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Development of Automatic Fracture Detection System using Image Processing and Classification Methods for Femur Bone X-Ray Images

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Abstract— Clinician and Practitioners suggest that detection of fractures from x-ray images is considered as an essential process in medical x- ray image analysis for diagnosis. Patients suffer in most cases seriously. So the study proposes a combined classification technique for automatic fracture detection from long bones, in particular the leg femur bones. The proposed system has following steps, preprocessing, segmentation, feature extraction and bone detection, which uses a combination of classification techniques of image processing for successful detection of fractures. The classifiers, Support Vector Machine Classifiers (SVM), feed forward Back Propagation Neural Networks (BPNN), and Naïve Bayes Classifiers (NB) are used during combination of classification. The results from various experiments showed that the proposed system is showing significant improvement in terms of detection rate of fractures.

Keywords— SVM, BPNN, Navie Base Calssification

I. INTRODUCTION

Medical image processing is a field of science that is gaining wide acceptance in healthcare industry due to its technological advances and software breakthroughs. It plays a important role in disease diagnosis and improved patient care and helps medical practitioners during decision making with regard to the type of treatment. Several state-of-the-art equipments produce human organs in digital form. Examples of such devices include X-Ray-based devices, Computed Tomography (CT), Magnetic Resonance Imaging (MRI), Ultrasound (US), Positron Emission Tomography (PET) and Single Photon Emission Computed Tomography (SPECT).

Out of these, X-Ray is one the oldest and frequently used devices, as they are non-invasive, painless and economical. Tamisiea [6] given that a bone x-ray image can be of any bone in the body, like the hand, wrist, arm, elbow, shoulder, foot, ankle, leg (shin), knee, thigh, hip, pelvis or spine. A typical bone ailment is the fracture, which occurs when bone cannot withstand outside force like direct blows, twisting injuries and falls. Fractures are cracks in bones and are defined as a medical condition in which there is a break in the continuity of the bone. Detection and correct treatment of fractures are considered important, as a wrong diagnosis often lead to ineffective patient management, increased dissatisfaction and expensive litigation.

The importance of fracture detection comes from the fact that in clinical practice, a tired radiologist has been found to miss fracture cases after looking through many images containing healthy bones. Computer detection of fractures can assist the doctors by flagging suspicious cases for closer examinations and thus improve the timeliness and accuracy of their diagnosis. Moreover, femoral fractures are the subject of ongoing controversy and discussion. Despite newer innovations, automatic detection of femoral fractures essentially remains unresolved as these injuries are different and variable in presentation and their outcomes are unpredictable. The main focus of this work is to automatically detect fractures in long bones and in particular, leg femur bone, from plain diagnostic x-rays using a series of sequential steps. The region of interest in femur is the shaft region.

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II. LITERATUE SURVEY

Since Wilhelm Roentgen discovered the existence of x-rays in 1895, medical imaging has advanced at a tremendous rate and has become the fundamental diagnostic tool in modern healthcare. This section reviews some works that has focused on the various steps during fracture detection.

(i) Preprocessing

X-ray images are frequently degraded by Poisson noise, which degrades the visual quality of the image and obscures important information required for accurate diagnosis. Sakata and Ogawa [4] given that including a denoising step in automatic fracture detection process are used by several researchers. For this purpose, a Wiener filter is recommended by Tsukahara [16]. The advantage of using this filter is that it is more effective at edge preservation but the result is often blurred, wavelets have been used by Niijima [15] where a decomposition step identifies noise dominant regions and different shrinkage thresholding techniques are used to reduce noise. Several proposals are for denoising which use wavelets Kaur [2]; Federico, [8]. They produce very effective with Gaussian noise but its performance slightly degrades when used with Poisson noise.

