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Robust Image Registration Based on an Adaptive Normalized Mutual Information Metric

Huda Algharib, Amal Algharib, Hanan Algharib, Ali Mohammad Alqudah

Abstract**—**Image registration is an important topic for many imaging systems and computer vision applications. The standard image registration techniques such as Mutual information/ Normalized mutual information -based methods have a limited performance because they do not consider the spatial information or the relationships between the neighbouring pixels or voxels. In addition, the amount of image noise may significantly affect the registration accuracy. Therefore, this paper proposes an efficient method that explicitly considers the relationships between the adjacent pixels, where the gradient information of the reference and scene images is extracted first, and then the cosine similarity of the extracted gradient information is computed and used to improve the accuracy of the standard normalized mutual information measure. Our experimental results on different data types (i.e. CT, MRI and thermal images) show that the proposed method outperforms a number of image registration techniques in terms of the accuracy.

Keywords**—**Image registration, mutual information, image gradients, Image transformations.

I. Introduction

MOST imaging systems need some form of registration operation. The necessity for such operation is that to integrate information from different devices (for example, structural information from CT or MRI with functional information from PET or SPECT), discover changes in images taken at different times or under different conditions, stitch multiple images into one panorama, or align images for the purpose of face/object recognition. The difficulty of image registration process is that the scene images come in different locations, shapes and sizes.

Over the past decades, many image registration approaches have been proposed. These approaches can be classified broadly into two categories [1]: feature-based and intensity-based. In feature-based methods, the distinctive features or structures (such as corners, edges, line intersections, region boundaries, etc.) in both scene and reference images are manually or automatically detected and then matched. However, these methods heavily rely on the accuracy of feature detection and any error during this stage will propagate into the registration and can hardly be recovered at a later stage. To avoid these drawbacks, intensity-based (or voxel-based) methods were proposed. These methods deal with the images without attempting to detect salient features. Mutual information, for example, is an intensity-based measure that does not require the definition of features. Several independent studies have shown the suitability of mutual information as a registration measure for multimodal medical images [2]-[6]. On the other hand, the mutual information registration function can be ill-defined when the images contain few information or when there is only a small area of overlap which result in misregistration [7]-[10]. More sophisticated methods aim to improve the image registration process such as multiresolution methods [7], a different entropy measure [8], invariance with respect to overlap [10], and 'higher-order' mutual information, using co-occurrence matrices of neighbouring voxels' intensities [11].

In this paper, we propose a new implementation for image registration called Adaptive Normalized Mutual Information. The method combines the normalized mutual information with the cosine similarity of the extracted gradient information. The importance of gradient information should be emphasized since it does not consider the value of the pixels in images, but on differences between the values of neighboring pixels such as local spatial transitions.

II. Image Registration

Registration is the process of determining an accurate geometrical transformation that applied to the scene (target) image to reach the reference image. More formally, the registration process can be considered as an optimization problem that aims to maximize the similarity or minimize the cost. On other words, in the registration process, a parametric transformation $T_g(.)$ is applied on the target image I_t in order to maximize its similarity with the reference image I_r. Note that the targeted similarity relies on the defined cost function $P(.)$. The optimization target can be represented as in Eq. (1) [12]:

$$T_g(.) = \arg\max_{T_g(.)} p\,(I_r, \mathrm{T}_g(I_t)) \tag{1}$$

The registration procedure consists of three basic components which are: transformation model, similarity metric and optimization procedure.

A. Transformation Model

The transformation model specifies the type of the geometrical transformation that should be applied to the target image to reach the reference image. In addition, it controls and preserves the geometrical aspects (e.g. size, shape, position, orientation, etc.) during the image registration process.

Huda M.S. Algharib is with Ankara Yildirim Beyazid University, Turkey (e-mail: huda_selem@yahoo.com).

