A Comprehensive Survey and analysis of Automated Registration of Brain Tomographs

D Chamundeshwari, **J Thirupathi**

Abstract— **Advances in computer science have led to reliable and efficient image processing methods useful in medical diagnosis, medical research and treatment analysis. The best segmentation can be done by the integration of useful data obtained from separate images. The images need to be geometrically aligned for good analysis. The method of mapping points from one image to corresponding points in another image is called Image Registration. It is used in computer vision, military automatic target recognition, medical imaging and compiling and analyzing images and data from satellites. "Image Registration" is used for the segmentation of brain tumors. Currently, brain cancer is one of the dangerous diseases in the world; both developed and developing nations are suffering due to different reasons. In human body, brain is an important part, it controls the function of all other organs. In medical images once object is segmented, the diagnosis and treatment planning can be easily performed by the doctors based on the nature and growth rate of the tumors.**

Image registration generally uses two types of images. Reference and Sensed image could be different because they are taken at different times(multi temporal), using different devices like Magnetic Resonance Imaging(MRI), Positron Emission Tomography(PET),Computer Tomography(CT), Single Proton Emission Tomography(SPECT) etc. (multimodal) and from different angles (multi-view)in order to have 2D or 3D view points. A Comprehensive Survey and analysis of Automated Registration of Brain Tomographs is the process of transforming different sets of data into one coordinate system. Tomography refers to imaging by sections or sectioning, through the use of any kind of carrying from one point to another. The registration is mandatory in order to be able to compare or integrate the data obtained from these different measurements. Image registration is performed based on different criteria. Depends on the control points, registration can be divided as area based methods and feature based methods. The main aim of the paper is to Survey and analysis of automation process is to avoid the human creates the possibility that process is applied on more number of cases with less time. It also improves Computational accuracy.

Index Terms:- Image Registration (IR), MRI, Fusion, Automatic Registration (AR) .

I. INTRODUCTION

The paper focuses on methods that explicitly combine segmentation and registration in a variational framework of brain tomographs. Advances in medical imaging technologies have enabled the diagnosis procedures not possible a decade ago. The acquisition speed and the resolution enhancements of imaging modalities have given doctors more information, less invasively about their patients. However, because of the multitude of imaging modalities[1,2]like Computed Tomography (CT), Positron Emission Tomography (PET), Magnetic Resonance Imaging (MRI) and the sheer volume of data being acquired. An increasing array of diagnostic images will be collected for each patient, either using different modalities (CT, MRI, PET), or the same modality at different times for research purposes and also for the treatment follow-up studies. Utilization of the new data effectively has become problem. To handle the potentiality of this raw data, these images can be merged into one integrated view through a procedure called image registration.

The comprehensive study of image registration techniques was published in 1992 by Brown. The main of this paper is to introduce techniques came after that and maps the current development of image registration. We did not go into the details of particular algorithm. Instead of it we summarize the useful approaches and point out interesting part of image registration. And paper shows the correlative experiments & results of automatic registration process.

II. REGISTRATION PROCESS

Several studies carried out on the registration of medical images. In the several review papers the following procedure is adopted for the global affine registration [3, 4]. Assuming that, the two images of the same object are available.

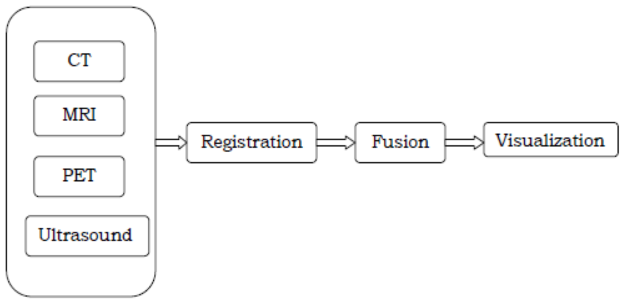

Fig 1: Registration process

A structural image and a functional image, Process of registration is composed of the following steps:

1. Acquiring information from two images
2. Pre-processing to improve the quality of images
3. Determination of the registration cost function (similarity measure)

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***D Chamundeshwari**, Asst. Professor* in *Department of Electronics and Communication Engineering, Vageswari College of Engineering JNTU, Karimnagar, Telangana, India.*

