Draft text: Hancharou, D. Histological Image Stitching Algorithm Based on Normalized Statistical Moment / D. Hancharou, A. Nedzved, V. Starovoitov / Proc. of The Eleventh Intern. Conf. on Pattern Recognition and Information Processing (PRIP2011). – Minsk, 2011. – P. 200–204.

Hystological Image Stitching Algorithm Based on Normalized Moment of Inertia

Dzmitry Hancharou [1], Valery Starovoitov [2], Alexandr Nedzved [2]
1) Belarusian State University, Nezavisimosti avenue 4, goncharovda@gmail.com
2) United Institute of Informatics Problems (UIIP NAS of Belarus), Surganova street 6, valerys@newman.bas-net.by

Abstract: *The problem considered in this paper is the automatic microscopic image stitching. In this paper, invariant local features based on normalized moment of inertia are used to select matching points and calculate the translation. This algorithm consists of feature detection, feature registration and spatial transition. The experimental results with more than 100 clinical medical images in different categories demonstrate this algorithm is fast, effective and does not require human interaction.*

Keywords**:** Image Stitching, Harris Detector, Normalized Moment of Inertia (NMI)

1. INTRODUCTION

Mosaic techniques have been used to combine overlapped signals into a new one with as little distortion of each signal as possible. Building a stitched image from a sequence of partial views is a powerful means of obtaining a complete, non-redundant view of scene [1]. Image stitching has been applied in medicine, computer vision and photogrammetry.

In general, most of image stitching methods developed in the past years can fall into two categories: template and feature based. Template based algorithms attempt to correlate the grey levels of image patches in the views being considered, assuming that they present some similarity [2]. Feature based algorithms establishing correspondences between points, lines or other geometrical entities and use properties of local intensity values to match them.

In our application, small overlapping images are used to construct an image with a far lager field of view. It solves the problem that microscopic image only covers a very small area without any more hardware. The approach proposed in this paper as shown in Fig.1 firs extracts interesting points by Harris corner detector and then matches them using a NMI technique followed by a statistical procedure. We choose Harris corner detector here due to its invariant to geometric transformations. NMI feature which belongs to invariant image feature is from physical conceptions. Experimental results show that the NMI feature of image has the ability of anti-tonal and geometric distortion (translation, rotation and scaling, TRS) and its extracting method is simple [3]. Thus, NMI feature offers a solution to correlate interesting points and recover the translation between images.

The paper is arranged as follows: Section 2 presents a detailed description of feature detection with Harris corner detector. In section 3, we discuss feature description while section 4 refers to feature matching. The experimental results and conclusions are given in section 5 and section 6.

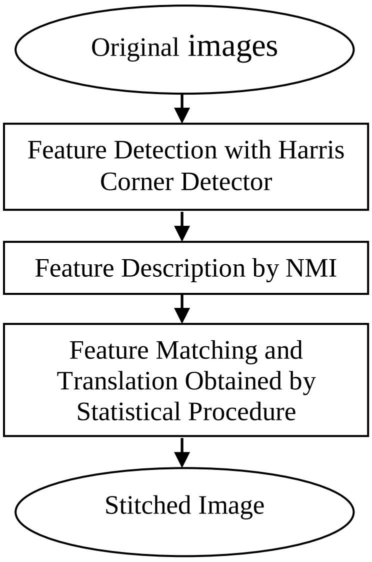

Fig. 1. The pipeline of image stitching

2. FEATURE DETECTION

The Harris measure M is the second moment matrix, describing the curvature of the autocorrelation function in the neighborhood of a point [4].

$$M = w_{u,v} * \begin{pmatrix} L_x^2 & L_x L_y \\ L_y L_x & L_y^2 \end{pmatrix}. \quad (1)$$

where * is convolution operator and $w_{u,v} = e^{\frac{-(u^2+v^2)}{2\sigma^2}}$ a Gaussian smoothing window. We can get image L_x from image I_x smoothed by a Gaussian $L_x^2 = I_x^2 * w_{u,v}$.

