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A Novel Approach for Medical Image Stitching Using Ant Colony Optimization

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Abstract
Image stitching is one of important technologies in medical image processing field. In digital radiography oversized images have to be assembled from multiple exposures as the flat panel of an X-ray system cannot cover all part of a body. The stitching of X-ray images is carried out by employing two basic steps: Registration and Blending. The classical registration methods such as SIFT and SURF search for all the pixels to get the best registration. These methods are slow and cannot perform well for high resolution X-ray images. Therefore a fast and accurate feature based technique using ant colony optimization is implemented in the present work. This technique not only saves time but also gives the accuracy to stitch the image. This technique is also used for finding the edges for land marking and features of different X-ray images. Correlation is found between landmarks to check the alignment between the images and RANSAC algorithm is used to eliminate the spurious feature points. Finally alpha- blending technique is used to stitch the images.
Keywords- Image stitching, feature extraction, image registration, image blending, Ant colony technique, Correlation, RANSAC

I. INTRODUCTION

Image stitching technology is an active area of research in the fields of image processing, photogrammetry, computer vision, and computer graphics (Zhan-long and Bao-long, 2008; Qidan and Ke, 2010). The process integrates two or more small images, which have some overlapped area, into a large-size image with a wild field of view. The goal is to create wide angle and high resolution panorama image from various image sources (Amrita and Neeru, 2013). Image stitching consists of Image matching, Image registration and Image blending.

Image matching is used to find the motion relationship between two images or several images and to determine the transformation between two images (Li, et al., 2008). Image registration is a process where two or more images are transformed in some geometrical manner so that the coordinates of the images become parallel and the images can be matched. The goal of registration is to find corresponding points between source and target images. Image stitching is the process the several images into a high resolution image and produces seamless results (Amrita and Neeru, 2013).

Image Stitching can be divided into two categories: Direct (Pixel) based method and Feature based method. Pixel based are classical methods which carry out pixel-wise comparison of the two images. This approach consists in to warp the images relative to each other and to look at how much the pixels agree. The disadvantage of pixel based techniques is that they have a limited range of convergence and is a very slow method. Therefore the method is not appropriate for real time image stitching applications which include large (high resolution) X-ray images. Feature based methods assume that feature correspondences between image pairs are available, and utilize these correspondences to find transforms which register the image pairs. Feature-based methods have higher accuracy, robust and can even be used for known object recognition from widely separated views (Xing and Miao, 2007). Therefore this method is selected to get faster stitching.

Medical image stitching is very important in medical diagnosis and treatment such as the measurement of scoliosis, lower limb deformity and extremity fractures correction and so on. The medical imaging technology involves the creation of images of a body part to diagnose the disease in the patient. The advent of digital technology has made the medical image processing easier and very fast. This computing technology helps physician diagnose diseases by real time and automated processing of medical images. In this paper, we have presented the stitching of 2D gray scale images like X-rays for imaging long parts of a human body e.g. legs, hands or spine etc. The proposed algorithm comprises Ant colony, Correlation, RANSAC and alpha- blending techniques, results of which is compared with traditional techniques, SIFT and SURF on the basis of performance matrices.

The organization of the paper is as follows: Section II Section III and IV cover the Methodology and Methods. Simulation result is discussed in Section V. Conclusion is given in Section VI and References in Section VII.

II. STITCHING ALGORITHM

The proposed has been implemented to stitch X- ray images of different body parts.