***J Thirupathi**, Associate. Professor in Department of CSE, College of Engineering and Technology.*

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4. Selecting the same characteristics and finding a mapping between two images to find out transformation functions
5. Reconstructing images based on above functions
6. Optimization of the similarity measure
7. Combining reconstructed images by overlapping them with an appropriate transparency
8. Verification and validation of registration algorithm

Images of a patient obtained by CT, MRI, SPECT and PET scanning are displayed as a 2-D array of pixels and stored in memory. 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 movement while scanning, they should be filtered and sharpened to improve visualization. According to Maintz.et.al [1] registration can be performed using different criteria. The registration can be area based and feature based methods [5, 6].According to typical image registration algorithm [7] consists of the following basic components:

- ***Similarity Measure***

Similarity measure is a cost function [1, 5, and 6] used as an alignment measure that quantifies the quality of alignment (one over other) i.e. match between the two images. There are two types of similarity measures: geometrical similarity measures (used for feature-based registration) and intensity similarity measures (used for 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.

- ***Finding a Transformation between Two Images***

Geometrical transformations [2, 4] align the corresponding objects in two or more images. The images could be two(2-D) or three dimensional (3-D). 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 by using scaling, rotation. Some spatial transformations are rigid, affine, projective, and curved. A class of admissible geometric transformations perform either point or region mapping that can be applied to the image(s) to warp the image(s) spatially [8, 9].

- ***Optimization***

Optimization [10, 11] 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) 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 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 no significant improvement in the value of the similarity measure. Optimization methods are classified as search based [26, 27] and evolutionary kind [90].

- ***Interpolation***

Image resizing is necessary to increase or decrease the total number of pixels, whereas remapping can occur under a wider variety of scenarios: correcting for lens distortion, changing perspective, and rotating an image. Even the same image is resized or remapped the results can vary significantly depending on the interpolation algorithm. It is the only an approximation; therefore an image will always lose some quality each time the interpolation [12, 13] is performed. given samples must satisfy the following requirements: $h(x) = 1$ if $x=0$

$=0$ if$x \neq 0$ for all x € z,

- ***Fusion***

There exist various interpolation kernels [12, 14] like nearest neighbor, bi-linear, bi-cubic and sinc functions etc. The type of interpolation function is a tradeoff between accuracy and computational time. It is a process of obtaining a single image from a set of input images. The fused image should have more complete information which is more useful for human or machine perception. With the development of new imaging methods in medical diagnostics, there arises the need of meaningful (and spatial correct) combination of all available image datasets. Examples for imaging devices include Computer Tomography (CT), Magnetic Resonance Imaging (MRI) or the newer Positron Emission Tomography (PET). Bellow fig.2.illustrates the fusion of a CT and a MRI image. Figure also depicts that it only fuses complementary information from two sensors (CT and MRI).Image fusion improves reliability and capability.

III. NON-RIGID REGISTRATION

Non-rigid registration is the process of determining such transformations given two images of an object. According to[17] non-rigid transformation models can be divided into physical and functional. The physical models in general, are derived from the theory of continuum mechanics [15] and can be divided into two main subcategories: elastic and fluid flow. Functional representations [15] originate from interpolation and approximation theory. They use basis function expansions to model the deformation. There are many different types of basis functions [9], e.g., radial basis functions, B-splines[16, 8] and wavelets [17].

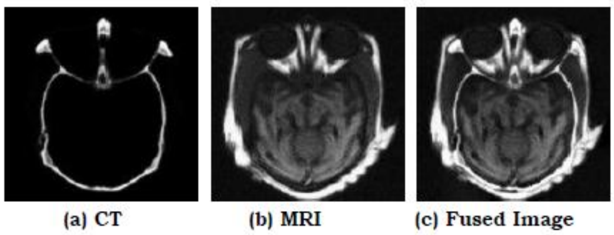

Fig 2: Fusion of CT and MRI Images

One approach is to delineate a structure of interest from one image, and use the deformation field calculated by non-rigid

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registration of that image to a second image to delineate the same structure in the second image. This approach is sometimes called segmentation

Propagation .Non-rigid registration [18, 19] can automatically quantify small changes in structures of anatomical structures over time by means of segmentation propagation. In this thesis a non-rigid registration algorithm based on optimizing mutual information to quantify small changes in brain due to tumors is considered. For the registration both intra- and inter-subject scans are used.

