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TIBIA FRACTURE DETECTION USING A MODIFIED EDGE DETECTION METHOD BASED ON BONE LENGTH

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Abstract

A bone fracture is a medical situation where there is an injury to any part of the bone. Bones are affected by stress, which can cause a simple or complicated fracture, and this can be difficult to diagnose by specialists. Medical image processing plays a very important role in disease diagnosis in order to improve patient care and helps medical physicians during decision making regarding the type of treatment. In this paper, a new bone fracture detection method is introduced, which can detect and highlight the fracture using threshold, histogram equalization and Canny edge detection methods. Using the tibia bone as an example, the length of the fractured tibia is measured, and compared with the length of the equivalent unfractured bone (i.e., the tibia in the uninjured leg) in the same patient. Then, a rapid and accurate decision can be taken by physicians regarding the existence of a bone fracture, and how severe the fracture is, especially when a very large number of patients exist in the emergency room as in transportation accidents or wars.

Keywords: Bone fracture detection, Bone length, Edge detection, Histogram equalization, Medical image processing.

1. Introduction

Bone fracture is a break or cracks in a bone. It occurs when the force applied on a bone is stronger than the ability of the bone to withstand it. This affects the bone structure and strength and causes pain, lack of function and sometimes injury and bleeding at the site of fracture. There are several kinds of bone fracture i.e. compound (open) fracture, simple (closed) fracture, greenstick fracture, hairline fracture and others. Some of these fractures are more severe than others, which depend on the strength and direction of the force, the specific bone involved, the age of the person, and the person's health in general [1]. Doctors can diagnose bone fractures by analysing the X-ray images of the injured part of the body, they may also use Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) scans.

Fractured bones usually heal by themselves, and the aim of medical treatment is to make sure that the pieces of bone are aligned in a correct way before healing [1, 2]. Medical image processing plays a very important role in bone fracture diagnoses, as we can obtain more specific details of the broken bone than with the usual X-ray and CT images. Using a processed medical image, physicians can decide on the type of fracture and the optimum healing process for the broken bone easily and quickly than with the regular diagnostic processes [3, 4].

There have been several studies searching for the optimum bone fracture detection process, which can detect the bone fracture in the original X-ray and CT images [3-5]. Liang et al. [6] have recommended a morphological method to recognize tibial bone fractures. The original image of the bone fracture was separated into some intervals, to assist in classifying the smallest interval with the fracture goal. Then, these regions were thresholded using Otsu's technique [7]. When the segmentation process was completed, the processed image would no longer have rough areas. Unlike Liang et al. [6] work, in this paper, Otsu's method is applied on the whole image as a second processing step after filtering the image and equalizing its histogram, the idea here is to separate the bone from the background, and prepare the image for the next step of processing.

Yelne et al. [8] have shown that the Canny edge detection method can assist in determining the position of bone fracture. They compared different edge detection methods and found that the best way was to use Canny edge detection over an enhanced image, which was analysed using a modified contrast stretching algorithm, rather than the regular histogram equalization technique. They filtered the images in frequency domain in order to remove the noise presented in the images. Because of Yelne et al. [8] conclusion, that compares between the different types of edge detection methods, the Canny method is chosen to be used to detect the tibia bone edges in the proposed work. It is applied as a third step after applying the processing steps mentioned above, which filtered the image in the spatial domain rather than in the frequency domain, it is simpler and efficient than Yelne et al. [8] filtration method.

Donnelley and Knowles [9] devised a method, which identified fractures automatically in lengthy bones. Firstly, bone boundaries were separated from the original image via a special method called "non-linear anisotropic diffusion method", which could smooth the image and prevent losing important information about boundary areas in the image. After that, a new Hough transform method with programmed peak recognition was presented to identify the long line features, which estimated the boundaries of the lengthy bones. Then, these features were employed in diaphysis segmentation, fracture discovering and centreline estimation in the extracted area. This method leads us to use Hough transform for a different reason, a calculation is made to find the tibia bone length and compare it with the length of the other leg of the same patient. It is the final step of fracture detection method proposed here.