To solve this problem, Luisier [1], proposed a fast interscale wavelet denoising method for Poisson-corrupted images. This model is referred to as 'PURESHRINK', which used in Haar wavelet transformation with soft thresholding to reduce Poisson noise. This method showed improved noise removal result but in some cases introduced 'staircase' artifacts. This can be enhanced by replacing haar with a decimated bi orthogonal Haar (Bi-Haar) transform in Zhang [7] and then use Independent Component Analysis (ICA) in Marusic [11] to remove dependencies between the data streams associated with each wavelet decomposition.

Use of anisotropic diffusion for denoising image has recently received a great deal of attention because of its impressive performance in preserving edge sharpness and suppressing noise in Tsukahara [16]. They work well with both Gaussian and Poisson noise. However, while considering x-ray images, consideration of edges and local details between heterogeneous portions can provide much enhanced performance. This work considers this by developing an edge enhanced adaptive anisotropic diffusion filter.

(ii) Segmentation

The solutions proposed for bone image segmentation can be categorized into two main groups, namely, gray level feature-based methods and texture feature-based methods in Sharma [3]. Gray level feature - based methods analyze the gray level or color features of an image to segment an image. Histogram-based methods, Edge-based methods, region-based methods all belong to this category. Textural features of an image are considered important from both segmentation and classification point of view. The aim here is to divide images into regions with similar texture properties. All these methods use random patterns/textures but work well for segmenting medical images. Apart from these, model based segmentation and Atlas based segmentation techniques have also been proposed. Model based methods involve active shape and appearance model during training. They work by determining and analyzing the statistical influence between the model and image during segmentation. These methods often require manual interaction and exhibits poor convergence to concave boundaries.

All these methods work on a common objective, that is, to provide solution for efficient automatic medical image segmentation. Recently the use of morphological transformation and wavelet transformation are gaining more attention for segmenting medical images. In wavelet based techniques the result of wavelet transform is used as features during segmentation. Morphological transformation combines geometrical features and edge features to segment the image. Use of morphological-based segmentation helps to avoid the problem of over and under segmentation as in Najman [18]. The advantage of using wavelet transform is that it provides a precise and unifying framework for the analysis and characterization of an image at different scales. This advantage can be fully exploited for efficient segmentation of X-Ray images. Further, the use of wavelets increases the speed of the segmentation and reduces the number of computations performed by selecting only the prominent pixels within an image.

(iii) Fracture Detection

The fracture detection techniques proposed can be loosely categorized into classification-based and transform-based. The first published work on the detection of fractures in x-ray images is that of Tian [14]. The method detected femur fractures by computing the angle between the neck axis and shaft axis. Subsequently, Gabor, MRSAR, and gradient intensity were used for fracture detection and a simple voting scheme was used to combine the individual classifiers that work on single features as in Lim [13]; Chen [12]. Since the individual classifiers tend to complement each other, the combined method improves both the accuracy and sensitivity significantly. A similar approach of combining classifiers was also proposed by Lim [10] who combined probabilistic combination methods for segmentation.

Hough transforms have long been used as computationally efficient methods for detecting particular shapes in images. The use of hough transformation in identifying fractures have also been proved advantages. The Hough transform as in Duda [19] is a feature extraction technique in image analysis, computer vision, and digital image processing. It is concerned with the identification of straight lines, position of arbitrary shapes, most circles or ellipses. The important case of Hough transform is the linear transform for detecting straight lines. Compared with other algorithms that detect straight lines, Hough transform can be used to find and link segments in an image. A line in the image space is mapped to a point in the parameter space. Similarly, each pixel of the image space is transformed to a parameterized curve of the parameter space. Each transformed point in the parameter space is considered as a candidate for being a line and accumulated in the corresponding cell of an accumulator. Finally, a cell with a local maximum of scores is selected, and its parameter coordinates are used to represent a line segment in the image space. The main advantage of the Hough transform technique is that it is tolerant of gaps in feature boundary description and is relatively unaffected by image noise.