And the first gradients I_x and I_y in x, y direction respectively are approximated by

$$I_x = I * (-1,0,1) \approx \partial I / \partial x . \quad (2)$$

$$I_y = I * (-1,0,1)^T \approx \partial I / \partial y . \quad (3)$$

Let α, β be eigenvalues of M. α and β will be proportional to the principal curvatures of local autocorrelation function and form a rotationally invariant description of M [5]. A corner point will have an M with two strong eigenvalues. An edge will present one strong and one weak eigenvalue and a flat region will have two weak eigenvalues.

Now, we can measure the corner response R with eigenvalues α and β, thus

Draft text: Hancharou, D. Histological Image Stitching Algorithm Based on Normalized Statistical Moment / D. Hancharou, A. Nedzved, V. Starovoitov / Proc. of The Eleventh Intern. Conf. on Pattern Recognition and Information Processing (PRIP2011). – Minsk, 2011. – P. 200–204.

$$R = Det(M) - kTr^2(M)\,. \tag{4}$$

Where $Det(M) = \alpha * \beta$, $Tr(M) = \alpha + \beta$. R is positive in the corner region, negative in the edge region, and small in the flat region [5]. An interesting point is selected as a corner pixel by applying high threshold as shown in Fig.2.

Fig. 2. Microscopic image with interesting points in blue with the threshold 5000

3. FEATURE DETECTION

The definition of NMI is as follows:

$$NMI = \frac{\sqrt{J_{(cx,cy)}}}{\sum_{x=1}^{M}\sum_{y=1}^{N} f(x,y)}\,. \tag{5}$$

where (cx, cy) is the center of mass of the image and $J_{(cx,cy)}$ the moment of inertia.

$$cx = \frac{\sum_{x=1}^{M}\sum_{y=1}^{N} x \times f(x,y)}{\sum_{x=1}^{M}\sum_{y=1}^{N} f(x,y)}\,. \tag{6}$$

$$cy = \frac{\sum_{x=1}^{M}\sum_{y=1}^{N} y \times f(x,y)}{\sum_{x=1}^{M}\sum_{y=1}^{N} f(x,y)} \tag{7}$$

$$J_{(cx,cy)} = \sum_{x=1}^{M}\sum_{y=1}^{N}((x-cx)^2 + (y-cy)^2)\, f(x,y)\,. \tag{8}$$

NMI feature is invariant to translation, rotation and scaling. In our application, we use NMI to describe the interesting points in images. The approach calculates NMI for a disk around the points and the same points in different images will have similar properties.

4. FIGURES AND TABLES

In our application we only consider translation between images though tiny rotation and scaling may exist from measure errors. Feature matching is performed with NMI and centers of gravity corresponding to interesting points between images. We define a measure of the strength of the match (SM for abbreviation), as

$$SM(NMI_{1i}, NMI_{2j}) = \frac{\left|NMI_{1i} - NMI_{2j}\right|}{0.5*(NMI_{1i} - NMI_{2j})}\,. \tag{9}$$

NMI_{1i} is the NMI of $i-th$ interesting point in the first image and NMI_{2j} the $j-th$ in the second image. Let $G_{1i}(x, y)$ and $G_{2j}(x, y)$ are the centers of gravity.

If $SM(NMI_{1i}, NMI_{2j}) \le 0.1$ and $Dist(G_{1i}, G_{2j}) \le 0.1$, then the pair of interesting points is a potential match. $Dist(G_{1i}, G_{2j})$ is defined as follows.

$$Dist(G_{1i}, G_{2j}) = \max(\left|x_{1i} - x_{2j}\right|, \left|y_{1i} - y_{2j}\right|)\,. \tag{10}$$

Until now the match relationship is multi-to-multi and the purpose is to contain correct matches in potential matches. For every pair of math points, calculate translation in x and y directions each, then we can get a statistical char of quantities of matching points at different translation as shown if Fig.4. Correct matching points will result in same translation and others are stochastic, so maximum exists at proper translation between images in theory. In practice, we use following expression to estimate.

$$score = \frac{Num_x(best)}{Num_x(\mathrm{sec}ond)} + \frac{Num_y(best)}{Num_y(\mathrm{sec}ond)}\,. \tag{11}$$

$Num_x(best)$ and $Num_x(\mathrm{sec}\,ond)$ mean the number of best and second best match in x direction in the statistical chart. If the condition $score > 1.2$ is met, these two images are treated as overlapped and the location of maximum in the chart is the translation between them.

5 EXPRERIMENTAL RESULTS

The proposed algorithm has been evaluated by clinical marrow images and pathological images and good stitching results have been obtained.

