5] presented a method for hand bone segmentation in radio absorptiometry images. Their method is based on the bone density for the segmented hand bones using the grey levels calibrated with a reference aluminum wedge. From the referenced methods it is clear that the thing which needs to be handled is the variation in bone intensity which occurs because of different reasons. Some of them are distance from the source and length of path of the X-ray from the source towards detector and others are more concerned to the type of tissue and physical dimension of each bone.

The proposed method for bone alignment uses partial segmentation along the entire bone's length to avoid variation in local intensity and later segmentation of the bone using Otsu's method. After segmentation it is important to detect the actual edge and approximate it with straight lines from which it is possible to calculate the rotation angle for which the image needs to be rotated in order to align the bone with the image edge.

This paper is organized as follows. In Section II we present bone segmentation method. Section III describes the automatic detection of bone position and calculation of the rotation angle. Section IV discusses results and drawbacks of the proposed method. Section IV draws the conclusions.

II. AUTOMATIC BONE SEGMENTATION

Bone segmentation process which we propose consists of couple of preprocessing steps. The first step is orientation detection which uses image dimensions as key information to decide whether to rotate image for a 90° angle or not. For this purpose we decided to try to align images to the x-axis, which gives larger horizontal than vertical dimension. The next step is finding the number of discrete pixel intensities stored in the image, which is usually around 2^12=4096. Since a standard computer display has possibility to show only 256 discrete intensities we have decided to convert the entire intensity range into space of 8-bits. This does not reduce image quality significantly but reduces the storage size and memory requirements, which makes computing faster. Conversion

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between arbitrary ranges of intensities into 256 discrete intensities can be expressed by:

$$p(x,y)\_8bit = \left\lfloor \frac{p(x,y) - min\_el}{max\_el - min\_el} \cdot 255 + 0.5 \right\rfloor, \qquad (1)$$

where $p\_8bit(x,y)$ is pixel at position (x,y) in the 8-bit image, $p(x,y)$ is pixel at the position (x,y) in the original image, min_el is minimal intensity in the original image and max_el is maximal intensity in the original image. The next step is defining an approximate threshold which should allow us to distinguish tissue from the background. In this case it is not necessary to know the exact tissue type but merely its position in the image. This knowledge provides us with the information about the bone position along vertical axis. To be able to correctly calculate center of the bone it is necessary to choose rather low threshold which can lead to some false positive segmentations. It is necessary, however, not to have any false negative segmentation to be able to use autocorrelation function. For the case of rectangular strip in the horizontal center of the image we can express autocorrelation of the segmentation mask as:

$$S_{pp}(x,y) = \sum_{x=1}^{x=sw} \sum_{y=1}^{y=h} p(x,y) \cdot p(sw - x - 1, h - y - 1), \qquad (2)$$

where $S_{pp}(x,y)$ is sum of elements without discontinuities starting from the top of the image, $p(x,y)$ are discrete pixel values of the segmentation mask which can be either 0 or 1, sw is width of strip in pixels and h is image height in pixels. Maximum of $S_{pp}(x,y)$ at position y should give the center of the segmented region. All possible false positive segmentations will be removed since they will provide value smaller than maximum of $S_{pp}(x,y)$. For the segmentation threshold we have chosen 1/5 of the maximal intensity in the image and according to (1) it gives the value of 51. Giving the correct center position of the tissue makes possible to subdivide original image into smaller segments which will contain only pixels belonging to the tissue so that we can use Otsu's thresholding method [6]. To be able to create different thresholds we divide image along the x-axis in 10 equally wide segments and according to the central position in y-axis we try to use only pixels belonging to bone or muscle tissue. Example of a slightly rotated forearm image is shown in Fig.1.

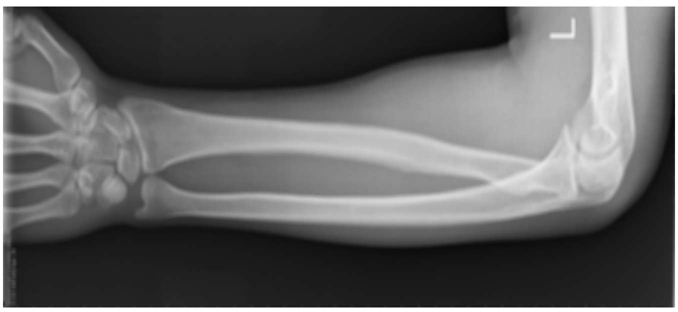


Fig. 1. Slightly rotated forearm image.

