Corrective Information Based Registration

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Abstract— It is a process of spatially matching two images i.e. Base image and target image, so that corresponding physical region of the scene is imaged. It is used to match the two images of the same scene taken at different times from different viewpoints, or from different sensors. The process of transforming the different sets of data into one coordinate system. Image registration is often used as a preliminary step in other image processing applications. After registration, you can compare features in the images to see how a river has migrated, how an area is flooded, or to see if a tumor is visible in an MRI (Magnetic Resonance Imaging) or SPECT (Single Photon Emission Computed Tomography) images. In this paper we are finding the mutual information between target and base image. Mutual information and joint entropy are computed for the overlapping parts of the images and the measures are therefore sensitive to the size and the contents of overlap. The goal of this paper is to register the medical images using the mutual information based registration. Image Registration defines a transform T that will map one image onto another image of the same object such that some image quality criteria are maximized. Our aim is to find out the mutual information and to accurately register the images.

Keywords- Entropy, MRI, CP, SPECT, Mutual Information

I. INTRODUCTION

The registration or alignment is one of the fundamental tasks in image processing. Image registration is the process of overlaying two or more images of the same scene taken at different times, from different viewpoints, and/or by different sensors. It geometrically aligns two images the reference (base) and sensed (target) images. The differences between images are introduced due to different imaging conditions. Image registration is a crucial step in all image analysis tasks in which the final information is gained from the combination of various data sources like image fusion, change detection, and multi channel image restoration. Registration is necessary in order to compare or integrate the data obtained from different measurements. Registration (e.g. for data of the same patient taken at different points in time) often additionally involves *elastic* and nonrigid registration. To cope with *elastic* deformations of the body parts imaged, *nonrigid* registration of medical images can also be used to register a patient's data to an anatomical atlas, such as neuroimaging.

During the last decades, image acquisition devices have undergone rapid development and growing amount and diversity of obtained images invoked the research on automatic image registration. The registration methods offer the outlook for the two-image registration methodology. Image registration, as it was mentioned above, is widely used in remote sensing, medical imaging, computer vision etc.

II. RELATED WORK

Image registration is the process of transforming the different sets of data into one coordinate system. The goal of image registration is to geometrically transform one image so that physical (medical images) correspondences line up. This is usually a precursor to comparison or fusion of the images. The problem is multi-modal, if images are obtained through two different imaging devices, e.g. functional Magnetic Resonance Imaging (fMRI). (Image registration aalgorithms fall within two classification.) Majority of the registration methods consists of the following four steps,

A. Feature Detection

Salient and distinctive objects (closed-boundary regions, edges, contours, line intersections, corners, etc.) are manually, automatically detected. For further processing, these features can be represented by their point representatives (centers of gravity, line endings, distinctive points), which are called control points (CPs). Formerly, the features were objects manually selected by an expert. During an automation of this registration step, two main approaches to feature understanding have been formed.

- *Area based methods*
- *Feature based methods*

The original image is often referred to as the reference image and the image to be mapped onto the reference image is referred to as the target image.

Area Based methods:

The original image is often referred to as the reference image and the image to be mapped onto the reference image is referred to as the target image. For area based image registration methods, the algorithm looks at the structure of the image via correlation metrics, Fourier properties and other means of structural analysis. However, most feature based methods, instead of looking at the overall structure of images, fine tunes its mapping to the correlation of image features lines, curves, points, line intersections, boundaries, etc.

Feature-based methods:

The second approach is based on the extraction of salient structures features in the images. Significant regions (forests, lakes, fields), lines (region boundaries, coastlines, roads, rivers) or points (region corners, line intersections, points on curves with high curvature) are understood as features here. They should be distinct, spread all over the image and efficiently detectable in both images. They are expected to be stable in time to stay at fixed positions during the whole experiment. The comparability of feature sets in the sensed and reference images is assured by the invariance and accuracy of the feature detector and by the overlap criterion. In other words, the number of common elements of the detected sets of features should be sufficiently high, regardless of the change of image geometry, radiometric conditions, presence of additive noise, and of changes in the scanned scene. Feature-based methods are recommended if the images contain enough distinctive and easily detectable objects. This is usually the case of applications in remote sensing and computer vision. The typical images contain a lot of details (towns, rivers, roads, forests, room facilities, etc). On the other hand, medical images are not so rich in such details and thus area-based methods are usually employed. Sometimes, the lack of distinctive objects in medical images is solved by the interactive selection done by an expert or by introducing extrinsic features, rigidly positioned with respect to the patient (skin markers, screw markers), dental adapters, etc.