However, using Hough transform introduces computation complexity, which in turn slows the feature extraction and fracture detection process.

III. Methodology

The methodology consists of the following steps during the identification of fractures in Femur bone from x ray images.

(i) Preprocessing – It includes steps that enhance the digital x- ray input image in a way that its result improves the fracture detection process.

(ii) Segmentation – It includes two steps. Firstly separate the bone structure from the x-ray image and the secondly, identifies the shaft region from the segmented bone structure.

(iii) Fracture Detection – A classifier combination method (CCM) is used, where results from different classifiers are combined to detect fractures.

a) Preprocessing

This phase consists of procedures that enhance the features of an input digital x-ray image so that the output image improves the performance of the subsequent stages of the proposed system. This stage proposes a new technique, called, SACEN (Simultaneous Automatic Contrast adjustment, Edge Enhancement and Noise Removal) algorithm, which can adjust contrast, enhance edges and remove noise from an x-ray image simultaneously. The SACEN has the following steps:

1. Read the input image and divide an image into 16 x 16 blocks and repeat steps 3 to 5 for each block
2. Use a classification process to separate edge and non-edge region
3. For edge region, apply Contrast limited Adaptive Histogram Equalization (CLAHE) algorithm (Pisano *et al.*,[17]) to enhance the edges
4. For non-edge region
   a. Perform Contrast-Based Segmentation (CBS) to separate the block into regions namely, clear and Blur regions.
   b. Use Wavelet-based Anisotropic Diffusion (WEAD) as in Rajan [9] method to remove noise from blurred regions
5. Reconstruct the image with enhanced blocks

b) Segmentation

This phase of the study has two algorithms. The first algorithm segments the bone image from the x-ray image and the second algorithm describes a technique that identifies the shaft region of a bone image. The two algorithms are independent and are used in different places during fracture detection.

The algorithm segments bone region from background uses a combination of wavelets (1-level Haar) and morphological transformation (dilation, erosion, opening and closing). Usage of mathematical operations for segmentation eliminates small objects and enhances the connectivity of objects, thus generating an image with areas that have elements with only connected regions. The resultant image after segmentation is referred to as "Bone Region Image (BRI)' in this paper. The BRI has shaft region along with fleshy region. An active-contour based segmentation is first performed to remove the fleshy region, followed by the application of shaft segmentation algorithm. The algorithm used for this purpose is proposed by Donnelley [5]. This image is termed as 'shaft Region Image (SRI)' in this paper.

The usage of these two segmentation techniques narrows down the search region during fracture detection and thus aids in accurate detection of fractures in a time efficient manner.

c) Fracture Detection

The final stage of the proposed system is the actual detection of fracture. It has been proved that the performance of fracture detectors can be improved both in terms of accuracy and sensitivity by combining classifiers as in Lim [10]; Chen [12]. Motivated by this fact, the present work uses a novel classifier-combination algorithm to identify and detect fractures from DRD. This paper uses the texture features for fracture detection. The texture features used are GLCM Mean, GLCM Variance, Energy, Entropy, Homogeneity, Gabor Orientation, Markov Random Field (MRF) and Intensity Gradient Direction (IGD).

A combination based classifier for fracture detection is proposed in this paper for fracture detection. All the selected classifiers are modeled to work as a binary classifier, thus reporting whether a fracture is detected or not detected. If detected, the position of the fracture is highlighted. Three classifiers are used, namely, Support Vector Machine (SVM) classifier, Feed Forward Back Propagation Neural Networks (BPNN) classifier, and a Naïve Bayes (NB) classifier. The combination of classifiers builds from base classifiers are

1. TBPNN Model (Texture features with BPNN)
2. TSVM Model (Texture features with SVM)
3. TNB Model (Texture features with NB)
4. Combined Classifier model(CCM) with texture features having combination of BPNN, SVM and NB

The basic combination rule used is that if more than 2 classifiers report fracture then the image is said to have fracture. A modified Hough transform with gradient analysis is used to identify the location of fracture need to be improved. The work flow is as in fig. 3.1

Fig3. 1: work flow

IV. Experimental Results

Several experiments were conducted, to analyze the performance of the proposed classifiers, using 300 test images. Out of these images, 143 were images with fractures and rest were normal x-ray images. One hundred and forty three fractured x-ray images and 153 from normal x-ray images were used during training. Sample images form database are as n fig (4.1). It shows Fr1- Fr3 was images with fracture, while N1-N3 was normal images.