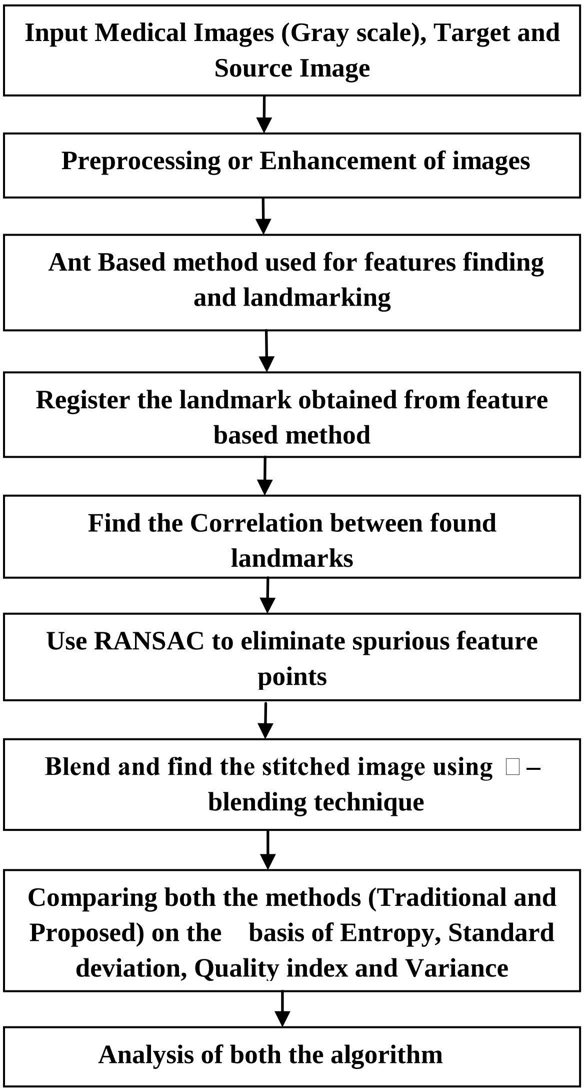


Figure 1: Proposed algorithm

III. METHODOLOGY

1. Enhancement of images

Image enhancement is the process of adjusting digital images so that the results are more suitable for display or further analysis. For example, we can remove noise or brighten an image, making it easier to identify key features. Two most important examples of image enhancement are: (i) increasing the contrast, and (ii) changing the brightness level of an image so that the image looks better. For the enhancement of X-ray images *Gaussian Filter* is used. In Gaussian filter, the image is convolved with the Gaussian function to reduce image noise. In digital image processing, a kernel window defines the effective neighborhood pixels. So, larger window size creates more blurred image. Fourier transform of a Gaussian function is another Gaussian, so Gaussian blur has the effect of reducing the high frequency components i.e. low pass filter.

$$L(x, y, \sigma) = G(x, y, \sigma) * I(x, y)$$

where * is a convolution operator in x, y.
Gaussian filter in 1-D has the form:

$$G(x) = \frac{1}{\sqrt{2\pi\sigma}} e^{-\frac{x^2}{2\sigma^2}}$$

where σ is standard deviation.

2. Ant colony optimization

Ant colony optimization (ACO) is a stochastic optimization technique attempting to achieve better solutions by referencing the feedback and heuristic information. It is an evolution simulation algorithm proposed by (Dorigo et al., 2006). This algorithm have been used for image processing problems, such as segmentation, feature extraction, image matching and texture classification.

Image feature selection based on ant colony optimization

According to (Blum and Langley, 1997) the feature selection algorithms consist of the following four components.

1. Starting point in the feature space

The search for feature subsets could start with

(i) No features (ii) All features (iii) Random subset of features.

In the first case, the search proceeds by adding features successively, while in the second case, features are successively removed. When starting with a random subset, features could be successively added/ removed or reproduced by a certain procedure.

2. Search procedure

The best subset of features can be found by evaluating all the possible subsets, which is known as exhaustive search. However, this becomes prohibitive as the number of features increases, where there are *2N* possible combinations for *N* features.

3. Evaluation function

It measure how good a specific subset can be in discriminating between classes, and can be divided into two main groups: filters and wrappers.

Filters operate independently of any learning algorithm, where undesirable features are filtered out of the data before learning begin. On the other hand, performance of classification algorithms is used to select features for wrapper methods (Deriche, 2009; Abd-Alsabour and Randall, 2010).

4. Criterion (or stopping the search)

Feature selection methods must decide when to stop searching through the space of feature subsets. Some of the methods ask the user to predefine the number of selected features. Other methods are based on the evaluation function, like whether addition/deletion of any feature does not produce a better subset, or an optimal subset according to some evaluation strategy is obtained.

In the current work we have proposed an ACO based feature selection algorithm, ACOFS to reduce the memory requirement and computational time. In this algorithm, the artificial ants traverse on a digraph with only 2*n* arcs. The algorithm adopts classifier performance and the number of the selected features as heuristic information, and selects the optimal feature subset in terms of the feature set size and classifier performance.