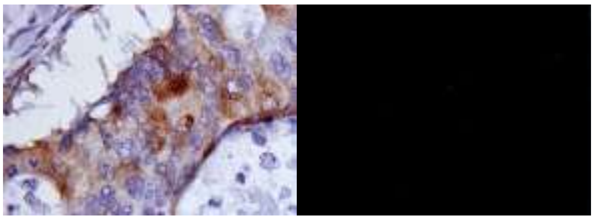

Fig.3. Two partially overlapped microscopic images (top) and the images with detected interesting points (bottom)

Fig.3 shows two original overlapped microscopic marrow images and interesting points which are detected by Harris corner detector with the threshold 5000. For such a color image, we only use intensity component to calculate interesting points and NMI.

After feature matching, the statistical cart of distance of matching points is shown in Fig.4. We can easily find maximums in each direction and this can demonstrate the robustness of our algorithm. The location of peak value on x and y axis is the translation between the two images to be stitched and in this case the peak is at (313, 50). The stitching result is shown in Fig.5.

This method can achieve fast image stitching and the time elapsed during the procedure of feature detection and feature matching is theoretical proportional to the number of interesting points. Table 1 compares the time consumed of NMI based method with Zernike moment [4], phase correlation [6] methods in image stitching and the results are average time of experiments on same size images. Fig.6 shows the mosaic results based on these two methods.

Fig.4. The statistical chart of quantities of matching

points at different translation in x direction (left) and y direction (right)

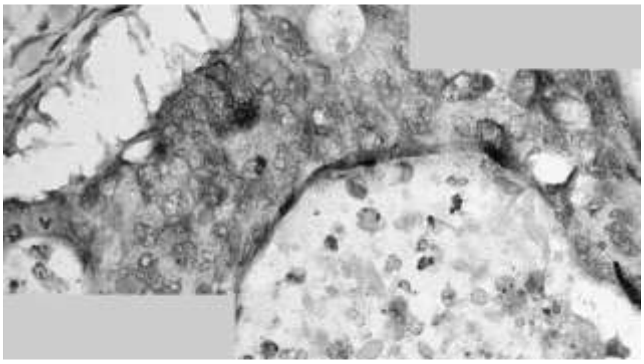

Fig.5. Stitching image by the translation obtained in Fig.4

NMI based mosaic result shown in Fig.5 is almost the same as Zernike moment and phase correlation based results shown in Fig.6, but their efficiency is distinct. Table 1 demonstrates that NMI based method is much faster in stitching images with translation. Its advantage becomes more prominent when the size of images increases. Fig.7 shows image stitching with NMI.

Table 1. A comparison of time-consuming of three different methods (unit: ms)

Image size	NMI	Zernike Moment	Phase Correlation
1798x1438	5601	47631	44692
2592x1944	9659	65798	174676

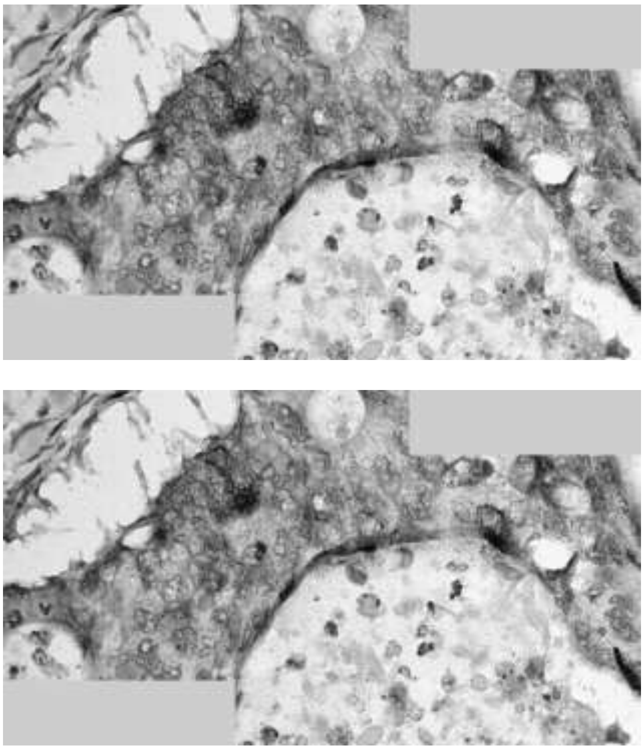

Fig.6. Mosaic based on Zernike moment (top) and phase correlation (bottom)

