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USING MUTUAL INFORMATION AND CROSS CORRELATION AS METRICS FOR REGISTRATION OF IMAGES

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ABSTRACT

The existence of numerous imaging modalities makes it possible to present different data present in different modalities together thus forming multimodal images. Component images forming multimodal images should be aligned, or registered so that all the data, coming from the different modalities, are displayed in proper locations. The term image registration is most commonly used to denote the process of alignment of images , that is of transforming them to the common coordinate system. This is done by optimizing a similarity measure between the two images. A widely used measure is Mutual Information (MI). This method requires estimating joint histogram of the two images. Experiments are presented that demonstrate the approach. The technique is intensity-based rather than feature-based. As a comparative assessment the performance based on normalized mutual information and cross correlation as metrics have also been presented.

Keywords: *Image Registration, Mutual Information, Normalized Mutual Information, Optimizer, Cross Correlation.*

1. INTRODUCTION

In computer vision, sets of data acquired by sampling the same scene or object at different times, or from different perspectives, will be in different coordinate systems. Image registration is the process of transforming the different sets of data into one coordinate system. To be precise it involves finding transformations that relate spatial information conveyed in one image to that in another or in physical space. Image registration is performed on a series of at least two images, where one of these images is the reference image to which all the others will be registered. The other images are referred to as target images. It plays an important role in all image analysis tasks in which combination of various data sources is necessary as in Image fusion. Technological advances in medical imaging in the past two decades have enabled radiologists to create images of the human body and its internal structures with unprecedented resolution and realism. Two basic types of medical images are made: functional body images (such as SPECT or PET scans), which provide physiological information, and structural images (such as CT or MRI), which provide an anatomic map of the body. Different medical imaging techniques may provide scans with complementary and occasionally conflicting information. The combination of images can often lead to additional clinical information not apparent in the separate images. The goal of image fusion is to impose a structural anatomic framework on functional images.

Medical image registration has been applied to the diagnosis of breast cancer, colon cancer, cardiac studies, wrist and other injuries, inflammatory diseases and different neurological disorders including brain tumors, Alzheimer's disease and schizophrenia. This method has also been utilized mostly in radiotherapy treatment planning, where CT is used mostly.

Registration in this case is multimodality registration. There also exist important application areas in monomodality registration. To detect key differences in images taken at different times, alignment of the images is necessary.

Typically registration is required in remote sensing, medical imaging, cartography etc.

Because of the variety of images to be registered and because of degradations a single registration approach may not be suitable for all the images. Hence a variety of registration methods have evolved suitable for different types of images. Nevertheless all registration methods include feature extraction, feature matching, transformation selection and image resampling.

In this work we concentrate on maximization of mutual information between the two images as the basic criteria for registration. For a comparative assessment of the performance, feature based registration was also tried out. The work discusses in detail the former part and results obtained for both have been presented for comparison.

The paper is organized as follows. Section 2 discusses the process of registration and Section 3 presents the technique we have used. Section 4 presents the comparison. In section 5, we discuss the results obtained on the images. Finally, some conclusions and future work are also addressed in the last section.

2. REGISTRATION

Image registration is performed on a series of at least two images, where one of these images is the reference image or source image to which all the others will be registered. The other images are referred to as target images. Registration problem is the task involved in finding the optimal spatial and intensity transformations so that the images are matched with regard to the misregistration source. Intensity transformation may not be necessary in all the cases. Finding the geometric or spatial transformation is the key to any registration problem.

We find the mapping $\boldsymbol{T}$ that transforms a position $\boldsymbol{x}$ from one image $\boldsymbol{A}$ to another $\boldsymbol{B}$

$$\boldsymbol{T}(\boldsymbol{x}_A) = \boldsymbol{x}_B$$

The type of transformation is related to the number of dimensions of the images. It also depends on the cause of misalignment which may or may not be all the distortions present between the two images. Although many types of distortion may be present in each image, the registration method must select the class of transformation which will remove only the spatial distortions between images due to differences in acquisition and not due to differences in scene characteristics that are to be detected.