Ant colony optimization of feature selection (ACOFS)

In this algorithm a discrete search space represented by a diagraph by a digraph with only $O(n)$ arcs as shown in Figure 1, where the nodes represent features, and the arcs connecting two adjacent nodes indicating the choice of the next feature is used.

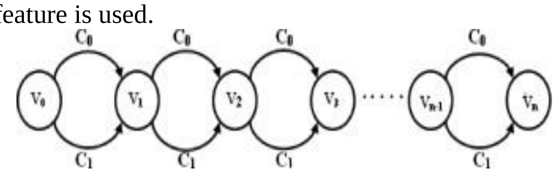


Figure 2: The diagraph

$f1, f2, \ldots, fn$, denote the n features, the i^{th} node v_i is used to represent feature f_i. An additional node v_o is placed at the beginning of the graph where each ant starts its search. The ants travel on the diagraph from v_o to v_1, and then to v_2 and so on. The ant terminates its tour and outputs this feature subset as it reaches the last node v_n. When an ant completes the search from v_o to v_n, the arcs on its trace form a solution. There are two arcs C_j^0 and C_j^1 and linking two adjacent nodes v_{j-1} and v_j. If an artificial ant at v_j selects arc C_j^0 (C_j^1), the jth feature is selected or not selected. On each arc C_j^i, virtual pheromone value τ_i^j is assigned as the feedback information to direct the ants searching on the graph. The pheromone matrix τ is initialized as $\tau_i^j = 1$ for all i=1,2…..,n and j=0,1.

The search for the optimal feature subset is the procedure of the ants traverse through the graph. Suppose an ant is currently at node v_{i-1} and has to choose one path connecting v_i to pass through. A probabilistic function of transition, denoting the probability of an ant at node v_{i-1} to choose the path C_i^j to reach v_i is designed by combining the heuristic desirability and pheromone density of the arc. The probability of an ant at node v_{i-1} to choose the arc C_i^j at time *t* is:

$$p_i^j(t) = \frac{\left[\tau_i^j\ (t)\right]^\alpha (\eta_i^j)^\beta}{[\tau_i^0(t)\ ]^\alpha (\eta_i^0)^\beta + [\tau_i^1(t)\ ]^\alpha (\eta_i^1)^\beta} \tag{1}$$

$(i = 1,2, \ldots\ldots n;\ j = 0,1\ )$

Here $\tau_i^j\ (t)$ is the pheromone on the arc C_i^j between nodes v_{i-1} and v_i at time *t*, which reflects the potential tend for ants to follow arc C_i^j *(j=0, 1).* η_i^j is the heuristic information reflecting the desirability of choosing arc C_i^j. α and β are two parameters that determine the relative importance of the pheromone and the heuristic information (Chen et al., 2011).

As it is clear from the equation 1, the transition probability used by ACO depends on pheromone intensity $\tau_i^j\ (t)$ and heuristic information η_i^j to effectively balance the influences of positive feedback information from previous high quality solutions and the desirability of the arc, proper values of the parameter α and β are selected. When $\alpha = 0$, no positive feedback information is used. Since the previous search experience is lost, the search degrades to a stochastic greedy search. When $\beta = 0$, the potential benefit of arcs is neglected, and it becomes an entirely random search. The heuristic information η_i^1 is the desirability of choosing the arc C_i^j between nodes v_{i-1} and v_i , which means the preference of ant to choose the feature f_i. Using F-score the value η_i^1 can be set, which is defined as follows:

$$\eta_i^1 = \frac{\sum_{k=1}^{m} (\bar{x}_i^k - \bar{x}_i)}{\sum_{k=i}^{m} \left(\frac{1}{N_i^k - 1} \sum_{j=1}^{N_i^k} (x_{ij}^k - \bar{x}^k)^2\right)} \tag{2}$$

$(i = 1, \ldots \ldots, n)$

m is the number of classes of the image set, n is the number of features, N_k^i is the number of samples of the feature f_i in class k where (k=1,2,…..,m, i=1,2,……n), X_{ij}^k is the j^{th} training sample for the feature f_i. of the images in the class k , (j=1,2,……. N_k^i), $\overline{X}_i$ is the mean value of the feature f_i of all the images , $\bar{x}_i^k$ is the mean of the feature f_i of the images in the class k.