After dividing image into 10 segments horizontally and applying thresholds using Otsu's method we get the results as shown on Fig. 2.

Fig. 2. Segmentation using Otsu's method.

Results shown in Fig. 2 are not usable for exact bone segmentation but give some information about actual bone boundaries and can help in providing orientation results. To determine those parameters we need to use some line characterization methods.

III. Calculating Rotation Angle

Once we have more or less accurate bone segmentation mask it is the time to refine it and to detect its edges. For refinement and "hole filling" we have decided to use morphological opening and closing operators with different structuring elements. First we have used small structuring element, a square of 5×5 pixels, for opening and then a large structuring element, a square of 25×25 pixels, for closing. Results of these operations are shown in Fig. 3.

Fig. 3. Segmented image after morphological operations.

Application of edge detection operators will give much less results on an image which does not have many "holes" and small objects and that is the main reason for using morphological closing. For the edge detection we have used Canny edge detector which gave the result for this segmentation mask as shown in Fig. 4.

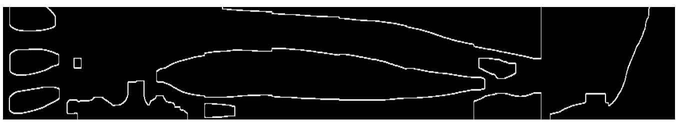
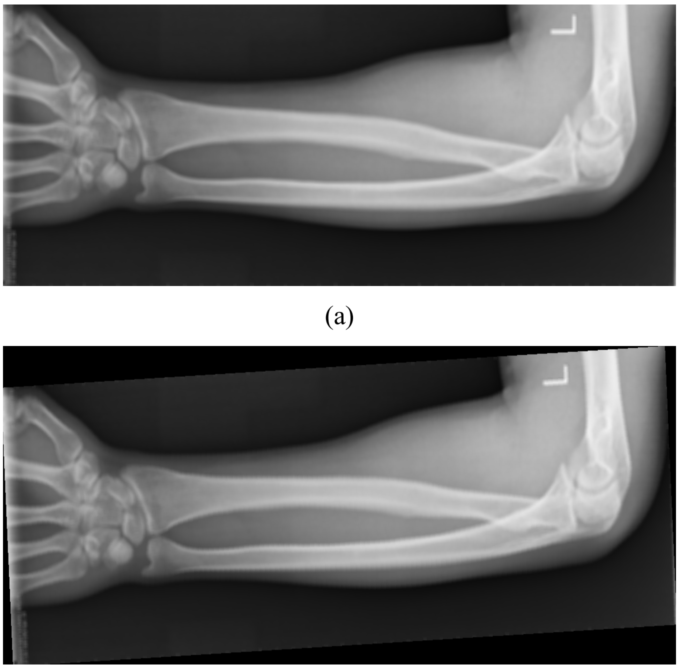


Fig. 4. Result of edge detection using Canny edge detector.

By observing Fig. 4 we can notice that it contains three almost straight lines which represent bone edges and from them we aim to calculate the desired rotation angle. To approximate some structure with straight lines we can use curve tracking and straight line fitting along that curve or we can use Hough transform. Hough transform is much less computationally expensive and its results can give a rather good estimate of straight line's angle. Hough transform is used to convert points from rectangular coordinate system into Hough space by applying the following expression:

$$r = x \cdot \cos(\theta) + y \cdot \sin(\theta), \tag{3}$$

where r is the distance from the origin of the coordinate system to the line along a vector perpendicular to the line and θ is the angle of the perpendicular projection from the origin to the line measured in degrees clockwise from the positive x-axis. Straight line will therefore be presented as a high-intensity point in the Hough space and curved lines which are rather close to straight lines will be presented as a cloud of high-intensity points with variations in orientations and distances from origin. Hough transformation can be applied with different angle and distance resolutions which will affect computational time and size of the Hough accumulator. Since for the bone rotation we expect to have rather small angled we will limit our search for maximum in the Hough space onto the region which contains expected angles. These angles can vary from +10° to -10° so we will only take that part of the Hough space into account unless it has no high-intensity points or clouds of points. For the example shown in previous figures calculated rotation angle which is obtained as the brightest point in the Hough space is 3°, which means that we need to rotate the observed image by -3°. That rotation results in an image shown in Fig. 5 (b).



