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Enhanced Multimodality Image Registration Based On Mutual Information

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Abstract: *Different modalities can be achieved by the maximization of suitable statistical similarity measures within a given class of geometric transformations . The registration functions are less sensitive to low sampling resolution, do not contain incorrect global maxima which are sometimes found in the mutual information. This paper proposes a novel and straightforward multimodal image registration method based on mutual information, in which two matching criteria are used. It has been extensively shown that metrics based on the evaluation of mutual information are well suited for overcoming the difficulties of multi-modality registration.*
Keywords: *multimodalities, mutual information, metric*

I. Introduction

Image registration is a process of a transformation that maps one image onto another same or similar object by optimizing certain metrics. It is an important step in medical image processing if clinicians require complementary information obtained from different images. Registration aims to fuse data about patients from more than one medical image so that doctors can acquire more comprehensive information related to pathogenesis. Mutual information is an automatic, intensity based measure, which does not require the definition of landmarks or features such as surfaces and which can be applied in retrospect. Furthermore, it is one of the few intensity based measures that is well suited to registration of multimodal images. Unlike measures based on correlation of grey values or differences of grey values, mutual information does not assume a linear relationship between the grey values in the images.

In order to associate the information from modality, corresponding data in each image must be successfully registered. In long range surveillance applications the alignment function will register all objects in the scene. The reference and the referred image could be different because were taken at different times and Using different devices like MRI, CT, PET, SPECT etc (multi modal).and From different angles in order to have 2D or 3D perspective (multi temporal).Image registration finds its applications in various fields remote sensing(multispectralclassification), environmental monitoring, change detection, image mosaicing, weather forecasting, creating super-resolution images, integrating information into geographic information systems (GIS)), in medicine (combining data from different modalities e.g. computer tomography (CT) and magnetic resonance imaging (MRI), to treatment verification, comparison of the patient's data with anatomical atlases ,in cartography (map updating) and in computer vision (target localization, automatic quality control). The concept of Mutual Information is derived from Information Theory and its application to One way to simplify the computation of the mutual information is to normalize the statistical distribution of the two input images.

Mutual information (MI) is one of the most popular matching criteria that are used in multi-modal image registration. Many studies have shown that MI has given satisfactory accurate results. Because of its high computational complexity, scientists have proposed the multiresolution scheme to accelerate MI-based registration. Though some researchers believe that a multiresolution scheme can also increase the capture range for there is less tendency to be trapped in local minima [2], our experiments show that the capture range is still not good enough especially in lower resolution registration. This is supported by the conclusion drawn in [5], i.e. the hope that a multiresolution approach to matching would be better equipped to avoid local optima seems unfounded. The statistical relation of image intensities that MI measures tends to decline when the image resolution decreases.

II. Implementation

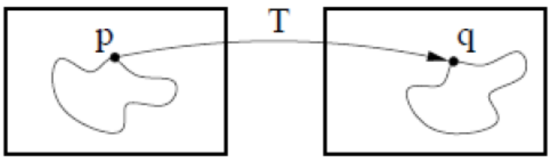
Mutual information

The mutual information of two images is a mixture of the entropy values of the images, both separately and jointly.One interpretation of entropy is as a measure of dispersion of a probability distribution. A distribution with only a few large probabilities has a low entropy value; the maximum entropy value is reached for a uniform distribution. The entropy of an image can be computed by estimating the probability distribution of the image intensities. In this paper, we use the Shannon measure of entropy, $-_{p\in P}\, p \log p$ for a probability distribution P. The joint probability distribution of two images is estimated by calculatinga normalized joint histogram of the grey values. Themarginal distributions are obtained by summing over the rows, resp. the columns, of the joint histogram. The definition of the mutual information I of two images A and B combines the marginal and joint entropies of the images in the following manner

$$I(A,B) = H(A) + H(B) - H(A,B).$$

Here, H(A) and H(B) denote the separate entropy values of A and B respectively. H(A,B) is the joint entropy, i.e. the entropy of the joint probability distribution of the image intensities. Correct registration of the images is assumed to be equivalent to maximization of the mutual information of the images. This implies a balance between minimization of the joint entropy and maximization of the marginal entropies. The joint entropy is minimal when the joint distribution is minimally dispersed, i.e. when it is crisp. This corresponds to registration,since any misalignment of the images will both introduce new combinations of grey values and decrease the probabilities of the 'correct' combinations. The overall result is a more dispersed joint probability distribution.Recently, it was shown that the mutual information measure is sensitive to the amount of overlap between the images and normalized mutual information measures were introduced. Mutual information-based registration begins with the estimation of the joint probability of the intensities of corresponding voxels in the two images. The use of information-theoretic measures such as mutual information has obviously benefited voxel-based registration. The present papers have demonstrated that mutual information can be used to parameterize and solve the correspondence problem in feature-based registration .They have appeared recently and represent the leading technique in multimodal registration. Registration of multimodal images is the difficult task, but often necessary to solve, especially in medical imaging. The comparison of anatomical and functional images of the patient's body can lead to a diagnosis, which would be impossible to gain otherwise. Remote sensing often makes use of the exploitation of more sensor types.

