

An Effective and Reliable Computer Automated Technique for Bone Fracture Detection

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Abstract

INTRODUCTION: In the year 1895 the X-ray images were discovered. Since then the medical imaging has got advanced tremendously. Anyhow the methods of interpretation have started progressing only by the evolution of Computer aided Diagnosis(CAD).

OBJECTIVES: To develop a Computer Aided Diagnosis (CAD) system to detect the bone fracture which helps the radiologists (or) the Orthopaedics by interpreting the medical images in short duration.

METHODS: In this paper, an effective automated bone fracture detection is proposed using enhanced Haar Wavelet Transform, Scale-Invariant Feature Transform (SIFT) and back propagation neural network. The former two techniques are used for feature extraction and the latter one is used for classification of fracture images. Simultaneously, the usage of enhanced Haar Wavelet Transforms and SIFT are phenomenally improves the quality of the X-ray image. Further in this work, k-means clustering based 'Bag of Words' methods are used to extract enhanced features extracted from SIFT. The classification phase of this proposed technique uses the classical back propagation neural network that contains 1024 neurons in 3-layers.

RESULTS: The experimental validation of this proposed scheme performed using nearly 300 different bone fractures x-ray images confirmed a better classification rate of 93.4%.

CONCLUSIONS: The experimental results of the proposed computer aided technique are proven to be better than the detection technique facilitated with the traditional SIFT technique.

Received on 16 November 2019; accepted on 19 December 2019; published on 03 January 2019

Keywords: Enhanced Haar Wavelet Transform, Scale-Invariant Feature Transform (SIFT), Binary Encoding Scheme, Backpropagation Neural Network

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doi:10.4108/XX.X.X.XX

1. Introduction

To provide an accurate diagnosis, a medical imaging examination depends on a high quality image, with an accurate interpretation by a skilled reader. Recently, the advancement in the imaging technology leads to the evolution of Computer Aided Diagnosis(CAD). As a result, the extremely high-quality images are produced for examination. For the radiologists (or)

the Orthopaedics, the automatic diagnosis by the CAD to take the second opinion while concluding the decision on a particular disease. This assist in image interpretation by improving the accuracy and consistency of radiological diagnosis and also by reducing the image reading time. From the recent past, image processing techniques are highly suitable and applicable in the medical domain [1].

However, computationally identifying fractures from X-ray images is quite a challenging task, since they have taken in low resolution conditions with added noise. In order to alliviate these problems this paper proposes a an intelligent fracture detection approach

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for effective determination of bone fractures using enhanced Haar Wavelet Transform and Scale-Invariant Feature Transform (SIFT) for feature extraction from original images. Further, the k-means clustering based 'Bag of Words' methods is used for enhanced feature extraction from the SIFT features. Finally Multi Layer Perceptron(MLP) is used for training and improving the rate of classification accuracy in detecting bone fractures. Further, wavelet transforms are considered to be the most optimal due to its outcome of minimized image size that facilitate the utilization of storage in an optimal manner [2]. Furthermore, wavelet transform-based image processing schemes are proven to be vital in achieving optimal, more accurate results and to enhance the learning ability of the artificial intelligence tools like that of the backpropagation neural schemes [3]. Enhanced Haar Wavelet is considered to be an optimal feature extraction scheme since it is reliable in processing the multiple number of features for learning in the subsequent processes[4-6]. The performance of the proposed intelligent fracture detection approach is also analyzed using classification accuracy, false positive and the number of connections used in MLP implementation.

The paper is organized as follows: In Section 2 related work done in this area is described, Section 3 explains the various stages involved in the development of the proposed system, The experimental results are discussed in Section 4, and Section 5 concludes the paper.

2. The three golden rules

A Fracture-detection scheme-based on scale invariant feature transform algorithm was proposed for the purpose of the potential feature extraction process [1]. This bone fracture detection scheme used the statistic methods to identify the image orientation intensities in gradient descendent directions to locate the cracks. This scale invariant feature transform method used the image intensities for the objective of accumulating image structures for each point of interest. The invariant feature extractor inherited the match associated interests derived from various bone images. In specific, this SIFT-based fracture detection is an attempt to detect and represent local features from the images. A digital geometry-based automated fracture detection scheme was proposed for tracing the bone contour [2]. This fracture detection approach utilized the merits of concavity index for potential identification of fracture locations. It also included relaxed digital straight line for the process of restoring false contour discontinuities that may be introduced through contouring error or segmentation. It was considered to be significant in eliminating the limitations of the existing fracture detection schemes that were attributed based

