Automatic 3D Brain Image Registration – Survey

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***Abstract*—Registration is frequently essential for integration brain information taken from different sensors, finding changes in images taken at different times or under different conditions, inferring 3D brain information from images. A registration procedure of brain can always be decomposed into three major parts: the problem statement, the registration paradigm and the optimization procedure. It is often helpful to remember that the three pillars are independent, since many papers do not describe them as such, often presenting the problem statement, paradigm and optimization procedure in a compounded way. 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 in image fusion, change detection, and multichannel image restoration.**

***Index Terms*—Alzheimer's disease, brain tumor, fuzzy clustering, optimization procedure.**

I. Introduction

The world of 3D incorporates the third dimension of depth, which can be perceived by the human vision in the form of binocular disparity [1]. Human eyes are located at slightly different positions, and these perceive different views of the real world. The brain is then able to reconstruct the depth information from these different views. A 3D display takes advantage of this phenomenon, creating two slightly different images of every scene and then presenting them to the individual eyes. With an appropriate disparity and calibration of parameters, a correct 3D perception can be realized [2], [3]. Brain image registration can be used in analyzing local anatomical variations that exist between images acquired from different individuals or atlases. It can serve as a powerful tool for combining information from multiple sources, monitoring changes in an individual, detecting tumors and locating disease, motion correction, image fusion, and many more.

An example of a 3-D image registration is shown in Fig. 1. The top row shows orthogonal cross-sections of a magnetic resonance (MR) brain image, the second row shows orthogonal cross-sections of a positron emission tomography (PET) brain image of the same person, the third row shows overlaying of the orthogonal cross-sections of the images before registration and the fourth row shows overlaying of the orthogonal cross-sections of the images after registration. MR images show anatomy well while PET images show function well. By registering PET and MR brain images, anatomical and functional information can be combined, making it possible to anatomically locate brain regions of abnormal function [4].

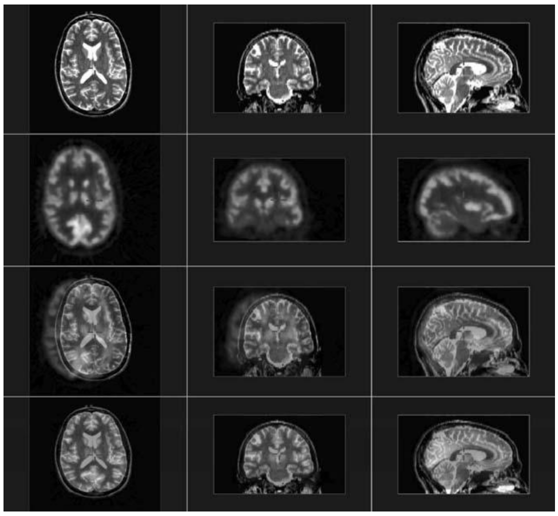

Fig. 1. Registration of MR and PET brain images.

Lashkari [5] introduced an automatic brain tumor detection method to increase the accuracy and yield, and decrease the diagnosis time. The goal in his work was to classify the tissues into two classes: normal and abnormal. MR images that were used in his work were images from normal and abnormal brain tissues. He tried to give clear description from brain tissues using Zernike Moments, Geometric Moment Invariants, energy, entropy, contrast and some other statistic features such as mean, median, variance, correlation between corresponding points, and values of maximum and minimum intensity. He used a feature selection method to reduce the feature space as well. His method used neural networks to do that classification. The purpose was to classify the brain tissues into normal and abnormal classes automatically; which saves the radiologist time, and increases accuracy and yield of diagnosis. Reddy *et al.* [6] showed an improvement to fuzzy clustering means (FCM). They introduced an earlier spatial constraint into FCM algorithm, in which the spatial information is encoded through mutual influences of neighboring positions. To detect the abnormalities of Brain MRI images, they used a new spatial FCM, and compared the results with k-means and FCM techniques.

Just like the rest of our bodies, our brains change as we age. Most of us notice some slowed thinking and occasional problems remembering certain things. However, serious memory loss, confusion and other major changes in the way our minds work are not a normal part of aging. These may be the signs of brain cells failure [7]. The brain has 100 billion nerve cells (neurons). Each nerve cell communicates with many others to form network. Nerve cell networks have

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special jobs. Some are involved in thinking, learning and remembering. Others help us see, hear and smell. Still others tell our muscles when to move. In Alzheimer's disease shown in Fig. 2, as in other types of dementia, increasing numbers of brain cells deteriorate and die [8].

