Medical Image Registration Based On Gradient Field Mutual Information

Matangi Raju
System Administrator, PGC, Anakapalli, India
Email: rajurock1707@gmail.com

Abstract: Medical imaging is one of our most powerful tools for gaining insight into normal and pathological processes that affect health. The role of image processing in medicine is expanding with the increasing importance of finding ways to improve workflow in reading environments where more images are being acquiring in more acquisition modalities. Image processing has an important influence on the medical decision making process and even on surgical actions. Image processing includes methods computing a new image from an initial one, computing characteristics and measurements from an image or extracting high level description from an image. Image registration is a Advanced Digital processing Technique. It is the process of systematically placing separate images in a common frame of reference so that the information they contain can be optimally registered or compared.

Keywords: Image Processing, Image Registration, Medical Image Process.

I. INTRODUCTION

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 and sensed images. This is becoming central tool for image analysis, understanding and visualization in both medical and scientific applications. The majority of the registration methods consists of the following four steps :1. Feature Detection, 2. Feature Matching, 3. Transformation model estimation, 4. Image resampling and transformation

Image registration is required in **Remote sensing** (multispectral classification, environmental monitoring, change detection, image mosaicing, weather forecasting, creating super-resolution images, integrating information into geographic information systems(GIS)), in **Medicine** (combining coputer tomography(CT) and NMR data to obtain more complete information about patient, monitoring tumor growth, treatment verification, comparision of patient,s data with anatomical atlases), in **Cartography** (map updating), and in **computer vision** (target localization, automatic quality control), to name a few.

Medical imaging is about establishing shape, structure, size and spatial relationships of anatomical structures within the patient, together with spatial information about function and any pathology or other abnormality. Establishing the correspondence of spatial information in medical images and equivalent structures in the body is fundamental to medical image analysis. So medical image registration has become so important.

Since the mid 1980s medical image registration has evolved from being perceived as a rather minor precursor to some medical imaging applications to a significant sub discipline in itself. It addresses the problem of finding a geometric transformation which is able to align two given medical images together. Multi modal medical image registration can provide enhanced information from different image modalities.

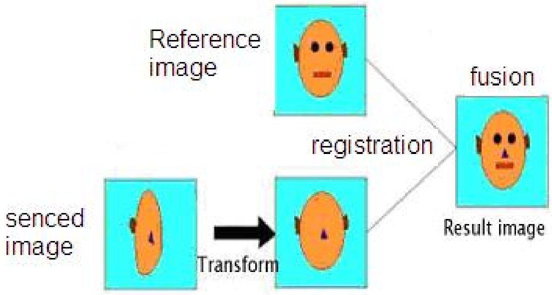

Fig.1 : The concept of registration

The majority of the registration methods consists of the following four steps

1. Feature Detection

2. Feature Matching

3. Transformation model estimation

4. Image resampling and transformation

Feature Detection:

Salient and distinctive objects (closed boundary regions, edges, contours, line

intersections, corners, etc.) are manually or, preferably, 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) in the literature.

Feature Matching:

In this step, the correspondence between the features detected in the reference image is established. Various feature descriptors and similarity measures along with the spatial relationships among the features are used for that purpose.

Transformation model estimation:

The type and parameters of the so-called mapping functions, aligning the sensed image with reference image, are estimated. The parameters of the mapping functions are computed by means of the established feature correspondence.

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.

II. MEDICAL IMAGE REGISTRATION PROCEDURE

The main components of any image registration algorithm are geometrical transformation, similarity measure, optimization strategy, and interpolation method.

Functional Block diagram of Registration Process

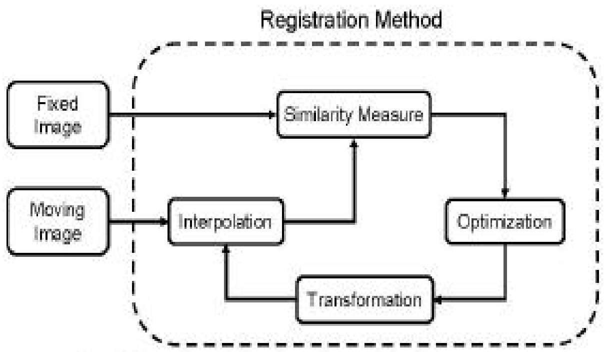

Fig: Functional blocks of a registration process.