Non-rigid registration is performed as a two stage process [20]. Because of large differences, first global changes and gross differences in size and orientation between the reference image and the subject images were compensated by the affine (12 degrees of freedom) registration algorithm. Secondly, local deformation was calculated using deformable models. The full brain image was used for the global coarse grid registration and the fine grid registration is performed using a region of interest (ROI) as shown in Fig 3.

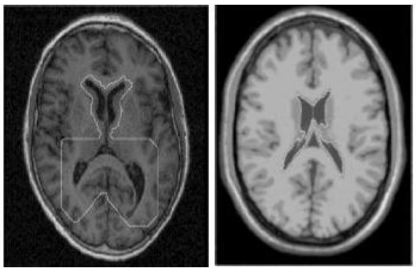

Fig 3: (a) Axial CT Image (b) Region of Interest

As per the studies, non-rigid registration is local and hence object is to be segmented before the analysis. The dynamic active contour method is used for the segmentation. Active contours and curve evolution methods usually define an initial contour C0and deform it towards the object boundary. In active contour models [21] one places a closed planar parametric curve C0(s)=(x(s), y(s)), s €[0, 1] around image parts of interest. Then this curve evolves under smoothness control and the influence of an image force. The active contours can be implemented in two ways namely Parametric Active Contours [21, 22] (PACs) and Geometric Active Contours [20] (GACs).

IV. ACTIVE CONTOUR BASED IMAGE SEGMENTATION

Deformable models are useful in segmenting, matching, and tracking anatomic structures by exploiting constraints derived from image data. They combine physics, geometry and approximation theory. Deformable models initiated a new approach known as physics based geometric design. One of the popular approaches to image segmentation is curve evolution and active contour models.

- ***Parametric Active Contour (PAC) Segmentation***

Kass.et. al. [21] introduced classic parametric deformable models also known as snakes [21, 22]for the segmentation based on energy minimizing snakes and dynamic snakes. Energy minimization is a static problem, whereas dynamic deformable models [13,15] unify the description of shape and motion i.e. shapes evolution through time. Dynamic models are suitable for time varying medical image analysis. In parametric methods the external forces can be derived by using various techniques called Gradient Vector Flow (GVF) [23, 29], Poisson Inverse Gradient (PIG) [30], and the Vector Field convolution (VFC) [22]. In GVF the field is calculated as a diffusion of the gradient vectors of a gray-level or binary edge map. The GVF framework might be the useful in defining new connections between parametric and geometric snakes, and might form the basis for a new geometric snake.

- ***Geometric (Implicit) Active Contour (GAC) Segmentation***

Geometric (Implicit) active contour models [21,23] constitute a very interesting application of levelset ideas with in active contour framework. They embed the active contour as a levelset[23] in a suitable image evolution that is determined by a Partial Differential Equation (PDE) [23]. The basic idea is that the user specifies the initial guess of an intensity contour (ex: an organ or a tumor or a person to be tracked). Then this contour is moved by image driven forces to the boundaries of the desired object. Then final contour is extracted when the evolution is stopped. Here the basic idea is to implement the initial curve C0(s) implicitly within the higher dimensional functions and to evolve this function under a PDE. Usually C0(s) is embedded as a zero level set into a function

u0:R2 u0(x)=d(x, C0) x is inside C0
= 0 x is on C0
= -d(x, C0) x is outside C0

Where d(x, C0) denotes the distance between the point x and the curve C0

is the main advantage of the implicit active contour are the automatic handling of topology changes, high numerical stability and independence of parameterization.

- ***Distance Transform***

The distance transforms [24] or distance functions are the basic feature of level set. A distance transform is applied to a binary image in which object pixels have the value 1 and other 0.All pixels in this image are labeled with their distance from the surface of the object. By pre-labeling all image pixels in this way the computational cost per iteration can be substantially reduced. Level set methods are mathematical tools for transforming surfaces. These surfaces are described by a signed- distance-function that returns the distance to the surface given a point. The surface separates the inside and the outside of some object; it is therefore often referred to as the interface. On a computer, one stores an implicit representation of the interface. That is, for each pixel a value is stored, representing the distance from that pixel to the surface. Inside the object, this distance is negative, and outside it is positive.

