A New Hybrid Approach Toward Spinal Deformities’ Radiographic Images Diagnosis

Somaya Adwan, Iqbal Alsaleh, Babak Hassibi, Khalid Alsafi and Rasha Majed

Faculty of Computing and Information Technology, Arab Open University, Jeddah, Saudi Arabia

Faculty of Computing and Information Technology, King Abdulaziz University, Jeddah, Saudi Arabia

Department of Electrical Engineering, California Institute of Technology, USA

Department of Radiology, School of Medicine, King Abdulaziz University, Jeddah, Saudi Arabia

Department of Surgery, King Abdulaziz Hospital and Oncology Centre, Jeddah, Saudi Arabia

In this study, a new hybrid method of Image stitching that utilizes both advantages of feature based and direct based methods to identify and merge pairs of x-ray medical images is presented. The performance of the proposed method based on this hybrid approach is investigated and discussed. The ability of the method to classify overlapping pairs of images is demonstrated. It is observed that the proposed method displays comparable or superior performance to the SIFT method described in the literature on the standard databases. These results reveal the potential of the proposed method for further development to tackle more advanced stitching problems.

Key words: Image stitching, spinal deformity, panorama image, x-ray image stitching

INTRODUCTION

X-ray imaging is an important diagnostic tool for injury or deformation affecting the skeleton. In spine x-ray the images are captured individually in three basic parts which are the neck (cervical), mid back (thoracic) and lower back (lumbar). To produce the full length of the spine, digitized images from the three different parts can be assembled by stitching.

The existence of different pathologies for spine deformities causing an abnormal spinal curve; make the x-ray images of importance to measure and quantify these curves for further treatment. In a process called stitching, we need to merge two or three different views in order for the x-ray image to be analyzed and the spine curvature to be measured.

Spinal deformity includes several conditions in which the spine is abnormally curved or aligned. These deformities include: (1) Scoliosis i.e., a side-to-side abnormal curvature of the spine, (2) Abnormal degrees of kyphosis i.e., an exaggerated rounding of the back that may occur by itself or in conjunction with osteoporosis, (3) Abnormal degrees of lordosis and spondylolisthesis, a slippage of one vertebra onto its neighboring vertebra there are many other spinal deformity conditions which has been cited in numerous studies such as spondylolysis and Scheuermann kyphosis (Asher and Burton, 2006).

Panorama image stitching, also known as image alignment is a process of overlaying a set of images into one coordinate system taken at different intervals of time by using different sensors and from different fields of view to generate a wider viewing panoramic image (Chen, 1998; Szeliski, 2006). The fundamental process in panorama image stitching is image registration. The portions of adjacent or consecutive images are model to be evaluated to find the positions for merging and the transformation for aligning the images. Once the image positively matched, the wider viewing panorama image will be blended together to make it seamless (Maintz and Viergever, 1998).

In present study, image registration process is restricted to find the correct translation to align and merge adjacent images. Generally, portions of two consecutive images are measured up in order to find the corresponding points of the required transformation that will be accustomed to blend the images seamlessly in image registration stage. Two main categories of image registration technique which are direct based method and feature based method. In direct based method, pixel to pixel corresponding is employed to enlarge the degree of
matching between two sub-images and consequently find a transformation to merge the two sub-images. On the other hand, feature-based methods get first the prominent features such as corners from the two sub-images and then establish reliable feature correspondences by comparing the features. Then images are “warped according to parametric transformations that are evaluated from those correspondences” (Milgram, 1975).

Direct methods have the elite that they use all of the accessible image data and hence can afford very precise registration but being iterative methods, they require initialization. Unlike direct based methods, feature-based methods do not require initialization but they are time overriding and for the majority of cases, finding features in sub-images are problematic task (Zitova and Flusser, 2003). Other different methods can be considered as the hybridization of the two above-stated methods (Zitova and Flusser, 2003; Maintz and Viergever, 1998).

A variety of point and corner detectors methods exist. They can be categorized into three sets: (1) Intensity based methods which indicate the presence of an interest point directly from the grey values, (2) Contour based methods, in first it extracts contours and then search for inflexion points along the contour chains and then search for intersection points and (3) Parametric methods which adapt a parametric intensity model to the signal. They often provide sub-pixel accuracy but they are limited to specific types of interest points, for example to L-corners. In present anticipated method, the image matching technique is developed via a group of local interest points which are traced back to the work of stereo matching on a corner detector (Kumar et al., 2010).

