

Orientation detection of X-ray images using Harris Corner Detector & Speed Up Robust Features Algorithms

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Abstract: The field of medical imaging sciences has ever been growing over the past couple of decades in terms of its vast database, which may itself seem to be detrimental towards the radiologists and physicians because of the very reason that they may be unable to distinguish and interpret the images amongst the others. Thus, the need of the automated view classification, detection of orientation and the diagnosis of diseases is very much inevitable, which can be employable by means of the state-of-the-art decision making algorithms in the modern era of computational excellence. In this work, X-ray images of six different classes namely chest, skull, foot, palm, spine and neck with different position namely anterior view, lateral view and oblique view have been taken. The position of the X-ray images are automatically detected using speed up Robust Features and Harris corner detector algorithm, out of which SURF out performing Harris corner detector with an accuracy of 95.22%

Keywords: X-ray images, M3 filter, anterior-posterior view, lateral view, oblique view, Speed Up Robust Features (SURF), Harris corner detector.

1. INTRODUCTION

The X-ray images that are available in the vast database of the problem concerned have to be identified with regard to their orientation, i.e., unto their radiographic positions viz. lateral, oblique, anterior-posterior, posterior-anterior etc., which are all so classified based on the way the X-ray images are radio graphed with respect to the object and the film. Thus, the X-ray images that are presented in different orientations are needed to be standardized for better positioning, so as to accurately interpret for the correct diagnosis by the physician and radiologists. So, orientation plays a pivotal role in viewing the particular portions or areas to be examined, which cannot be done manually from a heap of images that are of late ever increasing in nature. Hence, it is quite inevitable that there needs to be suitable computational algorithms for detection of the orientation of the X-ray image. In order to lucidly retrieve the desired images conforming to its sense of anatomy from the variety of medical X ray-images, umpteen automated-techniques having been introduced from time to time by the researchers from across the globe, which will be a boon as against the tedious manual classification. Such an automated classification in this area of research, which will not only results in less time consumption, but also with the least expertise from the physicians and radiologists. Thus, the automated view classification of X-ray images is very effective in the field of medical image processing.

Keeping such objectives in view, an attempt has been made in this paper so as to detect the orientation of the X-ray images. An effort has been made to automatically search and classify the X-ray images in to six classes namely chest, spine, foot, palm, head and neck. Each class consists of 30 images with position namely anterior view,

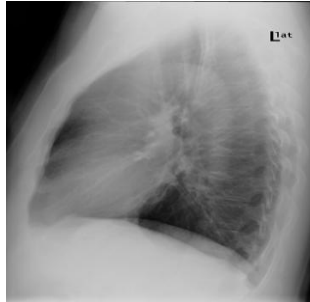
lateral view and oblique views are had been taken. When the X-rays passed through front to back of the patient, it is referred as anterior view, side of the patient is referred as lateral view and based on the angle is an oblique view, and three different position of the X-ray images are given in fig.[1]. In this work SURF and Harris corner method is applied for detecting the view of the X-ray images. The image dataset representing different ages, genders, views, positions and pathologists, wherein the classification techniques are very helpful in teaching , research, diagnostic, analysis and hence this method is proposed.



1(a) AP view



1(b) PA view



1(c) Lateral view

Fig.1 Views of X-ray images

2. PREVIOUS WORK

An extensive survey of the existing literatures has been made with a view to realize the on-going trends in the field of medical imaging for efficient retrieval of medical-images, which gives an insight into the issues and problems that are currently faced by the prevailing methodologies and by which their shortcomings can be addressed efficiently.