Assuming that we have two images of the same object, a structural image and a functional image, the process of registration is composed of following steps:

● Acquiring information from two images

● Pre-processing to improve the quality of images

● Find out the registration function(similarity measure)

● Selecting the same characteristics and finding a mapping between two images to find out transformation functions

● Reconstructing images based on above functions

●Optimize the similarity measure

● Combining reconstructed images by overlapping them with an appropriate transparency

● Image acquisition

Images of a patient obtained by CT, MRI and SPECT, PET scanning are displayed as an array of pixels (a two dimensional unit based on the matrix size and the field of view) and stored in memory.

In general, image registration applications can be divided into four main groups according to the manner of the image acquisition:

-Different viewpoints (multiview analysis). Images of the same scene are acquired from different viewpoints. The aim is to gain larger a 2D view or a 3D representation of the scanned scene.

Examples of applications: Remote sensing—mosaicing of images of the surveyed area. Computer vision—shape recovery (shape from stereo).

-Different times (multitemporal analysis). Images of the same scene are acquired at different times, often on regular basis, and possibly under different conditions. The aim is to find and evaluate changes in the scene which appeared between the consecutive image acquisitions.

Examples of applications:,Medical imaging—monitoring of the healing therapy, monitoring of the tumor evolution.

-Different sensors (multimodal analysis). Images of the same scene are acquired by different sensors. The aim is to integrate the information obtained from different source streams to gain more complex and detailed scene representation.

Examples of applications: Medical imaging—combination of sensors recording the anatomical body structure like magnetic resonance image (MRI), ultrasound or CT with sensors monitoring functional and metabolic body activities like positron emission tomography (PET), single photon emission computed tomography (SPECT) or magnetic resonance spectroscopy (MRS). Results can be applied, for instance, in radiotherapy and nuclear medicine.

-Scene to model registration. Images of a scene and a model of the scene are registered. The model can be a computer representation of the scene, for instance maps or digital elevation models (DEM) in GIS, another scene with similar content (another patient), 'average' specimen, etc. The aim is to localize the acquired image in the scene/model and/or to compare them.

Examples of applications: Remote sensing—registration of aerial or satellite data into maps or other GIS layers ,Medical imaging— comparison of the patient's image with digital anatomical atlases, specimen classification.

● Image Pre-processing

To find out a transformation between two images precisely, they should be pre-processed to improve their quality. If these images are too noisy or blurred (caused by instruments or patient's moving while scanning), they should be filtered and sharpened.

-Filters

In image processing, filters are mainly used to suppress either the high frequencies in the image, *i.e.* smoothing the image, or the low frequencies, *i.e.* enhancing or detecting edges in the image. An image can be filtered either in the frequency or in the spatial domain. For example the filters are Mean filter, median filter and Gaussian filter.

-Brightness and contrast adjustment

Histogram processing : Histogram is the basis for numerous spatial domain processing techniques.

Histogram manipulation can be used effectively for image enhancement. The horizontal axes of each

histogram plot corresponding to gray level values, rk The vertical axis corresponds to values of h(rk) = nk or

p(rk) = nk / n if the values are normalized.

● Similarity measure

Similarity measures quantify the quality of the match of the two images. There are two types of similarity measures: geometrical similarity measures (used on feature-based registration) and intensity similarity measures (used on The intensity-based registration). Geometrical similarity measures involve minimizing cost functions related to the distance between corresponding features in the two images. Intensity similarity measures involve minimizing cost functions computed using the intensity values (directly or indirectly) in regions of interest in the two images.

Similarity plays a crucial role in image registration. In the past few years, Mutual Information,MI (Intensity similarity measure) has been an intensively researched metric in image registration because of its reported favorable characteristics and good results. This information theoretic metric is fully automatic and needs no predefined landmarks. In addition, unlike other intensity based metrics, it is suitable to be applied on both mono-modality and multi-modality registration. However, MI has its own problem i.e it lacks sufficient spatial information to accurately measure the degree of alignment of two images. And its definition is based on Shannon's entropy, which assumes each pixel is independent of its neighbors , however , sometimes such independency is not held in medical images, so MI can lead to misregistration. MI based method requires estimating joint histogram of two images. As a result, it requires an extremely high computation time.

To overcome these problems, we are proposing a new criterion called gradient field mutual information. In this, calculating a term which is able to measure spatial information and then combining it with MI to form a hybrid metric. This spatial information can be calculated from the gradient of the images.

● Finding a transformation between two images

Geometrical transformations align corresponding objects in two or more images. The images could be two dimensional (2-D) or three dimensional (3-D), so the transformation could map points from a 2-D space to a 2-D space, from a 3-D space to a 3-D space, or between a 3-D space and a 2-D space.

