A NEW 2D CORNER DETECTOR FOR EXTRACTING LANDMARKS FROM MEDICAL IMAGES

Gelareh Mohammadi, Emadodin Fatemizadeh
Biomedical Signal & Image Processing Laboratory (BiSIPL), Sharif University of Technology, Tehran, Iran
Gelareh_mohamadi@yaoo.com, fatemizadeh@sharif.edu

ABSTRACT

Point-based registration of images strongly depends on the extraction of suitable landmarks. Recently, various 2D operators have been proposed for the detection of corner points but most of them are not effective for medical images that need a high accuracy. In this paper we have proposed a new automatic corner detector based on the covariance between the small region of support around a central pixel and its rotated one. The main goal of this paper is medical images so we especially focus on extracting brain MR image's control points which play an important role in accuracy of registration. This approach has been improved by refined localization through a differential edge intersection approach proposed by Karl Rohr. This method is robust to rotation, transition and scaling and in comparison with other grayscale methods has better results particularly for the brain MR images and also has acceptable robustness to distortion which is a common incident in brain surgeries. In the first part of this paper we describe the algorithm and in the second part we investigate the results of this algorithm on different MR images and its ability to detect corresponding points under elastic deformation and noise. It turns out that this method: 1)detect larger number of corresponding points that the other operators, 2)its performance on the basis of the statistical measures is better, and 3)by choosing a suitable region of support, it can significantly decrease the number of false detection.

1. INTRODUCTION

Nowadays, image and imaging are two important tools in medical science and medical images not only in diagnosis but also in cure planning, medical attention and medical studies or stereo tactic surgeries in which surgeon find necessary information by images, have an important role.
Medical imaging techniques could be categorized to two general types of imaging, anatomical imaging and functional imaging; anatomical images are related to the tissue's certain properties but functional images are related to the organic metabolism, for example CT, MRI, X-Ray are anatomical imaging but fMRI, PET, SPECT are functional imaging. The information of these two types is complementary so integration of them is very desirable. One of the image integrations methods is registration of two images and creating one image with specifications of both images and among different methods of registration [1-4], landmark-based registration has better results and precision but extracting landmarks with high accuracy in this approach is very important. Landmark extraction is used not only in medical registration but also in motion analysis, object identification, camera calibration and machine vision. There are so many researches after 1977 on corner detection [5] which is certain type of landmarks but only few of them were for medical images. There are two general approaches for this extraction: the first one is segmentation-based methods in which the border of area is brought out first and then the corner of the segmented area will be extracted; and the second one is gray level-based methods in which without any segmentation by the use of image gray level analysis, landmarks will be determined. Here we introduce some of these proposed approaches: Beaudet [6] used local exterima of the Hessian matrix determinant, Dreschler & Nagel[7] used local extrima of the Gaussian model of the image curves, Kitchen & Rosenfeld[8] used product of gradient direction variety on the contour border and the absolute size of the gradient on that place, Forstner [9] introduced calculation of local extrima of $\det(C)/trace(C)$ in which matrix C is a representative of gradient in a local window, Rohr[10-11] used a two-step approach for detecting corners in medical images; this approach improves the place of the corner, detected by Forstner method. Brady & Smith [12] introduced SUSAN method in which by using a circular mask and consideration of inside pixels intensity, landmarks would be extracted. Tsi[13] calculated the eigenvalues of a series points on the border of a contour and by use of this amount, he succeeded to extract rather precise corners. Zitova & Flusser[14] introduced a corner detector based on high contrast area extraction. Fatemizadeh[15] used a classification-based approach to detect landmarks in medical images, in this method corners are detected as the vertexes of a polygon.
Although there are several proposed approaches for corner detection, but none of them are perfectly reliable especially for medical images which need a higher accuracy in comparison with non medical images; so researches in this field are still continuing to reach a fast, reliable, high precise method.

In this paper a new gray level-based approach for extracting landmarks from images especially medical images is proposed. This method does not need any segmentation which decreases the speed of calculations and has better results in comparison with Rohr method which is designed for medical images and have a good accuracy in contrast with other methods. This new algorithm is robust to rotation, scaling and transition also. In the sequel, method, experiments and results are presented.

2. NEW 2D LANDMARK EXTRACTION PROPOSED ALGORITHM

This new method is based on the variety amount in image rotation around the vertex of an angle. In the first step, we describe an $n\times n$ window in which n is an odd number and this window will scan the entire image to determine the value of each pixel as a corner. As medical images usually have a specific size, n can be described constant in each similar group like adult men. The presented algorithm does some calculation on each window and the result of each window will refer to the central pixel. So if (i,j) is the coordinate of one pixel, window around this pixel will be like figure 1.