On the other hand, Syiam et al. [10] have presented an adaptive boundary factor, that worked together through a trained factor based on neural networks (NNs), and used them to construct the software boundary factor, which identified fractures in the lengthy bone. The results showed that the NN of the collaborating factors could assist to retain the appearance of the programmed discovery of bone ruptures. Their method based mainly on the user as he/she can choose the process needs to be applied on the loaded image. Unlike Syiam et al. [10] work, this paper presented an automated method for bone edge detection, and there was no need to choose the process as the method was suitable for any tibia bone image entered to the system.

Linda and Jiji [11] detected bone fractures based on fuzzy index measurements from X-ray images. Their image processing method included grid information, local thresholding, threshold value interpolation, segmentation using fuzzy index measure, background removal and morphological filtering to determine the site of the bone fracture. They proved that their method enhanced the accuracy of fracture detection compared with two other standard methods. The work presented here was different from Linda and Jiji [11] work because the existence of the fracture was the main goal and was no need to identify the site of the bone fracture.

Among the different bone imaging modalities (CT, X-ray, Ultrasound, MRI), fracture detection usually uses X-ray diagnosis unless the fracture is complicated, in this case, CT, Ultrasound or MRI might be desired for further diagnosis and surgery [12, 13].

In this paper, X-ray images of tibia bone were processed using a modified fracture detection method followed by measurement of bone length, providing a rapid and efficient decision about the existence of a fracture and its severity. The novelty of this method presented in the order of using histogram equalization, thresholding, edge detection and the Hough transform processes. In addition, the calculation of the bone length process was unique and had never been used to detect the existence of the fracture in tibia bones. This process will help physicians to decide quickly if the injured leg has a fracture or not depending on the difference between the left and right bones length. If there is a difference, that means the injured leg has a fracture, but if the lengths of the left and right leg are the same or very close to each other, then the injured leg has no fracture. This idea is novel, and to the best of our knowledge, there are no studies, that use bone length in fracture detection for tibia bones.

2. Image Processing

In this section, the main image processing steps used in this study were described. The flow diagram in Fig. 1 presents the steps in the tibia fracture detection process, starting from the original bone X-ray image and ending with a clear detection of the bone fracture along with measurement of the bone length, which will allow physicians to decide, whether there is a fracture in the bone or not. The process was faster and easier than regular diagnostic processes. The fracture detection process was applied to 20 X-ray images of the tibia, that were taken for 10 different adults, in which, five of those patients had one fractured tibia bone, while the others had normal (unfractured) tibia bones. It was somehow difficult to collect a suitable data for this work (i.e., x-ray images of the left and right leg of the same patient), and 10 patients were sufficient to prove that the method is efficient. In this work, MATLAB software and image processing toolbox were used to achieve the process [14].

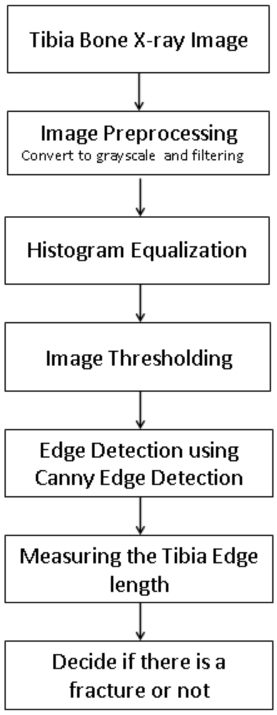


Fig. 1. Flow diagram of the tibia bone fracture detection process.

2.1. Image pre-processing

Each X-ray image of the tibia was first converted to a greyscale image using the luminosity method, which is one of the common colour transformation methods, which is a more sophisticated version of the averaging method. Then, the noise was removed using a smoothing filter to ensure, that any unwanted signals were removed from the image. Both steps are seen in Fig. 1 in the second block.