There are two basic categories of transformations: rigid (global) and non-rigid (elastic/local) transformations. The rigid transformations allow changes in translation, rotation or/and scaling (similarity transforms), also admit shearing (affine transformation). These transformations use 6, 7 and 12 parameters for 3D images. On the other hand, the non-rigid transformations, such as B-spline and thin-plate splines transformations represent the local deformations (warps) using a large number of parameters. However, using the suitable transformation model relies on the needs of the application. Fig. 1 shows some types of transformations.

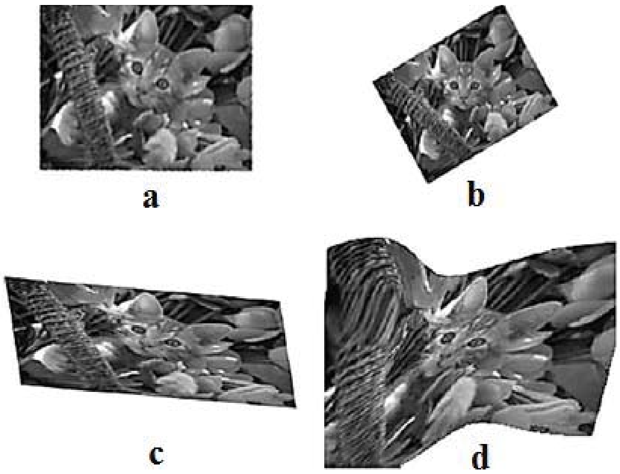


Fig. 1 Types of transformations: the reference image (a), similarity (b), affine (c) and B-spline (d)

B. Similarity Metric

The similarity metric is considered as the most important component of any image registration framework since it measures the quality of the alignment and the optimization procedure that perform the search for a suitable transformation [13]. The similarity metric depends on the nature of the registration method. In feature-based methods the similarity metric usually measures the distance between corresponding features [14]. Unlike the intensity-based approaches, similarity metrics are usually based on the resemblance of the intensity values in the two images. the next section discusses intensity-based methods since our proposed method is an intensity-based measure.

1) Mutual Information

The mutual information (MI) of two images measures the amount of shared-information between them that reduce the uncertainty in both images. High mutual information refers to a large reduction in uncertainty; low mutual information refers to a small reduction; and zero mutual information between two images means the images are independent. The most common way to define the mutual information is based on Shannon's entropy between two probability distributions, which can be expressed as following:

$$MI(A,B) = H(A) + H(B) - H(A,B) \tag{2}$$

here, *H(A)* and *H(B)* denote the entropy values of *A* and *B* respectively. *H(A,B)* is the joint entropy of the two images.

Fig. 2 shows the relationship between entropy and mutual information.

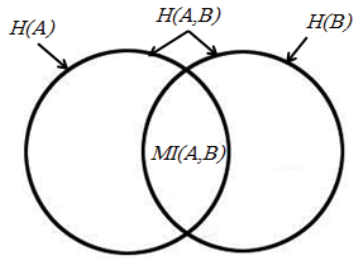


Fig. 2 Venn diagram for the relationship between entropy and mutual information

Accurate registration of the images assumes that the mutual information of the images is maximized as much as possible. However, it has shown that the registration quality might decrease despite an increasing *MI* value [10]. To overcome the problem of increasing *MI* with decreasing registration quality, normalized mutual information *(NMI)* measures were introduced.

2) Normalized Mutual Information

Studholme et al. [10] introduce an example of the normalized mutual information measures.

$$NMI(A,B) = \frac{H(A) + H(B)}{H(A,B)} \tag{3}$$

and the entropy correlation coefficient used by Maes et al. [3]

$$ECC(A,B) = \frac{2I(A,B)}{H(A) + H(B)} \tag{4}$$

The above measures have a one-to-one correspondence. Therefore, we will only use NMI *(A,B)* in this paper.