A number of registration algorithms for different images have been reported. A comprehensive survey of these methods has been published by Barbara Zitova & Jan Flusser [1] , Antoine Maintz & Max A.Viergever [6]. Accordingly the criteria used for classification can be described as

Dimensionality: 2D methods used for registering 2D images & 3D methods for 3D images. Special cases of registering 2D images with layers in 3D ones and when surface data is registered with the surface of an object in 3D where time can be the fourth dimension.

Domain of the transformation: The registering transformation can be global or local, according to whether it operates on the whole image or its part.

Type of the transformation: The transformation can be rigid, affine, projective or non-linear. The most commonly used is the affine transformation.

Tightness of feature coupling: The transformation can be either interpolating or approximating. In the former, the features of objects in one image are exactly transformed into features in the other one while in the latter , a non-zero fitting error appears, spread over the overlaid features.

Measure of the registration quality: Using the features derived from the data or the data itself, various measures are applied. Commonly used measures are the quadratic mean distance and the maximum distance in the Euclidean.

Method of parameter determination: In the direct methods, the parameters of the transformation are directly calculated from the data while in the search-oriented methods they are found by search techniques.

Subject of registration: Registration is intrasubject, if different images contain data on the same subject while it is intersubject, if the subjects are different.

Type of data: The data which controls the registration process can be raw data or features of data or even markers on data.

Source of features: These algorithms can use the intrinsic or extrinsic features. Intrinsic features are those present in the data like gray levels, edges, geometric features etc while extrinsic features are those added to the data from outside, like frames mounted to the patient's head etc.

The most important criteria seems to be that of the *Type of data* as the distinctions in respect of this criterion are the most closely related to the clinical problems analyzed with the use of the image registration methods. The methods using this criterion are classified as those using the markers, those using geometrical features as well as those working with raw data. We explored method of this class, namely the method of mutual information which is very promising. To prove the performance we also investigated using the feature of cross correlation. The results obtained have been presented and explained in sections 4 & 5.

3. OVERVIEW OF THE APPROACH

3.1. Mutual Information

The objective of the study was to address registration of images acquired from the same sensor under different conditions. Existing methods for the different steps in the registration process were reviewed and evaluated [3, 4, and 5].

Image similarity-based methods are broadly used in medical imaging. A basic image similarity-based method consists of a transformation model which is applied to reference image coordinates to locate their corresponding coordinates in the target image space, an image similarity metric, which quantifies the degree of correspondence between features in both image spaces achieved by a given transformation, and an optimization algorithm which tries to maximize image similarity by changing the transformation parameters.

The choice of an image similarity measure depends on the nature of the images to be registered. Common examples of image similarity measures include Cross-Correlation, Mutual Information, Mean-square difference and Ratio Image Uniformity. Mutual Information and its variant, Normalized Mutual Information, are the most popular image similarity measures for registration of multimodality images. Cross-correlation, Mean-square difference and Ratio Image Uniformity are commonly used for registration of images of the same modality.

Mutual information is an information theory measure of the statistical dependence between two random variables or the amount of information that one variable contains about the other. It can be qualitatively considered as a measure of how well one image explains the other. The most commonly used measure of information in image processing is the Shannon-Wiener entropy measure. Given *m* events occurring with probabilities $p_1 \ldots\ldots p_n$ the Shannon entropy is defined as:

$$H = \sum_{i=1}^{m} p_i \log 1/pi = -\sum_{i=1}^{m} p_i \log p_i$$

It is a measure of uncertainty or dispersion of the probabilities of events. For an image the entropy is calculated from the image intensity histogram in which the probabilities are the histogram entries. It will have a maximum value if all symbols have equal probability of occurring, minimum value of zero if the probability of one symbol occurring is 1 and the probability of all the others occurring is zero. In image registration since there are two images joint entropy will have to be also considered. Joint entropy measures the amount of information we have in the two images combined. The Joint entropy $H(I, J)$ can be calculated using the joint histogram of two images. If the images are totally unrelated, then the joint entropy will be the sum of the entropies of the individual images. The more similar the images are, the lower the joint entropy compared with the sum of the individual entropies.