on texture investigations. Intensity Invariant image phase measures-based bone fracture detection method was proposed for effective localization of cracks in the bone [3]. This Invariant image phase measures-based bone fracture detection method used the method of affine morphological features. A non-linear anisotropic diffusion-based bone fracture detection scheme was proposed for extracting potential information about boundary locations [4]. This method also identified the fractures of the bone based on enhanced Hough Transform by including definite parameters that contribute towards best approximation. An automated fracture detection scheme using a hierarchical algorithm was proposed for the purpose of boundary tracing and adaptive windowing [5]. This hierarchical algorithm was determined to be effective in extracting anatomical information through the enforcement of registered active shape model for accurate bone fracture detection. Then, a deep learning method for fracture detection was propounded for achieving maximum accuracy [6]. This deep learning approach used multiple numbers of classifiers for precise identification of bone boundaries. A Rotational Haar Wavelet Transform- based fracture detection was proposed for characterizing the assemblies available in two dimensional images used [7]. Rotational Haar Wavelet Transform-based fracture detection was identified to be significant in precision, recall and minimized false positive rate compared to recent automated fracture detection schemes. In addition, an edge detection approach for bone fracture detection was proposed for superior identification of cracks [8]. This edge detection scheme was propounded for accurate boundary detection with maximum number of morphological factors that could be feasibly derived from the images used for investigation. This edge detection scheme is potent in classification accuracy and reduced false positive rate compared to most of the automated fracture detection schemes.

3. Proposed Method

An intelligent bone fracture classification is proposed with three phases such as (1) preprocessing, (2) classification and (3) optimization. In the first phase of bone fracture image preprocessing, enhanced Haar Wavelet Transform and Scale-Invariant Feature Transform (SIFT) are used for potential feature extraction. Here, Enhanced Haar Wavelet Transform and Scale-Invariant Feature Transform (SIFT) techniques are incorporated as the feature extractor since they are essential for improving the image quality such that appropriate fracture portion of the bone can be extracted for feature extraction. Then, the extracted features are introduced as input to the back propagation neural network for classification phase. Back propagation neural network is generally used for achieving

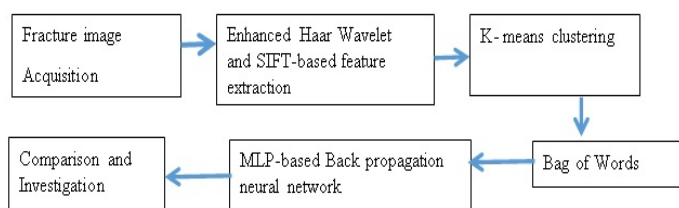


Figure 1. Block diagram of the proposed intelligent fracture detection Scheme

a better classification rate such that fractures of the bone can be detected with more accuracy. The schematic diagram of the work of the proposed fracture detection scheme is portrayed in Figure 1.

3.1. Enhanced Haar Wavelet Transform and SIFT-based feature extraction

Traditionally, transformations of images are necessarily used in the process of image filtering and image filtering applications and wavelets are potential in the activity of processing image, compression and denoising [13]. In this intelligent approach, Enhanced Haar Wavelet transformation is used as it is determined to be the optimal method of discrete medical image processing and transformations [14]. The most recent research work presented in [15] motivates the option of Enhanced Haar Wavelet transformation since they have been proven to produce an optimal rate of compression during its incorporation. In this paper, Enhanced Haar Wavelet transformation is applied for enhancing the features of bone fractures. During the application of Enhanced Haar Wavelet transformation, the original input image is transformed into gray scale for reducing the CPU time of execution. This also eliminates excess amount of data existing within the image during the process of image filtering. In addition, smoothing is applied for blurring the noise existing in the feature extracted image for future classification process. Further, enhanced Haar Wavelet transformations are independent of Fourier and thus the discontinuities in the data of the image can be optimal resolved with its implementation.

In SIFT-based feature extraction and matching, each and every feature point is portrayed as a 128-dimensional vector. If suppose, $N_{FP(1)}$ and $N_{FP(2)}$ be the total count of features extracted from the features that are obtained by employing enhanced haar wavelet transform over image pair then each of the matrix descriptor can be represented using $128 * N_{FP(1)}$ and $128 * N_{FP(2)}$ dimensions respectively. Further, the Euclidean distance is computed between extracted feature points of images and they are stored in ascending order based on distance. The first shortest

distance and second shortest Euclidean distance is identified, and are divided to check the ratio between them is less than the threshold (0.8) assigned for matching. In this threshold value is fixed based on the trail and error. Since only the orientation possibility of 128 dimension vector is considered for future less computational efforts and better storage utilization. This method also utilizes information that available local for optimizing the threshold. This method uses the scheme of matching point clusters for mapping the related local area points of one image over the local area points of another image. Furthermore, the method of inhomogeneous histogram approach is utilized for enhancing the robustness in the k-means clustering process.

