International Journal on Emerging Technologies (Special Issue NCETST-2017) **8**(1): 382-388(2017)
(Published by Research Trend, Website: www.researchtrend.net*)*

ISSN No. (Print) : 0975-8364
ISSN No. (Online) : 2249-3255

Nonrigid and Affine Registration of 2d and 3d images

Harendra Pratap Singh, Deep Chandra Andola and Mohit Giri Goswami
Assistant Professor, Amrapali Institute of Tech & Sciences Haldwani (U.K.), INDIA

ABSTRACT: Image registration has many real life applications. Affine image registration is one of the commonly-used parametric models. Iterative solution methods for the underlying least squares problem suffer from convergence problems whenever good initial guesses are not available. Variational models are non-parametric deformable models that have been proposed based on least squares fitting and regularization. The fast iterative solution methods often require a reliable parametric (affine) method in a pre-registration step. In this paper, we first survey and study a class of methods suitable for providing the good initial guesses for the affine model and diffusion based variational model. It appears that these initialization methods, while useful for many cases, are not always reliable. Then we propose a regularized affine least squares approach that can overcome the convergence problems associated with existing methods. Combined with a cooling idea in a multiresolution setting, it can ensure robustness and selection of the optimal coupling parameter efficiently.

Keywords: Image registration, Affine Image, variational model

I. INTRODUCTION

Many computer techniques have been developed in past which help to diagnose and predict the illness of the patient and help the doctor to cure the disease. In 1970s computerized topography (CT) was introduced in the field of clinical application. Other imaging modalities such as magnetic resonance imaging (MRI), positron emission topography (PET), and single photon emission computed topography (SPECT), functional magnetic resonance imaging (fMRI), came in to focus followed by CT scan into the surgical and radiotherapy applications. This type of diagnostic techniques helps physicians to obtain accurate and complementary information about a tumor or situation, which help to diagnose many of the diseases and cause of unhealthy conditions.

In Medical treatment and surgical procedures, patients have to perform many series of medical imaging studies CT, MRI, PET before the treatment. Each imaging strategy alters the orientation and positioning of the patient, the physician check the issue of how to compare and analyze the images from all the modalities. The best strategy is image fusion that integrates the useful information from all the images into one image. All the images need to be co-registered into the same spatial location before they can be integrated and visualized.

Function MRI analysis is a new way to learn and study various psychological behaviors associated with various physical and/or psychological stimulations like fear, hunger or other chemical stimuli. During the experiment, images are taken from a group of subjects to understand and explore the brain functional activities. All subjects are taken in Registration of images and it is a critical step to obtain an accurate composite activation map.

Medical image registration is very important in clinical and medical applications. Different images from the different scanners are analyzed first then all the images need to be aligned into the same position where the structure of tissues can be compared. Various registration strategies based on manual registration, landmark, voxel similarity were developed to satisfy the increasing needs of medical applications.

II. IMAGE REGISTRATION

Image registration is a key enabling technology in medical image analysis that has benefited from 20 years of development. It is a process for determining the correspondence of features between images collected at different times or using different imaging modalities. The correspondences can be used to change the appearance –by rotating, translating, stretching etc. – of one image so it more closely resembles another so the pair can be directly compared, combined or analyzed. The most intuitive use of registration is to correct for different patient positions between scans. Image registration is not an end in itself but adds value to images, e.g. by allowing structural (CT, MR, ultrasound) and functional (PET, SPECT, functional MRI (fMRI)) images to be viewed and analyzed in the same coordinate system, and facilitates new uses of images, e.g. to monitor and quantify disease progression over time in the individual or to build statistical models of structural variation in a population. In some application areas image registration is now a core tool; for example (i) reliable analysis of fMRIs of the brain requires image registration to correct for small amounts of subject motion during imaging; (ii) the widely used technique of voxel based morphometry makes use of image registration to bring brain images from tens or hundreds of subjects into a common coordinate system for analysis (so-called ''spatial normalization''); (iii) the analysis of perfusion images of the heart would not be possible without image registration to compensate for patient respiration; and (iv) some of the latest MR image acquisition techniques incorporate image registration to correct for motion. Historically, image-registration has been classified as being ''rigid'' (where images are assumed to be of objects that simply need to be rotated and translated with respect to one another to achieve correspondence) or ''non-rigid'' (where either through biological differences or image acquisition or both, correspondence between structures in two images cannot be achieved without some localized stretching of the images). Much of the early work in medical image registration was in registering brain images of the same subject acquired with different modalities (e.g. MRI and CT or PET). For these applications a rigid body approximation was sufficient as there is relatively little change in brain shape or position within the skull over the relatively short periods between scans. Today rigid registration is often extended to include affine registration, which includes scale factors and shears, and can partially correct for calibration differences across scanners or gross differences in scale between subjects.

