ISSN: 2278 – 1323
International Journal of Advanced Research in Computer Engineering & Technology (IJARCET)
Volume 2, Issue 3, March 2013

Comparison of Optimization Techniques for Mutual Information based Real Time Image Registration

Renu Maria Mathews, D. Raveena Judie Dolly, Ann Therese Francy

Abstract— **Image registration is the process of aligning two or more images of the same scene. A direct image registration approach uses Mutual Information (MI) as an image alignment. Mutual Information is a measure of the similarity of different images. It is robust, accurate and real-time for the both monomodal and multimodal images. It has the ability to perform robust alignment with illumination changes, multi-modality and occlusions. This method also helps to produce accurate image registration results in both monomodal and multimodal images. Time consumption is greatly reduced by this method. The optimization techniques used here are to protect the Mutual Information cost function.**

Index Terms—**Image registration, Mutual Information, Multi – modality, Optimization .**

I . Introduction

Image registration is the process of overlay two or more images of the same scene taken at different times with the help of different sensors. It is a fundamental image processing method and is very useful for integrating information from different sensors taken at different times. In this work, only image sequences are consider for registration. Such approach which can be seen as a 2D motion estimation issue is also often referred as direct tracking or region tracking methods. Major difficulties in such a registration process are image noise, illumination changes and occlusions. Along with robustness to such perturbations, we focus on registration and tracking considering different sensor modalities (e.g., infra-red and visible images) [10].

The main fundamental steps of the image registration can be identified as[6].

(1) Feature Detection: The object features are manually or automatically detected and for further processing, these features can be considered.

(2) Feature matching: The correspondence between the reference and target image is determined. By using the different feature descriptors and similarity measures the correspondence can be found out.

Manuscript received Mar 10, 2013.

Renu Maria Mathews, *Electronics and Communication Engineering, Karunya University. Tamilnadu, India.*

D.Raveena Judie Dolly, *, Electronics and Communication Engineering, Karunya University, Tamilnadu, India.*

Ann Therese Francy, *, Electronics and Communication Engineering, Karunya University Tamilnadu, India.*

(3) Transformation model estimation: From the feature correspondences a geometrical transformation, in terms of a mapping function is estimated.

(4) Image resampling and transformation: Sensed image is transformed with the help of mapping function and image values in non-integer coordinates are computed by any of the interpolation method.

The choice of a robust similarity measure is then fundamental. Mutual Information has been developed to define a similarity measure that helps to reduce many problems in image registration. The Mutual Information can be defined as a quantity that measures the mutual dependence of the two random variables. This is the classical similarity measure for both monomodal and multimodal images.

In monomodal applications both images belong to the same modality e.g. only CT images or just x-Ray or ultrasound data [1]. Growth monitoring and subtraction imaging, for example are key domains for monomodal registration**.** As opposed to monomodal, at multimodal registration the images to be registered belong to different modalities. The applications are innumerable and diverse. There are several examples of multi-modality registration algorithms in the medical imaging field [3]. Examples include registration of whole body PET/ CT images for tumour localization [4]. Registration of contrast-enhanced CT images against non-contrast-enhanced CT images for segmentation of specific parts of the anatomy and also registration of ultrasound and CT images for prostate localization in radiotherapy are widely used [5]. MR (Magnetic Resonance) and CT (Computed Tomography) feature space can be identified by this method.

Different methods are used to solve image registration problem. Histogram based approach is one of the technique. But this method does not help to estimate the complex movements of image. In this case, for estimating the motion of an image, consider that the 2D model as a reference image. Differential image registration method is performed to find out the motion between the current image and reference image. One example of such method is KLT [8]. It mainly makes use of spatial intensity information to direct the search for the position that yields the best match and it is faster than traditional techniques. But this is not effective in the case of illumination changes and occlusions.

For finding the maximum similarity of the images optimization is needed. Three optimization techniques are studied here for solving the problem.

II. METHODOLOGY

An image similarity measure quantifies the degree of similarity between intensity values of two images. The selection of an image similarity measure mainly depends on the modality of the images to be registered. Mutual Information is the best similarity measure for multimodal image registration. Normalized cross-correlation, sum of squared in differences and sum of absolute difference are commonly used for monomodal image registration.

A. Block Diagram

The figure 1 shows the design methodology of the proposed system. Image preprocessing is mainly for increasing the local contrast and highlights the fine details of the images.

The Mutual Information is the similarity measure for different images. Rather than comparing intensity values, Mutual Information is the quantity of information shared between two random variables. In this paper, Mutual Information between the reference and target images is taken first and then reference and registered image is considered. Affine transformation is applied for the target image and the transformation of the target image is developed. The transformed image and reference image are used for the registration in both monomodal and multimodal images.