(a)

(b)

Fig. 5. (a) Original image; (b) Result of rotation of the original image (a).

Rotation changes some image parameters because pixels are being rotated in a grid and their movement is not optimal for the grid size. Therefore, to ensure minimal loss in quality of the rotated image we have applied bicubic interpolation which should provide best overall results. Overall image quality of the rotated images therefore remains the same as of the original image. The entire method described in Sections II and III can be displayed in form of a diagram shown in Fig. 6.

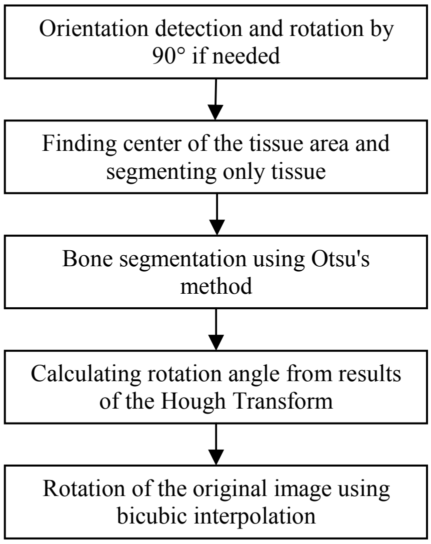
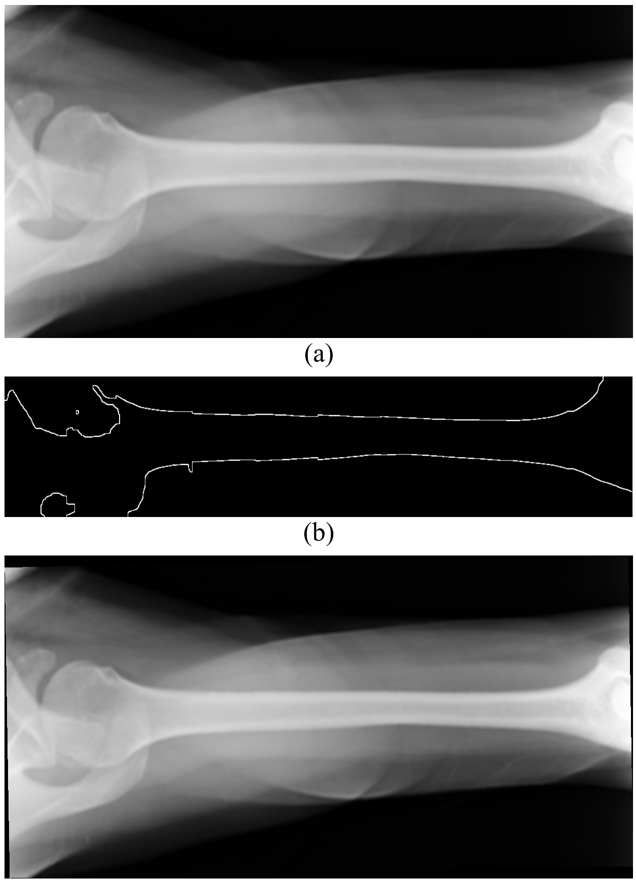


Fig. 6. Flowchart of the proposed method for image alignment.

Results of the proposed method can be used to align different types of bone images. Fig. 7 shows an example of a leg X-ray image which is being aligned by rotation to horizontal axis using the proposed method.



(a)

(b)

(c)

Fig. 7. (a) Original image; (b) Result of edge detection using Canny edge detector on the tissue region; (c) Final image with bone aligned to the horizontal axis.

IV. CONCLUSIONS

We have presented a method for automatic alignment of CR bone images which show forearms and legs. The proposed method uses thresholding based on Otsu's method for optimal threshold calculation and Hough transform for detection of straight line segments from which is possible to calculate the rotation angle. This method is not oriented on accurate bone segmentation but merely on finding most of bone's boundaries so that we are able to predict bone's position and rotation angles. According to the angle resolution used in Hough transform and by carefully choosing the appropriate neighborhood in the Hough accumulator we are able to obtain different levels of precision in angle calculation. Another thing which needs to be observed is the number of bones presented in the image and we need to define a rule according to which image will be rotated. This is mostly the case in forearm images because forearm consists of two almost parallel bones but in some projections they are not parallel and can significantly reduce quality of the final result. Our future work will be based on alignment techniques for multiple images which need to include registration so that multiple images of the same object can be stitched together to form one image according to its overlapping regions.

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