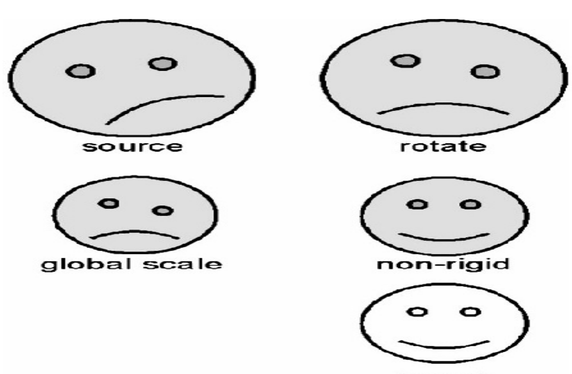

Fig.1. Schematic showing rigid and non-rigid registration.

The source image is rotated, of a different size and contains different internal structure to the target. These differences are corrected by a series of steps with the global changes generally being determined before the local changes areas in more detail. Clearly most of the human body does not conform to a rigid or even an affine approximation and much of the most interesting and challenging work in registration today involves the development of non-rigid registration techniques for applications ranging from correcting for soft-tissue deformation during imaging or surgery through to modeling changes in neuroanatomy in the very old and the very young. In this paper we focus on these non-rigid registration algorithms and their applications.

III REGISTRATION & CORRESPONDENCE

Image registration is about determining a spatial transformation – or mapping – that relates positions in one image, to corresponding positions in one or more other images. The meaning of correspondence is crucial; depending on the application, the user may be interested in structural correspondence (e.g. lining up the same anatomical structures before and after treatment to detect response), functional correspondence (e.g. lining up functionally equivalent regions of the brains of a group of subjects) or structural–functional correspondence (e.g. correctly positioning functional information on a structural image). A particular registration algorithm will determine correspondence at a particular scale, and even if this transformation is error-free, there will be errors of correspondence at finer scales. Sometimes the scale is set explicitly; in registration using free-form deformations the displacements of a regular grid of control-points are the parameters to be deduced and the initial millimeter spacing between these points defines a scale for the registration. In some other registration types the scale selection is more implicit; in the registration used in the statistical parametric mapping (SPM) package (http:// www.fil.ion.ucl.ac.uk/spm/) for example the number of discrete-cosine basis functions must be specified by the user with higher numbers introducing more flexibility into the registration and hence the ability to determine correspondences at a finer scale. It is worth emphasizing that increased flexibility comes at some cost. The most obvious penalty is that more parameter determination tends to mean more computer time is required. Rigid and affine registrations can typically be determined in seconds or minutes but most non-rigid registration algorithms require minutes or hours with that time being spent either identifying a geometric set of corresponding features to match directly (see below) or automatically determining a large number of parameters by matching voxel intensities directly. Another issue is that typically the transformation is asymmetric: although there will be a vector that, at the scale of the transformation, describes how to displace each point in the source image to find the corresponding location in the target image, there is no guarantee that, at the same scale, each point in the target image can be related to a corresponding position in the source image (see Appendix 1 for a description of common terminology such as source and target). There may be gaps in the target image where correspondence is not defined at the selected scale. Some work has been done on symmetric schemes which guarantee the same result whether image A is matched to image B or vice versa. This may be more appropriate for some applications (matching one normal brain to another) than others (monitoring the growth of a lesion). Finally, there is the question of redundancy. If geometrical features are used to match images then there will be many different possible deformation fields which can align those features but which behave differently away from those features or may be constrained in some way (e.g. to disallow situations where features can be ''folded'' to improve the image match but in a nonphysical way). Similarly there will also be many possible deformation fields that can result in voxel intensities appearing to be well matched between images. With all these possibilities how do we distinguish between equivalent fields and how do we know what is ''right'' for a particular application? These are issues of current importance and are discussed in the context of validation below.

Components of registration algorithms

A registration algorithm can be decomposed into three components:

- The similarity measure of how well two images match;
- The transformation model, which specifies the way in which the source image can be changed to match the target. A number of numerical parameters specify a particular instance of the transformation;
- The optimization process that varies the parameters of the transformation model to maximize the matching criterion.

