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Automatic Image Alignment and Stitching of Medical Images with Seam Blending

Abhinav Kumar, Raja Sekhar Bandaru, B Madhusudan Rao, Saket Kulkarni, Nilesh Ghatpande

***Abstract*—**This paper proposes an algorithm which automatically aligns and stitches the component medical images (fluoroscopic) with varying degrees of overlap into a single composite image. The alignment method is based on similarity measure between the component images. As applied here the technique is intensity based rather than feature based. It works well in domains where feature based methods have difficulty, yet more robust than traditional correlation. Component images are stitched together using the new triangular averaging based blending algorithm. The quality of the resultant image is tested for photometric inconsistencies and geometric misalignments. This method cannot correct rotational, scale and perspective artifacts.

***Keywords*—**Histogram Matching, Image Alignment, Image Stitching, Medical Imaging.

I. Introduction

ALGORITHM for aligning images and stitching them into seamless photo-mosaic are among the oldest and most widely used in computer vision[1]. Creating high resolution images by combining smaller images are popular since the beginning of the photography [2].

Even in medical imaging for better clinical diagnosis, a composite image needs to be formed starting from its component images. A complete panoramic image cannot be captured in a single scan. The input is a set of n *fluoroscopic images* (I1, I2, …, I*n*), where any two neighbors having a common area, can be merged together for obtaining a panoramic view. Manually aligning the overlap area and properly concatenating the component images together can be done using any commercial softwares. The method presented in this paper describes fully automatic stitching of component images into a composite image.

Because human recognition for alignment of component images is subjective so images cannot be concatenated in a simple manner. The images may not be joined properly, without seam because of the conditions in which the scan is performed (low brightness, for example) and the automatic alignment may not produce accurate results. A method to equalize the brightness of images before stitching has been described in this paper. Finally local image blending is needed to make the image a seamless composite image.

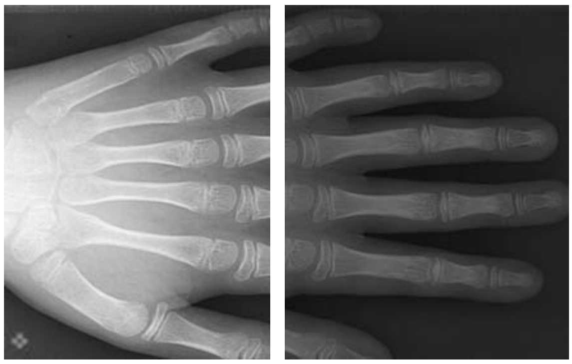

Fig. 1 X-ray images with different brightness [10]

Some algorithm uses feature based registration for aligning the component images [3] but they are time consuming and for generic cases, finding features inside component images are difficult [4]. A Gradient based approach avoid both photometric inconsistencies and geometric misalignment during stitching has been described at [5], but doesn't talk about alignment. Another algorithm to remove seam from an already stitched image is described in [6] which uses a relaxation method.

In this paper a novel algorithm is proposed which uses histogram matching coupled with mutual information or sum of squared difference to overcome the drawback of feature based registration method for image alignment. Section 2 presents the preliminaries and short description about histogram matching, mutual information and sum of squared difference. The Main algorithm is discussed in section 3.Result of the current algorithm is presented in Section 4 and future works are surveyed in section 6.

Abhinav Kumar is working with the Medical sub vertical of Product Engineering Services business unit and also contributes to Image processing CoE at Patni Computer Systems Ltd.(phone: +912039842000-2967; e-mail: abhinav.abhkumar@patni.com).

Raja Sekhar Bandaru is working with the Medical sub vertical of Product Engineering Services business unit and also contributes to Image processing CoE at Patni Computer Systems Ltd.(e-mail: rajasekhar.bandaru@patni.com).

B Madhusudhan Rao is working with the Medical sub vertical of Product Engineering Services business unit and also contributes to Image processing CoE at Patni Computer Systems Ltd. (e-mail: madhusudan.bellary@patni.com).

Saket Kulkarni is working with the Medical sub vertical of Product Engineering Services business unit and also contributes to Image processing CoE at Patni Computer Systems Ltd. (e-mail: saket.kulkarni@patni.com).