In eq. 2 the numerator indicates the discrimination between the classes of the image set, and the denominator specifies the discrimination within each class. A larger η_i^1 value implies that the feature f_i has a greater discriminative ability.

For the value of η_i^0 , we simply set

$$\eta_1^0 = \frac{\xi}{n}\sum_{i=1}^{n}\eta_i^1$$

where ξ∈ (0, 1) is a constant.

Implementation of the Algorithm:

In an ACO based optimization method, the design of the pheromone update strategy, and the measurement of the quality of the solutions are critical.

1. Pheromone updating

In each iteration, the algorithm ACOFS updates the pheromone value on each arc according to the pheromone and heuristic information on the arc. If an ant chooses the arc C_i^j , pheromone on this arc is assigned more increment, and ants select arc C_i^j with higher probability in the next iteration. This forms a positive feedback of the pheromone system. In each iteration, the pheromone on each arc is updated according to formula (3):

$$(t+1) = \rho.\tau_i^j(t) + \Delta\tau_i^j(t) \qquad (3)$$

2. Fitness function

The solution quality (based on Ant's solution) is evaluated by classifying the training data sets using the selected features. The test accuracy measures the number of examples that are correctly classified as well as the number of features in the data set is also considered in the quality function. The subset with less features could get higher quality function value. The quality function *f*(*s*) of a solution *s* is defined as follows:

$$f(s) = \frac{N_{corr}}{1+\lambda N_{feat}}$$

where N_{corr} the number of examples that are correctly classified, N_{feat} is the number of features selected in *s*, λ is a constant to adjust the importance of the accuracy and the number of features selected. The scheme obtaining higher accuracy and with less features will get greater quality function value (Chen et al., 2011).

3. Correlation

Correlation is used to finds the similarity from the obtained landmarks. In image processing applications it is necessary to form a pixel-by-pixel comparison of two images of the same object field obtained from different sensors, or of two images of an object field taken from the same sensor at different times. Also it is necessary to spatially register the images and thereby correct for relative translational shifts, magnification differences, and rotational shifts, as well as geometrical and intensity distortions of each image. So thus the normalized coefficient of correlation is given by the formula (Pratt, 1974):

$$CC(i,j) = \sqrt{\frac{\sum_W (W-E(W))\,(I_{(i,j)}-E(I_{(i,j)}))}{\sqrt{\sum_W (W-E(W))^2}\,\sqrt{\sum_{I(i,j)}(I_{(i,j)}-E(I_{(i,j)}))^2}}}$$

This measure of similarity is computed for window pairs from the sensed and reference images and its maximum is searched. The window pairs for which the maximum is achieved are set as the corresponding ones. If the sub pixel accuracy of the registration is demanded, the interpolation of the CC measure values needs to be used. Although the CC based registration can exactly align mutually translated images only, it can also be successfully applied when slight rotation and scaling are present.

Fig 3. shows feature -based matching methods: registration of small template to the whole image using normalized cross-correlation (middle row) and phase correlation (bottom row). The maxima identify the matching positions. The template is of the same spectral band as the reference image and of different spectral band.