This is usually referred to as a shape regularization term, where the curve’s length, curvature or interior area is typically incorporated into a penalty term. Such geometric

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shape priors are still widely used in general image segmentation when further shape prior information is not available. Region based active contour models are robust to noise and can detect objects with very diffuse boundaries.

- ***Joint Image Registration and Segmentation***

The segmentation is obtained by finding a non-rigid registration to the prior shape. Combining registration and segmentation has been motivated by the need to incorporate prior information to guide and constrain the segmentation process. The quality of the images acquired by the various medical screening modalities is often poor due to the presence of multiple noise sources in the acquisition system, degradation of data content during reconstruction processes (e.g. tomographic reconstruction with Radon transform), motion and respiratory artifacts introduced by motion of the patient and inherent limitations of system acquisition accuracy. The combination of these factors degrade the signal to noise ratio of the data, limit the spatial resolution, introduce inhomogeneities in the tissue appearance across volumetric slices, and deteriorate boundary definitions between specific organs and their surrounding tissues.

By combining registration and segmentation, one can recover the image region that corresponds to the organ of interest, given a model of this structure. Level set deformable models offer a very flexible framework to propagate a moving front with segmentation-driven constraints while registering the segmentation result (i.e. the level zero curve) to a given model. Distance transforms have been successfully applied in the past to registration problems. In a level set framework, Paragios [25, 26] has published several papers recently focusing on matching geometric shapes in a variational framework for global as well as local registration. The first attempt at combining segmentation and registration in a single geometric deformable model framework might be attributed to Yezzi.et.al. Their key observation is that multiple images may be segmented by evolving a single contour as well as the mappings of that contour into each image.

These issues are encountered with other medical imaging modalities such as ultrasound, MRI, PET and SPECT and CT. The segmentation is obtained by finding a non-rigid registration to the prior shape. The non-rigid registration consists of both a global rigid transformation and a local non-rigid deformation. In this model, a prior shape is used as an initial contour which leads to decrease the numerical calculation time.

V. IMPLEMENTATION OF AUTOMATIC REGISTRATION

The basic objective of the registration process is to bring the respective reference and target images into spatial alignment called registration in a common coordinate system. After registration, fusion is required for the integrated display of the aligned images. In this process the implementation of fully automatic registration of brain scans is explained with the help of Algorithm. Geometric transformations are used to correct the errors in translation, rotation and scaling of the input image to that of reference image. The objective of the process is geometric correction process is applied automatically without user interaction. Bellow Algorithm represents and explains the automatic image registration process. From the Algorithm the process can be summed up into four basic steps.

- ***Collecting Information from Two Images***

It is nothing but reading both the images. The images used in this process are of same size. If they are differ in size, reformatting of the image set (“floating” or secondary) is to be performed to match that of the other image set (the reference or primary image) i.e., both the images into a common format. Usually the higher spatial resolution (CT) image is the primary image and the functional image is the secondary image.

- ***Pre-Processing to Improve the Quality of Images***

Most of the times images acquired mix up with noise and hence image quality are insufficient. Image quality is improved with preprocessing operations like filtering and gray level adjustment and contrast enhancement.

- ***Finding a Mapping between Two Images to Determine Transformation Functions***

The transformation of the reformatted secondary image set is to be computed to spatially align it with primary image set. In a affine transformation, the secondary image is translated, scaled and rotated with respect to the primary image. A widely used automated registration algorithm is based on the statistical concept of Mutual Information (MI).MI measures the information about X that is shared by Y if X and Y are independent. If X contains no information about Y then MI is zero. If X and Y are identical then MI is maximized. If a patient is imaged by two different modalities like MRI and CT, then it is presumably considerable MI between the spatial distances of the respective signals in two image sets. Accurate spatial registration of the two such images sets then results in the maximization of their MI and vice versa. Optimization is used for further matching.

- ***Reconstruction of Images*** Fusion [2, 27] is the process for the integrated display of registered image.

VI. RESULTS AND ANALYSIS

The developed “fully automatic registration of brain algorithm” is applied on CT, MRI and PET images. In this case, affine transformation is applied with six degrees of freedom two translations along x and y, rotation and scaling. At first images should be reformatted to the same size. Then source image is moved along x and y in steps of two pixels, and also rotating the entire feature space in a step of 1/100 degrees in rotation respectively. Interpolation is performed using the nearest neighbor, bilinear and bi-cubic methods. Optimization is done using a simplex method. Mutual Information (MI) is computed in each case in all the directions. It is observed that MI is maximum when both the

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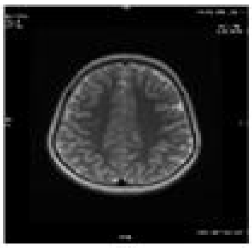
images are aligned properly and information is minimum.

