



Optimum Regularized Joint Registration and Segmentation Method for Medical Brain Images

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Abstract: Image registration and segmentation are the two important processes that are frequently used in medical image processing and computer vision applications. In traditional medical image applications both the techniques are applied independently even though the solution to one impacts the solution of the other. Currently medical image segmentation is very complex task due to the lack of sufficient contrast, SNR, and volume averages caused due to the non-uniform magnetic field. The problem is still high with MRI scans rather than other scans due to lack of real boundary. Availability of sophisticated diagnostic methods in the medical domain, demands the fusion of information from different sources for the better analysis. Similarity is enhanced by performing the non-rigid registration, where the local registration highly depends on segmentation of objects. This paper deals with the Atlas-based segmentation technique requires that the given atlas image is to be registered with the target image to find the desired shape segmentation in the target image. This paper discuss the joint registration and segmentation process is achieved through highly accurate variational cost effective Distance Regularized Level Set Evolution (DRLSE) method for medical scan images. The key features of this algorithm are, it can accurately converge towards sharp object boundary corners due to forward and backward diffusion and also applied for small and large deformations. It uses less computational cost due to large time steps.

Keywords: Medical Image Processing, Image Registration, Segmentation, Joint Registration and Segmentation, Distance Regularized Level Set Evolution, Deformations, Convergence, Computational time.

INTRODUCTION

Medical imaging plays an important role in the diagnosis and treatment of many diseases. Hence the medical image analysis community has become preoccupied with the challenging problem of extracting clinically useful information with the assistance of computers, from the anatomic structures imaged through CT, MR, PET, and other modalities. Segmented images are used in different applications such as quantification of tissue volumes, diagnosis and localization of pathology, study of anatomical structures, treatment planning, partial volume correction of functional imaging data and computer integrated surgery. At present the role of medical image processing has been expanded beyond the simple visualization and inspection of anatomic structures due to large number of diagnostic methods available in the current world. It has become a tool for surgical planning and simulation, intra-operative navigation, radiotherapy planning, and for tracking the progress of disease. Medical Image segmentation still remains a difficult task due to tremendous variability of object shapes and the variation of the image quality. In particular conventional techniques such as edge detection and thresholding can cause

considerable difficulties when applied to clinical segmentation of medical images which are often corrupted by noise and sampling artifacts.

Image registration [1-4] is one of the critical steps in medical image analysis. In some cases like neuro-medical applications it is very difficult to aim the problem based on a single modality. Hence in such cases information from more than one source is to be registered. Registration is a process of determining the correspondence [5-9] of features of same brain organ collected at different times or using different modalities with complementary information. Variations in patient orientation and differences in resolution and contrast of the modalities make it difficult for a clinician to mentally fuse all the image information accurately. In many medical image processing applications it is necessary to register, multi modal images from different sensors based on different physical principles and, temporal images taken by the same sensor but at different times. In general registration and segmentation can be carried out independently shown in Figure.1 (a) and (b) respectively. In Figure.1 (a) MRI and MRI images are aligned (registered) and fused image is obtained which contains more information. Figure.1 (b) is a CT image with brain tumor. Tumor was segmented for analysis purpose is shown in

Figure.1 (b) with red line. But in medical imaging with the increasing dependence of segmentation on registration and vice versa, the solution can be obtained in a simultaneous way instead of independently as in the case of traditional methods. In this paper registration and segmentation are performed simultaneously with the objective of increasing similarity and proper segmentation of objects from brain modalities.