Nilesh Ghatpande is working with the Medical sub vertical of Product Engineering Services business unit and heading Image processing CoE at Patni Computer Systems Ltd.(email: nilesh.ghatpande@patni.com).

II. PRELIMINARIES

Fig. 2 shows the block diagram of the proposed method. Taking two component images as shown in Figure 1, as input images, the goal is to form a single composite image. One image is considered as model (reference) image which is to be concatenated with the target image. Both the images are brought to the same brightness level for accurate correspondence of the overlap region. Brightness is equalized by histogram matching.

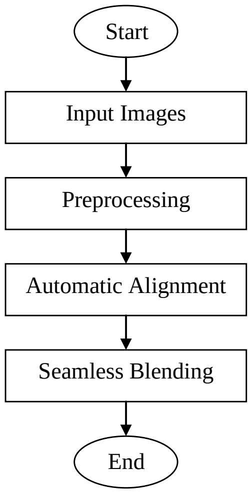

Fig. 2 Automatic Stitching with seam blending

Assuming there is an overlapping region between the two images, the model image is registered with the target image using similarity measure to find the aligning parameters. Mutual information and sum of squared difference are most commonly used image similarity measures.

Although the histogram of the component images is changed in alignment algorithm, it is to find the correct correspondence between them. During the process of stitching, the original images are used, hence image quality of the composite image which is obtained after stitching remains same as of component images. Problem of automatic alignment and stitching can be divided in two major components.

(1) Firstly, matching the histogram of the component images in parts and finding correct correspondence between them (correct pixel coordinates of relating pixels)
(2) Secondly, stitching them together seamlessly to get a single composite image.

2.1 Preprocessing

Presence of noise may affect the calculation of alignment position by mutual information and sum of squared difference method. So a preprocessing step to remove noise is required [7][8][9].

2.2 Brightness equalization by histogram matching

The common problem in fluoroscopic scan is presence of contrast artifacts due to different illumination conditions, brightness variation and shadows. A panoramic image generated by stitching these images will not have uniform intensity through out and may lead to wrong diagnostic sometimes. To avoid non-uniform intensity distribution histogram of target image is matched with histogram of reference image.

2.3 Mutual Information

Mathematically, mutual information (MI) [7],[8] between any two random variables A and B can be defined as

$$I(A,B) = \sum_{a\in A}\sum_{b\in B} p(a,b)\log\left(\frac{p(a,b)}{p(a)p(b)}\right)$$

where, *I(A,B)* is Mutual information value between random variables *A* and *B*, *p(a)* and *p(b)* are probability distribution function of *A* and *B* respectively and *p(a,b)* is joint probability distribution function of *A* and *B*.

Mutual information measures the information that random variables *A* and *B* share. It can also be represented in terms of entropy [8] as:

$$I(A,B) = \frac{H(A)+H(B)}{H(A,B)}$$

Where, *H(A)* and *H(B)* are the entropies of images *A* and *B* respectively, and *H(A,B)* is the joint entropy of the two images.

Entropy can be computed for an image based on distribution of grey values. An image consisting of almost a single intensity will have a low entropy value; it contains very little information. A high entropy value will be yielded by an image with more or less equal quantities of many different intensities, which is an image containing a lot of information. A distribution with a single sharp peak corresponds to a low entropy value whereas a dispersed distribution yields a high entropy value [7]. A joint probability distribution can be estimated by generating a 2-D histogram where each axis is number of possible grey level values in each image. A joint histogram of two images can be used to estimate a joint probability distribution of their grey values by dividing each entry in the histogram by the total number of entries.

2.4 Sum of Squared difference

The distance from any point in a collection of data, to the mean of the data, is the deviation. This can be written as,

$$D = \frac{1}{n}\sum_{i=1}^{n}\left[Xi - X\right]$$

Where, *Xi* is the *i*th data point, and *X* is the estimate of the mean. If all such deviations are squared, then summed, "sum of squares" for these data is obtained.

In terms of image processing, pixel wise difference between the images are squared and then summed to obtain sum of squared difference value. Sum of squared difference (SSD) can be found between two images as [1][9]:

$$SSD = \sum \sum \left[R(x, y) - T(x, y) \right]^2$$

Where, $R(x,y)$ is reference image and $T(x,y)$ is target image.