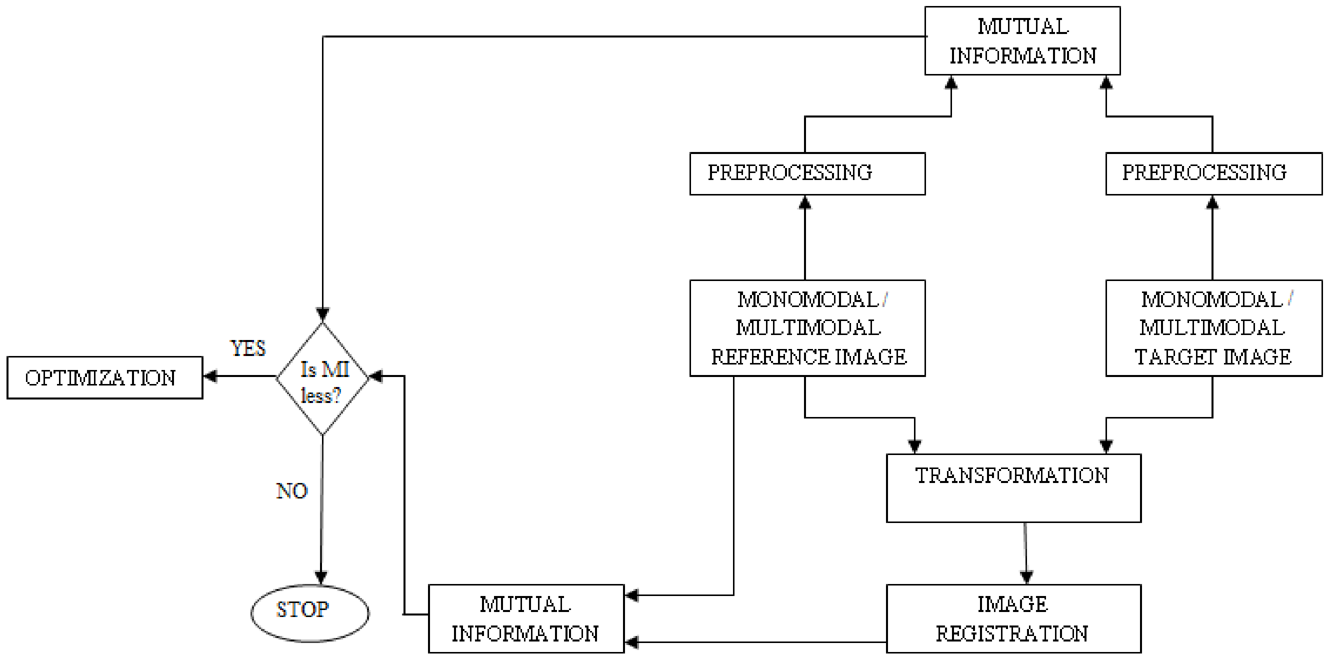


Figure 1. Design methodology

A. Mutual Information

Mutual Information is the similarity measure for the different images. Mutual Information can be calculated with the help of entropy values. Entropy is the measure of the uncertainty associated with a random variable. Mutual Information related to the entropy is given by the following equations [7]:

$$\begin{aligned} I(A,B) &= H(A) + H(B) - H(A,B) \\ &= H(A) - H(A|B) \\ &= H(B) - H(B|A) \end{aligned} \quad (1)$$

Given that H (A) and H (B) are the entropy of the A and B respectively, then the joint entropy is H (A,B). H (A|B) and H (B|A) is the conditional entropy of A given B and B given A respectively.

Marginal entropy and joint entropy can be computed from [8].

$$H(A) = \sum_a - P_A(a) \log P_A(a) \quad (2)$$

$$H(B) = \sum_b - P_B(b) \log P_B(b) \quad (3)$$

$$H(A,B) = \sum_{a,b} - P_{A,B}(a,b) \log P_{A,B}(a,b) \quad (4)$$

Let $P_A(a)$ and $P_B(b)$ be the marginal probability mass function and $P_{AB}(a, b)$ be the joint probability mass function. These probability mass functions can be obtained from the following equation [8],

$$P_{A,B}(a,b) = \frac{h(a,b)}{\sum_{a,b} h(a,b)} \quad (5)$$

$$P_A(a) = \sum_b P_{A,B}(a,b) \quad (6)$$

$$P_B(b) = \sum_a P_{A,B}(a,b) \quad (7)$$

Where h is the joint histogram of the two images. If the two variables are equal then Mutual Information is maximal. If one of the variables is constant then it shares no information with the other variable, so Mutual Information is null. If the formulations are differentiable then it helps to smooth the Mutual Information function [9].