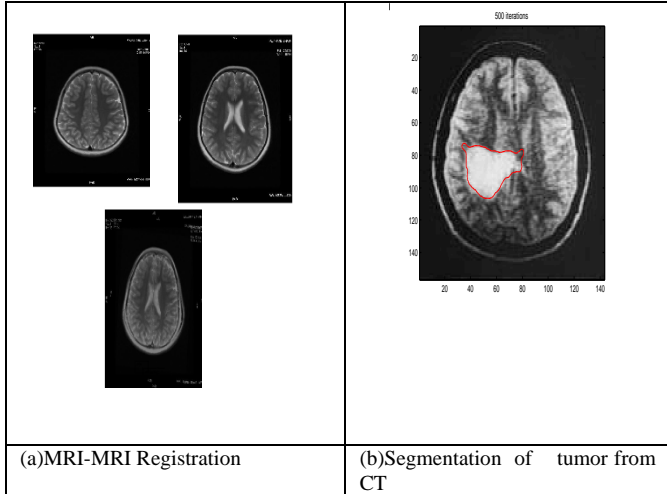


Figure1. Conventional registration and segmentation processes

NEED OF JOINT REGISTRATION-SEGMENTATION

In human body many organs heart, lungs and muscles involve with certain kind of motion(cardiac ,involuntary) creates local tissue deformations can be modeled with the deformable contours. In such cases to perform non-rigid registration and segmentation jointly is an effective process. Joint registration-segmentation can be performed in two methods. 1. Registration first and segmentation later. 2. Segmentation first and Registration later.

In case of feature based method [2] requires that features are identified or segmented from the images prior to their registration i.e. After segmentation registration is performed. In intensity based methods [2] no prior segmentations are required. Most of the medical images acquainted with noise registered using area based methods. Registration is performed prior to the segmentation [12-15]. Hence MI [5-19] is very effective metric for the registration of medical images. Low level segmentation methods do not need any registration, in this segmentation is performed based on the ground knowledge of a person. But it is required to add information such as shape, appearance or relative geometry to complete the segmentation process.

The work present in this paper is motivated with the desire to interleave the process of segmentation [16-17] and registration so that both solutions may be simultaneously carried out and hence to eliminate the need to completely deliver the solutions before being able to start the other. This challenge has been approached with geometric [18-19] variational DRLSE segmentation and registration method applying to different medical brain scans. The Atlas once constructed in various ways can be used as template and can

be registered non-rigidly to the images being segmented. This approach is very useful.

PREVIOUS WORK

Many of the methods used for segmentation are atlas based estimating the non-rigid [20] deformation existing between the atlas image and the target image and then applying the estimated deformation to the desired shape in the atlas to achieve the segmentation of the corresponding structure in the target image. The computed deformation field [21-24] is then applied to the atlas to detect the corresponding shape in the target image. Approaches that use shape priors like gradients, minimizing energy function [26-27] are used in contour based segmentation, using parametric and geometric methods. The aim of the paper is to apply simple, accurate DRLSE based variational level [28] set for estimating deformation field and simultaneously registration is performed on medical brain images. This method avoids the problems in curve evolution at the corners faced by the energy variational method. In general joint registration and segmentation can be implemented using two methods [28]. (1) PDE based formulation and (2) Variational formulation. The solutions of these methods yields desired goal of registration-segmentation [29].

A. PDE based Approach:

The basic idea in this technique is to let the source image evolve by letting its level sets move along their respective normal with a speed that is proportional to the difference between the target and the evolving source image. The evolution automatically stops when the evolved source becomes the target image. The resulting partial differential equation is solved using upwind finite difference equation. Let $I_1(x)$ and $I_2(x)$ are two given images and we want $I_1(x)$ to evolve into $I_2(x)$ i.e. by letting $I_1(x)$ to evolve along its gradient until it becomes $I_2(x)$. The evaluation can be represented as follows

$$I_t(x, t) = s \|\nabla I(x, t)\|$$

$$\text{with } I(x, 0) = I_1(x)$$

$$s = I_2(x) - I(x, t) \quad \text{---(1)}$$

$$I_t(x, t) = [I_2(x) - I_1(x)] \|\nabla I(x, t)\|$$

The (1) covers the intensity transformations but not the geometrical changes.