III. The algorithm of Automatic Image Alignment and Stitching

The process of image alignment and stitching for two images is as follows:

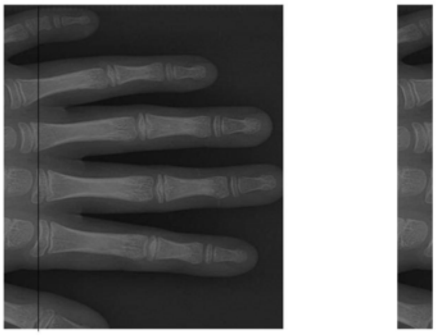

Fig. 3 Images (left) R and (right) R1

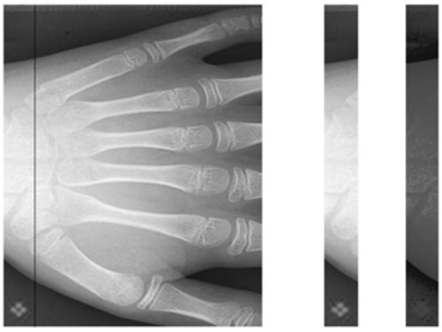

Fig. 4 Images (left) T, (center) T1 and (right) T1 histogram matched with R1

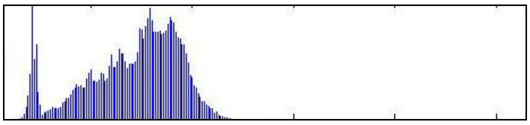

Fig. 5 Histogram of R1 (X-axis represents grey level and Y-axis represents frequency of their occurrence)

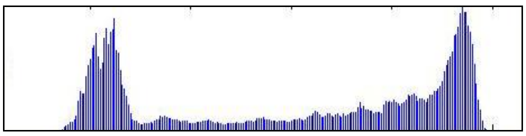

Fig. 6 Histogram of T1

3.1 Alignment

3.1.1 Two component images reference R and target T are taken.

3.1.2 Images are convolved with a median filter to remove noise.

3.1.3 An appropriate window $R1(xR',yR)$ where xR' is approximately 20% of xR is selected from the reference image $R(xR,yR)$. Where xR is maximum heigth and yR is maximum width of image R.

3.1.4 From the target image $T(xT, yT)$, a window $T_{i=1}(xT', yT)$ *where* $xT' = xR'$ *is selected.*

3.1.5 Histogram of $T_{i=1}$ is matched with histogram of $R1$

3.1.6 Similarity measure criteria among "sum of squared difference", SSD and "mutual information" MI is selected to find a similarity measure value between $R1$ and T_i.

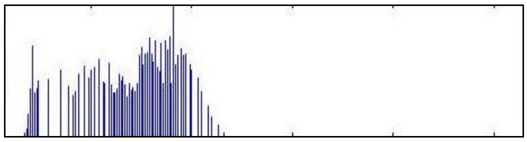

Fig. 7 Histogram of T1 matched with R1

3.1.7 Step 3.1.4 to Step 3.1.6 are repeated to get an array of similarity measure value (While repeating Step 3.1.4, for getting window T_{i+1}, T_i is shifted by 1 pixel).

3.1.8 Largest value in case of MI and least value in case of SSD will give the exact position in T where R is to be aligned.