3.2. Bag-of-words

The 'Bag-of-words' model is a simplifying representation in natural language processing and information retrieval. In this model, a sentence or a document is represented as the bag of its words, disregarding its grammar and even word order but keep its multiplicity. In image processing area, the 'BoW' model can be applied to image classification, by treating image features as 'words'. A 'bag-of-words' is a vector of occurrence counts of a vocabulary of local image features. Based on SIFT features as discussed earlier, the main process of 'Bag-of-words' model can be described into 4 steps:

- SIFT feature extraction of images from different class: for example, an image of normal x-ray and an x-ray image with fractured case have been taken and extracted SIFT features from the two images, as shown in Figure 2. After this step, each image is a collection of vectors of the same dimension (128 dimensions for SIFT), where the order of different vectors is not important;
- After feature extraction, assigning those extracted SIFT feature descriptors from those two images to a set of predetermined clusters. The applied approach is k-means clustering algorithm. The centroid of each cluster stands for a 'vocabulary'. It is shown in figure 2. The number of clusters can be regarded as the length of the 'word';
- For each image, mapping extracted SIFT feature descriptors to those created 'vocabulary'. Specifically, for one SIFT feature descriptor, calculate the euclidean distance between itself and each 'vocabulary' and put into the cluster with the least distance. Each image can be represented as a histogram of 'vocabulary'. It is shown in Figure 3. What should be mentioned here that each histogram should be normalized.

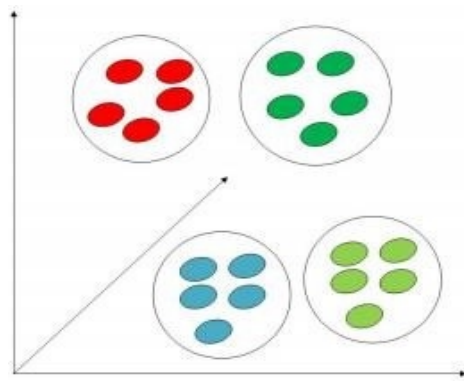


Figure 2. The creation of 'Vocabularies' in 'BoW' model.

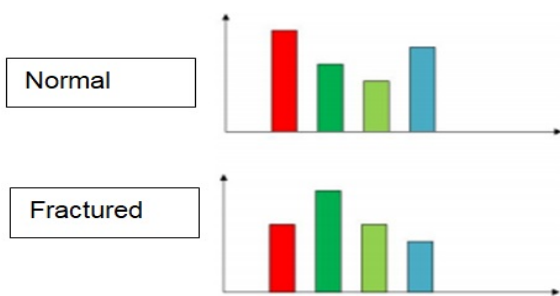


Figure 3. 'Word' creation of each image

- Applying a multi-class classifier, treating the histogram of each image as the feature vector of itself. Depending on these feature vectors, train classifiers for identification.

3.3. SIFT features to 'word'

In 'Bag-of-words' method, each 'word' is created based on SIFT Features extracted from sample image from each class. Here the 'words' that is created represents the particular object, these 'words' are used to create classifiers for object identification. The generation of one 'word' from one sample image is shown in Figure 4: So in the process, SIFT features from all sample

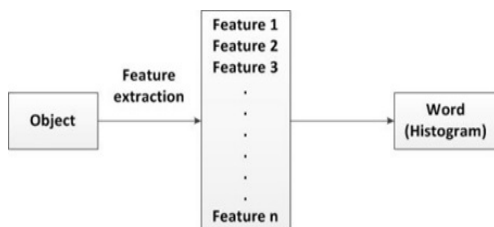


Figure 4. The process of 'word' generation in 'Bag-of-Words'

images in the train set are extracted and these feature descriptors from different classes of object are put

together. After K-means clustering, those K centroids of the K cluster are regarded as K 'vocabularies'. 'Object_i' in Figure 5 stands for one sample image in the train set. And for each class, there are several samples existed. For one sample image in the train set, each feature