3) Normalized MI with Gradient Information

This method is an extension of normalized mutual information measure to include spatial information that is present in each of the images [19]. The extension is accomplished by multiplying the mutual information with a gradient term. The gradient term is based on both the magnitude and the orientation of the gradients and thus yields a better registration function than normalized mutual information. The similarity metric of this method can be defined as:

$$NMI_{new}(A,B) = G(A,B)\, NMI(A,B) \tag{5}$$

where $G(A,B) = \sum_{(x,x')\in(A\cap B)} w\,(\alpha_{x,x'}(\sigma))\ min\ (|\nabla x(\sigma)|, |\nabla x'(\sigma)|)$ represents the gradient information between the images A, B. $\nabla \mathbf{x}(\sigma)$ denoting the gradient vector at point *X* of scale σ, $|.|$ denoting magnitude, $\alpha_{x,x'}(\sigma)$ the angle between the gradient vectors and w is a weighting function that favors angles that are either very small or close to π.

4) Proposed Method

In order to calculate the gradient of image stably (i.e. the numerical calculation of gradient is much more stable in calculation), the image is smoothened first by convolving with Gaussian kernel function as following:

$$I' = I * \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2+y^2}{2\sigma^2}\right) \quad (6)$$

where * represents the image convolution operation, and σ is a standard deviation value between 0 and 1. Next considering two adjacent pixel points (x,y) and $(x, y+\Delta y)$, the gradient of image I in Y direction can be computed as:

$$I_{y-gradient} = \partial I'(x,y)/\partial y \quad (7)$$

Similarly, the gradient of image I in X direction can be expressed as:

$$I_{x-gradient} = \partial I'(x,y)/\partial x \quad (8)$$

Compute the ratio of y-gradient of I to x-gradient of I as following:

$$I_{(x,y)-gradient} = I_{y-gradient} \big/ I_{x-gradient} \quad (9)$$

To avoid the division by zero which may occur in real world cases, the inverse tangent function of (9) is applied. This leads to following definition:

$$I_{(x,y)-gradient} = \arctan\left(I_{y-gradient} \big/ I_{x-gradient}\right), G \in \left[-\frac{\pi}{2}, \frac{\pi}{2}\right] \quad (10)$$

Thus, if we have two images A and B, we can obtain the gradient information of each image by applying (10).

$$A_{(x,y)-gradient} = arctan \quad (A_{y-gradient}/A_{x-gradient}) \quad (11)$$
$$B_{(x,y)-gradient} = arctan \quad (B_{y-gradient}/B_{x-gradient}) \quad (12)$$

Finally, we compute the cosine similarity of two images treated as vectors.

$$Similarity(A,B) = cos\,\theta = \vec{A}.\vec{B}/\|\vec{A}\|\ \|\vec{B}\| \quad (13)$$

The adaptive normalized mutual information becomes:

$$ANMI = similarity(A,B) + NMI(A,B) \quad (14)$$

C. Optimization Procedure

This procedure decides the best transformation based on the similarity measure. Each optimization procedure has a different search strategy that depends on the nature of the algorithm and can be classified into parameter-based methods and feature-based methods.