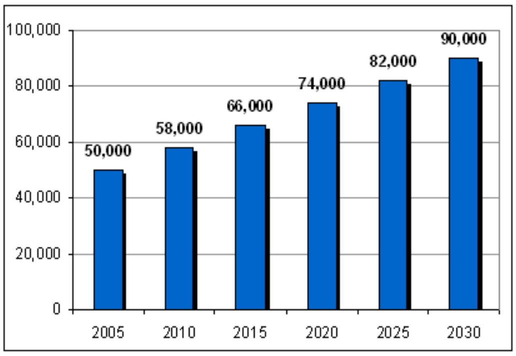

Fig. 2. Alzheimer's patients' census.

In this survey paper, the brain image registration decomposed into three major parts: the problem statement, the registration paradigm and the optimization procedure.

II. Problem Statement

The problem statement of brain image registration determines the classification according on the modalities involved, subject and object [9], [10] and has a direct bearing on the criteria dimensionality and nature of transformation. The patient to modality registration tasks appear almost exclusively in intra-operative [11] and radio therapy [12]. In monomodal applications, the 3D brain images to be registered belong to the same modality, as opposed to multimodal registration tasks, where the 3D brain images to be registered stem from two different modalities. In modality to model and patient to modality registration only one brain image is involved and the other "modality" is either a model or the patient himself. Hence we use the term "modality" in a loose sense, not only applying to acquired brain images, but also to mathematical models of anatomy or physiology, and even to the patient himself. Monomodal tasks are well suited for growth monitoring, intervention verification, rest-stress comparisons, ictal-interictal comparisons, subtraction imaging (also DSA, CTA), and many other applications. The applications of multimodal registration are abundant and diverse, predominantly diagnostic in nature. A coarse division would be into anatomical-anatomical registration, where images showing different aspects of tissue morphology are combined, and functional-anatomical, where tissue metabolism and its spatial location relative to anatomical structures are related. When all of the brain images involved in a registration task is acquired of a single patient, we refer to it as intrasubject registration. If the registration is accomplished using two brain images of different patients (or a patient and a model), this is referred to as intersubject registration. The use of intersubject and atlas matching can notably be found in the areas of gathering statistics on the size and shape of specific structures, finding (accordingly) anomalous structures, and transferring segmentations from one image to another [13].

III. Registration Paradigm

Image registration essentially consists of following steps as per Zitova and Flusser [14]. Fig. 3 illustrates the process [15].

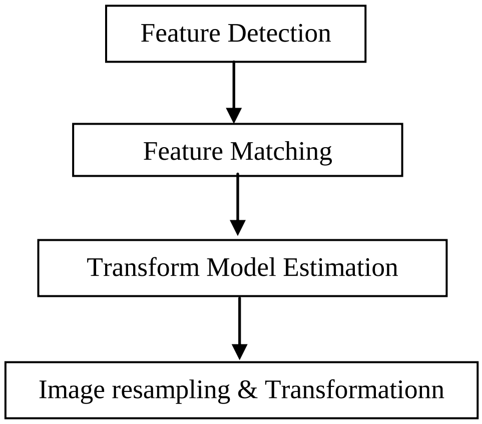

Fig. 3. Steps involved in Image registration.

- 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 resampling and transformation: The sensed image is transformed bymeans of the mapping functions.
- The registration paradigm influences the criteria nature of registration, nature and domain of transformation and interaction [9], [10]. 3D to 3D of more widespread applicability is the accurate registration of multiple 3D images such as MR and CT volumes. The assumption is usually made that the internal anatomy of the patient has not moved or distorted and hence the 6 degrees of freedom of rigid body motion (3 translations and 3 rotations) will bring the images into registration. Careful calibration of each scanning device is required to determine image scaling, i.e. the size of the voxels in each modality [16]. In a recent paper [17] the authors presented a method for integration of 3−D medical data by utilizing the advantages of 3−D multiresolution analysis and techniques of variation calculus. They first expressed the data integration problem as a variation optimal control problem where the displacement field was written in terms of wavelet expansions and secondly they wrote the components of the displacement field in terms of wavelet coefficients.
- Ali Akinlar *et al.*, solved this optimization problem with a block wise descent algorithm and demonstrated the application of the method by the registering 3−D brain MR images in the size of $257 \times 257 \times 65$. Duration of the medical data integration process was about 2 minutes and the registered image seems has features of both reference and template image. Detailed information

about this method can be seen at. Ali Akinlar *et al.*, introduces several mathematical image registration models [18] employing some curvature driven diffusion based techniques, in particular, Perona–Malik, anisotropic diffusion, mean curvature motion (MCM), affine invariant MCM. Adopting the steepest-descent marching with an artificial time, Euler-Lagrange (EL) equations with homogeneous Neumann boundary conditions are obtained. These EL equations are approximately solved by the explicit Petrov-Galerkin scheme. The method is applied to the registration of brain MR images of size 257 × 257. Computational results indicate that all these regularization terms produce similarly good registration quality but that the cost associated with the AIMCM approach is, on the average, less than that for the others. Duration of the registration with each model was around 1 to 3 minutes depending on the diffusion term and the quality of the registered images was quite good as well. An image registration method might be described as efficient if the quality of the registered images is good, duration of the registration process is short and the amount of the similarity measure is small.