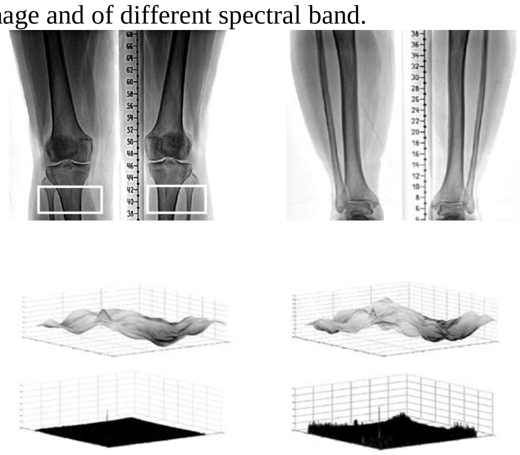


Figure 3: Channel Matching

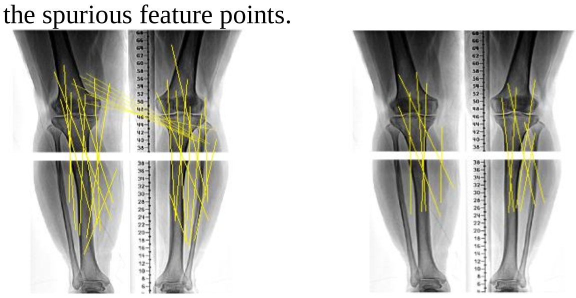
IV. RANSAC

The Random Sample Consensus algorithm (RANSAC) proposed by Fischler and Bolles (1981) as a method to estimate the parameters of a certain model starting from a set of data contaminated by large amount of outliers. A basic supposition is that the data consists of inliers i.e. data whose distribution can be explained by some set of model parameters, though may be subject to noise and outliers which are data that do not fit the model. The outliers can come e.g. from extreme values of the noise or from erroneous measurements or incorrect hypothesis about the interpretation of data. RANSAC also assumes that, given a set of inliers, there exists a procedure which can estimate the parameters of a model that optimally explains or fits this data.

2.1 The RANSAC algorithm

1. Select randomly the minimum number of points required to determine the model parameters.
2. Solve for the parameters of the model.
3. Determine how many points from the set of all points fit with a predefined tolerance.
4. If the fraction of the number of inliers over the total number points in the set exceeds a predefined threshold τ, re-estimate the model parameters using all the identified inliers and terminate.
5. Otherwise, repeat steps 1 through 4 (maximum of N times).

The following diagram depicts that a set contains both inliers (points which can be fitted in the model) and outliers (points which cannot be fitted). RANSAC produce a model which is only computed from the inliers therefore leading to elimination of the spurious feature points.



(a) (b)

Figure 4: (a) Before RANSAC (b) After RANSAC

An advantage of RANSAC is the ability to do robust estimation of the model parameters i.e., it can estimate the parameters with a high degree of accuracy even when a significant number of outliers are present in the data set.

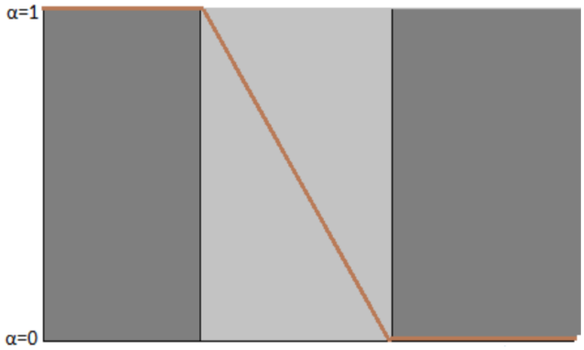
Alpha- Blending

Alpha blending is the technique to merge two images by using transparency parameter called alpha. Blending plays a vital role to show or evolve the impression of two or more than two images to form a single image. In our application we find the edge landmarks and features and based on these features as well as landmarks we blend two or more than two images end to end. Alpha blending is simple but effective algorithm. This technique is also called feathering. Alpha blending assigns the weight values (α) to the pixels of the overlapping area. For α= 0.5 simple averaging is achieved where both the overlapped area will contribute equally to create stitched image.

The value of α ranges 0 to 1. If α =0 then the pixel has no effect in composite region and if α =1 the pixel is copied there. Suppose composite image I is created from horizontally aligned images I_1 (left) and I_2 (right), then

$$I = \alpha I_1 + (1-\alpha) I_2$$

Starting with α=1 (fully opaque) from I_1 until the overlap region is reached. Decreasing the value α until it reaches to 0 (fully transparent) at the end of overlap region



Left image Overlapped image Right image

Figure 5: Alpha-blending

The advantage of alpha blending is its simplicity and we can tweak it to make it faster e.g. Look Up Table (Rankov et al., 2005)

V. RESULTS AND DISCUSSION

Two traditional techniques, Scale invariant feature Transform (SIFT) and Speeded Up Robust Features (SURF) have been implemented and compared with the proposed technique on the basis of performance parameters. SIFT (Lowe. 1999) can solve the scenes changed in perspective, in part due to occlusion and rotation, scaling, the image deformation and so on, effectively improve the alignment of feature accuracy. Whereas SURF (Bay et al., 2006) is quick scale invariant feature detection based on scale space theory. It has simplified but accurate feature detection algorithm and reduces descriptor size while keeping it sufficiently distinctive. The correspondence between referenced image and sensed image relies on extracted keypoints. SURF detector is mainly based on the approximated Hessian Matrix. On comparing the performance parameters like Entropy Quality index, Standard deviation and Variance, we have found that the proposed technique is better than the traditional techniques in terms of accuracy, performance and speed.