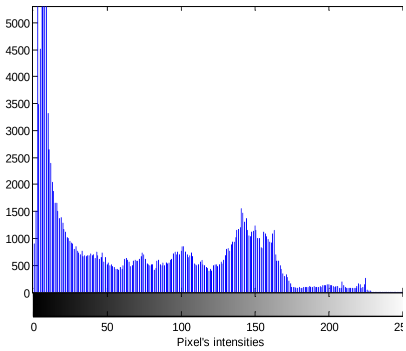
2.2. Histogram equalization

As seen in the flow diagram (Fig. 1), the next process after filtering was histogram equalization. This is a procedure for regulating image intensities to improve contrast. This process basically enhanced the image's contrast, especially when the greyscale image is represented by specific contrast intensities [15]. Using this modification, the intensities were distributed in an improved way on the histogram, which will permit areas having low contrast to have higher contrast. Histogram equalization achieved this by professionally broadening out the most frequent intensity levels throughout the image. This technique often fabricates unrealistic effects in photographs, though it is very beneficial for scientific images such as thermal, satellite or X-ray images. The method is effective for all kind of intensity images, which have dark or bright intensities, and it enhances the views of bone structure in X-ray images and gives improved details in photos, which are over or underexposed [16].

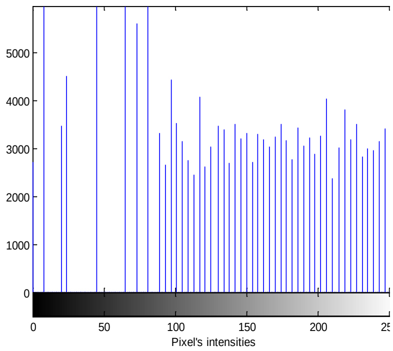
The main benefit of the histogram equalization method is that it is an honest straightforward method and a reversible machinist. Figure 2(a) shows an instance of an X-ray image of a tibia bone, and a corresponding histogram equalized image is presented in Fig. 2(b). Figure 2(c) shows the histogram of the image in (a), where it can be noticed that the intensities were cumulative, while Fig. 2(d) shows the histogram of the equalized image of Fig. 2(b). The resulting effect will be an image, that presents a great deal of grey level detail with a high dynamic range.

(a) Original tibia X-ray image.

(b) Tibia X-ray image after histogram equalization.



(c) Intensities of original tibia X-ray image.



(d) Intensities of tibia X-ray image after histogram equalization.

Fig. 2. Example of X-ray image of tibia bone before and after histogram equalization.

2.3. Image thresholding

Thresholding is an image segmentation method, and a greyscale image can be converted to a binary image using this technique. Thresholding method basically replaces pixels with intensities $I(i,j)$ less than a threshold level T (i.e., $I(i,j) < \mathrm{T}$) with black colour and white colour, if $I(i,j) > T$ [15]. The constant T is called a threshold point, which is a normalized intensity value, that has a value in the range [0, 1].

Many methods are used to select a proper threshold value for a segmentation task. One technique is Otsu's method, which selects the threshold level to decrease the variation of the black and white pixels [7]. Perhaps the most common method is to choose the threshold level interactively, where the user changes the value and check the thresholding result until a satisfactory segmentation has been achieved. In this work, the Otsu's method was first used with an auto-selection of the thresholding level, but it was noticed that the threshold level, that was generated was not appropriate to separate the bone from the background, so the resulting threshold level was multiplied by a suitable constant in the interval [1.5, 2], which in turn gave better thresholding results for the X-ray images.

2.4. Edge detection in the threshold image using Canny edge detection

The main idea that edge detection processes have in common, is to simplify the analysis of the digital images by reducing the quantity of data to be investigated, while simultaneously protecting useful structural information about object boundaries [17]. The Canny edge detection method is an edge detection machinist, that uses a multiple stages mechanism to distinguish a wide range of edges in each image. The method finds edges by looking for local maxima of the gradient of the image. The process of this algorithm was broken down into five steps: 1. Removing the noise from the image by using a Gaussian filter to have a smooth image 2. Calculating the image intensity gradients 3. Getting rid of false responses using non-maximum suppression before edge detection step 4. Determining possible edges by applying a double threshold, 5. Finalising the detection of edges by eliminating all the other edges, that are weak and disconnect to significant edges [18-20]. In this paper, the Canny edge detection method was used to detect the edges of the tibia bone and make the bone fracture clear for further processing.

