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A Detailed Review On Atlas Based Segmentation Of MRI Brain Images

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Abstract
Normal and abnormal tissues can be segmented by registering the target image by using atlas. The atlas is a template contains intensity information and segmented label. After registration the information from the template is propagated to the target image. In this paper we present review of atlas based segmentation of Magnetic Resonance Imaging (MRI) and point out pros and cons of the methods and suggest new research direction. Given the advantage of MRI over the other diagnostic methods the survey focuses on MRI tumor segmentation.

Keywords: Image segmentation, Magnetic Resonance Imaging, Atlas, Image registration.

Introduction

MRI is the most widely used diagnostic tool [1]. This is due to the non invasive nature of MRI and good resolution fast acquisition excellent performance in visualization of differences in body tissues .Segmentation is major problem in medical image analysis it refers to the process of separation of pixels to different regions with region of interest and background. Traditional approach of segmentation is manual delineation of region of interest by trained expert. The process slow and Vary with performance of expert .automatic and semi automatic segmentation can address the problem by offering speed, reliability and repeatability.

Some segmentation algorithms, such as those that assign voxels to tissue types [2], might not require the availability of training data in the form of manually delineated images (commonly called “atlases”). The goal of atlas-guided segmentation is to use to encode the relationship between the segmentation labels and image intensities observed in the atlases, in order to assign segmentation labels to the pixels or voxels of an unlabeled image.

The automated segmentation is challenging task due to image intensity variation and due to different anatomical structure share same tissue have same contrast. The priori anatomical information is necessary to simplify the segmentation. Prior information may be provided in different ways by pre defined rules or set of manual expert annotation. Anatomical priori from an atlas is matched to the target image we wish to segment. The atlas consist of two image volume one intensity image and labeled image or active appearance model[4]can also be considered as a atlas. The segmentation is converted to image registration problem which is done in two steps first global registration is done by affine or rigid transformation to obtain initial alignment at low computational cost. Secondly local registration is applied to general model to a specific anatomy local registration provide better match between brains at high computational cost. Multi-resolution strategy is used to reduce computational cost [5].

The rest of the paper is organized as follows section 2 we introduce atlas types section 3generation of atlas, offline learning, registration, label propagation, label fusion, post processing section 4 conclusion section 5 future trends.

TYPES OF ATLAS

Construction of a realistic anatomical brain atlas is time consuming task. Public atlas is available for research community with MRI data manually segmented by expert radiologist. The public atlas serves the purpose of training new segmentation algorithm and they allow evaluation data to be standardized for developed algorithm.

A. Topological atlas

The atlas is constructed using single subject is called topological, single subject or deterministic atlas. Single subject atlas is often volume image that has been selected from data set to be representative of the object to be segmented in other images. The brain is represented in streotaxic coordinates by talarich atlas [6-7].

The first topological atlas provided by visible human project national library of medicine [8].The project created three dimensional representation of brain anatomy of normal male and female. The McConnell Brain Imaging Center [9] provides the research community with a digital brain phantom, based on 27 high-resolution scans from the same individual. Its average resulted in a high-resolution (1 mm isotropic voxels) brain atlas with an increased signal- to-noise ratio. This brain template is the reference data in the Brain Web Simulated Brain Database [10]. Recently, 20 new normal anatomical models have become available as well as an anatomical model of a brain with Multiple Sclerosis (MS) lesions. Surgical Planning Laboratory’s (SPL) digital brain atlas, developed by the Harvard Medical School [11], is based on a 3D MR atlas of the human brain to visualize spatially complex structures.

B. Probabilistic atlas

The single subject atlas is not constructed to represent diversity in human anatomy. The better way represent is in

terms of population these atlas is often called population based atlas, statistical or probabilistic atlas. Such atlases continuously evolve by addition of new images. The probabilistic atlas can easily subdivided group specific criteria eg., age, sex etc., like single subject atlas the first population based atlas were based on talairich space[6-7].
A composite MRI data set was constructed by Evans et al. [12] from several hundreds of normal subjects (239 males and 66 females of 23.4 ± 4.1 years old). All the scans were first individually registered in the Talairach coordinate system. Following this they were intensity normalized and, finally all the scans were averaged voxel-by-voxel and probabilistic maps for brain tissue were created. The same procedure for constructing an average brain was later used by the International Consortium for Brain Mapping (ICBM) on 152 brains and later on 452 brains [13].
The UCLA Laboratory of Neuro Imaging (LONI), which is a member of the ICBM, provides also atlases for MR brain imaging contrasts, such as T2-weighted or Diffusion Tensor Imaging (DTI) [14].
Another widely used repository for MRI brain data is the Internet Brain Segmentation Repository (IBSR) [15]. The MRI studies contained in this database have also been used either to define a set of topological atlases for multi-atlas strategies (using the included manual segmentations). When generating population-based atlases, such as selecting a reference space or the registration method for the data alignment. Many researchers have proposed new strategies to create unbiased average templates and multi-subject registration [16–23].