TABLE I
CT KIDNEY IMAGES REGISTRATION BY MI, NMI, GRADIENT NMI AND THE PROPOSED METHOD, RESPECTIVELY

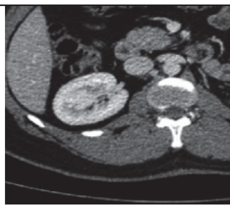
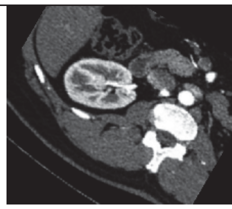
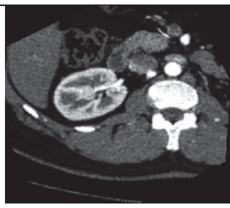
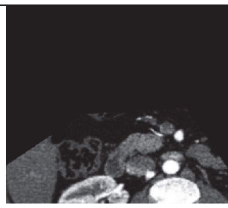
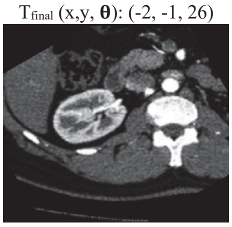
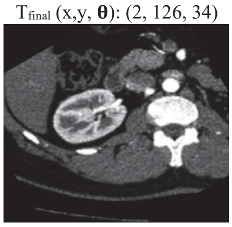
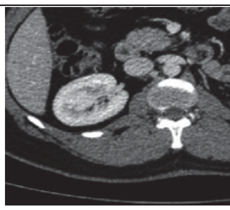
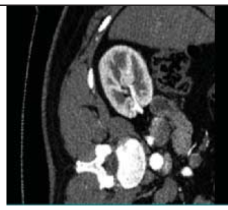
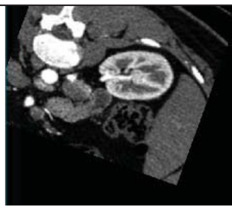
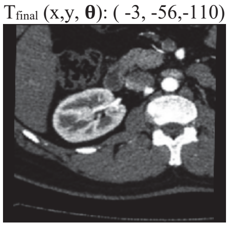
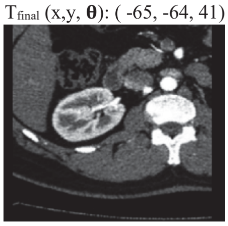
Trial 1	
	
Reference Image	Target Image T_0 (x, y, $\boldsymbol{\theta}$): (-1, 2, -30)
After registration	
	
MI T_{final} (x,y, $\boldsymbol{\theta}$): (-2, -1, 26)	NMI T_{final} (x,y, $\boldsymbol{\theta}$): (2, 126, 34)
	
Gradient+ NMI T_{final} (x,y, $\boldsymbol{\theta}$): (0, 1, 30)	Proposed T_{final} (x,y, $\boldsymbol{\theta}$): (1, -1, 30)
Trial 2	
	
Reference Image	Target Image T_0 (x, y, $\boldsymbol{\theta}$): (-2, 3, -90)
After registration	
	
MI T_{final} (x,y, $\boldsymbol{\theta}$): (-3, -56,-110)	NMI T_{final} (x,y, $\boldsymbol{\theta}$): (-65, -64, 41)
	
Gradient+ NMI T_{final} (x,y, $\boldsymbol{\theta}$): (1, 0, 89)	Proposed T_{final} (x,y, $\boldsymbol{\theta}$): (1, -1, 90)

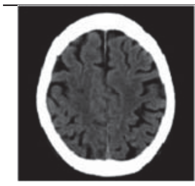
TABLE II
THE RETURNED VALUES IN EACH ITERATION OF TRIAL 1

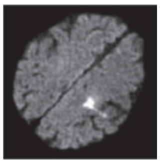
iteration	x-shift	y-shift	rotation	*Cos similarity*	*NMI*	*Cos similarity + NMI*
1	0	0	0	0.8977	1.041464	1.939164
2	0	0	23	0.9059	1.064529	1.970429
3	0	0	34	0.9219	1.064525	1.986425
4	0	0	29	0.9171	1.084556	2.001656
5	0	0	29	0.9171	1.084556	2.001656
6	2	-1	30	0.9254	1.080117	2.005517
7	1	-1	30	0.9264	1.08203	2.008430
8	1	-1	30	0.9264	1.08203	2.008430

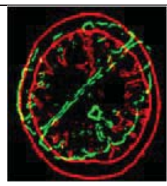
The parameter-based algorithms implement the search directly in the space of the transformation parameters. This treats the registration as continuous optimization problem. Examples of these optimization algorithms such as Gradient descent, Newton's method, Powell's method and discrete optimization [15]. On the other hand, feature-based methods consist in searching for a matching between features such as the iterative closest point algorithm (ICP) [16].

