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A MULTIMODAL IMAGE REGISTRATION USING MUTUAL INFORMATION

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***Abstract*— Medical imaging is the technique and process used to create images of the human body for clinical purposes seeking to reveal, diagnose medical science. It is often perceived to designate the set of techniques that noninvasively produce images of the internal aspect of the body. The development of multimodality methodology based on nuclear medicine (NM), positron emission tomography (PET) imaging, magnetic resonance imaging (MRI), and optical imaging is the single biggest focus in many imaging and cancer centres worldwide and is bringing together researchers and engineers from the far-ranging fields of molecular pharmacology to nanotechnology engineering. This paper presents a new technique for registration of multimodal images (CT and MRI) using mutual information. The optimization of the images is done by using down sampling technique and also the same algorithm is tested by sub sampling. The speed and computation of both the sampling methods are compared and the results are plotted.**

***Key Words*: multimodality, mutual information, down sampling, sub sampling**

I. INTRODUCTION

The goal of image registration is to determine a spatial transformation that will bring homologous points in images being registered into correspondence. It is the process of transforming different sets of data into one coordinate system. A broad range of image registration techniques have been developed for a wide variety of imaging problems. It is used in computer vision, medical imaging, military automatic target recognition, and compiling and analyzing images and data from satellites. When the registering images acquired from the same subject, it is often possible to assume that the body part being imaged can be treated as a rigid body, which leads to a highly constrained spatial transformation model [4].

Multi-modality registration methods are often used in medical imaging as images of a subject are frequently obtained from different scanners. Examples include registration of brain Computer Tomography (CT)/Magnetic Resonance Imaging (MRI) images or whole body Positron Emission Tomography (PET)/CT images for tumor localization, registration of contrast-enhanced CT images against non-contrast-enhanced CT images for segmentation of specific parts of the anatomy, and registration of ultrasound and CT images for prostate localization in radiotherapy.

The most widely used application of multimodal registration is aligning three dimensional MRI, CT, Single Positron Emission Tomography (SPECT) & PET images [3]. In such case the registration transformation is usually assumed to have the six degrees of freedom of rigid body motion.

II. IMAGE REGISTRATION PROCESS

Registration of two images is done by assuming one image to be the floating image and the other is the base image. The overall registration process is shown in fig.2.1. For registration of images A and B, the variance of intensity ratios (VIR) can be calculated in two ways, either as the sum of the normalized standard deviation of voxel values in B for each intensity a in A (VIR_B) or as the sum of the normalized standard deviation of voxel values in A for each intensity b in B (VIR_A) shown in (1) & (2) respectively:

$$VIR_B = \sum_{a=A} \frac{n_A(a)}{N} \frac{\sigma_B(a)}{\mu_B(a)} \qquad (1)$$

$$VIR_A = \sum_{b=B} \frac{n_B(b)}{N} \frac{\sigma_A(b)}{\mu_A(b)} \qquad (2)$$

Here μ_B (a) & σ_B (a) are the mean & standard deviations of the values of voxels in image B that co-occur with value a in image A, n_A (a) is the number of voxels with intensity in image A, & N is the total number of voxels and similarly for μ_A (b) & σ_A (b) & n_A (b).

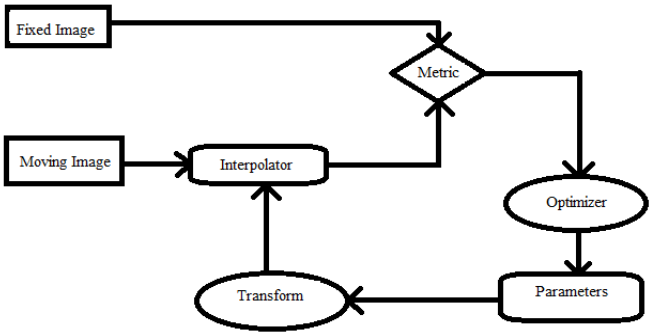

Fig. 2.1 Process of Image Registration

A. Joint Histogram

A joint histogram is a useful tool for visualizing the relationship between the intensities of the corresponding voxels in two or more images. For two images A & B, the joint histogram is two dimensional and it is constructed by plotting the intensity ' a' of each voxel in image A against b of the corresponding voxel in image B. The value of each histogram location h(a,b) will therefore correspond to the number of image voxels with intensity a in modality A and intensity b in modality B[4]. When a joint histogram is being produced from two images of different modalities, the resolution and field of view are likely to be different. Before calculating a joint histogram, it is necessary to exclude from the histogram all places where the two image volumes do not overlap.