In the presented work MATLAB R2009a (Version 7.8.0) language & tools is used for a total of fifteen 2D gray scale X-ray images are used as a testing data. The results of 4 X-ray images are presented below:

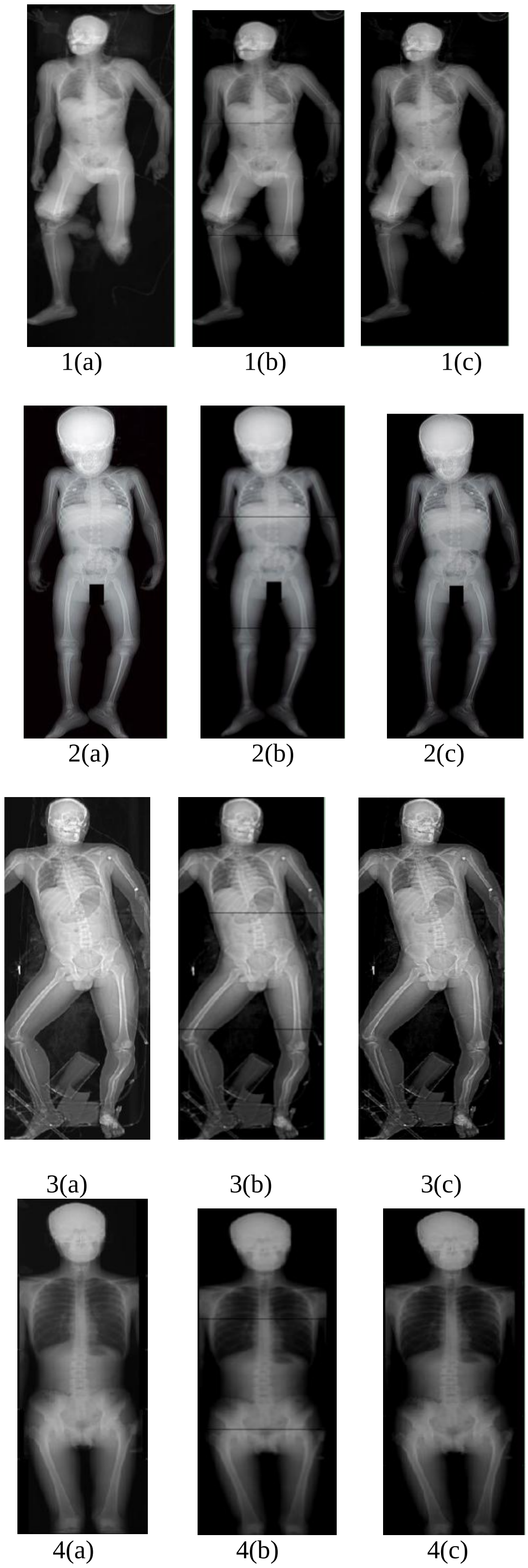


**Figure 6: 1(a) Proposed, 1(b) SIFT and 1(c) SURF
2(a) Proposed, 2(b) SIFT and 1(c) SURF
3(a) Proposed, 3(b) SIFT and 3(c) SURF
4(a) Proposed, 4(b) SIFT and 4(c) SURF**

DISCUSSION

In this section, Experimental results on image stitching and reason for choosing ant colony optimization algorithm is discussed using a total of 15 2-D gray scale X-ray images as testing data. On the basis of proposed technique implementation, we will find the best result for medical image stitching and then result of this method will be compared with the traditional SIFT and SURF methods using performance matrices which are as follows: Entropy Quality index, Standard deviation and Variance.