Similarity measures

Registration based on patient image content can be divided into geometric approaches and intensity approaches. Geometric approaches build explicit models of identifiable anatomical elements in each image. These elements typically include functionally important surfaces, curves and point landmarks that can be matched with their counterparts in the second image. These correspondences define the transformation from one image to the other. The use of such structural information ensures that the mapping has biological validity and allows the transformation to be interpreted in terms of the underlying anatomy or physiology.

Corresponding point landmarks can be used for registration provided landmarks can be reliably identified in both images. Landmarks can either be defined anatomically (e.g. prominences of the ventricular system), or geometrically by analyzing how voxel intensity varies across an image. When landmarks are identified manually, it is important to incorporate measures of location accuracy into the registration. After establishing explicit correspondences between the pairs of point landmarks, interpolation is used to infer correspondence throughout the rest of the image volume in a way consistent with the matched landmarks. Recent work has incorporated information about the local orientation of contours at landmark points to further constrain the registration. In other studies, linear features called ridges or crest lines are extracted directly from three dimensional (3D) images, and non-rigidly matched. Then, as above, interpolation extends the correspondences between lines to the rest of the volume. For some anatomy linear features are a natural way of summarizing important structure. For instance in the brain, a large subset of the crest lines correspond to gyri and sulci and in Subsol et al these features were extracted from different brains and registered to a reference to construct a crest-line atlas. Such atlases succinctly summarize population anatomical variation. As point and line matching is relatively fast to compute, a large number of solutions and potential correspondences can be explored. Other related applications include the registration of vascular images where the structures of interest are ''tubes''. Many non-rigid registration methods based on 3D geometric features use anatomical surfaces, for example the shape of the left ventricle. Typically, surface-based registration algorithms can be decomposed into three components: extracting boundary points of interesting structures in the image, matching the source and reference surface, and then extending the surface-based transformation to the full volume. There are many different ways to implement each of these steps. For example, Thompson et al extract the surfaces of the lateral ventricle and the cerebral cortex in a subject's brain scan and in a corresponding brain atlas automatically. In Audette et al brain and skin surfaces in pre-operative MR and CT images and intra operative range images are extracted using the powerful level-set framework and registered to track intra operative brain deformation. Other authors have used elastic and boundary mapping techniques. The related task of tracking MR brain deformation in intra operative images is achieved in Ferrant et al by registering cortical and ventricle surfaces and using a biomechanical model of brain tissue to infer volumetric brain deformation. A detailed survey of surface-based medical image registration can be found in Audette et al.

Intensity-based registrations match intensity patterns over the whole image but do not use anatomical knowledge. Geometric registration uses anatomical information but usually sparsely distributed throughout the images. Combining geometric features and intensity features in registration should result in more robust methods. Hybrid algorithms are therefore of particular current interest, combining intensity-based and model-based criteria to establish more accurate correspondences in difficult registration problems, e.g. using sulcal information to constrain intensity-based brain registration or to combine the cortical surface with a volumetric approach. Surfaces are also used to drive volumetric registration in Thompson et al to analyze normal and Alzheimer brains with respect to an anatomical image database. In Christensen et al the registration task is to correct for large displacement and deformation of pelvic organs induced when intracavity CT applicators are used to treat advanced cancer of the cervix. Anatomical landmarks are used to initialize an intensity driven fluid registration with both stages using the same model for tissue deformation. In this application the more robust but less flexible landmark registration produces a robust starting position for the less robust but more flexible fluid registration and the two steps run serially (there is further discussion of fluid registration in the next section). Other researchers have attempted true hybrid solutions where intensity and feature information are incorporated into a single similarity measure, e.g. in Russakoff et al a rigid registration is computed between a pre-operative spinal CT and an intra operative X-ray by maximizing the difference of mutual information based intensity measure and a distance between corresponding landmarks. As is often the case, an additional parameter has to be chosen empirically to appropriately weight the intensity and landmark parts of the similarity measure. A more sophisticated approach built on the same principles is used in PASHA (Pair And Smooth Hybrid Algorithm) where the similarity measure is the weighted sum of an intensity similarity, a term expressing the difference between the landmark correspondence and the volumetric deformation field, and a smoothing term. In Hellier and Barillot a framework for incorporating landmark constraints with image-based non-rigid registration is described for the application of inter subject brain registration where the constraints ensure that homologous sulci are well matched.