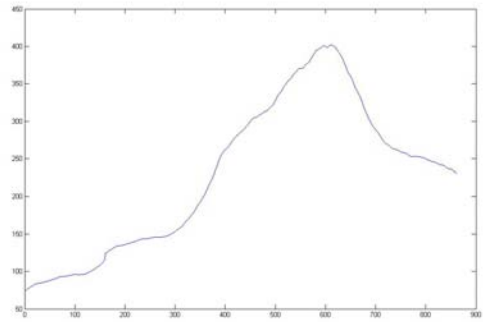

Fig. 8 Mutual information as similarity measure

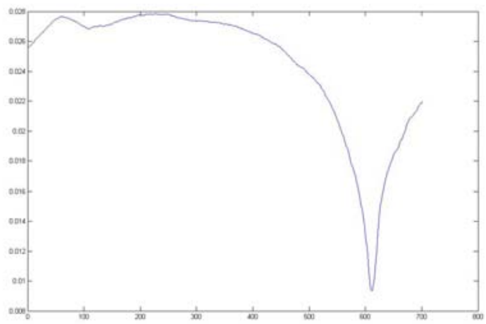

Fig. 9 SSD as similarity measure

Figure 8 shows the graph between MI value at y-axis and number of iteration (position of T_i) at x-axis. Figure 9 shows the graph between SSD on y-axis and number of iteration (position of T_i) on x-axis. From figure 8 and 9 it is clear that

R1 in Figure 3 is matched at pixel location 610 of T. At i = 610, T_i is obtained as evident in figure 10.

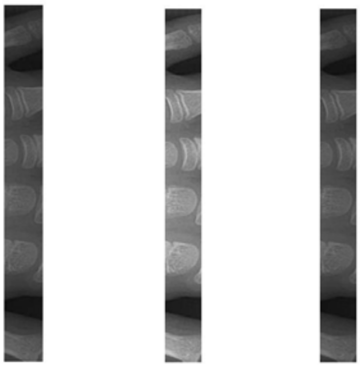

Fig. 10 Image (left) R1, (center) Ti for i = 610 and (right) Ti with histogram matched with R1

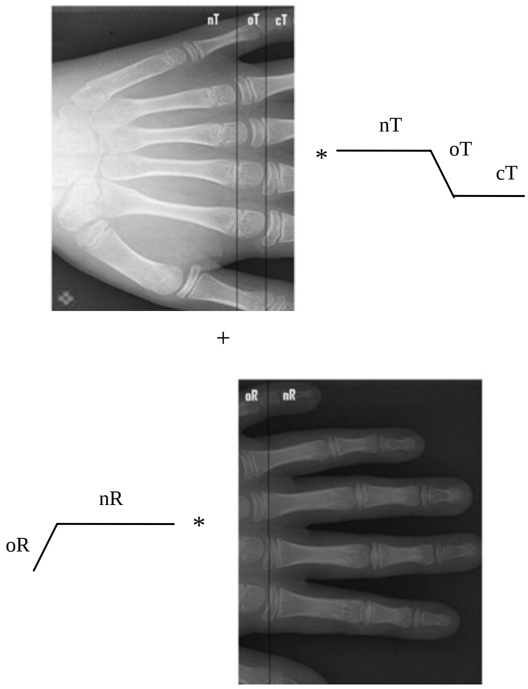

Fig. 11 Image T and R and their overlapping areas as marked with vertical lines.

3.2 Seamless Stitching Algorithm

3.2.1 Overlap area is obtained from alignment steps, overlapping part in *R* is *oR* and in *T* it is *oT*, non overlapping part in *R* is *nR* and in *T* is *nT*. So, *R = oR+nR* and *T = oT+nT*.

3.2.2 For obtaining a seamless stitching, triangulation averaging is applied on the overlapped area of the images. Region *cT* is cropped out from *T* and then the overlapped area *oT* is multiplied with averaging image whose intensity starts from 1 and decreases to 0 to obtain *oT'*.

3.2.3 Similarly, *oR* is multiplied with an averaging image whose intensity starts with 0 and changes to 1 to obtain *oR'*.

3.2.4 *oT'* and *oR'* are added to obtain *O*, and final stitched image *F* is obtained as *F = nT+O+nR*.

Figure 11 represents image *T* and averaging image (in 1D) to be multiplied with *T*. Non-overlapped area of *T*, *nT* is multiplied with 1s resulting no effect on that part of image. Overlapped area *oT* is multiplied with linearly decreasing value from 1 to 0 in the overlapping range. *cT* can be cropped off from *T*. Similarly, for the Reference image *R*, non overlapping part *nR* was multiplied by '1's resulting in no effect on that part of the image and overlapped area *oR* is multiplied with a linearly increasing value from 0 to 1 in the overlapping range.