$$H(A, B) \leq H(A) + H(B)$$

As the images become misaligned, dispersion of their joint histogram increases. Therefore registration of two images can be accomplished by minimizing the joint entropy of the images, but mutual information is a better criterion as marginal entropies *H (I)* and *H (J)* are taken into account.

$$MI(A,B) = H(A) + H(B) - H(A,B)$$

The optimal transformation can be gained by maximizing mutual information of the two images. So if the images are of the same object, when they are correctly registered, corresponding pixels in the two images will be of the same anatomical or pathological structure.

Normalized measure of mutual information is defined as follows:

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

Normalized mutual information has been shown to be more robust for intermodality registration than standard mutual information.

3.2 Optimization

Generally a direct transformation will not be enough to establish correspondence between the images. Only two regularly used algorithms directly calculate this transformation. The first is the Procrustes method based on point correspondence and the other is when the two images have very similar intensities and the transformation required to establish correspondence is very small. In all other algorithms a process of optimization is required. That is the algorithm takes a series of guesses from an initial starting position. The starting position has to be sufficiently close for the algorithm to converge to the correct answer. The algorithm computes a cost function or similarity function relating to how well the two images are registered. Mutual Information, correlation coefficient etc are examples of cost functions. Some cost functions increase as the images come into alignment while others decrease. The registration algorithm proceeds by recalculating the cost function. Progression towards an optimal registration is then achieved by seeking transformations that increase the cost function until a maximum of the cost function is found. The best registration that can be achieved is defined by this maximum. Because of the existence of this local maxima, the choice of optimization routine has a large influence on the results of the registration method, particularly on the robustness of the method with respect to the initial transformation.

A second important property of the registration function that influences the choice of optimization method is the capture range of the optimum. For intensity-based registration measures it is possible that a large mis-registration of two images results in a higher value of the measure than the correct transformation. The desired maximum may not be the global maximum of the search space and only part of the search space leads to the desired maximum. This has two consequences to the registration function. Firstly, an optimization started outside the capture range of the desired maximum has little chance of leading to a correct registration of the images. Secondly probabilistic optimization routines, such as some multistart methods and genetic algorithms, may prove to be less suitable for optimization of the mutual information measure, because they can move outside the capture range.

Simplex method and Powell's routine [6] are commonly used for registration problem. Both these methods do not require function derivates to be calculated. The simplex method considers all degrees of freedom simultaneously and is not known for its speed of convergence. Powell's method optimizes each transformation parameter in turn and it is relatively sensitive to local optima in the registration function.

4. NORMALIZED CROSS-CORRELATION METRIC – A COMPARISON

The correlation between two images (cross-correlation) is a standard approach to feature detection. It can be used as a measure for calculating the degree of similarity between two images. Its mathematical definition is as given below:

$$CC(i,j) = \frac{\sum_W (W - E(W))(I_{(i,j)} - E(I_{(i,j)}))}{\sqrt{\sum_W (W - E(W))^2}\sqrt{\sum_{I_{(i,j)}} (I_{(i,j)} - E(I_{(i,j)}))^2}}$$

This metric computes pixel-wise cross-correlation and normalizes it by the square root of the auto-correlation of the images. Misalignment between the images results in small measure values. The metric is insensitive to multiplicative factors between the images and produces a cost function with sharp peaks and well-defined minima.

The correlation coefficient is a good measure of alignment in the case of images of the same subject acquired with the same modality at different times in order to detect subtle changes in intensity or shape of a structure.