B. Feature Matching:

In this step, the correspondence between the features detected in the sensed image and those detected in the reference image is established. Various feature descriptors and similarity measures along with spatial relationships among the features are used for that purpose. The detected features in the reference and sensed image can be matched by means of the image intensity values in their close neighborhoods, the feature spatial distribution or the feature symbolic description. Some methods, while looking for the feature correspondence, simultaneously estimate the parameters of mapping functions and thus merge the second and third registration steps. The two major categories (area-based and feature-based methods, respectively) are retained and further classified into subcategories according to the basic ideas of the matching methods, they are as follows.

Area-based methods:

Area-based methods, sometimes called correlation-like methods or template matching merge the feature detection step with the matching part. These methods deal with the images without attempting to detect salient objects. The limitations of the area-based methods originate in their basic idea. Firstly, the rectangular window, which is most often used, suits the registration of images, which locally differ only by a translation. If images are deformed by more complex transformations, this type of the window is not able to cover the same parts of the scene.

The disadvantage of the area-based methods refers to the ‘remarkableness’ of the window content. There is high probability that a window containing a smooth area without any prominent details will be matched incorrectly with other smooth areas in the reference image due to its non-saliency. The features for registration should be preferably detected in distinctive parts of the image. Windows, whose selection is often not based on their content evaluation, may not have this property.

Classical area-based methods like *cross-correlation* (CC) exploit for matching directly image intensities, without any structural analysis. Consequently, they are sensitive to the intensity changes, introduced for instance by noise, varying illumination, and/or by using different sensor types.

Correlation-like methods:

This measure of similarity is computed for window pairs from the sensed and reference images and its maximum is searched. The window pairs for which the maximum is achieved are set as the corresponding ones. If the sub pixel accuracy of the registration is demanded, the interpolation of the CC measure values needs to be used. Although the CC based registration can exactly align mutually translated images only, it can also be successfully applied when slight rotation and scaling are present.

Mutual Information Methods:

The mutual information (MI) methods are the last group of the area-based methods. 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 MI, originating from the information theory, is a measure of statistical dependency between two data sets and it is particularly suitable for registration of images from different modalities. MI between two random variables X and Y is given by represents entropy of random variable and the probability distribution of X and Y. The method is based on the maximization of MI. Often to speed up the registration implementation, exploiting the coarse-to-fine resolution strategy (the pyramidal approach).

Powell's proposed to model, the global deformation present between the images by a combination of the affine transformations and the spline-based free form deformation. *Likar* and *Pernus* studied the performance of different methods for the joint probability estimation in registration of muscle fiber images. The relation of MI to other area based similarity (correlation coefficients, correlation ratio) measures is described using the formulation of maximum likelihood estimation problem. The above-mentioned MI methods work with the entire image data and directly with image intensities. Rangarajan applied MI on extracted features (points of the area borders), but this approach is still rare. Similar to MI, coming form the theory of information, is similarity measure based on cross-entropy.

C. Transform Model Estimation:

Image registration algorithms can also be classified according to the transformation model used to relate the reference image space with the target image space. The type and parameters of the so-called mapping functions are estimated. The parameters of the mapping functions are computed by means of the established feature correspondence.

The first broad category of transformation models includes, which are a combination of translation, rotation, global scaling, shear and perspective components. are global in nature, thus not being able to model local deformations. Usually, perspective components are not needed for registration. The second category includes 'elastic' or 'nonrigid' transformations. These transformations allow local wraping of image features, thus providing support for local deformations. Nonrigid transformation approaches include polynomial wrapping, interpolation of smooth basis functions and, and physical continuum models (viscous fluid models and large deformation).

D. Image Resampling and Transformation:

The sensed image is transformed by means of the mapping functions. Image values in non-integer coordinates are computed by the appropriate interpolation technique. Image registration is the process of transforming the different sets of data into one coordinate system. It is process of spatially matching two images i.e. the reference image and target images, so that corresponding coordinated points in the two images corresponding to the sane physical region of the scene being imaged. Image registration algorithms fall within two realms of classification:

Search-Based vs Direct Methods:

Image registration methods can also be classified in terms of the type of search that is needed to compute the transformation between the two image domains. In search-based methods the effect of different image deformations is evaluated and compared. In direct methods, such as the phase-based methods, an estimate of the image deformation is computed from local image statistics and is then used for updating the estimated image deformation between the three domains.