Note that, although the actual overlapping area between *T* and *R* is different and larger than *oT* and *oR*, it is restricted to a smaller overlapping area *oT* and *oR* found from alignment step described above, to reduce the calculation and improve image quality (if the complete overlapping area would have been selected, then triangulation averaging has to be performed on the larger area leading to change in intensity level of larger portion of the image). Now, the three images *nT*, *O* and *nR* as shown in Figure12 can be simply concatenated to obtain seamless stitched image shown in Figure 14 (b).

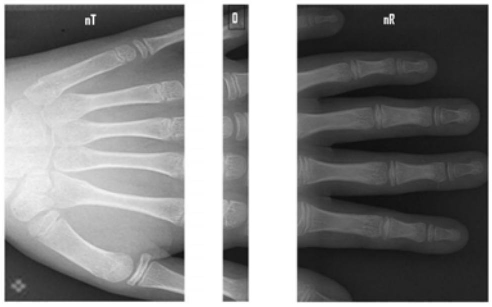

Fig. 12: Image nT, O and nR

IV. Result

The above algorithm can be applied to automatically align component images together and stitch them to obtain seamless composite image. The algorithm does not change the original quality of the image (intensity level) except in the overlapped area where triangulation averaging is performed. Time wise, performance is low when MI is selected as similarity measure criteria. On the other hand, SSD is faster and give accurate result. Figure14 (a) shows manual stitching of component images, 2 components taken with different exposure. Note the presence of seam in the composite image. Furthermore, alignment of component images manually is time consuming and erroneous task. The algorithm is tested for its accuracy in finding the alignment parameters and for multiple dataset and found to work properly.

TABLE I ALIGNMENT CORRECTION

Figure	Actual offset - Before alignment (in pixels)	Corrected Offset - After automatic alignment (in pixels)	Percentage difference / correction
Figure 14 (hand)	194	5	97
Figure 15(body)	175	10	94
Figure 16(arm)	500	14	97.2

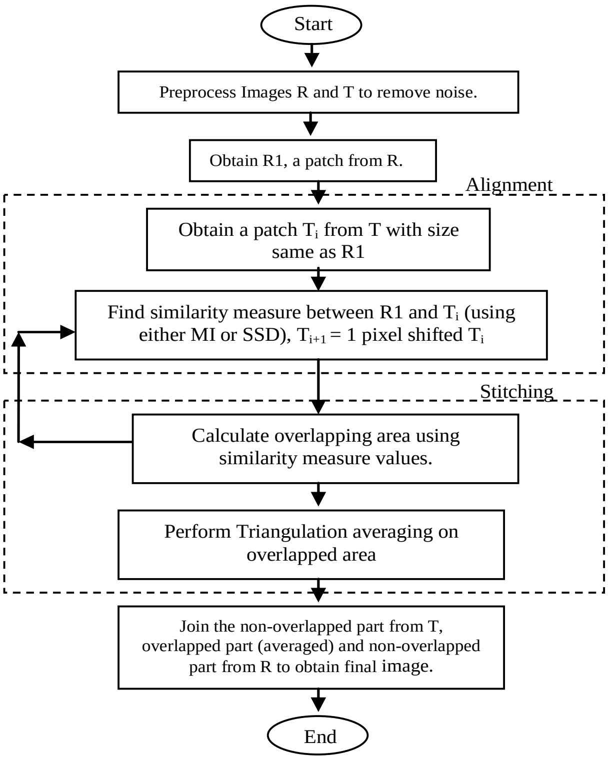

Fig. 13 Complete Algorithm Flowchart

V. CONCLUSION

Most of the existing methods as mentioned in section 1 assumes images to be aligned properly and removes only the visible seam. A precise automatic image alignment and stitching algorithm has been proposed here which joins component images to composite seamless image. Since the alignment algorithm does not extract any features and no segmentation is required in aligning process, it is easy to implement. This algorithm can also be used when component images are taken with different exposure.

VI. DISCUSSION

The proposed algorithm works fine for overlapping area of approx. 10% of total size of image, but its exact value is yet to be found. Size of the overlap area should be at least comparable in size to the largest prominent features in the image and should not be much larger than smallest prominent features [13]. For a smooth transition in the overlap area sigmum function may be used instead of triangular averaging. The current implementation is not scale, rotation and translation invariant. The algorithm can be enhanced to accommodate a preprocessing step which will register the component images for alignment.