The presented results in the tabular and graphical forms clearly reveal that the proposed method achieves best results in terms of performance matrices. Table 1 and Figure 7 shows that significantly higher values of performances matrices are obtained from the proposed method as compared to the traditional techniques. Moreover it has been inferred from the analyzed database (Table 2 and Figure 8) that on comparison with SIFT, proposed technique gives an increment of 5.76 for E, 30.29 for QI, 0.91 for STD and 0.05 for V calculated on average basis. On comparison with SURF the following results have been obtained, an increment value of 1.24 for E, 22.08 for QI, 6.94 for STD and 0.46 for V (calculated same as above). Therefore better contrast, texture of input image and visual look of the image can be obtained by using the proposed technique. Thus we can conclude that Ant colony technique outperforms SIFT and SURF techniques in terms of accuracy, performance and efficiency.

Table 1: **Comparison of efficiency of different methods on the basis of performance matrices**

Performance Matrices	*Proposed	SIFT	SURF
Entropy	6.61	0.85	5.37
Quality Index	75.48	45.19	53.4
Standard deviation	62.25	61.34	55.31
Variance	7.85	7.80	7.39

*Database values calculated on average basis

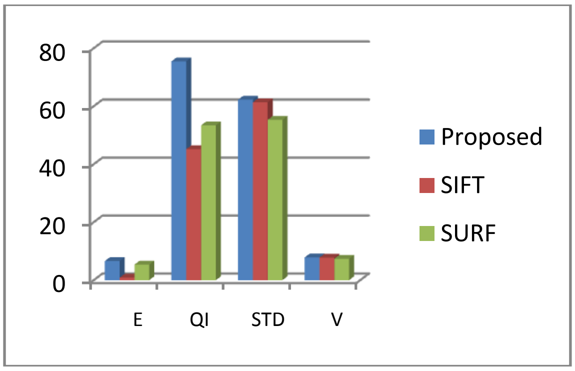


Figure 7: Comparison of efficiency of different methods on the basis of performance Matrices

Table 2: Comparison on the basis of Average Increment of performance parameters of different methods

Database of a Total of 15 2-D gray scale X- ray images		
Performance Parameters	**Average increment Values**	
	***Proposed with SIFT**	***Proposed with SURF**
Entropy	5.76	1.24
Quality Index	30.29	22.08
Standard deviation	0.91	6.94
Variance	0.05	0.46

*comparison of database values of proposed technique with SIFT and SURF

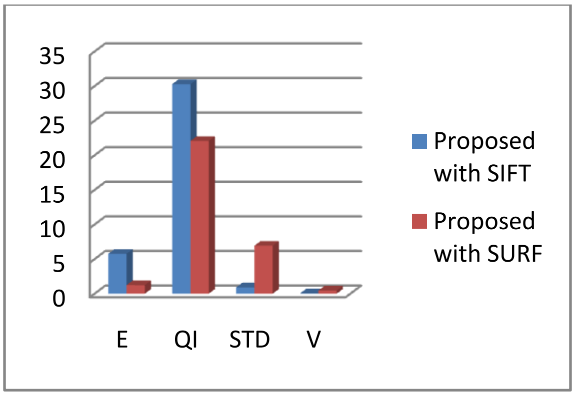


Figure 8: Comparison on the basis of Average increment of performance parameters of different methods

VI. CONCLUSION

The proposed technique outperforms SIFT and SURF techniques in terms of accuracy, performance and efficiency as significantly higher values of performances matrices are obtained from this method. Moreover average increment values of 5.76 for E, 30.29 for QI,0.91 for STD and 0.05 for V 1.24, for E, 22.08 for QI, 6.94 for STD and 0.46 for V are obtained on comparing the proposed method with SIFT and SURF respectively. Therefore it can be concluded that better contrast, texture of input image and visual look of the image can be obtained using the proposed method as compared to traditional methods.

Future scope of research work

1. In future we can stitch 3D CT and MRI images as well as tomography of dental panoramic construction of more than 4000 slices using some more efficient technique which can take less time and gives better quality can be carried out.
2. An X-ray image generally consists of a lot of background region which consists of very little or no information for image stitching. So, we can implement some technique that selects bones and muscles and discard the other areas in the image.

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