The geometric transformation between images is achieved using the following velocity equations.

$$V_t = [I(x) - I_1(x)] \frac{\nabla I_1(V(x))}{\|\nabla I_1(V(x))\|} \text{ with } V(x, 0) = 0$$

$$V = (u, v)^T$$

$$V(x) = (x - u, y - v)^T$$

V is centered in the image I_2 . i.e $I_1(x - u, y - v) = I_2(x, y)$

DRLSE VARIATIONAL APPROACH

Compared with pure PDE driven level set methods, the variational level set methods are more convenient and natural for incorporating additional information, such as region-based

information and shape-prior information into energy functional that are directly formulated in the level set domain, and therefore produce more robust results. By incorporating region-based information into their energy functional with an additional constraint, their model has much larger convergence range and flexible initialization. The distance regularization term is defined with a potential function such that the derived level set evolution has a unique forward-and-backward (FAB) diffusion effect, which is able to maintain a desired shape of the level set function, particularly a signed distance profile near the zero level set. This yields a new type of level set evolution called distance regularized level set evolution (DRLSE). The level set evolution in t is derived as the gradient flow that minimizes an energy functional with a distance regularization term and an external energy that drives the motion of the zero level set toward desired locations. The distance regularization effect eliminates the need for reinitialization and thereby avoids its induced numerical errors. Relatively large time steps can be used in the finite difference scheme to reduce the number of iterations, while ensuring sufficient numerical accuracy. This section presents the mathematical modeling of DRLSE.

The energy functional $E(\phi)$ in DRLSE is defined as follows

$$E(\phi) = \mu R_p(\phi) + E_w \text{-----} (9)$$

The Gateaux derivative represents the evolution is defined as follows

$$\frac{\partial E(\Phi)}{\partial \Phi} = \mu \frac{\partial R_p(\Phi)}{\partial \phi} + \frac{\partial E_w}{\partial \phi} \text{-----} (10)$$

The evolution of levelset curve related to the defined energy functional is as follows

$$\frac{\partial \Phi}{\partial t} = - \frac{\partial E(\Phi)}{\partial \phi}$$

IMPLEMENTATION OF JOINT REGISTRATION & SEGMENTATION

In this paper joint registration and segmentation is implemented on brain CT, PET and MRI images. In the first phase non-rigid registration along with the affine registration is performed and then segmentation is carried out. The algorithmic steps are shown below.

A. Algorithm:

- a. Reading source and target images
- b. Pre-processing images
- c. Estimation of deformation field
- d. Determine the transformation so that similarity enhances (If necessary global is done first)
- e. Reconstruction and fusion of images
- f. Segmentation of the object using DRLSE from the fused and registered image
- g. Validation of the joint registration and segmentation