Performance of the alignment algorithm can be further improved using multi-step adaptive search which includes coarser search for finding similarity in the first go and finer in the similar region. This method will reduce the time taken because of reduction in number of iteration.

VII. REFERENCE

[1] Richard Szeliski, "Image Alignment and Stitching: A Tutorial". Handbook of Mathematical Models in Computer Vision, pages 273–292, Springer, 2005.
[2] Shmuel Peleg, Benne Rouso, "Mosaicing on adaptive manyfolds". IEEE transaction on pattern analysis and machine intelligence vol 22 no. 10 October 2000.
[3] Yao Li, Lizhuang Ma, "A Fast and Robust Image Stitching Algorithm" ,Proceedings of the 6th World Congress on Intelligent Control and Automation, June 21 - 23, 2006, Dalian, China.
[4] Paul Dare, Ian Dowman, "A New Approach to Automatic Feature Based Registration of Spot Images". Images International Archives of Photogrammetry and Remote Sensing. Vol. XXXIII, Part B2. Amsterdam 2000.
[5] C.V. Veena, "Minimising Seam Artifacts in Image Stitching". Asian journal of Information Technology 6 (2) : 209-214 ,2007.
[6] Shmuel Peleg, "Elimination of Seams from Photomosaics.". Computer Graphics and Image Processing 16 90-94 (1984).
[7] Josien P. W. Pluim, J. B. Antoine Maintz and Max A. Viergever, "Mutual Information Based Registration of Medical Images: A Survey". IEEE Transactions on medical imaging, Vol. XX, No. Y, Month 2003.
[8] Darko Skerl, Bostjan Likar, "A Protocol for Evaluation of Similarity Measures for Rigid Registration". IEEE Transactions on medical imaging, Vol. 25, No. 6, JUNE 2006.
[9] Zhou Wang, Alan C. Bovik, "Mean Squared Error: Love it or Leave it?". IEEE signal processing magazine, jan 2009
[10] [Online]Available: http://www.historyofmedicineseries.com/images/xray.jpg
[11] [Online]Available: http://upload.wikimedia.org/wikipedia/commons/9/9b/Abdominal_Xray_with_uretal_stent.jpg
[12] [Online] Available: http://upload.wikimedia.org/wikipedia/commons/8/8c/XrayOITypeV-Kid-Vardhan.jpg
[13] Peter J. Burt and Edward H. Adelson, "A Multiresolution Spline with Application to Image Mosaics". ACM Transactions on Graphics, Vol. 2. No. 4, October 1983, Pages 217-236.

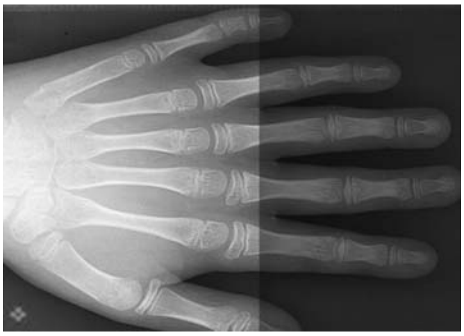

Fig. 14 (a): Normal stitched result

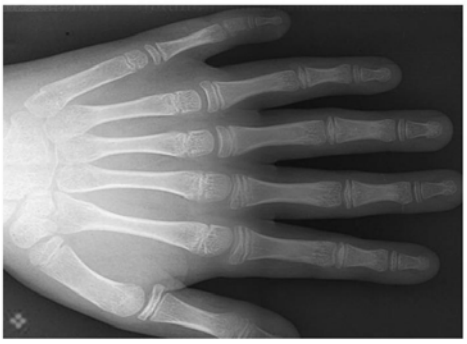

Fig. 14 (b): Seamless stitched result

Fig. 15 (a) [11]: Normal stitching
(Vertical Direction)

Fig. 15 (a) [11]: Seamless stitching
(Vertical Direction)

Fig. 16 (a) [12]: Normal stitching
(Vertical Direction)

Fig. 16 (b) [12]: Seamless stitching
(Vertical Direction)