B. Transformation

Image registration algorithms can be classified based on the transformation models they use to relate the target image space to the reference image space. Linear and nonlinear transformations are available. The linear transformations include rotation, scaling, shearing etc. But translation is not a linear transform. This transform cannot model local geometric differences between images. The non linear transformations are capable of locally warping the target image to align with the reference image.

Most of the geometrical attacks can be identified using the general affine transforms [11]. This is represented by the 4 coefficients a,b,c and d helps to forming a matrix V for the linear component, plus the two coefficients t_x,t_y for the translation part $\hat{t}$:

$$V = \begin{bmatrix} a & b \\ c & d \end{bmatrix} \qquad \hat{t} = \begin{bmatrix} tx \\ ty \end{bmatrix} \qquad (8)$$

D. Image Registration

Image registration is the process of aligning two or more images of the same scene taken at different times. Here, one image is taken as the reference image and the other is target image. The transformation is applied to the target image and compared it with reference image. The differences between the input image and the output image might have occurred as a result of terrain relief and changes due to same scene from different viewpoints. Cameras and other internal sensor distortions between sensors can also cause distortion [1].

E. Optimization Methods

The following methods are used to solve the optimization problem for getting proper registered image. An objective function is used to measure similarity of the reference and target image and also used to find the local minima.

1.Conjugate Gradient Optimization

This is an iterative optimization technique which is mainly used for solving the sparse systems. And it works with the help of conjugate directions. This search direction is linearly independent to all previous directions. This method is more complicated than the gradient descent method [15].

2.Random Search optimization

This iterative optimization technique does not require any gradient of the images. This work is based on generation of the starting points. The starting point is sampled by each iteration. The optimization is applied to the objective function (error function) and the local minimum is found [14]. This method is very simple and quick but not effective for many cases.

3.Gradient Descent Optimization

Most of the searches methods tend to converge slowly towards the local minimum. The main reason of this is the incomplete use of objective function at the current sampling point [12]. For obtaining the local optimum, have to travel in the opposite direction to the gradient of the objective function [13]. This method is very effective and more accurate comparing with above two methods.

II. RESULTS AND DISCUSSION

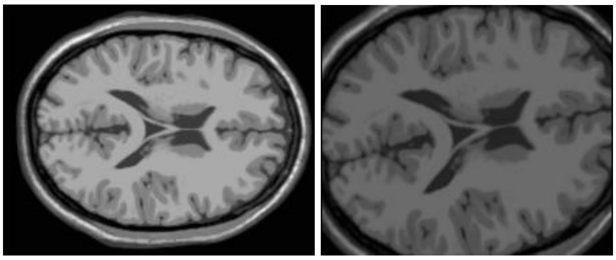
A. Data Sets

For determining the image registration between the two monomodal images, the input images are taken from a video. The video is converted in to different frames and two frames are considered as reference and target images. The Figure 2 shows the reference and target image of monomodal images with size of 256 X 256.

(a) (b)

Figure 2. Input images for the monomodal registration (a) reference image and (b) Target image.

For the multimodal images, the images are taken at different time and from different camera view points. The following multimodal images are taken from the brain web database. 181 X 217 is the size of the images used here.

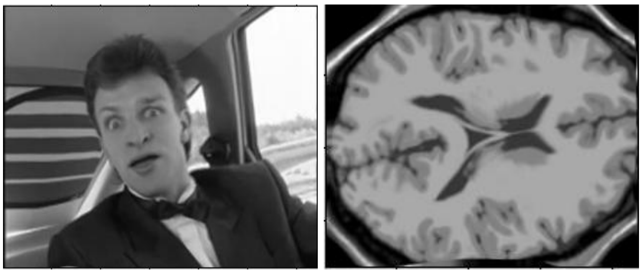


(a) (b)

Figure 3. Input images for the multimodal registration (a) Reference image and (b) Target image.

B. Image Registration

Typically reference image is considered the reference to the target images, are compared. In the image registration process is to bring the target image into alignment with the reference image by applying a spatial transformation to the target image. In this work, affine transformation is applied to the target image. The following figure shows the registration of the monomodal and multimodal images.



(a) (b)

Figure 4. (a)Registered monomodal image and (b) registered multimodal image

C. Comparison Table

For comparing the Mutual Information of the monomodal and multimodal images before and after registration the following tables are used.

The Mutual Information can be obtained with the help of entropy. Below table shows the entropy values of the monomodal and multimodal images before and after registration. Where H(A) and H(B) are the entropy values of two images A and B and H(A,B) is the joint entropy.