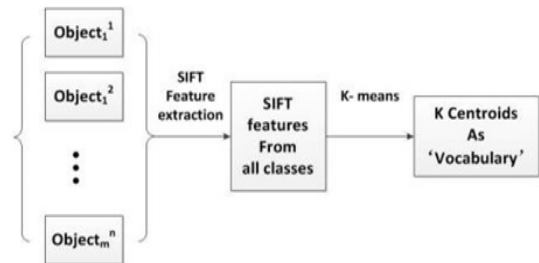


Figure 5. The process about creating vocabularies. Objects are sample images from different classes in the train set. And in each class, there may contain several samples.

extracted from this image will be put into the "nearest" cluster. It is based on its Euclidean distance to each "vocabulary". It will be put into the cluster based on its distance to that cluster's centroid is minimum. It can be seen as the similarity between one feature and the 'vocabulary'. In each class of object, there are several samples. So for each class there are several 'words', which can be regarded as feature vectors of this class. The specific process is shown in Figure 6.

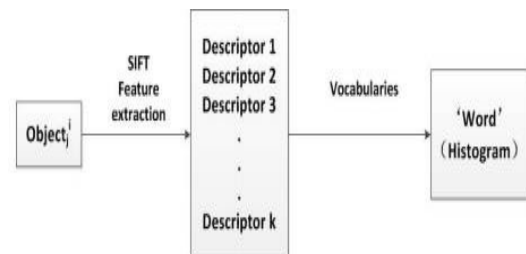


Figure 6. The process about creating a 'word' for one sample image in the train set.

3.4. Multiple Layer Perceptron-based bone fracture detection process

Finally, this bone fracture detection scheme incorporates the Multiple Layer Perceptron-based ANN that comprises of 1024 input neurons. Then the output neurons are used for classifying the intensities of the bone images into bone with fracture and bone without fracture based on the method of binary coding. Thus the bones with fractures are assigned to the vector [1 0] and in contrast, the bones without fractures are set

Table 1. Proposed SIFT+BoW method-implementation parameters

Parameter used	Assigned values
Nodes in the input layer	1024
Nodes in the output layer	2
Training rate	0.004
Minimum error	0.0023
Number of iterations	3500
Training time	28 seconds
Rate of momentum	0.5

to the vector [0 1]. Further, the sigmoid function is responsible for activating neurons in the output and hidden layers of the MLP. Furthermore, an MLP network which belongs to the supervised back propagation scheme of training is used for this automated bone fracture detection process. In this phase, the process of training and testing are accomplished with 70 images as the training set images and 230 images as the testing set images. In this supervised learning process, the random weights are set between the values ranging between -0.4 and 0.4 respectively. In this intelligent bone fracture detection process, the momentum rate and the learning rate are adaptively changed for facilitating the necessary least error rate in order to improve the process of training in an iterative manner. In addition, the error rate of 0.0023 is considered as the suitable value for determining better classification accuracy rate.

4. Results and discussions

The experiments of the proposed intelligent bone fracture detection schemes are implemented using the MATLAB 2013a toolbox that is essential and suitable in the process of designing MLP for better classification and accuracy. The performance of the proposed bone fracture detection schemes is analyzed using validation error and classification accuracy. The implementation parameters with its associated values are presented in Table 1.

Figure 7 shows the graphical user interface (GUI) of the proposed system. The test x-ray image is selected as an input by the user and a result is displayed as fractured or non fractured, also an bounding box is plotted to locate the fracture region. Figures 8, 9 and 10 highlights the performance of the proposed SIFT+BoW method with the SIFT+SPATIAL CLUSTERING and SIFT+HAAR method evaluated based on classification accuracy, false positive rate and the number of connections used in MLP implementation. The classification accuracy of the proposed SIFT+BoW scheme is proved to be better by a significant margin of 12% and 15% compared

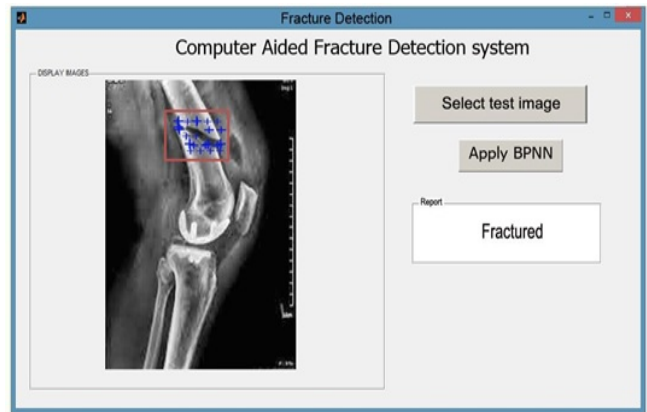


Figure 7. GUI of the proposed fracture detection system

to the SIFT+SPATIAL CLUSTERING and SIFT+HAAR methods used for analysis. In contrast, the false positive