A spatial transformation maps locations in one image to new locations in another image. Determining the parameters of the spatial transformation needed to bring the images into alignment is the key to the image registration process.

- **Point mapping**: In point mapping, we pick points in a pair of images that identify the same feature or landmark in the images. Then, a spatial mapping is inferred from the positions of these control points.

- **Region mapping:** CT and MRI images in most cases have discriminated regions. For example, bone region in CT images could be distinguished easily from tissue region by using threshold algorithms.

A spatial transformation modifies the spatial relationship between pixels in an image, mapping pixel locations in an input image to new locations in an output image.

Here are some spatial transformation types:

- **Affine**: Transformation that can include translation, rotation, scaling, and shearing. Straight lines remain straight, and parallel lines remain parallel, but rectangles might become parallelograms.

- **Rigid** : Rigid transformation is also spatial kind of affine transformation. This is the transformation which includes translations and rotations.

- **Projective**: Transformation in which straight lines remain straight but parallel lines converge toward vanishing points. (The vanishing points can fall inside or outside the image -- even at infinity.)

- **Curved :** if it maps lines onto curves

- **Box :** Special case of an affine transformation where each dimension is shifted and scaled independently.

- **Composite** : Composition of two or more transformations.

● Image Reconstruction – Interpolation method

Once a spatial transformation is established, we can proceed to reconstruct the image. X = f(x,y), Y = g(x,y); where (x,y) is the coordinate of a pixel on original image and (X,Y) is the coordinate of a pixel on transformed image.

In digital images, the discrete picture elements, or pixels, are restricted to lie on a sampling grid, taken to be the integer lattice. The output pixels, now defined to lie on the output sampling grid, are passed through the mapping function generating a new grid used to resample the input. This new re-sampling grid, unlike the input sampling grid, does not generally coincide with the integer lattice. Rather, the positions of the grid points may take on any of the continuous values assigned by the mapping function. Since the discrete input is defined only at integer positions, an interpolation stage is introduced to fit a continuous surface through the data samples. The continuous surface may then be sampled at arbitrary positions. This interpolation stage is known as image reconstruction.

The accuracy of interpolation has significant impact on the quality of the output image. As a result, many interpolation functions have been studied from the viewpoints of both computational efficiency and approximation quality. Popular interpolation functions include cubic convolution, bilinear, and nearest neighbor. They can exactly reconstruct second-, first-, and zero-degree polynomials, respectively. More expensive and accurate methods include cubic spline interpolation and convolution with a sinc function.

●Optimization

Optimization refers to the iterative approach of adjusting the transformation parameters (in the intensity-based registration) or the alignment between features (in feature based registration) in an attempt to improve (maximize or minimize) the similarity measure. In the feature-based registration, the transformation is computed directly from the correspondences between features. The optimization procedure starts with an initial estimate of the transform (or procedure starts with an initial estimate of the transform (or correspondence). Based on this estimate, the similarity measure is computed. The optimization procedure then makes a new estimate of the transformation parameters, computes the similarity measure, and continues the process until there is not significant improvement in the value of the similarity measure.

The estimation of the transformation parameters is done following approaches that use information that is either local or global. Approaches using local information can either use similarity measure’s derivatives or not. Examples of optimization approaches using derivatives are gradient descent and quasi-Newton. Examples of optimization approaches that do not use derivatives are downhill search and Powel's method. Approaches using global information include search techniques based on the principles of natural selection and evolution theory. The main global optimization techniques used for medical image registration are genetic algorithms, simulated annealing, and deterministic annealing.

For the optimization procedure to converge to the correct answer, the initial estimate has to be sufficiently close to the expected solution, i.e., the initial estimate has to be within a portion of the parameter space known as the capture range. Because the capture range cannot be known a priori (it depends on the similarity measure and on image properties such as modality, field of view, and contents), it is important to visually inspect the initial estimate to make sure it is close to the correct solution. A further implication of the existence of a capture range is that global optimization methods must be used with caution because they can move outside the capture range.

● Image Fusion:

Image fusion is the process by which two or more images are combined into a single image retaining the important features from each of the original images. It aims at integration of complementary data to enhance the information apparent in the images as well as to increase the reliability of the interpretation. Images after being reconstructed are combined by overlapping at an appropriate transparency. In fact, every pixel value from the result image is a combination of all pairs of corresponding pixel values from base and reconstructed images with a coefficient (trans) which determines the transparency.