Spatial-Domain Methods:

Many image registration methods operate in the spatial domain, using features, structures, and textures as matching criteria. In the spatial domain, images look 'normal' as the human eye might perceive them. Some of the feature matching algorithms are out growths of traditional techniques for performing manual image registration, in which operators choose matching sets of control points (CPs) between images.

Frequency-Domain Methods:

Some algorithms use the properties of the frequency-domain to directly determine shifts between two images. Applying this method to a pair of overlapping images produces a third image which contains a single peak. The location of this peak corresponds to the relative translation between the two images. Unlike many spatial-domain algorithms, the phase correlation method is resilient to noise, occlusions, and other defects typical of medical or satellite images. Additionally, the phase correlation uses the to compute the cross-correlation between the two images, generally resulting in large performance gains. The method can be extended to determine rotation and scaling between two images by first converting the images to log-polar coordinates. Due to properties of the, the rotation and scaling parameters can be determined in a manner invariant to translation. This single feature makes phase-correlation methods highly attractive vs. typical spatial methods, which must determine rotation, scaling, and translation simultaneously.

Image Similarity-Based Methods:

Image similarity-based methods are broadly used . A basic image similarity-based method consists of a image , which is applied to reference image coordinates to locate 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 which tries to maximize image similarity by changing the transformation parameters.

III. MUTUAL INFORMATION BASED REGISTRATION

The paper is aimed to introduce and explain mutual information and give an overview on mutual information based registration for medical application, we are going to divide the methods into two main categories methodological aspects and matter aspects of application. The aspect of the method is subdivided into preprocessing, measure, transformation and implementation, most of which have a further sub-classification. The research eventually led to introduction of mutual information as a registration measure dates back to the early 1990's. Woods [5] introduced a registration measure for multimodality images based on the assumption that regions of similar tissue (and hence similar gray values) in one image would correspond to regions in the other image that consist of similar gray values (though probably different values to those of the first image). Ideally, the ratio of the gray values for all corresponding points in a certain region in either image varies little. Consequently, the average variance of this ratio for all regions is minimized to achieve registration. Hill [7] proposed an adaptation of Woods [5] measure. The difference with Woods [5] method is that instead of defining regions of similar tissue in the images, regions are defined in the histogram. These regions are based on the clustering one finds in the histograms for registered images, changes, as the alignment of the images changes. When the images are correctly registered, corresponding anatomical structures overlap and the joint histogram will show certain peaks for the gray values of those structures or images. Using this characteristic of the histogram of two images, measures of dispersion emerged, to use for image registration. Hill[7] proposed the third order moment of the histogram, which measures the skew ness of a distribution. Both Collignon[2] and Studholme[1] suggested using entropy as a measure of registration. Entropy measures the dispersion of a probability distribution. A histogram of two images can be used to estimate a joint probability distribution of their gray values by dividing each entry in the histogram by the total number of entries. The Shannon entropy for a joint distribution is defined as

$$-\sum i,j \ \ p\,(i, j) \log p\,(i , j)$$

We will describe mutual information for two images, as used in image registration, and not in a general sense. The first form of definition is one that best explains the term "Mutual Information". For two images *A* and *B*, *can* be defined as

$$I\,(A, B) = H\,(B) - H\,(B\,|A)$$

Where H (B) is the Shannon entropy of image B, computed on the probability distribution of the gray values. H (B $|A$) denotes the conditional entropy, which is based on the conditional probabilities $p(b\ |a)$, the chance of gray value b in image B given that the corresponding voxel in A has gray value a.

Hence, it is *Mutual Information*. Registration is assumed to correspond to maximizing mutual information, the images have to be aligned in such a manner that the amount of information they contain about each other is maximal. The second form of definition is most closely related to joint entropy. That is

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

A problem that can occur when using joint entropy on its own is that low values (normally associated with a high degree of alignment) can be found for complete miss registration. Mutual information is better equipped to avoid such problems, because it includes the marginal entropies H (A) and H (B). These will have low values when the overlapping part of the images contains only background and high values when it contains anatomical structure. The marginal entropies will thus balance the measure somewhat by penalizing for transformations that decrease the amount of information in the separate images. Consequently, mutual information is less sensitive to overlap than joint entropy, although not completely immune. The final form of definition we discuss is related to *the Kullback-Leibler* distance analogous to the *Kullback-Leibler* measure; the mutual information of images *A* and *B* is defined as

$$p(a,b).\log(p(a,b)/(p(a)p(b)))$$

A. Definitions of Mutual Information

Three commonly used definitions:

1) $I\,(A, B) = H\,(B) - H\,(B \mid A) = H\,(A) - H\,(A \mid B)$

Mutual information is the amount that the uncertainty in B (or A) is reduced when A (or B) is known.