Algorithm:

i. *Start*
ii. *Read Reference Image.*
iii. *Read Sensed Image*
iv. *IF size is of Ref Img= SenImg*
v. *Apply Transformation*
vi. *Calculate Mutual Information*
vii. *Else Resize GoTo step 4*
viii. *IF MI (Mutual Information) Maximum GoTo step 4*
ix. *Taking Transformation Results and applying on the Image*
x. *Applying Optimization*
xi. *Applying Fusion*
xii. *Stop*

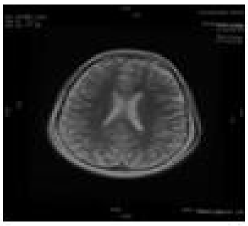
At the end, information is fused into a single image by using Wavelet Transformation method. This algorithm is applied to MRI-MRI and multi-modal CT-MRI images.



a) Reference Image

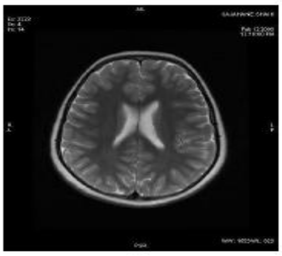
b) Sensed Image

c) Aligned Image

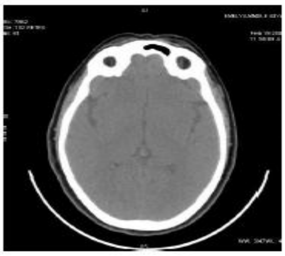


d) Registered Image

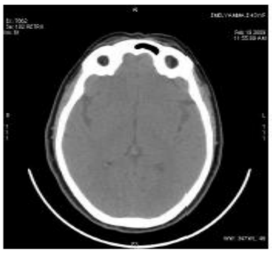
Fig 4: MRI-MRI Registration



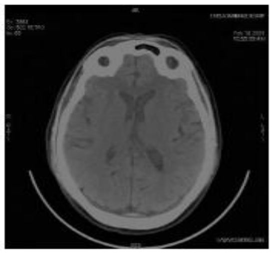
a) Reference Image



b) Sensed Image



c) Aligned Image



d) Registered Image

Fig 5: CT-MRI Registration

Sno. Method	Techno	1	2	3
MRI-MRI	Registered	0.833	0.921	0.985
	Fused	0.974	0.983	0.994
CT-MRI	Registered	0.234	0.245	0.252
	Fused	2.944	3.143	3.262

Table1: Comparison of Automatic Registration Process

For registered images MI is more for MRI-MRI (0.985) compared to CT-MRI (0.253) due to more exact alignment from i.e. geometric match is more.

CONCLUSION

Segmentation and registration of medical images have been the focus of intense research for the past decade producing very promising results. Major advantages of the method include its robustness to noisy conditions, its aptitude in extracting curved objects with complex topology and its clean numerical framework of multi-dimensional implementation. Registration with various interpolation and Optimization techniques is automated. The automation of the process avoids the human creates the possibility that process is applied on more number of cases with less time. Computational accuracy is also improved. The process is more useful for the doctors in integrating the information and diagnosing the problem.

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D Chamundeshwari, Post Graduated in Embedded Systems M.Tech form VITS, JNTUH. Graduated in Electronics and Communication Engineering B.Tech from JITS JNTUH India. Have 6+ years of teaching experience, Presently working as an Asst Prof in Department of Electronics and Communication Engineering Vageswari College of Engineering, JNTUH, Karimnagar, Telangana, India. Research interests including Image processing, wireless communication systems, VLSI.

Thirupathi Jangapally, (PhD) Post graduated in Computer science and engineering M.Tech from JNTUH and Graduated in CSE B.Tech from JNTU TS, INDIA. Have 9+ years of teaching experience, presently working as an Associate Professor in Department of Computer Science and Engineering. Research interests include Image processing, Data mining, Cloud computing and Information Security.

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