*result_img(i,j,k) = (1-trans)*base_img(i,j,k)+ trans* constructed_img(i,j,k).*

Image Geometric Transformations

A geometrical transformation TG is a mappings of points (pixels) from an image to the transformed points of a second image. The transformation TG applied to a point x = (x1; x2) of an image I produces a transformed point $X'=(X_1',X_2')$*of the*

transformed image I’such that x’ = TG (x)

The most common global geometric distortions are the rigid geometrical trans

formations. These transformations preserve all distances and also preserve the straightness of lines. In addition, the overall geometric relationships between points do not change and, in consequence, the shapes of objects in the image do not change. In this type of transformations, there are two components to the specification, a translation and a rotation components. The translation is a two-dimensional vector that may be specified by giving its two parameter in x and y directions while the rotation angle can be specified by one parameter. Hence, a combined transformation of these types typically has tree parameters, tx1, tx2 and θ, which maps a point (x1,x2) of the first image to a point (X_1',X_2') (x_1',X_2')*of the transformed image I’ as follows:*

$$I' = \tau_G(I) = T(t_{x1}, t_{x2}) + R(\theta)I, \quad \text{… (2.1)}$$

where T and R represent translation and rotation operations respectively. In detail, this can be represented as

$$\begin{pmatrix} x_1' \\ x_2' \end{pmatrix} = \begin{pmatrix} t_{x1} \\ t_{x2} \end{pmatrix} + \begin{pmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \end{pmatrix}, \quad (2.2)$$

where tx1 and tx2 are translation parameters in x and y directions respectively and θ is a rotation angle.

The aforementioned transformations can be accompanied with uniform image

Scaling and, therefore, a combined transformation of this type has four parameters,

tx1, tx2, s and θ, which can be defined as

I ' = T G(I) = T(tx1; tx2) + sR(θ)I …(2.3)

In detail, this can be represented as

$$\begin{pmatrix} x_1' \\ x_2' \end{pmatrix} = \begin{pmatrix} t_{x1} \\ t_{x2} \end{pmatrix} + s \begin{pmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \end{pmatrix}, \quad (2.4)$$

where s is the scaling parameter. Examples of rigid transformations are shown

in Fig. 2.1.

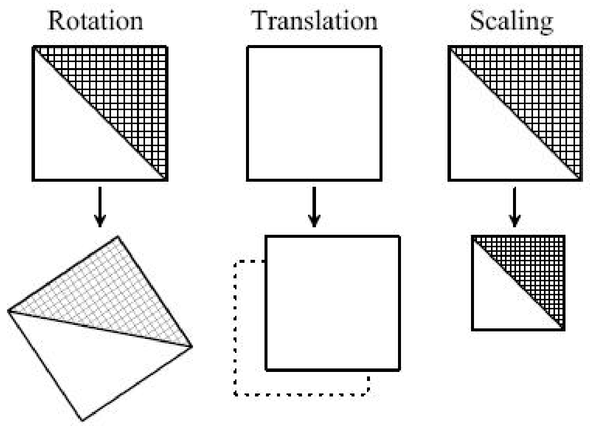

Figure :examples of rigid transformation

A more general type of rigid global transformations is the 2D affine transformation. Examples of affine transformation are image shearing, in x or y directions, and changes in aspect ratio due to non uniform scaling. The general form of affine transformation can be represented as

$$\begin{pmatrix} x_1' \\ x_2' \end{pmatrix} = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} + \begin{pmatrix} t_{x1} \\ t_{x2} \end{pmatrix}, \quad .(2.5)$$

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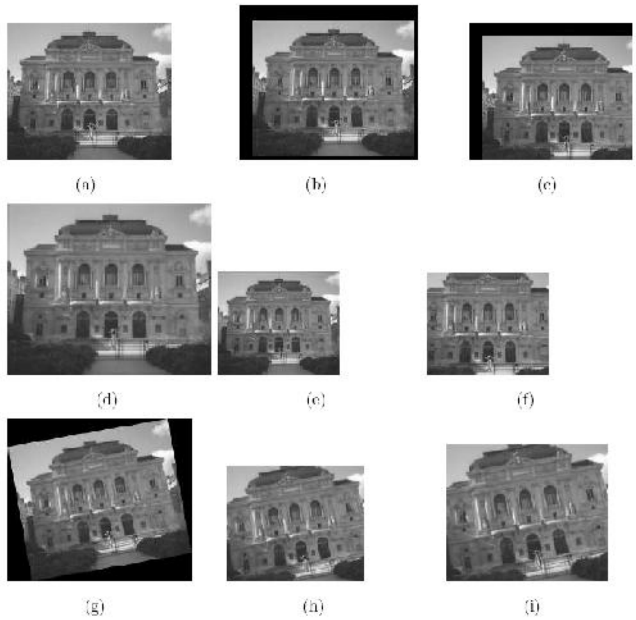