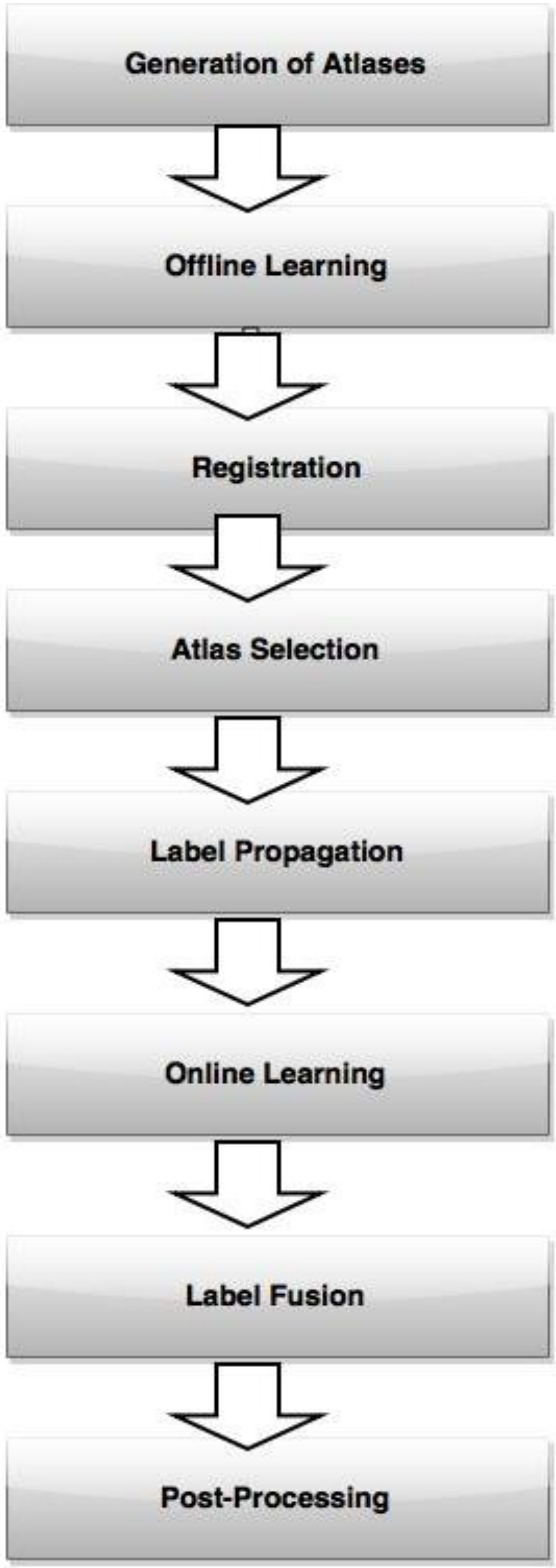

Fig.1. Building block of atlas based segmentation

C. Multi-atlas
Multiple atlases are used to avoid registration errors when using a single atlas and also get better anatomical variability.

With an atlas database, those voxels with low agreement between different label propagations can be discarded in order to minimize outliers. Due to its strengths over simple single atlas this technique presents an improvement in accuracy when dealing with the segmentation of objects with well-defined shape that may present slight deformations between images.
There are two important considerations to take into account when dealing with a set of atlases. The first is related to the number of atlases to be used to segment a new patient and how to select them. Different studies [24–27] conclude that using more than one topological atlas improves accuracy, but that it is not necessary to use all the cases in a database.

SEGMENTATION STRATEGY

A. Generation of Atlases

Atlas forms the basis for multiple atlas segmentation algorithms. They are obtained from experts with anatomical knowledge relies on interactive software tool [28-29]. Before seeing each image most algorithm treat each manually segmented image equally. To improve performance, high quality training classes is to be identified by visual inspection [30] feature selection [31]. Prior knowledge can be used in selection of atlas. The narrow lumen in noontime segmentation method [32] in coronary optical coherence tomography (OCT) since neointima only exist in coronary arteries with narrow lumen such approach can increase accuracy of segmentation by discarding low quality training data segmentation quality may be reduced due to small atlas size . Another way of improving accuracy is by population level preprocessing to increase the signal to noise ratio [33].A strategy uses small number of labeled cases and a model of MAS based on non-parametric regression in the space of images, in order to predict the total number of atlases that need to be manually segmented to obtain a desired level of segmentation accuracy within a MAS framework [34]. This technique can be useful for planning the manual segmentation phase.