2.5. Measuring bone length

In this section, the length of the tibia bone was measured using the Hough transform technique, which is a feature extraction technique used in many areas such as image analysis, computer vision, and digital image processing. In general, the Hough transform is a method used to separate features of a specific shape within an image. In this method, the desired features should be specified in some parametric form, thereby the classic Hough transform is generally used for curves detection, for instance, lines, circles, ellipses, etc. [20]. In addition, a generalized Hough transform can be used in more complicated applications [13, 19, 20].

The motivating idea behind the Hough technique for line detection is that each input measurement (e.g., coordinate point) designates its involvement in a globally reliable solution (e.g., the line, which gave rise to that image point). The Standard

Hough Transform (SHT) uses the parametric representation of a line, which is given by Eq. (1):

$$x\,cos(\theta) + y\sin(\theta) = r \tag{1}$$

where r is the distance from the origin point to the line and θ is the direction of r regarding the x-axis. Figure 3 illustrates the parametric explanation of a straight line. In an image investigation framework, the coordinates of the point(s) of edge segments (i.e., $(x_i\,, y_i)$) in the image are known so assumed as constants in the parametric line equation, whereas r and θ are the unknown variables, that are being looked for [20].

In this procedure, the edges in the image were first detected using the Canny edge detection method, and then the Hough transform technique was applied. The next step was to look for the peak values and the endpoints of each detected line in the image, and the last step was to choose the maximum length from all of the resulting lines in the image and consider it as the final length of the bone in that image.

The symmetry of the human body was taken, where the length of the injured bone could be compared to the length of equivalent uninjured bone from the same person. The main idea was to measure the bone length for both the injured and uninjured legs from the same person and compare the results. To the best of our knowledge, there are no studies in the literature, that used Hough transform in measuring the bone length, and there are no studies using the bone length in predicting the existence of the bone fracture. This would help physicians to decide if there was a bone fracture or not in the injured leg and make a rapid diagnosis with regard to the existence of a bone fracture, especially when a large number of patients are present at the emergency room.

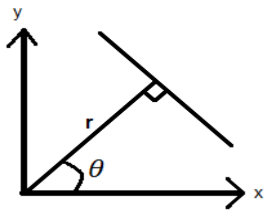


Fig. 3. Parametric description of a straight line.

3. Results and Discussion

The detection and measurement procedure discussed in the previous section was applied to X-ray images of the fractured and unfractured tibia bone. Figure 4(a) presents the original X-ray image taken for a patient, who had an injured leg, while Figs. 4(b) and (c) show the images after filtration and after histogram equalization, respectively. Figure 5 presents the result of the next three process steps i.e., Fig. 5(a) shows the image after thresholding, Fig. 5(b) the image after edge detection using Canny edge detection method explained previously in section 2.4. Finally, Fig. 5(c) shows the bone edges indicated with green lines, where this step is done using the Hough transform method, which was explained in section 2.5.

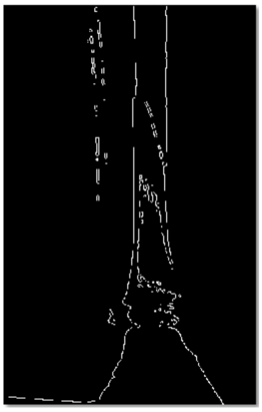
(a) X-ray image of tibia bone fracture.

(b) X-ray image after filtration.

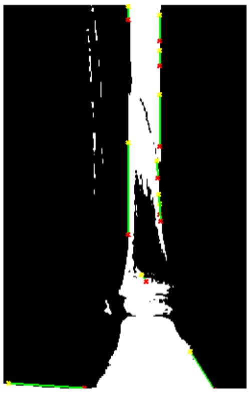
(c) X-ray image after histogram equalization.