Figure 2.2: An image and the results of applying different geometric operations: (a)

Original image, (b) Translation without cropping, (c) Translation with cropping, (d)

Scaling up by 150%, (e) Scaling down by 75%, (f) Central cropping of 25%, (g)

Rotation by 10^0*, (h) Rotation and cropping by* 10^0*, (i) Rotation and rescaling by* 10^0*.*

where a11, a12, a21, a22, tx1, and tx2 are the transformation parameters.

Projective transformation is another type of transformation that is obtained when adding two more parameters to the above transformation and that introduces an additional distortion in the image [6, 7]. This transformation describes what happens when viewing an object from some arbitrary viewpoint at a finite distance. It maps lines to lines, but does not necessarily preserve parallelism. The general form of Projective transformations can be represented as

$$\begin{aligned} x_1' &= \frac{a_{11}x_1 + a_{12}x_2 + a_{13}}{a_{31}x_1 + a_{32}x_2 + 1} \\ x_2' &= \frac{a_{21}x_1 + a_{22}x_2 + a_{23}}{a_{31}x_1 + a_{32}x_2 + 1}, \end{aligned} \quad (2.6)$$

where a11, a12, a13, a21, a22, a23, a31, a32 and a33 are the transformation parameters. Examples of affine and projective transformations are shown in Fig. 2.3.

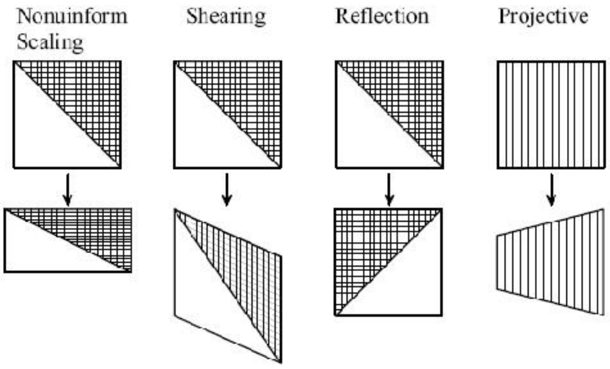

Figure 2.3: Examples of affine and projective transformations.

Another geometric distortions, which can occur, include bilinear and curved

transformation as in 2.7 and 2.8, respectively. The general forms of these transformations can be represented as

$$\begin{pmatrix} x_1' \\ x_2' \end{pmatrix} = x_1 x_2 \begin{pmatrix} a_{11} \\ a_{21} \end{pmatrix} + \begin{pmatrix} a_{12} & a_{13} \\ a_{22} & a_{23} \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} + \begin{pmatrix} t_{x1} \\ t_{x2} \end{pmatrix} \quad (2.7)$$

And

$$\begin{pmatrix} x_1' \\ x_2' \end{pmatrix} = \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} + \begin{pmatrix} ((1-\beta)a_{11} + \beta a_{12})\sin(\alpha\pi) \\ ((1-\beta)a_{21} + \beta a_{22})\sin(\alpha\pi) \end{pmatrix} \quad (2.8)$$

A more complex distortion includes applying the aforementioned transformation locally in small blocks instead of the whole image area [8]. The visual distortion due to this kind of local geometrical transformation are more difficult to model, even with a simple local transformation like the one in 2.4. Fig. 2.4-a shows the image in Fig. 2.2-a after applying local random distortions. As shown in the figure, the effect of such local transformation might be unnoticeable. In order to demonstrate the effect of the transformation, a grid image in Fig.2.4-b is operated by the transformation; the result is shown in Fig.2.4-c after applying local random distortions.

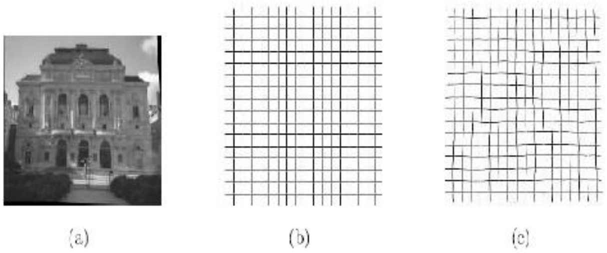

Figure 2.4: (a) A local random distorted image , (b) Original grid image , (c) Local random distorted grid image.

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