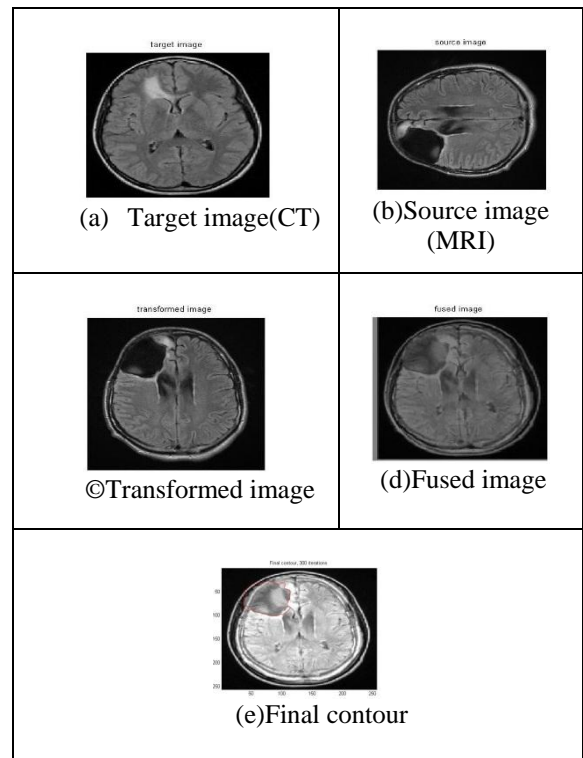


Figure 2. Multi-modal joint registration-segmentation

VI. RESULTS AND CONCLUSIONS

In this section, results of joint registration and segmentation are presented by applying DRLSE variational approaches for MR, CT and PET brain images. The aim of the simulation is to show that our active contour not only provides an appropriate segmentation but also provides accurate estimates of the registration parameters. In this paper we provided an outline framework for joint registration and segmentation via DRLSE variational method. In the first part Joint registration and segmentation is performed on monomodal (CT-CT) and Multimodal (CT-MRI) image sets. Results are shown qualitatively in Figures 2-3 respectively and quantitatively in the table. 1. Figures 2-3(a) represents the target image. . Figures 2-3(b) represents the source image on which transformation is to be applied to enhance the similarity between both the images. In this case global affine is used. Figures 2-3(c) are the transformed images. Figures 2-3(d) are the fused imagers which are obtained by the fusion of CT, MRI and CT-CT respectively. We can compare the performance quantitatively using MI. It is observed that MI is more after transformation and fusion shown in table 1 row 3, columns 3 and 5 respectively. After registration, segmentation can be performed using distance functions.

Figures 2-3(e) represents the dynamic DRLSE contour based segmented images. The red curve around the object represents the segmented tumors. The Performance is also Compared in terms computational time. The high resolution CT –CT registration takes more time compared to the CT_MRI as shown in table 1 row 3, columns 4-6 respectively.

In phase 2 inter and intra subject registration and segmentation is performed with energy minimization and

DRLSE variational methods. Results are shown in Figures 4-5 respectively. Quantitative results are shown in tables 3 and 4 respectively.

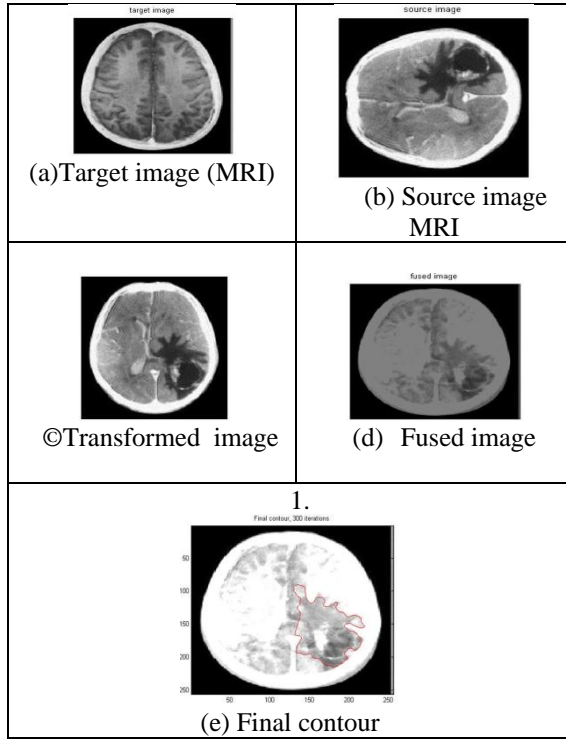


Figure 3. Mono-modal joint registration-segmentation

Table.1. Performance of mono and multi modal processes

S. NO	Image Description	CASE-I CT - MRI		CASE – II CT - CT	
		Mutual Information MI	Computation Time	Mutual Information MI	Computation Time
1	Source and target images	1.2938	0.643000	1.0379	0.598000
2	Target and transformed images	1.4642	0.824000	1.1007	0.861000
3	Target and fused images	1.5158	0.985000	1.8946	1.076000

In Figure 4, 1 and 2 columns indicates intra-subject and 3 and 4 indicates inter-subject registration. The basic objective is to segment the tumors after registration of 2 scans. In both the images row1 the source image.Row2 is the target image.3 and 4 rows indicates registered and fused images respectively. Row5 depicts images with segmented tumors. Similarity is observed in each case and compared. It is observed that with the same images and transformations MI is high in DRLSE table3column6 than energy minimization method table2 column6.

VII. CONCLUSION

The work presented in this paper is motivated by the desire to interleave the process of Segmentation and registration so that both individual process may be built simultaneously and hence to eliminate the need to completely deliver the solution before able to start the other. The work is based on maximum entropy so that frame work to segment and register images. This will be much benefit to add more modalities information while segmenting objects or segmentation aids the registration is align 2 images if the boundary of a common object have been detected in both images beforehand.

VIII. ACKNOWLEDGMENT

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