The metric requires a number of parameters to be selected, including the standard deviation of the Gaussian kernel for the fixed image density estimate, the standard deviation of the kernel for the moving image density and the number of samples use to compute the densities and entropy values. We should now define the number of spatial samples to be considered in the metric computation. Image registration is the process of determining the spatial transform that maps points from one image to homologous points on a object in the second image



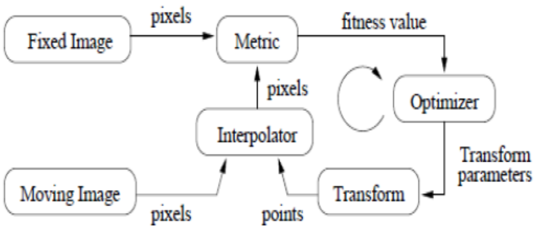


Fig: registration framework

The components of the registration framework and their interconnections are shown in Figure.The basic input data to the registration process are two images: one is defined as the fixed image f (**X**) and the other as the moving image m(**X**). Where **X** represents a position in Ndimensional space. Registration is treated as an optimization problem with the goal of finding the spatial mapping that will bring the moving image into alignment with the fixed image. The transform component T(**X**) represents the spatial mapping of points from the fixed image space to points in the moving image space. The interpolator is used to evaluate moving image intensities at non-grid positions. The metric component $S(f, m \circ T)$ provides a measure of how well the fixed image is matched by the transformed moving image. This measure forms the quantitative criterion to be optimized by the optimizer over the search space defined by the parameters of the transform. In our algorithm, two similarity metrics are utilized, namely MI and coefficients at different resolutions Originating from information theory, MI is an entropy-based concept and denotes the amount of information that one variable can offer to the other. In terms of marginal distributions p(a) and p(b) for images A and B respectively and the joint distribution p(a, b), MI can be defined as:

$$I(A,B) = \sum_{a,b} p(a,b) \log \frac{p(a,b)}{p(a)p(b)},$$

where a and b represent the intensity of image A and B respectively. MI measures the statistical dependence between the image intensities of corresponding voxels in both images, which is assumed to be maximal . The metric requires a number of parameters to be selected, including the standard deviation of the Gaussian kernel for the fixed image density estimate, the standard deviation of the kernel for the moving image density and the number of samples use to compute the densities and entropy values.

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III. Results:

The results presented in this study indicate that the measures yield registration functions outperforming the mutual information function with respect to smoothness. Our study shows that the accuracy obtained by image registration in both MR and CT.

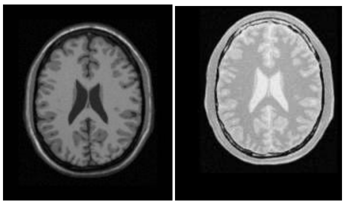

fig: input to the registration method

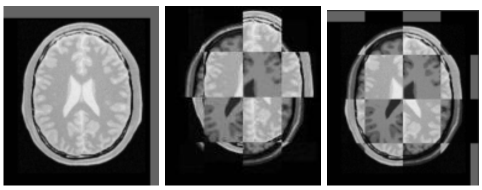

Fig: composition of fixed and moving images before (center) and after (right) registration. With mutual information

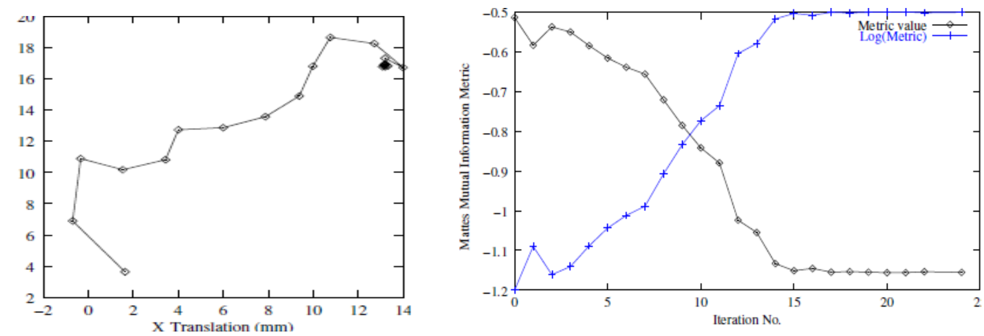

Fig: sequence of metric values at each iteration

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