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

Maximizing the mutual information is equivalent to minimizing the joint entropy (last term), advantage in using mutual information over joint entropy is it includes the individual input's entropy. This will works better than joint entropy in regions of image background (low contrast) where there will be low joint entropy but low individual entropies offset this as well, so the overall mutual information will be low.

3) $I(A,B)=\sum p(a,b).\log(p(a,b)/(p(a)p(b)))\ldots$

This above definition is related to the *Kullback-Leibler* distance between two distributions. This will measure the dependence of the two distributions. The image registration I (A, B) will be maximized when the images are aligned. In feature selection choose the features that minimize I (A, B) to ensure they are not related.

B. Entropy

The measure of information (commonly termed entropy) of a message. The entropy is a measure of registration this entropy theory is emerges from communication theory. This field concerns the broadcast of a message from a sender to a receiver. The first attempts to arrive at an information measure of a message focused on telegraph and radio communication, sending *Morse code* or words. However, Picture transmission (television) was already considered in the important paper by *Hartley [3]*. In 1928, he defined a measure of information of a message that forms the basis of many present-day measures.

Entropy can be measured using this theory in the images; entropy can be detected using the probability of occurrence of the particular gray level in reference and sensed image (target image).

Hartley wanted a measure *H* that increases linearly with *n*, i.e. $H = Kn$, where *K* is a constant depending on the number of symbols *s*. *Hartly* further assumed that, given messages of length n1 and n2 from s1 and s2 numbers of symbols, respectively,

if sn1 1 = sn2 2, i.e.

The number of possible messages is equal, and then the amount of information per message is also equal. These two restrictions led him to define the following measure of information

$$H = n \log s = \log s^n$$

Hartley's information measure depends on the number of possible outcomes the larger the number of possible messages, the larger the amount of information you get from a certain message. If there is only a single message possible, you gain no information.

A drawback of *Hartley's* measure is that it assumes all symbols (and hence all messages of a given length) are equally likely to occur. Clearly, this will often not be the case. In the previous paragraph, for example, the letter 'e' has occurred 25 times and the letter 'q' only twice. *Shannon* introduced an adapted measure in 1948 [4], which weights the information per outcome by the probability of that outcome occurring. Given events $e_1 \ldots e_m$ occurring with probabilities $p_1, \ldots, p_m$, the *Shannon* entropy is defined as

$$H = \sum_i p_i \cdot \log \frac{1}{p_i}$$

If we apply to Shannon's entropy the assumption that all outcomes are equally likely to occur, we get

$$H = -\sum 1/s^n \log 1/s^n = \sum 1/s^n \log 1/s^n = \log s^n$$

An image consisting of almost a single intensity will have a low entropy value, it contains very little information. A high entropy value will be yielded by an image with more or less equal quantities of many different intensities, which is an image containing a lot of information. In this manner, the **Shannon entropy i**s also a measure of dispersion of a probability distribution. A distribution with a single sharp peak corresponds to a low entropy value, whereas a dispersed distribution yields a high entropy value.

- **Hartley** defined the first information measure
    - $H = n \log s$
    - n is the length of the message and s is the number of possible values for each symbol in the message. Assumes all symbols equally likely to occur.
- **Shannon** proposed variant (Shannon's Entropy)

$$H = \sum_i p_i \cdot \log \frac{1}{p_i}$$

Weighs the information based on the probability that an outcome will occur.

Second term shows the amount of information an event provides is inversely proportional to its probability of occurring.

IV. REVIEW OF LITERATURE

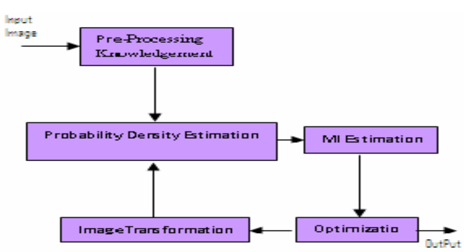
The subjects covered in the report have been taken from different books and special issues of journals. The IEEE transaction on medical imaging "Mutual Information Based Registration of Medical Images" a survey. The book of Anil K Jain [27] and Kenneth.R.castleman excellent references on basic principal of image processing. From these books, the basic concepts of the image have been taken. The article by S.A.Hojjtoleslami (1998), an excellent reference about region growing method. From this article how to register the region of CT (Computed Tomography) images using mutual information was given.