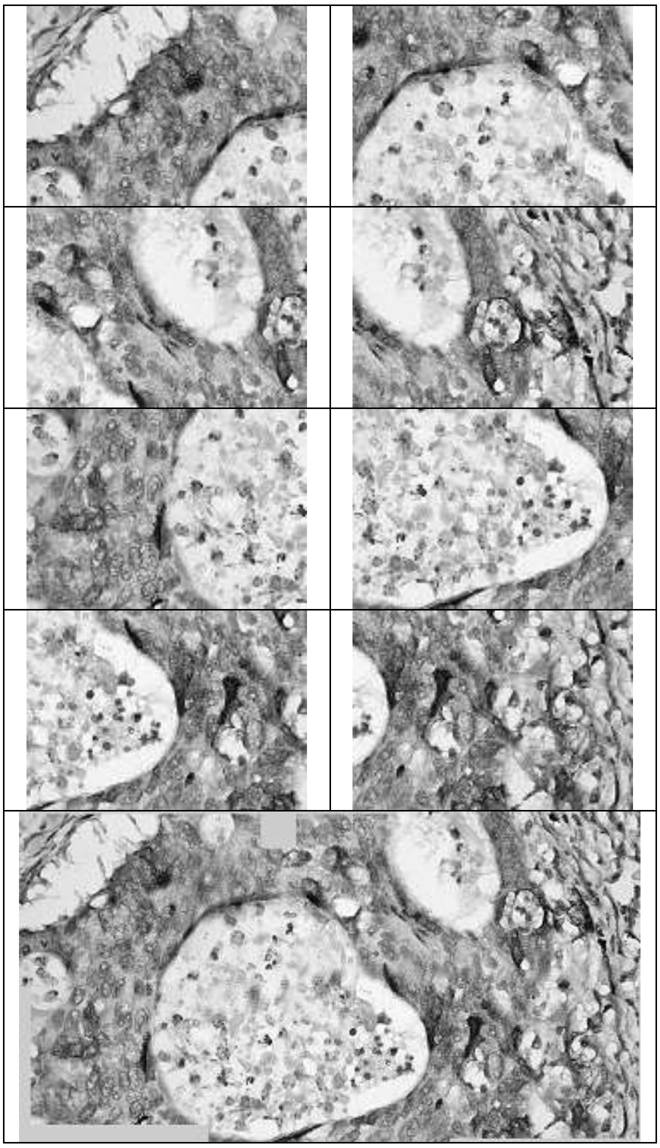

Fig.7. Original partially overlapped images to be stitched (top) and the stitching result with NMI (bottom)

6. CONCLUSION

In this paper, a novel approach based on normalized moment of inertia to solve the microscopic image stitching problem has been proposed. The algorithm can calculate and recover the translation between the images quickly and efficiently to completely meet the demands of stitching microscopic medical images. Our experiments with more than 100 clinical images in different categories have demonstrated the proposed algorithm's robustness and speed, so it has been successfully integrated in our automatic microscopic image analysis system. One limitation of current algorithm is its inadaptability of the images with rotation and scaling.

7. REFERENCES

[1] M. Irani, P. Anandan, S. Hsu: Mosaic Based Representations of Video Sequences and Their Applications. *Proc. IEEE Int. Conf. on Computer Vision (1995)*, p. 605-611

[2] Z.Y. Zhang, R. Deriche, O. Faugers, Q.T. Luong: A Robust Technique for Matching Two Uncalibrated Images Through The Recovery of The Unknown Epiipolar Geometry, INRIA (1994)

[3] Yang X.G., Fu G.Y., Miao D., Zhang W.J.: A New Approach to Target Recognition Based on Image NMI Feature, Computer Engineering (2002)
[4] Pizarro O., Singh H.: Toward Large-Area Mosaicing for Underwater Scientific Applications, IEEE Journal of Oceanic Engineering, 28 (2003)
[5] Harris C., Stephens M.: A Combined Corner and Edge Detector, Proc. Alvey Conf., Manchester, U.K. (1988) 189-192