TABLE III
CT AND MRI REGISTRATION OF BRAIN IMAGES BY MI, NMI, GRADIENT NMI AND THE PROPOSED METHOD, RESPECTIVELY

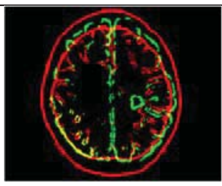
Trial 1

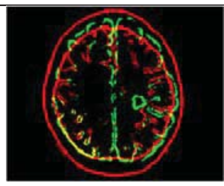

Reference Image

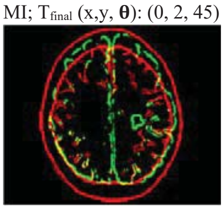

Target Image; T_0 (x, y, $\boldsymbol{\theta}$): (-1, 2, -45)

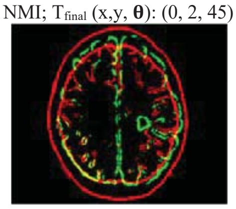

Before registration

After registration

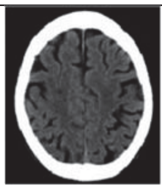

MI; T_{final} (x,y, $\boldsymbol{\theta}$): (0, 2, 45)

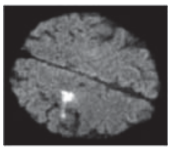

NMI; T_{final} (x,y, $\boldsymbol{\theta}$): (0, 2, 45)

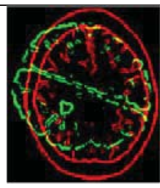

Gradient+NMI; T_{final} (x,y, $\boldsymbol{\theta}$) : (0 ,1 ,46)


Proposed; T_{final} (x,y, $\boldsymbol{\theta}$): (0, 2, 45)

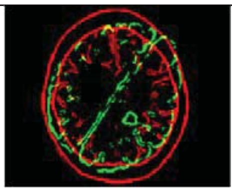
Trial 2

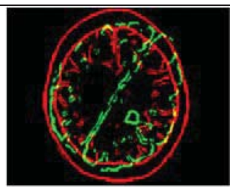

Reference Image

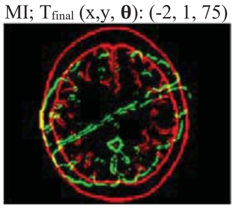

Target Image; T_0 (x, y, $\boldsymbol{\theta}$): (-3, 4,-110)

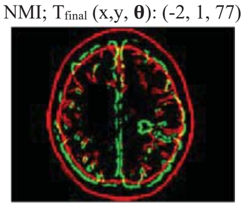

Before registration

After registration


MI; T_{final} (x,y, $\boldsymbol{\theta}$): (-2, 1, 75)


NMI; T_{final} (x,y, $\boldsymbol{\theta}$): (-2, 1, 77)


Gradient+ NMI; T_{final} (x,y, $\boldsymbol{\theta}$): (0, 2, 47)


Proposed; T_{final} (x,y, $\boldsymbol{\theta}$): (-5, 4, 110)

In our paper, Powell's method is used to perform the optimization of the registration function [17]. This method repeatedly iterates the dimensions of the search space, performing one-dimensional optimizations for each dimension, until convergence is reached.

III. Experimental Results

A. Experiment 1: CT Kidney Images Registration

In this experiment, two CT Kidney Images are captured at different times and locations. The scene images differ from reference images in terms of rotation and translation. The initial transformation with horizontal shift X, vertical shift Y and rotation angle $\boldsymbol{\theta}$ is denoted by T_0 (x, y, $\boldsymbol{\theta}$); the final transformation after the registration is denoted by T_{final} (x, y, $\boldsymbol{\theta}$). The results compared with standard image registration methods (MI, NMI and Gradient+ NMI) are shown in Table I.

As shown in Table I, our method gives the best results and returns the best parameters in both trials. Note that the MI/NMI-based registration methods have a common drawback in that it does not take into account the spatial relationships between adjacent pixels or voxels. Therefore, they have less accuracy in both trials.

Table II shows the values of parameters in each iteration of Trial 1.

B. Experiment 2: CT and MRI Brain Images Registration

The experiments were conducted on CT and MRI registration of brain images of the same patient. The reference images and the scene images were captured from different sensors with different structural information. The results from different trials of this experiment are shown in Table III.