IV. Optimization Procedure

The optimization procedure shown in Fig. 4 influences criterion interaction and controls the parameters. The parameters that make up the registration transformation can either be computed directly, i.e., determined in an explicit fashion from the available data, or searched for, i.e., determined by finding an optimum of some function defined on the parameter space [9], [10].

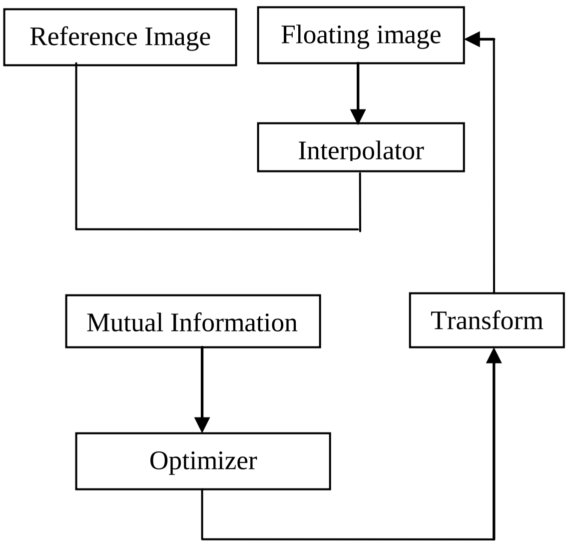

Fig. 4. Optimization procedure.

In the former case, the manner of computation is completely determined by the paradigm. The only general remark we can make is that the use of computation methods for finding global transformations is restricted almost completely to applications relying on very sparse information, e.g. small point sets [19]. If local transformations are sought, it is often possible to compute the local displacement directly from the available local image data, e.g. in optical flow-based methods. In the case of searching optimization methods, most registration methods are able to formulate the paradigm in a standard mathematical function of the transformation parameters to be optimized. This function attempts to quantify the similarity as dictated by the paradigm between two images given a certain transformation. Such functions are generally less complex in monomodal registration applications, since the similarity is more straightforward to define. Hopefully, the similarity function is well-behaved (quasi-convex) so one of the standard and well-documented optimization techniques can be used. Popular techniques [20]-[22] are:

Powell's method
The downhill simplex method
Brent's method and series of one-dimensional searches
Levenberg–Marquardt optimization
Newton–Raphson iteration
Stochastic search methods
Gradient descent methods
Genetic methods
Simulated annealing
Geometric hashing
Quasi-exhaustive search methods

Many of these methods are documented in [23]. Frequent additions are multi-resolution (e.g. pyramid) and multi-scale approaches to speed up convergence, to reduce the number of transformations to be examined (which is especially important in the quasi-exhaustive search methods) and to avoid local minima. Some registration methods employ non-standard optimization methods that are designed specifically for the similarity function at hand, such as the ICP algorithm, created for rigid-model-based registration. Kio Kim *et al.*, [24] presented a procedure to automatically register slice stacks of fetal MR images, and reconstruct a high isotropic resolution 3-D volume that is consistent with the original slice stacks. Matching the intersections between slices provided a direct measure to evaluate the mismatch between slices. Many applications use more than one optimization technique, frequently a fast but coarse technique followed by an accurate yet slow one. Application in skull-base surgery demonstrates overlay of critical structures (e.g., carotid arteries and optic nerves) and surgical target volumes with sub mm accuracy. Phantom and cadaver experiments show consistent improvement in target registration error (TRE) in video overlay over conventional tracker-based registration – e.g., 0.92 mm versus 1.82 mm for image-based and tracker based registration, respectively [25].

V. Conclusion

In our survey paper, we concluded that the fundamental problems in the analysis of functional and structural imaging data include data transport, boundary identification, volume estimation, three-dimensional reconstruction and display, surface and volume rendering, shape analysis, and image overlay. These problems require that research investigators have access to suitable methods of image analysis, implemented on a set of software programs, in order to conduct neuro imaging research. Different cost functions, different minimization methods, and various sampling, smoothing, and editing strategies were compared. Internal consistency measures were used to place limits on registration accuracy for MRI data, and absolute accuracy was measured using a brain phantom for PET data. All strategies are consistent with subvoxel accuracy for intrasubject, intramodality registration. Estimated accuracy of registration of structural MRI images was in the 75 to 150 μm range. Sparse data sampling strategies reduced registration times to minutes with only modest loss of accuracy. Registration strategies can be tailored to meet different needs by optimizing tradeoffs between speed and accuracy.

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