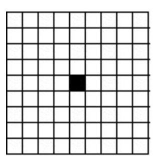


Figure 1.

Matrix $W_{i,j}$ which is $n\times n$, is contributed for pixel (i,j) as follow:

$$W = \begin{bmatrix} p_{i-n,j-n} & \cdots & p_{i-n,j+n} \\ . & & . \\ . & p_{i,j} & . \\ . & & . \\ p_{i+n,j-n} & \cdots & p_{i+n,j+n} \end{bmatrix} \quad (1)$$

In which P(x,y) is the amount of pixel (x,y) intensity. In next step we define a new description covariance between matrix $W_{i,j}$ and $W_{i,j}$, covariance between $W_{i,j}$ and $W'_{i,j}$ and covariance between matrix $W_{i,j}$ and $W''_{i,j}$. $W'_{i,j}$ and $W''_{i,j}$ are defined as follow:

$$W'_{i,j} = Rot90(W_{i,j}) \quad (2)$$

$$W''_{i,j} = Rot180(W_{i,j}) \quad (3)$$

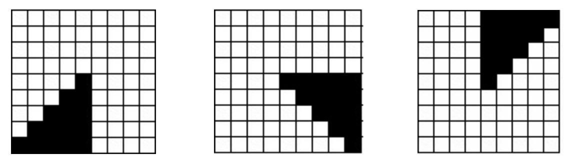
In which $Rot\theta$ is a rotation function by the scale of θ degree. The covariance CO1, CO2 and CO3 will be described as follow:

$$CO1(i,j) = \sum_{k,h} \left| W_{i,j}(k,h) - P(i,j) \right| \times \left| W_{i,j}(k,h) - P(i,j) \right| \quad (4)$$

$$CO2(i,j) = \sum_{k,h} \left| W_{i,j}(k,h) - P(i,j) \right| \times \left| W'_{i,j}(k,h) - P(i,j) \right| \quad (5)$$

$$CO3(i,j) = \sum_{k,h} \left| W_{i,j}(k,h) - P(i,j) \right| \times \left| W''_{i,j}(k,h) - P(i,j) \right| \quad (6)$$

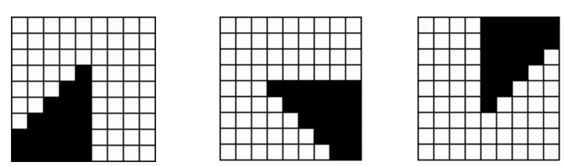
In this new description of covariance we use central pixel amount instead of mean value. In these definitions, CO1 is an index of contrast in the mask; CO2 and CO3 are indexes of central pixel cornerness. Here there is an example to clarify the criteria more, assume a 9×9 mask like figure 2a, in this window black pixels intensity are 0 and white pixels intensity are 255;



a b c

Figure 2.

If you contribute $W_{i,j}$ from figure 2a then $W'_{i,j}$ and $W''_{i,j}$ would be contributed from 2b and 2c and the value of CO1 for this mask is 66×255^2 , CO2 is 52×255^2 and CO3 is 52×255^2. Now, if the mask moves one pixel down like figure 3 , the values of CO1, CO2 and CO3 will be 61×255^2, 43×255^2 and 43×255^2 respectively and you can see the difference between these indexes for a real corner and its nearest neighbor. So we can use of these criteria to determine the corners with out any necessity to segmentation.



a b c

Figure 3.

Final criterion is defined like follow:

$$Cornerness(i,j) = CO1(i,j) + CO2(i,j) + CO3(i,j) \quad (7)$$

The local maxima of this index are the pixels more candidate for being corners. This algorithm is robust to scaling, rotation and transition and it also have good results against distortion. Although it is sensitive to noise

but its results show improvement in comparison with Rohr algorithm sensitivity to noise. As this new method does not use any segmentation so it is rather fast and it does not need any initial condition.
This algorithm has been applied to MRI brain medical images and it gives better results than Rohr algorithm. In the next part we will show the experiments and results of this new approach.

3. EXPRIMENTS AND RESULTS

This algorithm has been applied to a number of images included medical and non-medical images. Here we show some of these results; in figure 4 you can see results of the proposed method and the results of Rohr algorithm on some non-medical images; but as mentioned our main target is brain MR images.