IV TRANSFORMATION MODELS

The transformation model defines how one image can be deformed to match another; it characterizes the type and number of possible deformations. The most well known example is the rigid or affine transformation that can be described very compactly by between 6 (3 translations and 3 rotations) and 12 (6 + 3 scaling + 3 shears) parameters for a whole image. These parameters are applied to a vector locating a point in an image to find its location in another image. The transformation model serves two purposes; first it controls how image features can be moved relative to one another to improve the image similarity and second it interpolates between those features where there is no useable information. Transformations used in non-rigid registration range from smooth regional variation described by a small number of parameters to dense displacement fields defined at each voxel. One of the most important transformations is the family of splines that have been used in various forms for around 15 years. Spline-based registration algorithms use corresponding (‘‘control’’) points, in the source and target image and a spline function to define correspondences away from these points. The ‘‘thin-plate’’ spline has been used extensively to investigate subtle morphometric variation in schizophrenia. Each control point belonging to a thin-plate spline has a global influence on the transformation in that, if its position is perturbed, all other points in the transformed image change. This can be a disadvantage because it limits the ability to model complex and localized deformations and because, as the number of control points increases, the computational cost associated with moving a single point rises steeply. By contrast, B-splines are only defined in the vicinity of each control point; perturbing the position of one control point only affects the transformation in the neighborhood of the point. Because of this property, B-splines are often referred to as having ‘‘local support’’. B-spline based non-rigid registration techniques are popular due to their general applicability, transparency and computational efficiency. Their main disadvantage is that special measures are sometimes required to prevent folding of the deformation field and these measures become more difficult to enforce at finer resolutions. Such problems have not prevented these techniques finding widespread use. Elastic models treat the source image as a linear, elastic solid and deform it using forces derived from an image similarity measure. The elastic model results in an internal force that opposes the external image matching force. The image is deformed until the forces reach equilibrium. Since the linear elasticity assumption is only valid for small deformations it is hard to recover large image differences with these techniques. Replacing the elastic model by a viscous fluid model [69] allows large and highly localized deformations. The higher flexibility increases the opportunity for misregistration, generally involving the growth of one region instead of a shifting or distorting another. According to BroNielsen and Gramkow another non-rigid technique, the ‘‘demons’’ algorithm, can be thought of as an approximation to fluid registration. Finite element (FE) models allow more principled control of localized deformations and have been applied particularly to the head for surgical scenarios. These models divide the image into cells and assign to these cells a local physical description of the anatomical structure. For instance, soft tissue can be labeled as elastic, bone as rigid and cerebrospinal fluid (CSF) as fluid. External forces such as landmark correspondences or voxel similarity measures are applied to the model, which deforms according to the material behavior in each cell. Such approaches tend to be used where there are strong biomechanical constraints in operation, i.e. they are appropriate for serial registration of images of brains undergoing some mechanical intervention but not appropriate for inter subject registration. Where registration speed is important some researchers have applied optical flow techniques that were originally developed in the computer vision and artificial intelligence community. Some adaptation has been required for medical applications because the ‘‘constant intensity’’ assumption is often (usually!) broken in serial medical images and optical flow methods have not been widely adopted.

Optimization

Optimization refers to the manner in which the transformation is adjusted to improve the image similarity. A good optimizer is one that reliably and quickly finds the best possible transformation. Choosing a good optimizer requires a good understanding of the registration problem, the constraints that can be applied and knowledge of numerical analysis. An in depth discussion of optimization is far beyond the scope of this paper. In non-rigid registration applications choosing or designing an optimizer can be difficult because the more non-rigid (or flexible) the transformation model the more parameters are generally required to describe it. For the optimizer this means that more time is required to make a parameter choice and that there is more chance of choosing a set of parameters, which result in a good image match which is nevertheless not the best one (the ‘‘local minima’’ problem). A more subtle problem is that a transformation parameter choice that gives a good image or feature similarity may not be physically meaningful. The most common example of this is when we have a prior belief that the registration of one image onto another should be diffeomorphic; in simple terms this means that if the transformation were applied to a real physical object to deform it then no tearing of the object would occur. The problem is that tearing can often result in a transformation that makes the images more similar despite it being physically invalid. Therefore in many situations, e.g. serial MR brain registration of a subject undergoing diffuse atrophy, there is a prior expectation that folding or tearing should not be required to secure a good match. One of the attractions of fluid registration that has been successfully used in this application is that the transformation model implicitly forbids tearing. Often, tearing is a result of correspondence problems. For instance, intersubject brain registration where one subject has a large extrinsic tumor and abdominal registration where fluid and gas filled spaces can appear and disappear between scans are examples where correspondence is not well defined and where tearing or folding may be necessary to describe the underlying physical transformation. Other constraints can be implicit in the choice of the transformation model, e.g. that the transformation should be consistent with the behaviour of a deforming elastic body. Much of the work of optimizers is therefore to balance the competing demands of finding the best set of correspondences subject to application-specific constraints.