The joint histogram can be normalized by dividing the total number of voxels and regarded as a joint probability distribution function or PDF P_{AB} of images A & B. Because of the quantization of image intensity values the PDF is discrete, and the values in each element represents the probability pairs of image values occurring together. The joint entropy is therefore given by (3).

$$H(A,B) = -\sum_{a=A}\sum_{b=B} P_{AB}(a,b) \log P_{AB}(a,b) \qquad (3)$$

The number of elements in PDF can be determined by the range of intensity values in two images or from a reduced number of intensity bins. For example MRI & CT images being registered could have up to 4096(12 bits) intensity values, leading to a very sparse PDF with 4096 by 4096 elements.

B. Mutual Information

Although the information content of the images being registered is constant, the information content of the portion of each image that overlaps with other image will change with each change estimated registration transformation [4]. Therefore a suitable technique for measuring joint entropy is to measure with respect to marginal entropy. This measure is known as MUTUAL INFORMATION I(A,B) and was independently and simultaneously proposed for multimodal medical image registration by researchers as in (4) [1,5].

$$I(A,B) = H(A) + H(B) - H(A,B) \qquad (4)$$

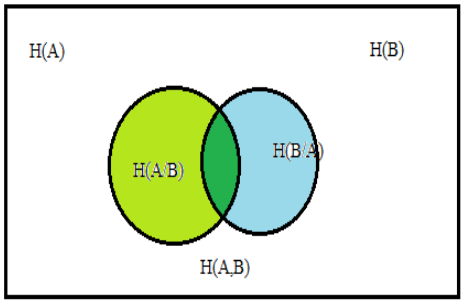

Fig. 2.2 Mutual Information

Mutual information is a direct measure of the amount of information common between the two images as shown in fig. 2.2. During image registration, however, different transformation estimates are evaluated, and these transformation estimates will result in varying degree of overlap between images, though it is better than joint entropy [3]. The problem has been addressed by proposing various normalized form of mutual information that are more overlap independent as in (5).

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

This version of normalized mutual information has been shown to be considerably more robust than standard mutual information.

Mutual information can qualitatively be thought of as a measure of how well one image explains the other; it is maximized at the optimal alignment. The maximizing of mutual information is an appealing voxel similarity measure for inter modality registration both because of its success across several application areas [6].

III. SEARCH & OPTIMIZATION

The similarity measure considered in this paper is being mutual information a search strategy is used to optimize the similarity criterion [9]. The search examples include local and global searches, multi resolution approaches and other optimization techniques. The focus of this paper is to find a suitable optimizing technique for effectively maximizing the similarity measure for registering single slice biomedical images to 3-D volumes, where the images were obtained from different modalities [6]. Single slice to 3-D registration is useful in such areas as image-guidance during interventional procedures. It is challenging because of the low amount of data from which to compute the similarity metric. The voxel similarity measures are to be incorporated into an iterative optimization scheme in order to register images.

A. Multi Resolution Search by down sampling

It is a simple step based optimization technique chosen by Studholme[8]. The starting estimate is assumed to lie within the capture range, and then the similarity measure is evaluated at that starting estimate, and with a single increment & decrement in each parameter of the spatial transformation model. The translational step size is chosen as approximately the resolution of the data. This scheme is run starting at low resolution, and when the algorithm terminates at that resolution, the resolution is increased. At highest resolution, the step size is further reduced to provide subvoxel registration solution. This approach can be computationally expensive, but it is robust and easy to implement [5].

B. Multi Resolution Search by Sub sampling

The idea of this method is based on using higher sub sampling factors for the regions which contain more information. The common sub sampling method applies a fixed factor a for all areas of an image. In multi-resolution techniques, sub sampling is done by averaging or other methods, but again a is the same for all regions, whereas tissue regions deserve more attention than background. Furthermore, edge or tissue transition regions contain important information for adjustment [7].