B. Offline Learning

The processing is absent in classical multiple atlas technique or very little preprocessing done in atlas data offline. The data from the atlas is manipulated based on image to be segmented. The offline learning is the process of analyzing the data that can be used during segmentation. The rough region of interest can be obtained from offline processing for more accurate result [35]. The learning algorithm is used to construct train of image to propagate label.

C. Registration

The registration is the process to find similarity between the input image and the atlas image. The registration done in three steps; transformation, similarity measure and optimization. The choice of the optimization algorithm depends on application [36] in which it is used and computational capacity. At the end of registration spatial transform can be used to map one image to another. In recent research patch matching strategy such that the target image is represented linear combination of the atlas [37].

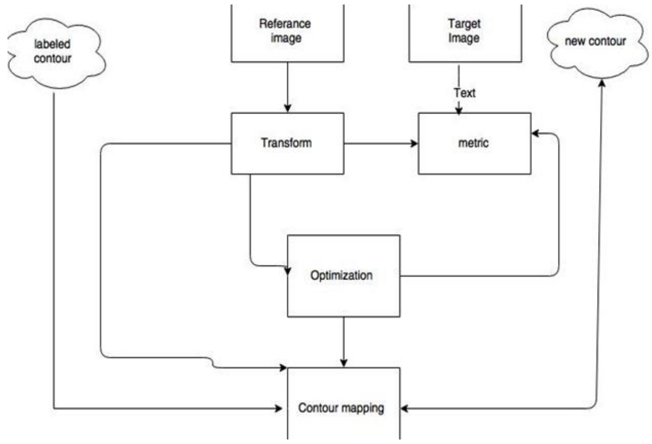

Fig.2. Process of registration of two images

D. Atlas Selection

The main criterion in the atlas selection is to reduce the number of atlas utilized and memory required. The multiple atlas segmentation demand computational time with respect to atlas utilization therefore the computation time is reduced by half when the number of atlas is reduced by half. Irrelevant atlas must be removed to improve segmentation accuracy .The selection of atlas can improve accuracy in majority voting [38] but not in weighted fusion [39]. The effectiveness of atlas is dependent on registration. If the nonlinear registration is done the atlas selection will have minimum effect on computation cost. To improve efficiency only linear registration is always chosen for majority of the atlas and nonlinear for particular atlas. Earlier atlas selection is based on similarity measures such as sum and square difference. In recent Isomap linear embedding is used [40] is used .Typically the atlas selection is done heuristics such computational time.

E. Label Propagation

Once the atlas is selected the spatial correspondent is established with the input image. The classical method uses nearest neighborhood interpolation in which atlas is transferred single label to the input image voxel. The nearest neighborhood search is conducted among voxels with tissue segmentation consistent with target voxel result of this type depends atlas pool. The nearest neighborhood is refined using linear interpolation [41] where voting is spread on multiple label with weights reflect partial volume.
The alternate approach involves using signed distance map of atlas label. The distance map is positive value close to the corresponding structure and negative value outside the structure. The distance map is not normalized. This is use to calculate probability. Instead of transferring atlas label via geometric deformation learning algorithm trained to each atlas to generate voxel label for each atlas .The method does not increase accuracy of the algorithm but reduces computation time.

F. Online Learning

The labels of the atlas are propagated to the input image co-ordinate is then merged directly to the single estimate of segmentation. The online learning is used to increase the performance relation between registered atlas and input image.

Iterative methods are used in atlas selection. The selected atlas can determine similarity between the form label and current estimate of segmentation which is used to increase accuracy by excluding outliner atlas from fusion. The other approach uses relation between intensity of input image to assist fusion

G. Label Fusion

The label fusion is combining the propagated atlas label. The simple fusion method uses majority voting [43]. The extension of majority voting is weighted voting were each atlas is given weight which is associated with similarity between input image and atlas .another family of fusion is staple [44] develop to manual segment noisy images.

H. Post-processing

The label fusion result is not necessarily represented in final segmentation .It is used as input to another algorithm to estimate label. Some method uses output of the label fusion to the subsequent algorithm that ie detection boundary box where segmentation is Applied to start active contour [45].

Conclusion

The multiple atlas segmentation gives accurate segmentation result. In earlier days multiple atlas segmentation used majority voting method consist of registration and fusion, the technique has now become sophisticated employs optimization, machine learning strategy. The multiple atlas segmentation needs high computation power and substantial amount of memory. The multiple atlas segmentation technique is not widely used in clinical practice. Current Research suggest efficient technique obtain robust segmentation method address everyday aspect clinical practice.

FUTURE TRENDS

The machine learning and computer vision can be used in multiple atlas segmentation. Advancement in the fields such as unsupervised feature learning in machine vision on deep architectures improves performance. Recent developments suggest that researchers are currently working on translating such ideas to biomedical image analysis problems in multiple atlas segmentation.

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