Literature survey is the most important step in software development process. Before building the system the above consideration are taken into account for developing the proposed system. Image processing and pattern recognition techniques are practically important to provide the required information in diagnosis and treatment for medical imaging. The progress in these techniques is reflected in the sophisticated software tools some of which are commercially available, and others may still be in research and development stage [1 &2]. The paper in [3] describes about M3 filter for pre-processing to reduce the undesired distortions and noise in the X-Ray images. The work in [4] investigates the effectiveness of two Mutual Information Feature Selector (MIFS) algorithm to select the textural features to describe the information for multispectral imagery classification. In paper[5] the local informative descriptors such as Scale Invariant Feature Transform (SIFT), Haar wavelets, and SURF are described. The paper in [6] gives the information about recently used algorithm for object detection or recognition[5&6]. The performance of two robust feature detection algorithms namely Speeded up Robust Features (SURF) and Scale Invariant Feature Transform (SIFT) is summarized in [7]. The description about key-point detection and key-point description are described in paper [8]. Classification of three basic cardiac views using morphological operations is proposed in [9], a distance based approach for cardiac view classification of echocardiogram using SURF features to handle various conditions and to achieve high accuracy. The detection of orientation of X-ray images by using Harris corner algorithm is presented in paper [10&11].

The paper in [12] proposes a modified Harris corner detector to solve the clustering problem and successfully identify the representative feature points of IR breast images. The work in [13] presents a flexible feature detectors using FPGA Based Implementation of Edge and Corner Detection in MRI Brain Tumour Image.

3. DATA SOURCE

This collection compiles anonymous radiographs, which have been arbitrarily selected from routines at the Department of Diagnostic Radiology, Aachen, and University of Technology (RWTH) Aachen, Germany and some of the X-ray images from Department of Radiology of the Raja Muthaiah Medical College and Hospital, Annamalai University.

4. PROPOSED WORK

The block diagram of the proposed system is shown in Fig. [2]. The X-ray images are given as input to the proposed system and it is pre-processed to enhance the image features for further processing, since the noise present in the images affects the feature extraction. The feature points are calculated in order to detect the orientation of the X-ray images.

In this work, three different views that are taken into account are AP, Lateral and Oblique for the view classification of the X-ray images. Out of these three views, in general the AP and Lateral views are considered for the four different classes of X-rays namely chest, skull, spine and neck, while the Oblique and AP views are considered for the images of the foot and palm since the side view of the palm and foot are not used for any prediction. The Orientation of the X-ray images are detected by using Harris corner detector and SURF algorithm.

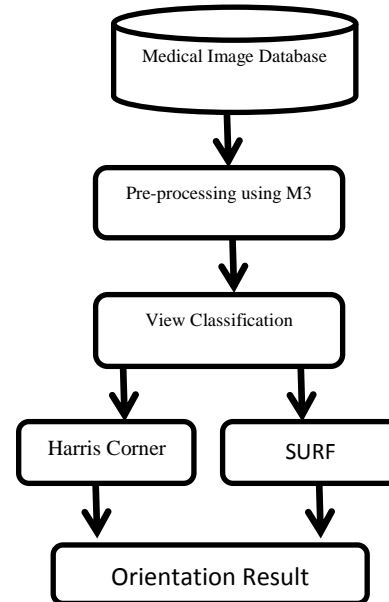


Fig.2 Block Diagram of the proposed work

4.1. Pre-processing

The view classification methodology initiates with the pre-processing, which is used to reduce the undesired distortions and noise in the X-Ray images. In this work, M3 filter is used for pre-processing. It is hybrid of mean and median filter. It replaces the central pixel by the maximum value of mean and median for each sub-image. It preserves the high frequency components in image and it is shown in fig.[3].