Harris and Stephens (1988) developed the Moravec detector to develop more recursively method under small image distinctions and near edges. Harris (1993) also provided its value for efficient motion tracking and 3D structure from motion recovery. In addition, Harris corner detector has been utilized enormously for matching tasks of different images.

Schmid et al. (1998) utilized Harris corners detector to select interest points but rather than matching with a correlation window, they used a rotationally invariant descriptor of the local image region. This allowed features to be matched under arbitrary orientation change between the two images. Furthermore, they revealed that multiple feature matches could accomplish general recognition under obstruction and clutter by detecting consistent clusters of matched features. Harris (1993) corner detector is very sensitive to variations in image scale, so it does not offer a good foundation for matching images of different sizes.

Brown and Lowe (2007) suggested a fully automatic panoramic image stitching using Scale Invariant Features Transform (SIFT) for extracting features among all of the images. From the features matching step, images that have a large number of matches between them are acknowledged. Random Sample Consensus (RANSAC) is used to select a set of inliers that are attuned with a homography between the images. Next, a probabilistic model is implemented to validate the match. Bundle adjustment is used after that to solve for all of the camera parameters jointly. By applying a global rotation such that up-vectors u is vertical (in the rendering frame) effectively removes the wavy effect from output panoramas. Brown and Lowe (2007) had efficaciously matched multiple panoramas in unordered image set and stitch them fully automatically without user input.

On the other hand, cross-correlation is a basic statistical direct based approach used as a similarity metric in many image registration processes. It is a matching measure between two sub-images. This similarity metric is widely used since it can be calculated significantly using the Fast Fourier Transform (FFT) specially for combining large sub-images of the same size. Furthermore, both direct correlation and correlations using FFT have costs which grow at least linearly with the image area (Milgram, 1975).

Correlation kernels have been utilized in different applications for instance the ART (automatic target recognition) (Samsudin et al., 2012) and in different biometric approaches (Harris, 1993; Kumar et al., 2010). The simplest correlation kernels is identified as Matched Spatial Filter (MSF) (Samsudin et al., 2013). It performs well at detecting a reference image corrupted by additive white noise but this approach demonstrated distortion variance, poor generalization and poor localization properties. The reason of this poor performance is that MSF uses a single training and generates broad correlation peaks (Harris, 1993). This constraint was tackled by introducing another correlation filter that is known as Synthetic Discriminant Function (SDF). It is a linear combination of MSFs. It linearly associate a set of training images into one filter which further allows one to constrain the filter output at the origin of correlation filter (Kumar et al., 2010). These preset constraints are also known as ‘peak constraints’. SDF filters afford some degree of distortion invariance but like MSFs they result in large side-lobes, this exhibition of broad correlation peaks makes localization difficult.

Kumar et al. (2010) proposed a direct based method for stitching medical images using histogram matching combined with sum of squared difference in order to overcome the shortcoming of feature based method for image alignment, they still suffer complexity and the degree of freedom of the transformation are increased regardless of the fact that their method developed the effectiveness of the similarity measure and searching techniques. Furthermore, it is not well suited to gradient descent methods hence the sum of squared difference method is not differentiable at the origin.

In this study, a new approach to image stitching and panoramic image creation for radiographic images of spinal deformities’ x-ray image is presented as extend to the author work in (Samsudin et al., 2013). The image registration stage is based on hybrid method that utilizes Harris corners detection as a salient feature based detection method with Minimum Average Correlation Energy (MACE) filter as a correlation direct based method.
MATERIALS AND METHODS

Proposed approach for image stitching system: The functional flow presented in this study for Image stitching method is elicited in Fig. 1. It comprises of seven phases. Specification are as following: First, Images Pre-processing techniques is implemented and the Salient Point Detection using Harris Detector is applied followed by the Frequency Domain Transformation, the main task of this phase is to convert temporal domain values of images into frequency domain values, after that the Images Filter Computing technique implements MACE filter and yields correlation plane of input images. Correlation Filter Module takes input test image and MACE filter correlation plane of template image to find the similarity match between them. Then, Time Domain Transformation employs a logic of transforming the frequency domain values to temporal domain values. And lastly the image blending processes are applied which utilizes the information received from all phases to create the panoramic image and output the stitched image. Figure 1 depicts the framework of the proposed image stitching method.