The Biomedical engineering handbook by Joseph D. Bronzing gives an excellent reference about MRI (Magnetic Resonance Imaging) and CT images. From our survey of the different aspects of mutual information based registration, we have defined a classification scheme, which builds on earlier scheme for medical image registration. The main subdivision of the classification is in aspects concerning the method and those concerning application. Brown published a comprehensive survey of image registration methods in 1992. The first aspects of the class 'Application' is the type of modalities. It concerns the images can be of the same kind acquired by different techniques, a type of model can be involved or images are registered to physical space. By later we mean registration of previously acquired image to a person, as is used for image guided surgery or radiotherapy treatment. Subjects denote whether images of a single person are involved, which is called intra-subject registration, or images of different person are involved, which is called inter-subject registration. Lastly, the anatomy that the registration focuses on is what we term objects.

The research that eventually led to the introduction of mutual information as registration measure dates back to the early 1990's. Woods first introduce the registration measure for multimodality images based on the assumption that regions of similar tissue (and hence similar gray values) in one image would correspond to regions in the other image that also consist of similar gray values. Ideally, the ratio of the gray values for all corresponding point in a certain region in either image varies little consequently the average variance of this ratio for all regions are minimized to achieve registration. Hill [2] proposed an adaptation of Wood's [5] method. They constructed a feature space, which is a two dimensional plot showing the combinations of gray values in each of the two images for all corresponding points shows the feature space for MRI and CT images. The difference with Wood's method is that instead of defining regions of similar tissue in the images, regions are defined in the feature space for registered images.

V. Implementation

A. Processing Flow



Diagram

B. Algorithm

STEP-1: [Read the input image].
Read Im1, Im2

STEP-2: [Initialize memory buffer and scaling factor entropy variables]

Read buffer, f(scaling factor=1000) Hx=0,h_xy,MI.

STEP-3: [Preprocessing remove the noise present in the image]

Get the filter mask.

STEP-4:[Display the images]
Write Im1, Im2;

STEP-5: [Call the subroutine for registration of image] Call_fminsearch()

STEP-6: [Display the registered images]
Write Im1, Im2;

STEP-7: [Finished]
Stop

BASE IMAGE

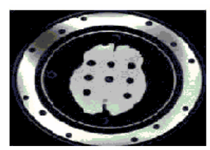


Figure (1a)

TARGET IMAGE

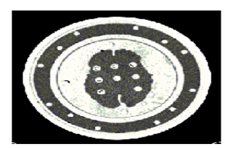


Figure (1b)

JOINT ENTROPY

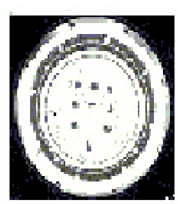


Figure (1c)

REGISTERD IMAGE

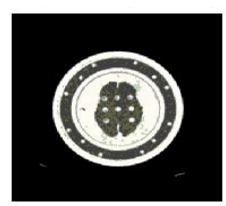
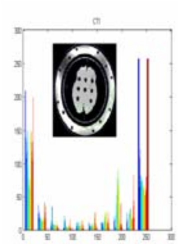
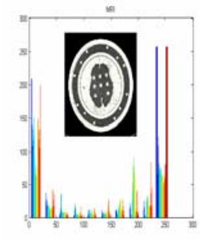


Figure (1d)

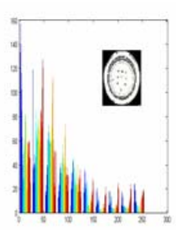
Figure 1. Registration of Abnormal CT and MRI images

BASEIMAGE TARGET IMAGE





JOINT ENTROPY REGISTERD IMAGE



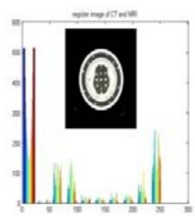


Figure 2. Histogram of Abnormal CT and MRI images is shown

The abnormal region of the CT and MRI images are shown in figure (1) in which, the figure (1a) is called base image and figure (1b) is called target image and the figure (1c) the joint entropy of the base and target images is shown. In the figure (1d) we have the registered image. The histogram for those images is as shown in (2).Where we can observe that the registered image histogram is almost same as that of base image histogram. It also contains some minute information of target image. We can keep that as a reference for future work in the medical field for diagnosis of some diseases.

VI. CONCLUSION

It shows the better performance in the registered image than the base image. Visually we can't make out the changes in between the base and the registered image so, for the performance evaluation we have plotted the histogram for individual images. By comparing the histogram of base image and the registered image we come to know that the registered image histogram is almost same as that of base image. It also contains some minute information of target image.

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