5. EXPERIMENTAL RESULTS

The proposed method was applied to register two sets of images. The following figures present the reference image, target image and registered image for all the three metrics. The resulting values are summarized in Tables 1 and 2. Fig.4 represents MI functions for a rotation parameter.

Figure 1. Reference image

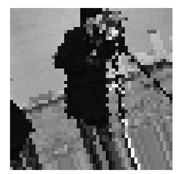

Figure2.Target image

Figure 3. Registered image

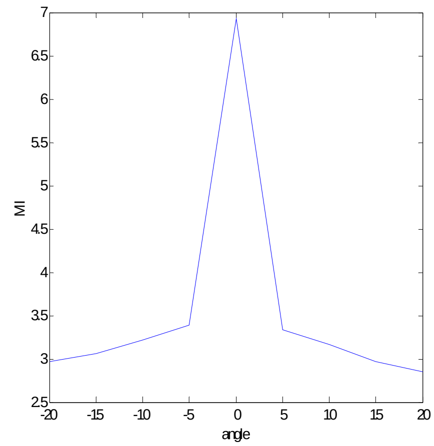

Figure 4. MI function for proposed method

Table 1. MI, NMI, NCC (normalized cross correlation coefficient) obtained for various rotation angles for the above images

MI	NMI	NCC	Angle of rotation	MI	NMI	NCC	Angle of rotation
2.9605	1.2740	0.2265	−20	2.8538	1.2691	0.3468	+ 20
3.0616	1.2844	0.3148	−15	2.9662	1.2795	0.4120	+15
3.2147	1.3017	0.4577	− 10	3.1646	1.3006	0.5045	+10
3.3905	1.3231	0.5786	− 5	3.3366	1.3193	0.5887	+ 5
6.9297	2.0000	1.0000	0	6.9297	2.0000	1.0000	0

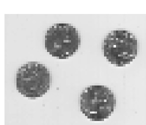

Figure5.Reference image

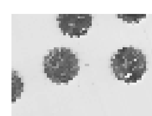

Figure 6. Reference image

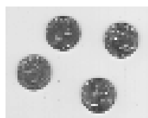

Figure 7. Registered image

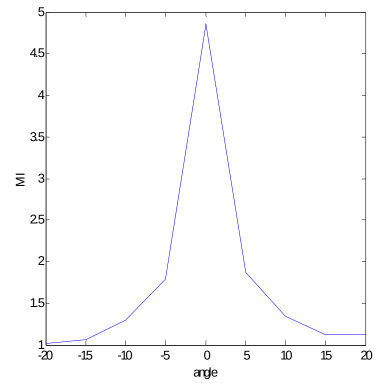

Figure 8. MI function for proposed method

Table 2. MI, NMI, NCC obtained for various rotation angles for the above images

MI	NMI	NCC	Angle of rotation	MI	NMI	NCC	Angle of rotation
1.0202	1.1290	0.0981	−20	1.1274	1.1303	0.0521	+ 20
1.0637	1.1313	0.0517	−15	1.1195	1.1301	0.0243	+15
1.2955	1.1592	0.2573	− 10	1.3502	1.1621	0.2705	+10
1.7899	1.2289	0.6177	− 5	1.8687	1.2379	0.6172	+ 5
4.8497	2.0000	1.0000	0	4.8497	2.0000	1.0000	0

From the above results we find that the metric based on mutual information is more robust than correlation since it is insensitive to and not affected by the negation of either of the signals.

6. CONCLUSIONS

The registration of images from various sources is of importance in remote sensing, medicine, computer vision etc. Image registration based on mutual information in conjunction with Powell method has been presented. The proposed method requires neither segmentation nor any ad-hoc assumptions about the nature of the imaging modalities. In addition to being effective and efficient, the technique is quite general.

The performance results have been compared to the use of normalized mutual information and cross-correlation as metrics.

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