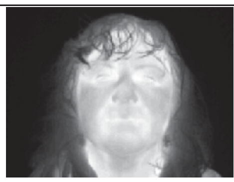
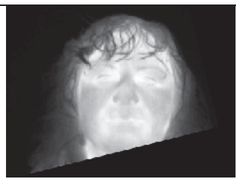
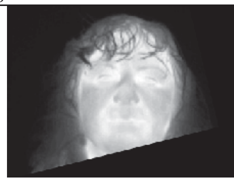
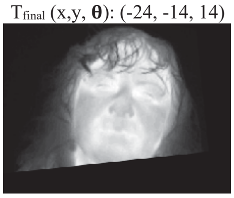
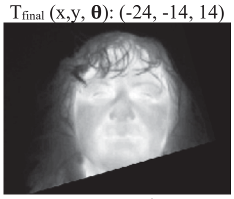
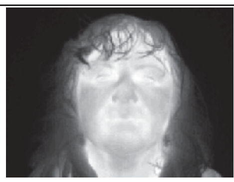
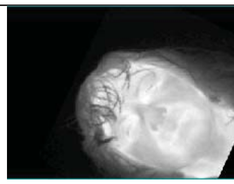
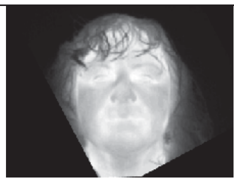
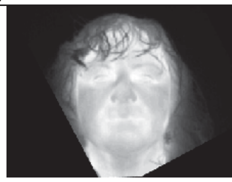
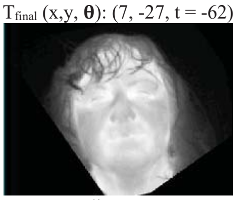
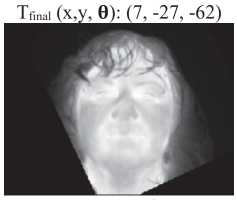
C. Experiment 3: Facial Image Alignment

In this experiment, we have taken into account the challenges in face recognition systems caused by the variation in the image acquisition process such as rotation and translation variations, which result in difficulties in face recognition. The experiments were conducted on a sample thermal facial image from Carl face database [18]. As shown in Table IV, the proposed method gives the best alignment among the traditional similarity metrics.

IV. Conclusion

We have proposed a modified version of the normalized mutual information measure, by incorporating gradient information. Although Josien et al. [19] confirm the importance of emphasizing the spatial information to mutual information, but there is a need to include the gradient information such that it takes the changes in both horizontal and vertical directions that caused by large changes in the translation and rotation as addressed in this paper. The results mentioned in this paper prove that the proposed mechanism to combine the normalized mutual information with gradient information is efficient and robust.

TABLE IV
THE ALIGNMENT OF A SAMPLE THERMAL FACIAL IMAGE FROM CARL FACE DATABASE [18]

Trial 1	
	
Reference Image	Target Image; T_0 (x, y, $\boldsymbol{\theta}$): (20, 20, -15)
After Alignment	
	
MI T_{final} (x,y, $\boldsymbol{\theta}$): (-24, -14, 14)	NMI T_{final} (x,y, $\boldsymbol{\theta}$): (-24, -14, 14)
	
Gradient+ NMI T_{final} (x,y, $\boldsymbol{\theta}$): (-22, -21, 6)	Proposed T_{final} (x,y, $\boldsymbol{\theta}$): (-22, -18, 15)
Trial 2	
	
Reference Image	Target Image T_0 (x, y, $\boldsymbol{\theta}$): (20, 20,65)
After Alignment	
	
MI T_{final} (x,y, $\boldsymbol{\theta}$): (7, -27, t = -62)	NMI T_{final} (x,y, $\boldsymbol{\theta}$): (7, -27, -62)
	
Gradient+ NMI T_{final} (x,y, $\boldsymbol{\theta}$): (3, -27, -55)	Proposed T_{final} (x,y, $\boldsymbol{\theta}$): (10, -27, - 65)

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