Figure 4.1 sample images from the dataset.

The performance of the proposed system is analyzed using performance metric fracture detection rate. The experiments are carried out using MATLAB 2013a and all the experiments were conducted on Intel(R) Core(TM)2 Duo CPU E7500 @ 2.93 GHz machine with 2GB RAM.

(i) Detection Rate

Detection rate is the number of correctly detected fractures to the total number of fractured/normal images and the results from the experiments is shown in Table 4.1.

Table 4.1: Detection Rate

Bone type	TBPNN	TSVM	TNB	CCM
Fractured	84.20	86.10	87.00	90.20
Non-Fractured	92.10	95.12	96.10	97.40

The classification accuracy shows correctly identified images from the total number of fractured and normal images as shown in Table 4.2

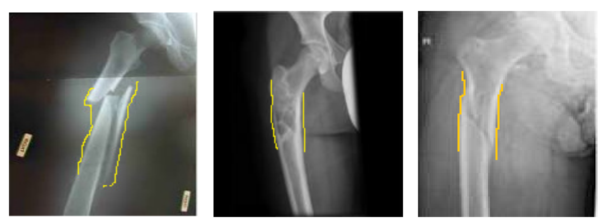
Table 4.2: Detection Rate and classification accuracy

Results/ classifiers	TBPPN (Bayesian classifier)	TSVM (Probabilistic SVM classifier)	TNB Naïve bayes classifier)	CCM (Combined Classifier Model)
Fracture Detection rate	84.20	86.10	87.00	90.20
Classification Accuracy	93.50	92.60	95.40	97.10

From the tables, it is evident that the proposed combined classifier model (CCM) that combines three classifiers BPNN, SVM and NB produce better detection results, 90.20% than single classifiers.

(ii) Results

Fig. 4.2 displays the results of the proposed fracture detection system. Figures ---a, b and c shows correctly identified fractures. It is evident from the displayed results that the performance of the proposed system is greatly improved and can identify more than one fracture (if present) in the image.



a b c

Figure 4.2: Results

Several experiments were conducted to analyze the performance of the proposed fracture detection systems based on texture features and classifiers with a common aim of finding the best combination of features and best fusion of classifiers to identify fractures in x-ray bone images. Experimental results showed that the proposed combination of techniques showed improved results in terms of accuracy in detecting fractures. The two-step segmentation used to identify the shaft region significantly improves the speed of detection.

V. Conclusion

Bone fractures are a common affliction and even in most developed countries the number of fractures associated with age-related bone loss and accidental fractures are increasing rapidly. From both orthopedic and radiologic point of view, the fully automatic detection and classification of fractures in long-bones is an important but difficult problem. The present work focuses on providing a solution to the automatic discovery of bone fracture in leg long bones. For this purpose several image processing techniques (for preprocessing, segmentation and feature extraction) were used. The extracted features were then given as input to a combination-based classification system to detect the presence / absence of fracture(s) in an image. Several experiments were conducted to analyze the performance of the proposed combination classifier-based detection system with respect to its efficiency in terms of correct detection of the algorithm. The performance was compared with its traditional single classification system. Experimental results proved that the proposed combination of techniques showed improved results in terms of accuracy in detecting fractures. In future, other features like shape are to be considered and its affect on detection rate is to be analyzed. Its applicability to other long bones, like hand, back bone can also be analyzed.

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