Original images

Pre-processed images

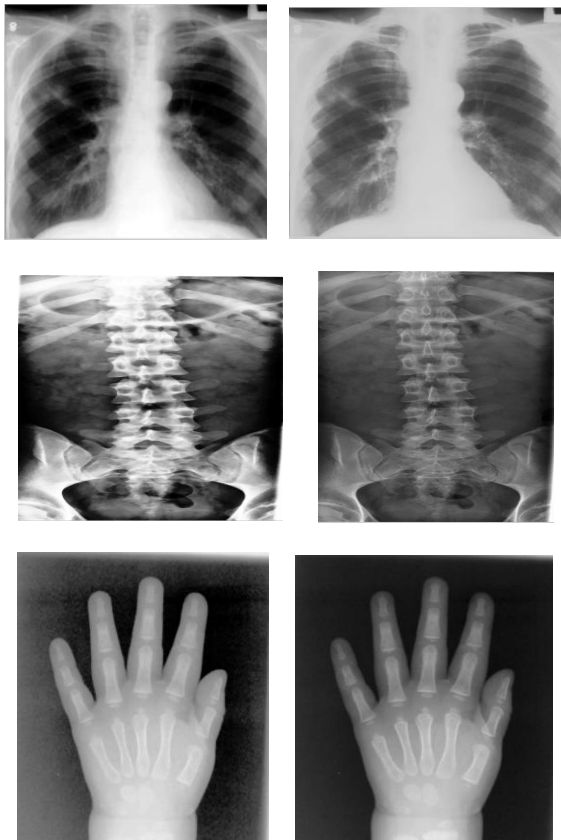


Fig.3 Pre-processed X-ray images of (a) Chest (b) Spine (c) Palm

4.2. Harris Corner Detector

In this work, the orientation detection is based on the feature points of the images using Harris corner detector. In order to obtain the best features of medical X-ray images for the recognition of the X-ray view, the detection of corners of the images is more important, which is facilitated by the algorithm of Harris corner detector. It aims at finding and joining points of the corner of the image over any direction without any limits on its angle.

Using the Harris corner detection, the rotation and transformation of various images are broadly distinguished from its 2 distinct variants pertaining to the X-ray images. Using this algorithm images are equally partitioned on its vertical directions by $(x/2, y)$. Feature points on both sides are compared with its threshold, the threshold is computed by using the following algorithm and it is represented in the figure[4]

1. Compute x and y derivatives of image

$$G_{\sigma}^x \quad G_{\sigma}^y \tag{1}$$

2. Compute products of derivatives at every pixel

$$I_x = G_{\sigma}^x * I \quad I_y = G_{\sigma}^y * I \tag{2}$$

3. Compute the sums of the products of derivatives at each pixel

$$S_{x_2} = G_{\sigma 1} * I_{x_2} \quad S_{y_2} = G_{\sigma 1} * I_{y_2} \quad S_{xy} = G_{\sigma 1} * I_{xy} \tag{3}$$

4. Define at each pixel (x, y) the matrix

$$H(x, y) = \begin{bmatrix} S_{x_2}(x, y) & S_{xy}(x, y) \\ S_{xy}(x, y) & S_{y_2}(x, y) \end{bmatrix} \tag{4}$$

5. Compute the response of the detector at each pixel

$$R = Det(H) - k(Trace(H))^2 \tag{5}$$

(k – Empirical constant, $k = 0.04-0.06$)

6. Threshold on value of R .

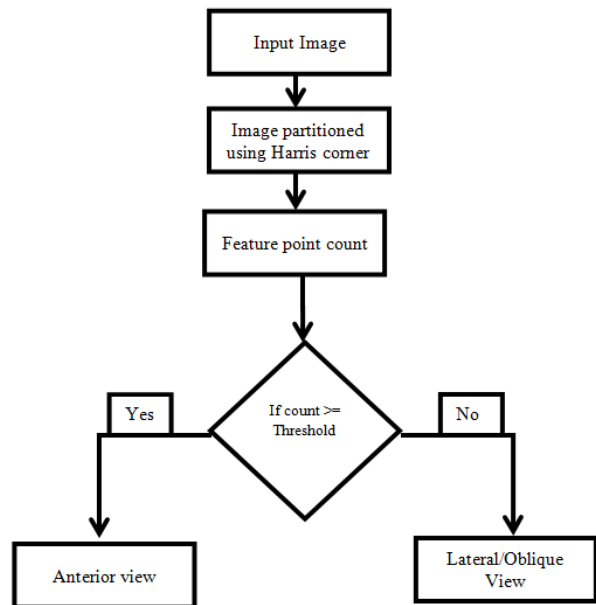
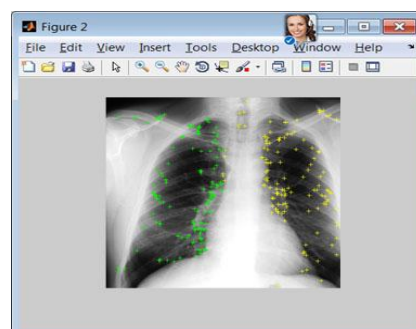
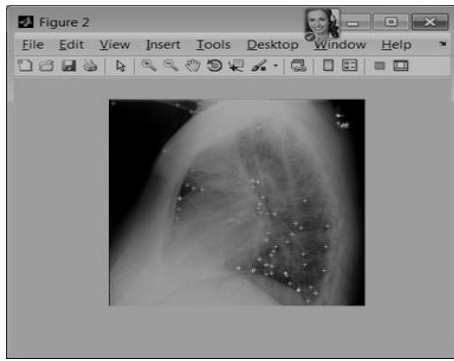