Image pre-processing: Image pre-processing is the principal step needed to prepare the image for image stitching processes. First, if the inputs are colored images they will undergo color conversion to grey scale. This is followed by histogram equalization to get rid of intensity deviation affected by exterior reasons such as incongruent illumination of the light. Next, windowing is carried out using Hanning window to avoid the leakage in the signal of the image over a wide frequency range in the FFT caused by signal energy smearing. After that Fourier transformation (FFT) is applied on the pre-processed images.

Salient point detection: In order to establish correspondences among a collection of images; first it is essential to identify a set of salient points in each image. A point detector should exploit only the information contained in one single image.
because the transformation that relates the images is not known a priori (Samsudin et al., 2013). Intensity based methods achieve this goal by assigning to each point a value that defines its fitness as a tie point. This is done by evaluating the image intensity values in a vicinity of the point. Harris and Stephens (1988) methods are considered as an Intensity based methods. In this study we have implemented Harris corner detector presented in the study of Harris and Stephens (1988) as demonstrated in the upcoming subsection.

Harris detector: An improved point detector method by using the auto-correlation matrix is proposed by Harris and Stephens (1988). To apply Harris detector there are six basic steps to follow as presented in Harris and Stephens (1988). The auto-correlation matrix is used to drive the auto-correlation function which is used to detect interest points.

Further details of steps for creating the auto-correlation matrix is shown by Harris and Stephens (1988). If the auto-correlation matrix has two significant eigenvalues then the interest points are detected. The Harris computes the derivatives of the matrix by convolution with the mask [-2 -1 0 1 2]. A Gaussian ($\sigma = 2$) is used to weight the derivatives summed over the window.

To avert the extraction of the eigenvalues of the auto-correlation matrix, the strength of an interest points is measured by $\text{Det}(R) - k \times (\text{Trace}(R))^2$. The auto correlation function defined in the mentioned formula is used to detect interest points by using the auto-correlation matrix. Where $\text{Det}(R)$ is the determinant of the auto-correlation matrix $R$. The second term is used to eliminate contour points with one strong eigenvalue, $k$ is fixed to 0.05.

Non-maximum suppression using a $3\times3$ mask is then applied to the interest point strength and a threshold is used to select the interest points. The threshold is set by trial and error to 2% of the maximum observed interest point strength. Once $M$ is computed for every point in the image, points where $M$ is above a threshold are chosen. Once determination of the key points has been done, the next step is to construct a descriptor for the feature positioned at each point of interest. This descriptor will be the key to compare features in different images to locate the overlapping points in images.

Points matching using fourier transformation and correlation calculation: Correlation provides the measure of similarity between two signals. In the time domain, the correlation of signals $g$ and $h$ can be computed by multiplying the Fourier transform of one of them to the complex conjugate of the Fourier transform of the other (Samsudin et al., 2012, 2013). Figure 2 shows the structure of the correlation process in frequency domain, where the Fourier transform of signal $g$ is multiplied to the complex conjugate of the Fourier transform of signal $h$. Correlation measurement is the foundation of the registration step of the stitching methods.

When stitching two images, after evaluating and computing the interest points out of the two input images, the key points from the first image is needed to construct the correlation filter, in this study we are going to use the same technique for correlation calculation and MACE filter building as presented in Samsudin et al. (2013) study First, Fourier transformation is performed on both key points of the two images using the Fast Fourier Transform (FFT). Each key points resulted from the interest point detector of the two images can be regarded as two dimensional signals $f_1(n_1, n_2)$ and $f_2(n_1, n_2)$ and their Fourier transform coefficients are $F_1(k_1, k_2)$ and $F_2(k_1, k_2)$ given by Eq. 1 and 2, respectively:

$$F_1 (k_1, k_2) = \sum_{n_1} f_1 (n_1, n_2) W_{n_1}^{k_1} W_{n_2}^{k_2} = A_{11} (k_1, k_2) e^{i\phi(k_1, k_2)}$$

$$F_2 (k_1, k_2) = \sum_{n_1} f_2 (n_1, n_2) W_{n_1}^{k_1} W_{n_2}^{k_2} = A_{12} (k_1, k_2) e^{i\phi(k_1, k_2)}$$

where, $k_1 = -M_1, ..., M_1, k_2 = -M_2, ..., M_2$:

$$WN_1 = \exp \left( -\frac{j2\pi}{N_1} \right), \quad WN_2 = \exp \left( -\frac{j2\pi}{N_2} \right)$$

If $f_1(n_1, n_2)$ is the image chosen to construct the filter, the MACE filter equation turned out to be:

$$\text{MACE} (K_1, K_2) = \frac{F_1(K_1, K_2)}{F_2(K_1, K_2)}$$

where, MACE represents the Correlation filter, $F_1(K_1, K_2)$ is the FFT transformed image $f_1(n_1, n_2)$ and $F_2(K_1, K_2)$ denotes the complex conjugate of $F_1(K_1, K_2)$.

The correlation between the MACE filter and the second image is then computed as follows:

$$\text{CF} = F_2(K_1, K_2) \times \text{MACE} (K_1, K_2)$$

where, $F_2(K_1, K_2)$ in Eq. 4 represents the complex conjugate of $F_2(K_1, K_2)$. The flow diagram of the proposed points matching method using MACE Filter is revealed in Fig. 3.

Time domain transformation (inverse transform): The correlation has to be inverse transformed so that the relative values of correlation at various positions can be observed. The inverse Fourier transform of the correlation function is given by Eq. 5:
The values of $c_{f1f2}(n_1, n_2)$ are stored in a 2D correlation plane where the absolute value and position of the highest peak are recognized. This location provides the highest correlation between the two input images.

**Geometric transformation by using random sample consensus:** The geometric transformation can be used to find the transformation matrix which maps the greatest number of point combines between the two images. In the present proposed method for image stitching, the Random Sample Consensus (RANSAC) algorithms have been used to calculate the metric distance for finding the transformation matrix.

Fischler and Bolles (1981) proposed the Random Sample Consensus (RANSAC) algorithm. This algorithm is a broad boundary estimation technique created with a big amount of excessive rates in the input data. RANSAC is a method that creates nominated solutions via set of minimum number of points required from the input data to assess the model parameters (Fischler and Bolles, 1981).

Details of the elementary algorithm is briefly describe in Derpanis (2010) and is depicted in Fig. 4.

**RANSAC algorithm:**

- First elect at random the minimal number of N data points required from total M data points to decide the model parameters

\[
C_{f1f2}(n_1, n_2) = \frac{1}{N_1N_2} \sum_{k_1k_2} c_{f1f2}(k_1, k_2) W_{k_1}^{-k_1} W_{k_2}^{-k_2} \quad (5)
\]

Fig. 3: Framework of the proposed points matching method using correlation filter

Fig. 4: Framework of the best point selection using RANSAC algorithm

- Find the mean value of the parameters of the model
- Define how many points are in the set of all points M fit with a predetermined parameter vector within a user given tolerance parameter. Call this points K
- Set a predefined threshold $\alpha$ and if the number of fraction of the inliers over the total number points in the group that exceeds $\alpha$, re-evaluate the model parameters by using all the identified inliers and concluded
- On the other hand, keep repeating steps 1 through 4 for maximum of N iterative times

The number of iterations, N, is chosen high enough to certify that the probability $p$ (usually set to 0.99) that at least one of the sets of random samples does not contain an outlier. Let U represent the probability that any selected data point is an inlier.

**Image blending:** Once the best matching points are found, the points will be further processed for selection of the best point. First the matched points from image 1 and image 2 will pass through random point selection; to select randomly between entire points the best point. Homography transformation vector is applied on the selected points, then a transformation is applied to transform the best points resulted into a vector. Once we get the transformed vector, the matched points will be countered and finally the stitched image will be created by blending the input images based on the location of transformed vector.