Fig. 4. Example of applying filtration and histogram equalization to the original X-ray image of tibia.

(a) X-ray image after thresholding (conversion to binary image).



(b) X-ray image after edge detection step.



(c) Bone edges are indicated and labelled with green lines.

Fig. 5. Thresholding, edge detection and edge labelling.

Figure 6 shows the process of calculating the length of these lines and obtaining the final result for bone length and then comparing it with the length of the tibia in the other uninjured leg to decide if there was a fracture in the injured leg. Table 1 presents the bone length of the uninjured and injured tibia bones in four different patients. For the same patient, both the injured and uninjured leg length was measured and compared together, if there was a difference in bone length between the injured and uninjured leg, then the doctor could decide, whether the injured leg has a fracture or not.

In addition, if the difference in lengths is large, the doctor will have an indication that the fracture is not simple, and that it may be a severe fracture. In the table, for patients 1 and 2, the injured leg has a fracture, and the algorithm gave an indication about that by having a large difference in the injured and uninjured bone lengths, while the other two got a very small difference, which gave an indication that the injured leg has no fracture, and that was correct. So, this method can speed up the diagnostic process and make it easier than the usual diagnostic processes, especially in the case of transportation accidents or wars, and in the case of remote diagnostics.

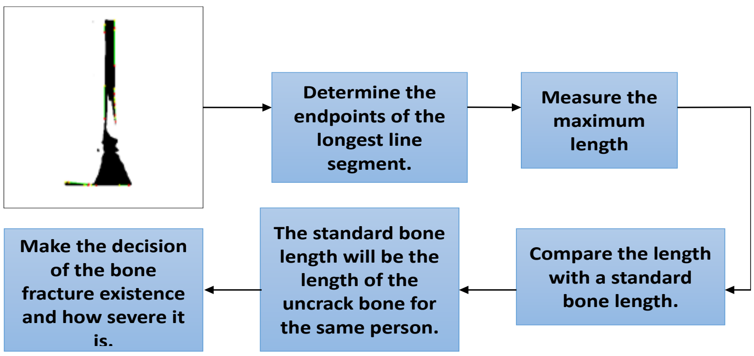


Fig. 6. Flow diagram for the process of calculating the bone length using the Hough transform algorithm and deciding on the existence of a bone fracture.

Table 1. Examples of four normal lengths for some unfractured tibia bones, and another four examples of length for some fractured tibia bones using the detection method.

	Maximum tibia bone length in uninjured leg (pixels)	Maximum tibia bone length in injured leg (pixels)	Tibia length difference (pixels)	Diagnosis
Patient # 1	148	125	23	Fractured
Patient # 2	133.3	102.9	30.4	Fractured
Patient # 3	100.5	100	0.5	Unfractured
Patient # 4	96.3	89.3	7	Unfractured

4. Conclusions

The proposed method could play a significant role in improving the regular diagnosis processes from X-ray images of possible tibia bone fractures. In our study, X-ray images of tibia bones were processed, and modified images created, where the bone edges were detected and highlighted. This can provide physicians with a rapid and accurate assessment of the existence and type of tibia bone fracture. In addition, the length of the injured tibia bone can be measured and compared with the bone length of the equivalent uninjured bone in the same patient. Doctors can decide quickly, whether the injured leg is broken, if there is a difference between the length of the injured and uninjured Tibia bones. This procedure could help both physicians and patients by decreasing the diagnosis time and enhancing the accuracy of choosing the optimum treatment or medical action especially in a situation, where a large number of people are injured as in transportation accidents or wars. The field of medical image processing is growing rapidly, thus the work in this paper could be extended, for example, to detect bone fractures in other long bones in the body.

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Nomenclature

I	Image intensity
r	Distance of a normal from the origin to a line
T	Threshold point

Greek Symbols

θ	Direction of r depends on the x-axis

Abbreviations

CT	Computed Tomography
MRI	Magnetic Resonance Imaging
SHT	Standard Hough Transform

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