Fig.4 Block Diagram of Harris Corner Detector

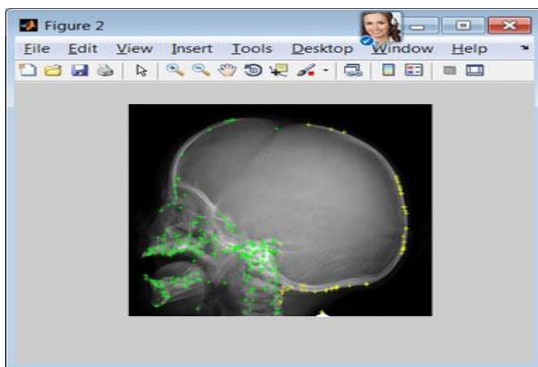
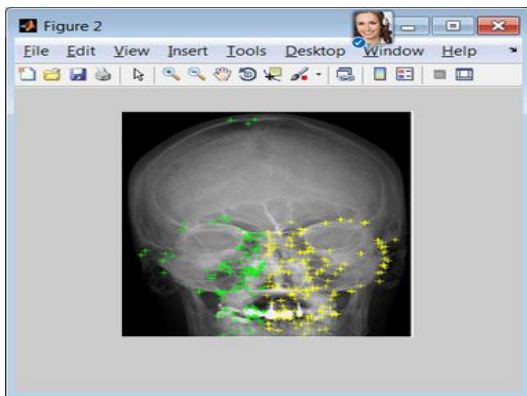
In this work, X-ray images are given as input, X and Y derivatives of the images have been calculated, then the product and sum of the product of the derivatives at each pixel have been calculated. Using this values its eigenvalue 'H' have been computed in order to compute the threshold 'R'. In this the green points represent the feature points detected by the right portion of the images and yellow points represent the left portion of the images and it is shown in Fig.[---]. The feature points on the right and left portion of the image is compared with threshold 'R', if it is greater than or equal, it is an anterior view else it is a lateral/Oblique view. The performance measures of the Harris corner detector for the orientation of the X-ray images are given in table[---].

The Fig.5 shows the view classification result of chest using Harris corner detector





The Fig.5 shows the view classification result of skull using Harris corner detector



4.3. SURF

Among the fast tracking algorithm, SURF seems to be mainly useful dealing with similar images to find out quickly some correspondences, it is effective in collecting more class-specific information, robust in dealing with view point changes. The block diagram of the SURF is given in fig. [6]

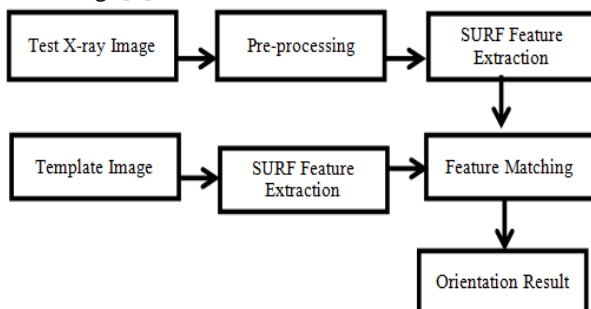


Fig.6 Block Diagram of SURF

SURF is becoming one of the most popular feature detectors and descriptor in computer vision field. It is able to generate scale-invariant and rotation-invariant interest points with descriptors. Evaluations show its superior performance in terms of repeatability, distinctiveness, and robustness.