In image blending, information from the location of the best selected points of the correlation plane is used to translate...
the images to the right position before merging them. Then the intensities of pixels at the borderline between the two images are adjusted so that the transition from one image to the next is smooth. In our image stitching system we employ alpha blending to adjust the local pixel intensity around the borderline area.

Figure 5 illustrates the progress of blending two images to form a panorama image. Suppose \( mx \) and \( my \) represent the \( x \) and \( y \) coordinates of the peak in the correlation plane. In this case, when merging the two images, the second image will be translated by \( mx \) horizontally and \( my \) vertically from the shared origin denoted as \( (xo, yo) \). The hatched area in the figure shows the overlapping area. At the border of the hatched area, there exists an edge line caused by a sudden change of pixel intensity. To overcome this problem, an alpha blending method is used to minimize the edge so that the two images blend smoothly. The formula of the alpha blending is given as:

\[
c = (1-\alpha) a + \alpha b
\]

where, \( \alpha \) is defined by the user ranging from 0 to 1, \( a \) referred to the first image, \( b \) is the second image and \( c \) is the resulting panorama image. The objective of blending is to make seamlessly transition between overlapping area (Samsudin et al., 2013).

RESULTS

The proposed algorithm is implemented in MATLAB 2010a running on a computer with 2.5 GHz Intel(R) Core(i3) CPU and 6 GB RAM. The experiments were carried out using databases containing 50 x-ray images for different types of spine deformities. These radiographic images are secured from Royal Medical Services King Hussein Medical Center/Amman, Prince Ali Bin Al-Hussein/Al-karak. The system successfully calculated the key-points and the peak values of each pair of input images. Figure 6 shows a pair of overlapping images that are correctly detected as overlapped image. In our experiment, performing Harris detector on the images shown in Fig. 6; results in 59 key-points that are found in the first image and 61 key-points found in the second image. The experiment is further processed to find the matching points between the key-points in both images by using MACE filter as a correlation filter to calculate and find the similar points in the two images. Figure 7 shows their correlation plane. Since their interests points are 59 and 61, respectively, the matched points after applying MACE filter is just eight points.

After processing the MACE filter to find the overlapping points between the two images, then the matrix of transformation is generated by applying a transformation function to translate the image onto the panorama plan. At this stage the two images will be stitched after finding the best matching points between them using RANSAC algorithm, they are stitched into a single image as depicted in Fig. 8 with best matching points appearing on the image. Table 1 shows the statistical results of stitching the pair of images presented in Fig. 6.
Table 1: Statistical results when running the experiment on the two images shown in Fig. 6

| Algorithms   | Execution description                        |
|--------------|---------------------------------------------|
| Harris detector | 59 keypoints found in first image            |
|              | 61 keypoints found in second image           |
| MACE         | Found 8 matching points                      |
| RANSAC       | Inliers: Harris (1993)                      |
|              | 320 iterations                              |

The performance of the proposed method is compared against that of the Scale Invariant Features Transform (SIFT) method presented by Brown and Lowe (2007) using our databases. The relative performances of the methods are measured by two main quantities and they are True Positive Rate (TPR), False Positive Rate (FNR). TPR is the ratio of the number of overlapped images stitched correctly by the system to the total number of images. In contrast, FNR is the ratio of the number of overlapped images that wrongly stitched with seam and wrong matching points confirmed by the system to the total number of images. They are expressed by the following equations:

\[
TPR = \frac{\text{No. of overlapped image correctly detected and stitched}}{\text{Total No. of image}} \tag{7}
\]

\[
FNR = \frac{\text{No. of overlapped image wrongly detected and stitched}}{\text{Total No. of nonoverlapped image}} \tag{8}
\]

Another performance index that indicates the efficiency of the two methods is the execution time. It is found that the execution time of the proposed method is about two times less than that of the SIFT method. The comparison results are summarized in Table 2.