A method of incorporation spatial information of edges with mutual information that was introduced in [4] uses gradient vectors of corresponding points but calculation of gradient vectors in each iteration increases the computational cost. By using variant sub sampling factors, we can emphasize the role of edge regions in MI measure [8].

IV. EXPERIMENT & RESULTS

In mutual registration is performed within a framework of pluggable components that can easily be interchanged. This flexibility means that a combinatorial variety of registration methods can be created with respect to their specific application.

A. Experiment

We use two human-brain images, a MRI image as the fixed image, and a CT image as the moving image, which was translated 13 pixels along X axes and 17 pixels along Y axes.

The joint histogram of two images is determined after aligning the CT image geometrically with respect to the fixed MR image. The optimization is done by multi resolution search technique. The transformed image is down sampled and then the probability density function is calculated. The search technique is now modified from down sampling to sub sampling. Here the sampling size ‘a’ is varied throughout the image depending on the mutual information between the two images. The image samples with higher information are subjected to samples with smaller intervals and the image samples with least matching information is sub sampled at a lower rate. The optimization has multiple implementations of the mutual information metric. Thus the sampling rate variation likely fastens the computation time.

B. Results

The CT image after transforming according to the alignment of MR image is now down sampled .We stop it at the 60th iteration, and it produces the following results shown in fig. 4.1:

Best angle of rotation is 6 degrees anticlockwise.

The coordinates of left top corner of matched area within large IMAGE2 (MRI) is 61 & 61.

The Sub sampling is done by choosing a pixel and the surrounding area is replaced with that same pixel. It produced the fastest output but provided a least clarity as in fig. 4.2. The

mutual information obtained by using different sampling techniques is been shown in table 1.

Sampling Technique / Results	Down Sampling	Sub Sampling
Mutual Information	0.44	2.51
	0.46	2.53
	0.51	2.91

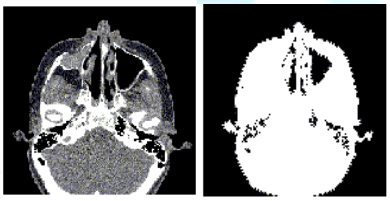

Fig. 4.1 CT image (Left) & down sampled CT Image (Right)

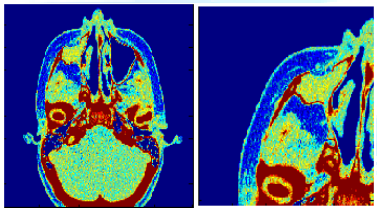

Fig. 4.2 Registered Image by Down Sampling (Left) & Registered Image by Sub Sampling (Right)

TABLE 1 COMPARISON BETWEEN DOWN SAMPLING AND SUB SAMPLING

Down sampling is done by when pixels in a sample area are replaced with the average pixel color. It produces a medium output offering a medium clarity as in fig.4.2.

The distortions due to sub sampling can be eliminated by adding FIR filter along with Hamming window. This can be added up with another method of bi cubic down sampling which is a weighted average of the pixels and the sequence of translation is shown in fig. 4.3. This yields even though a slowest output but gives best clarity. The tradeoff between the computation time and clarity of the registered output can be overviewed with respect to the applications.

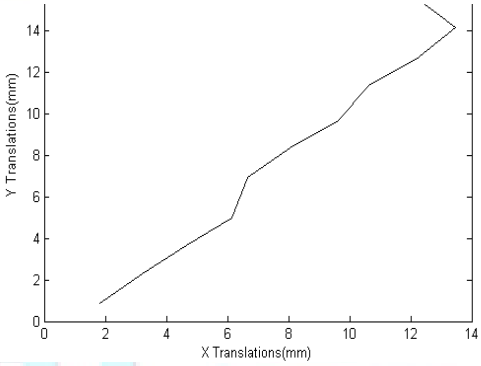

Fig. 4.3 Sequence of Translation

V. CONCLUSION

The registration of multimodality images is a fundamental task in numerous applications in medical image processing. This paper introduced the theory of mutual information and its application in the medical image registration field. Two experiments based on optimization gives a vivid idea of sampling methods that can be chosen based on the applications. Our next work is to study the improvement in image fusion by using this method of image registration.

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