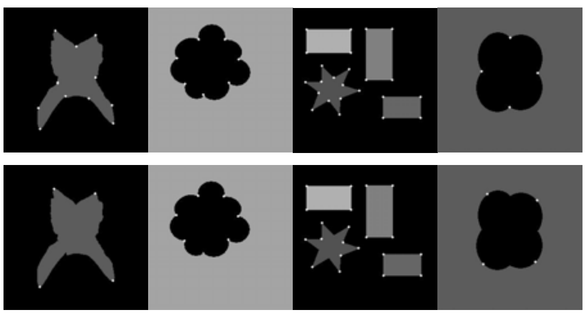


Figure 4. First row is the results of new algorithm and the second row is the results of Rohr algorithm

This algorithm was performed on 4 complete brain MRI slices each includes more than 100 slices with size 256×256. One of these databases was simulated and others were real images. In figure 5 you can see 4 slides of simulated images and the results of Rohr algorithm and our new method beside each other. In these results the conditions for both algorithm were the same and the used mask was 9×9; results revealed in figure 6 are related to real database and the conditions are like figure 5.
As you know in brain images the corners on brain ventricular system are more valuable so to valid the results we asked an expert to label the slides for ventricular system and calculate the FAR (False Acceptance Ratio), FRR (False Rejection Ratio) and ME(Mean Error, distance from background) for both new method results and Rohr algorithm results; these consequents are showed in table 1 and you can see improvement in every three indexes especially in FRR which illustrate the ability of this new method in not accept of false points as corner point . The comparison is also performed for distorted slides and noisy slides.

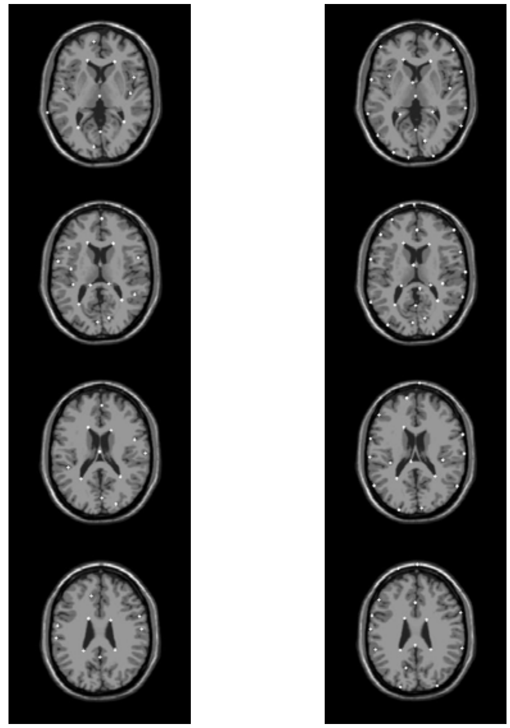


Figure 5. left column is the results of new algorithm and right column is Rohr algorithm's results on simulated images

To make the results comparable we contaminated images with 3% Gaussian noise and after performance of both algorithms on noisy and clean images we calculated two indexes: the first one is the number of acceptable landmarks on brain ventricular system and the second one is the number of landmarks which are repeated in both noisy and un-noisy images   Table 2 shows the gained consequents for 40 brain MRI noisy slides included simulated and real slides. Table 3 shows the same indexes for 40 distorted slides which are deformed randomly by different filters of Photoshop software. In figure 7 and figure 8 the results of both algorithms on 3 noisy slides and 3 distorted slides are showed. So we can say that by this new method we can reach better results in different aspects in comparison with one of the previous best algorithm (Rohr algorithm).

Table 1. Results of both algorithm for 160 different slides.

	FAR	FRR	ME
new algorithm	6.8%	4.6%	4%
Rohr algorithm	7.9%	8.1%	5%

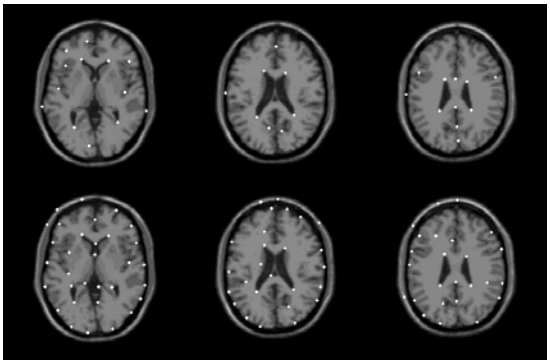


Figure 6. first row is the results of new algorithm on noisy images & second row is the results of Rohr algorithm on noisy images