The most common optimizer for registering point sets is the Iterative Closest Point algorithm of Besl and McKay, which does not require all the pair-wise correspondences of landmarks to be pre-defined and which iterates towards the nearest local error minimum. Some more recent algorithms solve a similar problem with similar performance and some claimed advantages in robustness to local minima and convergence properties. Many registration algorithms are amenable to existing optimization schemes in that they seek to choose a set of parameters to maximize (or minimize) a function. This is a standard problem and there are standard ways to solve it. Fluid and elastic transformations that can be described in terms of a partial differential equation (PDE) can be obtained using existing numerical solvers. Which optimization scheme is suitable for a particular registration application depends on the cost function, the transformation, potential time-constraints, and the required accuracy of the registration.

Validation

Validation usually means showing that a registration algorithm applied to typical data in a given application consistently succeeds with a maximum (or average) error acceptable for the application. For geometric approaches a real-world error can be computed, which for landmark methods expresses the distance between corresponding landmarks post-registration. For rigid-registration this form of error analysis has been studied intensively and it has been found that an average target registration error for the whole volume can be estimated from knowledge of the landmark positions. Such an analysis is not generally possible for non-rigid techniques so although the error at landmarks can be established, the error in other parts of the volume is dependent on the transformation model and must be estimated using other means. In intensity-based approaches the registration itself, usually cannot inform the user of success or failure, as the image similarity measure is not related to real-world error in a simple way. For these problems, validation is usually performed by making additional measurements post registration or showing that an algorithm performs as desired on pairs of test images for which the transformation is known. One common approach is to identify corresponding landmarks or regions independently of the registration process and establish how well the registration brings them into alignment. In Schnabel et al a biomechanical model of the human breast is used to simulate MR images of a breast subject to mechanical forces as might be experienced during biopsy or movement during dynamic contrast-enhanced imaging. Pre- and post contrast images subject to known deformation were generated and used to validate a B-spline based nonrigid registration. Of course in many applications the true point-to-point correspondence can never be known and may not even exist (e.g. intersubject brain registration). Various kinds of consistency test are also used in validation; the most common are establishing that registration of source to target produces the same alignment as from target to source (this is commonly not the case for non-rigid registration) or that for three images, A, B, C, registration of CRA gives the same result as CRB compounded with BRA. It is important to carefully pose the registration task in application specific terms that make use of available information in the image and prior knowledge. These issues are discussed in some depth for brain registration problems in Crum et al. In most applications, careful visual inspection remains the first and most important validation check available for previously unseen data.

Steps involved in Image Registration

Image registration essentially consists of following steps as per Zitova and Flusser illustrates the process.

- Feature detection: Salient and distinctive objects (closed-boundary regions, edges, contours, line intersections, corners, etc) in both reference and sensed images are detected.
- Feature matching: The correspondence between the features in the reference and sensed image established.
- Transform model estimation: The type and parameters of the so-called mapping functions, aligning the sensed image with the reference image, are estimated.
- Image re-sampling and transformation: The sensed image is transformed by means of the mapping functions

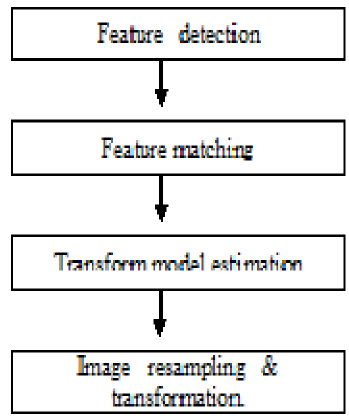

Fig. 2. Steps involved in Image Registration.

V. CONCLUSION

Rigid registration techniques have become widely accepted in a variety of clinical applications. In contrast, non-rigid registration is very much an area of ongoing research, and most algorithms are still in the stage of development and evaluation. One of the main reasons for the successful impact of rigid registration techniques is the fact that these techniques can be assessed and validated against a gold standard. The lack of a gold standard for assessing and evaluating the success of nonrigid registration algorithms is one of their most significant drawbacks. Currently, the only accepted method for assessing nonrigid registration is based on manually.

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