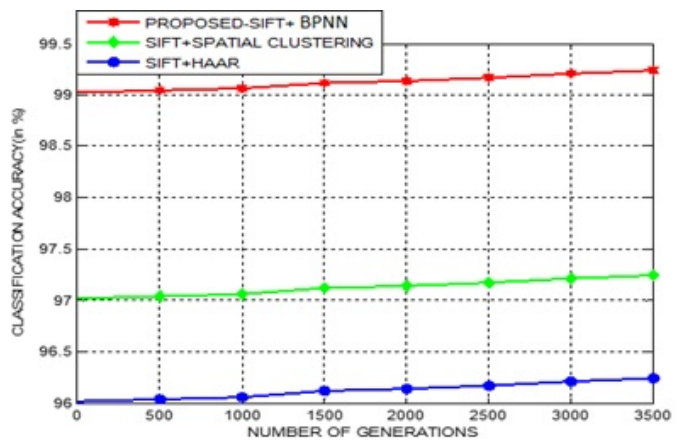


Figure 8. Classification accuracy of the proposed scheme

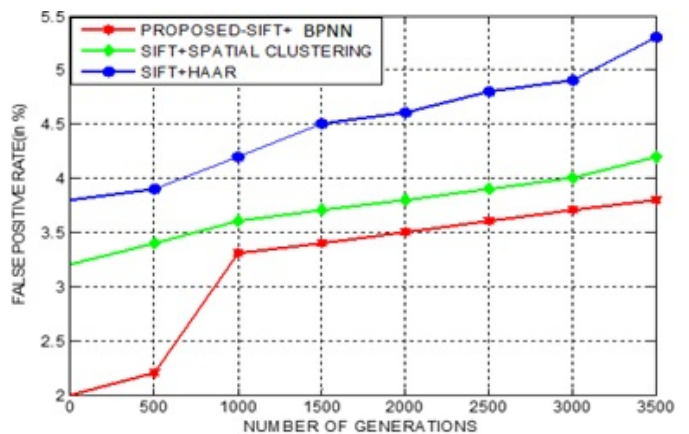


Figure 9. False positive rate of the proposed scheme

rate of the proposed SIFT+BoW scheme is proved to be better by decreasing the significant margin of 10% and 13% compared to the SIFT+SPATIAL CLUSTERING and SIFT+HAAR methods used for analysis.

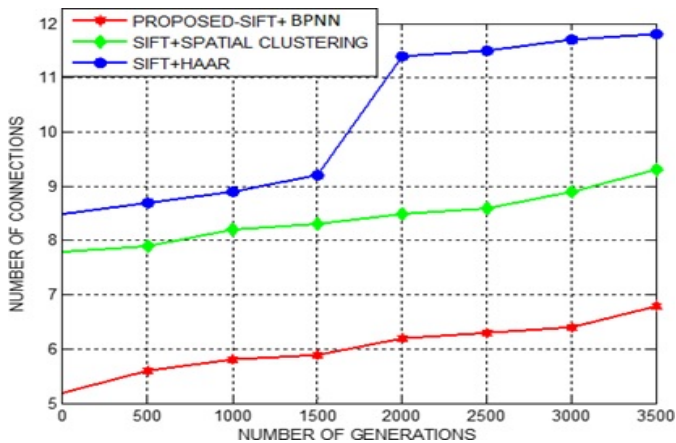


Figure 10. Number of connections utilized in the proposed scheme

5. Conclusion

An effective computer aided technique was presented based on the merits of Haar Wavelet Transform, k-means clustering, 'Bag of Words' and SIFT for feature extraction and classification using the back propagation neural network. The contributed scheme is proving to be improvised in classification since it uses 'Bag of Words' for efficient feature extraction and classification. The proposed scheme has the potential of preprocessing and resizing the fracture and non- fracture bone x-ray images for effective dissemination. The experiments are conducted using 300 X-ray images collected from the Sona Scans Private Limited, Puducherry. The experimental results of the proposed computer aided technique are proven to be better than the detection technique facilitated with the traditional SIFT technique.

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