Table 2. results for noisy images

	Total number of landmarks	Number of correct points	Number of common points
new algorithm	170	136	145
Rohr algorithm	226	148	143

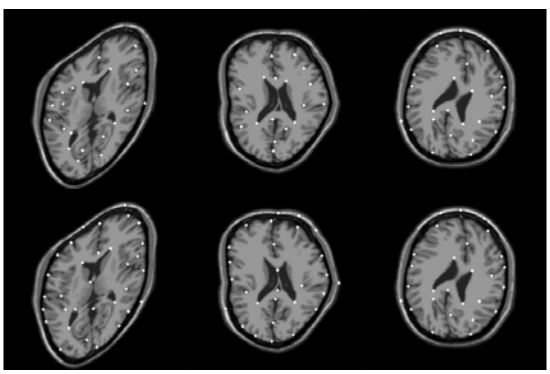


Figure 7. first row is the results of new algorithm on distorted images & second row is the results of Rohr algorithm on distorted images

Table 3. results for distorted images

	Total number of landmarks	Number of correct points	Number of common points
new algorithm	153	129	131
Rohr algorithm	195	114	135

4. CONCLUSION

Although pointed out in previous chapters, despite of various proposed approaches for extraction of corner points as landmarks but there is not a complete and high accurate method for extracting corners from medical images which need more precision than the other images; In this research we tried to improve the accuracy of landmark extraction from medical images by describing a new method based on the covariance between intensity variety in a certain mask and its rotated one. The results show an acceptable improvement in different aspects in comparison with Rohr algorithm. This method is robust to scaling, rotation and transition. For noisy and distorted images this algorithm gives rather desirable consequents. We hope to be able to improve this method and getting better results. This method is extended for 3D images and has desirable consequent which will be published soon.

REFERENCES

[1] J.B. Antoine Maintz , “A survey of medical image registration”, Med. Image Anal., vol. 2, pp. 1-36, 1998.

[2] D.L.G. Hill, P.G. Batchleor, M. Holden, “Medical image registration”, Phys. Med. Biol., vol. 46, pp. R1-R45, 2001.

[3] P.J. Kostelec, S. Periaswamy, “Image registration for MRI”, Modern Sig. Proc., MSRI Publications, vol. 46, pp. 161-183, 2003.

[4] B. Zitova, J. Flusser, “Image registration methods:a survey”, Image & Vis. Comp., vol. 21, pp. 977-1000, 2003.

[5] K. Rohr, “Localization properties of direct corner detectors”, Journal of mathematical Imaging and Vision, 4, pp.139-150, 1994.

[6] P.R. Beaudet, “Rotationally invariant image operators”,Proc. Int. Joint Conf. Pattern Recognition, pp.579-781, 1987.

[7] L. Dreschler,H. Nagel, “Volumetric model and 3D trajectory of a moving car derived from monocular tv frame sequences of a street scene”, IJCAI-81, pp. 692-697,1981.

[8] L. Kitchen, A. Rosenfeld, “Gray level corner detection”, Pattern Recognition Letters, pp. 95-102,1982.

[9] W. Forstner, “A feature based correspondence algorithm for image matching”, Int. Arch. Photogramm. Remote Sensing, vol. 26, pp. 150-166, 1986.

[10] K. Rohr, “Modeling and identification of characteristic intensity variations”, Image Vis. Comput., vol. 10, pp. 66-76, 1992.

[11] S. Frantz, K. Rohr, “Multi-step differential approaches for localization of 3D point landmarks in medical images”, Jour. of Comp. & Info. Tech., vol. 6(4), pp. 435-477, 1998.

[12] S.M. Smith, J.M. Brady, “SUSAN-a new approach to low level image processing”, Int. Jour. Of Comp. Vis., vol. 23, pp. 45-78, 1997.

[13] D.M. Tsi, H.T. Hou, H.J. Su, “Boundary-based corner detection using eigenvalues of covariance matrices”, Patt. Recog. Lett., vol. 20, pp. 31-41, 1999.

[14] B. Zitova, J Flusser, “feature point detection in multiframe images”, Czech Pattern Recognition Workshop, 2000.

[15] E. Fatemizadeh, C. Lucas, H. Soltanian Zadeh, “Automatic landmark extraction from image data using modified growing neural gas network”, IEEE Trans. On Information Technology and Biomedicine, 2003.