SURF is selected as the interest point detector and descriptor for the following reasons: 1) X-ray image could be taken under the conditions of i) view variation, ii) Size variation and iii) Shape variation. Interest points with descriptors generated by SURF are invariant to variation and location changes. 2) Computational cost of SURF is small, which enable fast interest point localization and matching.

The SURF detector is based on the Hessian matrix for its good performance in computational cost and accuracy. For a point (x,y) in an image I, The Hessian matrix $H(X, \sigma)$ with is defined as

$$H(X, \sigma) = \begin{bmatrix} L_{xx^2}(x, y, \sigma) & L_{xy}(x, y, \sigma) \\ L_{xy}(x, y, \sigma) & L_{yy^2}(x, y, \sigma) \end{bmatrix} \quad (6)$$

Modern feature extractors select prominent features by first searching for pixels that demonstrate rapid changes in intensity values in both the horizontal and vertical directions. Such pixels yield high Harris corner detection scores and are referred to as keypoints. Keypoints are searched over a subspace of $\{x, y, \sigma\} \in \mathbb{R}^3$. The variable σ represents the Gaussian scale space at which the keypoint exists. In SURF, a descriptor vector of length 64 is constructed using a histogram of gradient orientations in the local neighbourhood around each keypoint.

Our method extracts salient features and descriptors from images using SURF. This extractor is preferred over SIFT due to its concise descriptor length. Whereas the standard SIFT implementation uses a descriptor consisting of 128 floating point values, SURF condenses this descriptor length to 64 floating point values.

The template consists of a sample image of each view to be classified from which the proposed system extracts knowledge. SURF first detects the interest points and generates corresponding descriptors. The pre-computed SURF descriptors of template images in each category are then used to match with the extracted descriptors of the input X-ray image, and it result is shown in Fig.[7]





Fig.7.1 View classification result for Palm using SURF

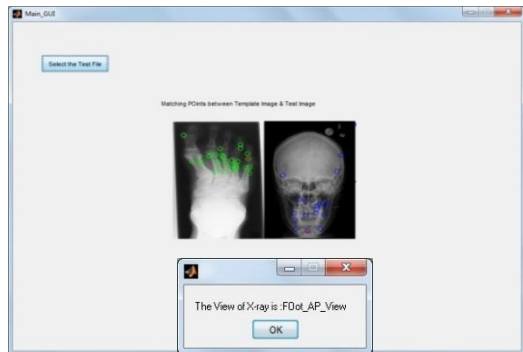


Fig.7.2 View classification result for Palm using SURF

5. PERFORMANCE MEASURE

Several performance metrics are measured such as sensitivity, specificity and accuracy. The performance of classification is measured from a confusion matrix which records correctly and incorrectly recognized examples for each class. The actual and predicted cases produced by classification system can be provided by a confusion matrix and it is given in table[----]. TP is number of true positives, FP is number of false positives, TN is number of true negatives and FN is number of false negatives. Accuracy measures the quality of the classification by finding the true and false positives and true and false negatives. Whereas sensitivity deals with only positive cases and specificity deals with only negative cases.

Measures	Formula
Sensitivity	$TP/(TP+FN)$
Specificity	$TN/(TN+FP)$
Accuracy	$(TP+TN)/(TP+FP+TN+FN)$

Metrics to measure the classification performance

6. EXPERIMENTAL RESULTS

In this work, six different classes of three different views are taken. The performances are measured by using

various performance measures such as sensitivity, specificity and accuracy by examining TN, TP, FN& FP. The performance measures for the Harris corner detector and SURF algorithm are shown in tables. [] & []. The Comparison between Harris corner detector and SURF algorithm for X-ray view classification are shown in table. [] and it is graphically represented in Fig.[], Fig.[]& Fig.[]. The overall accuracy obtained for Harris corner algorithm is 92.03% and the SURF algorithm is 95.22%.