Figure 9 shows the results of one of an overlapped images from the database after applying the SIFT method (Fig. 9a)
Table 2: Evaluation of matching precision of medical stitching system using TPR and FNR rates

| Methods                  | Total No. of x-ray images in database | No. of overlapped images correctly stitched | TPR (%) | FNR (%) | Average processing time (sec) |
|--------------------------|--------------------------------------|---------------------------------------------|---------|---------|------------------------------|
| Proposed                 | 50                                    | 46                                          | 92      | 8       | 0.102                        |
| Brown and Lowe (2007)    | 50                                    | 39                                          | 78      | 22      | 0.210                        |

and our proposed method (Fig. 9b); it can be seen from the figure that the overlapped images are stitched improperly in part a of Fig. 9 while part b shows the same image with correct matching points and stitching seamlessly.

**CONCLUSION**

In this study, a new hybrid image stitching technique is presented. The performance of the proposed method based on the hybrid approach which utilizes both advantages of feature based method and direct based method is investigated through the experiment. The ability of the method to classify overlapping pairs of images is demonstrated using deformities’ radiographic images in our repository databases. The proposed method is performed on these databases. After the results have been revealed to consultant, it is observed that the proposed method displays comparable or superior performance to the methods described in the literature on the standard databases. These results are promising and demonstrate the potentials of the proposed method for further development to tackle more advanced stitching problems that may involve image warping, rotation and scale variations, slant and tilt.

**ACKNOWLEDGMENT**

This project was funded by the Deanship of Scientific Research (DSR), King Abdulaziz University, Jeddah, under grant no. (4-611-1434-HiCi). The authors, therefore, acknowledge with thanks DSR technical and financial support.

**REFERENCES**

Asher, M.A. and D.C. Burton, 2006. Adolescent idiopathic scoliosis: Natural history and long term treatment effects. Scoliosis, Vol. 1. 10.1186/1748-7161-1-2

Brown, M. and D.G. Lowe, 2007. Automatic panoramic image stitching using invariant features. Int. J. Comput. Vision, 74: 59-73.

Chen, C.Y., 1998. Image stitching-comparisons and new techniques. CITR-TR-30, Computer Science Department of The University of Auckland CITR at Tamaki Campus, October 1998.

Derpanis, K.G., 2010. Overview of the RANSAC algorithm. http://cite姬ex.ist.psu.edu/viewdoc/download?doi=10.1 .1217.3024&rep=rep1&type=pdf

Fischler, M.A. and R.C. Bolles, 1981. Random sample consensus: A paradigm for model fitting with applications to image analysis and automated cartography. Commun. ACM, 24: 381-395.

Harris, C., 1993. Geometry from Visual Motion. MIT Press, Cambridge MA., USA., ISBN: 0-262-02351-2, pp: 263-284.

Harris, C. and M. Stephens, 1988. A combined corner and edge detector. Proceedings of the 4th Alvey Vision Conference, Volume 15, August 31-September 2, 1988, Manchester, UK., pp: 147-151.

Kumar, A., R.S. Bandaru, B.M. Rao, S. Kulkarni and N. Ghatpande, 2010. Automatic image alignment and stitching of medical images with seam blending. World Acad. Sci. Eng. Technol., 65: 91-96.

Maintz, J.B. and M.A. Viergever, 1998. A survey of medical image registration. Med. Image Anal., 21: 1-36.

Milgram, D.L., 1975. Computer methods for creating photomosaics. IEEE Trans. Comput., 100: 1113-1119.

Samsudin, S., S. Adwan, H. Arof, Z. Saleh and F. Ibrahim, 2012. A new approach to medical image stitching using minimum average correlation energy filter and peak to side-lobe ratio. Int. J. Imag. Syst. Technol., 22: 166-171.

Samsudin, S., S. Adwan, H. Arof, N. Mokhtar and F. Ibrahim, 2013. Development of automated image stitching system for radiographic images. J. Digital Imaging, 26: 361-370.

Schmid, C., R. Mohr and C. Bauckhage, 1998. Comparing and evaluating interest points. Proceedings of the IEEE 6th International Conference on Computer Vision, January 4-7, 1998, Bombay, India, pp: 230-235.

Szeliski, R., 2006. Image alignment and stitching: A tutorial. Proceedings of the Foundations and Trends® in Computer Graphics and Vision, Volume 2, June 17-22, 2006, Hanover, MA., USA., pp:1-104.

Zitova, B. and J. Flusser, 2003. Image registration methods: A survey. Image Vision Comput., 21: 977-1000.