TABLE I: ESTIMATION OF ENTROPY

TYPE OF IMAGES	CASES	ENTROPY		
		H(A)	H(B)	H(A,B)
BEFORE REGISTRATION	MONOMODAL IMAGE	7.3847	7.3555	11.8098
	MULTIMODAL IMAGE	5.5006	5.4738	10.3543
AFTER REGISTRATION	MONOMODAL IMAGE	7.3847	7.3796	11.6694
	MULTIMODAL IMAGE	5.5006	6.3439	10.9047

Mutual Information of the two images is given below. The table shows that the similarity measure is increased after the registration. Here the target image was transformed and tried to make similar as the reference image.

TABLE II: ESTIMATION OF MUTUAL INFORMATION

MUTUAL INFORMATI ON	BEFORE REGISTRATI ON	MONOMODAL IMAGES	2.9304
		MULTIMODAL IMAGES	0.6202
	AFTER REGISTRATI ON	MONOMODAL IMAGES	3.0949
		MULTIMODAL IMAGES	0.9398

The error value calculation of the monomodal and multimodal images are given in the below table. By comparing three methods, gradient descent method gives the much better result. If the value of the error function decreases the similarity of the images is increases.

TABLE III: ESTIMATION OF ERROR VALUES OF MONOMODAL IMAGES

METHOD	NO. OF ITERATION S	TIME (S)	ERROR VALUES
GRADIENT DESCENT	39	0.909	1.0e-003
CONJUGAT GRADIENT	918	4.0236	1.0e+003
RANDOM SEARCH	100	0.0122	3.4104e+003

TABLE III: ESTIMATION OF ERROR VALUES OF MULTIMODAL IMAGES

METHOD	NO. OF ITERATIONS	TIME (S)	ERROR VALUES
GRADIENT DESCENT	39	1.099	1.0e-005
CONJUGAT GRADIENT	982	6.668	1.0e+003
RANDOM SEARCH	100	0.007 1	3.9526e+00 3

III. Conclusion

This method supports Mutual Information with respect to its robustness toward illumination variations, images from different modalities and occlusions. It is fast and computationally inexpensive. The calculations of the Mutual Information show that the similarity of the images increases after the registration process. It also helps the accurate image registration of both monomodal and multimodal images. The maximum similarity of the image was obtained with the help of gradient descent optimization.

REFERENCES

[1]. J.V. Hajnal, D.L.G. Hill, and D.J. Hawkes (editors): “Medical Image Registration”. The Biomedical Engineering Series, CRC Press, 2001, chapters 2 and 3.
[2]. A.Comport, E. Marchand, M. Pressigout, and F. Chaumette. “Real-time markerless tracking for augmented reality: the virtual visual servoing framework”. IEEE Trans. on Visualization and Computer Graphics, 12(4):615–628, July 2006.
[3]. N. Ritter, R. Owens, J. Cooper, R. Eikelboom, and P. Van Saarloos. “Registration of stereo and temporal images of the retina”. IEEE Trans.on Medical Imaging, 18(5):404–418, May 1999.
[4]. J. Hajnal, D. G. Hill, and D. Hawkes. “Medical Image Registration”.CRC Press, 2001.
[5]. D. Townsend and T. Beyer. “A combined PET/CT scanner: the path to true image fusion”. The British Journal of Radiology, 75:S24S30, 2002.
[6]. B. Zitova and J. Flusser, “Image registration methods: a survey,” ELSEVIER Image and Vision Computing, vol. 21, pp. 977–1000, 2003.
[7]. C. Studholme, D. Hill, and D. J. Hawkes. Automated 3D registration of truncated mr and ct images of the head. In British Machine Vision Conference, BMVC’95, pages 27–36, Birmingham, Surrey, UK, Sept.1995.
[8]. Juan Wachs, Helman Stern,Tom Burks, Victor Achanatis “ Multi-modal Rgistration Using Combined Similarity Measure” .
[9]. H. Chen, P. K. Varshney, and M. K. Arora, "Mutual information based image registration for remote sensing data." International Journal of Remote Sensing, Vol. 24, no. 18, pp. 3701-3706, 2003.

[10]. Amaury Dame and Eric marchand "Second order optimization of mutual information for real-time image registration"IEEE Trans on image processing,2012.

[11]. Frédéric Deguillaume, Sviatoslav Voloshynovskiy, and Thierry Pun "A method for the estimation and recovering from general affine transforms in digital watermarking applications".

[12] S. Chapra, R. Canale. "Numerical Methods for Engineers, 4th Ed."; McGraw-Hill; USA; 2002.

[13] T. Marwala. "ELEN 5015 Course Notes: Optimisation"; School of Electrical and Information Engineering; University of Witwatersrand; 2004.

[14] Anne Auger, Raymond Ros "Benchmarking the Pure Random Search on the BBOB-2009 Testbed" ACM-GECCO Genetic and Evolutionary Computation Conference (2009).

[15]Jonathan Richard Shewchuk, "An Introduction to the Conjugate Gradient Method Without the Agonizing Pain" August 1994.