Performance Measure of Harris Corner Detector

X-ray Image	Accuracy (%)	Sensitivity (%)	Specificity (%)
Chest	90	73.33	93.33
Foot	95.56	80	98.67
Palm	93.33	73.33	97.33
Neck	94.44	73.33	98.67
Skull	91.11	80	93.33
Spine	87.78	66.67	92
Overall Performance	92.03	74.44	95.55

TABLE 1 Performance Measure of Harris Corner Detector

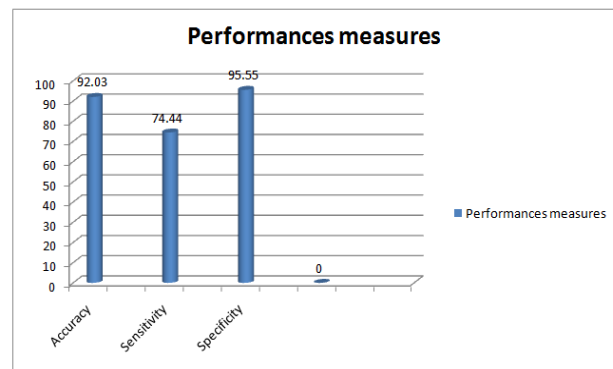


Fig 4: Graph showing Performance Measure of Harris Corner Detector

X-ray Image	Accuracy (%)	Sensitivity (%)	Specificity (%)
Chest	88.89	66.67	93.33
Foot	97.78	100	97.33
Palm	98.89	100	98.67
Neck	97.75	92.86	98.67
Skull	90.56	76.67	93.33
Spine	97.18	92.59	98.00
Overall Performance	95.22	88.13	96.55

TABLE 2 Performance Measure of SURF

Classifier	Accuracy (%)	Sensitivity (%)	Specificity (%)
Harris corner	92.03	74.44	95.55
SURF	95.22	88.13	96.55

TABLE 3 Comparison between Harris corner detector and SURF for X-ray view classification

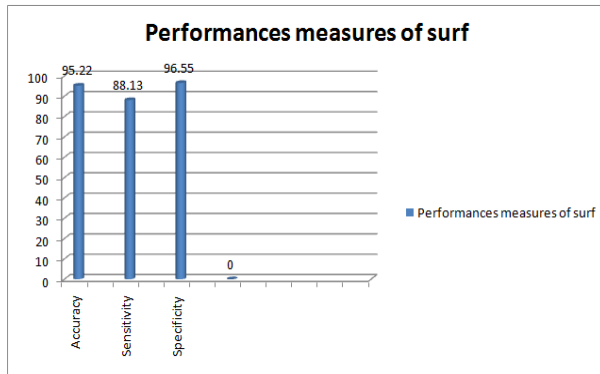


Fig 4: Graph showing Performance Measure of SURF

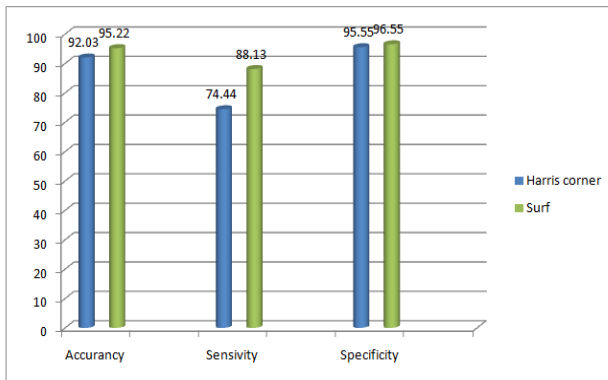


Fig 4: Graph showing Comparison between Harris corner detector and SURF for X-ray view classification

7. CONCLUSION

In this paper, the effort has been made to detect the orientation of X-ray images using Harris corner detector and SURF algorithm. Six different classes of X-ray images namely chest, spine, foot, palm, skull and neck with three different positions namely anterior view, lateral view and oblique views have been taken. For orientation detection using Harris corner detector the overall accuracy is 92.03%, specificity is 95.5% and sensitivity is 74.44% and for SURF algorithm the overall accuracy is 95.22%, specificity is 96.5% and sensitivity is 88.13%.

The results obtained for the three classes of X-ray images are promising as obtained through the Harris corner detector in terms of accuracy for chest, skull and spine, whereas for the foot, palm and neck, accuracy yielded by SURF algorithm has been proven better. It has been found from the performance measures that SURF yields a better result with overall accuracy than that of Harris corner detector algorithm.

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