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PROSTATE CANCER DETECTION USING LABEL IMAGE CONSTRAINED MULTIATLAS SELECTION

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ABSTRACT

In a recent era, many American peoples are suffering from Prostate Cancer. It is the second reason of death amongst American men. In a field of medical image segmentation multiatlas selection method is frequently used. Manifold ranking methods are now becoming popular. It is not easy to get accurate atlas selection results because of complexity of the prostate structures within raw images through measurement of distance among raw images on manifolds. This paper uses the manifold projection constrained by the label images to reduce the influence of surrounding structure. The problem of MRI image segmentation done manually by expert is solved by proposing a new automatic method called label image constrained multiatlas selection useful for diagnosis of prostate cancer.

Keywords*: *Atlas selection, computer vision, image segmentation, manifold ranking normalization.

I. INTRODUCTION

A traditional medical image segmentation method involves the segmentation of medical image by the experts according to their knowledge about anatomical structure of the subject. However, the manual segmentation is dull and time consuming. So to achieve more accuracy there are various automatic segmentation methods. The medical images may be magnetic resonance imaging (MRI), computed tomography (CT), digital mammography and other imaging modalities which provide an effective means to map the anatomy of a subject. These technologies effectively improve the knowledge about normal anatomy and diseased anatomy for medical research. As there is number of medical images, it will generate the need of computers for processing and analysis. The computer algorithms are useful for the description of the anatomical structures and other region of interest.

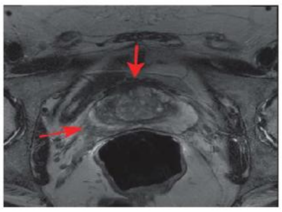

Fig. 1. Original MR Image

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Fig. 1 shows the original MR image with the red arrows to indicate the weak boundary. Expert segments this area on the basis of their knowledge regarding the anatomical structure of the subject. This is shown in fig. 2 with red contour.

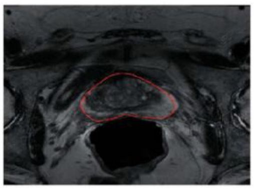

Fig.2. Prostate segmentation done by experts of original MR image.

The manual segmentation is time consuming as well as tedious. So automatic segmentation methods are required. Multiatlas selection method is mostly used medical image segmentation technique. In this technique atlas selection and combination are considered as two important factors which affect the performance. The atlas essentially depicts the shapes and locations of anatomical structures and together with the spatial relationships between them. Thus, atlas based segmentation is one of the most common techniques applied to the automatic segmentation of the prostate MRI image. Generally, an atlas consists of a raw image and label image. In the process of multiatlas selection method, each atlas is first registered to the target image, which will generate deformed atlas that closes to the image to be segmented. Based on certain of selection criteria a subset of atlases is selected from the deformed atlases. Finally, the selected atlases are combined into a single binary template for segmentation. The approach of atlas selection is one of the most vital factors affecting the correctness of segmentation in all the three steps of multiatlas based method. Besides that, atlas combination is another important ingredient, where assigning the proper weight for each selected atlas is a crucial factor.

II. RELATED WORKS

2.1 Literature Survey

A. Discrete deformable model guided by partial active shape model for TRUS image segmentation, P. Yan, S. Xu, B. Turkbey, and J. Kruecker,[2] presents discrete deformable model guided by partial active shape model for TRUS image segmentation, PROSTATE cancer is the second cause of cancer death among American men. Accurate segmentation of the prostate can be helpful for assisting the diagnosis of the prostate cancer. Traditionally, the prostate magnetic resonance (MR) image segmentations are performed manually by experts. However, manual segmentation is tedious, time consuming, and not reproducible.

B. Current methods in medical image segmentation, D. Pham, C. Xu, and J. Prince,[3] presents current methods in medical image segmentation. Image segmentation plays a crucial role in many medical-imaging applications, by automating or facilitating the delineation of anatomical structures and other regions of interest. We present a critical appraisal of the current status of semi automated and automated methods for the segmentation of anatomical medical images. Current segmentation approaches are then reviewed with an emphasis on the advantages and disadvantages of these methods for medical imaging applications.

C. Automatic segmentation of the prostate in 3D MR images by atlas matching using localized mutual information, S. Klein,[4] presents Automatic segmentation of the prostate in 3D MR images by atlas matching using localized mutual information. An automatic method for delineating the prostate in three dimensional magnetic resonance scan is presented. The method is based on non-rigid registration of a set of pre labeled atlas images. Each atlas image is no rigidly registered with target patient image. Subsequently, the deformed atlas label images are focused to yield a single segmentation of the patient image. This method is evaluated on 50 clinical scans, which were manually segmented by three experts.

D. LEAP: Learning embeddings for atlas propagation," Neuroimage , R. Wolz, P. Aljabar, J. Hajnal, A. Hammers, and D. Rueckert,[5] proposed a novel framework for the automatic propagation of a set of manually labeled brain atlases to a diverse set of images of a population of subjects. A manifold is learned from a coordinate system embedding that allows the identification of neighborhoods which contains images that are similar based on chosen criteria. Within the new coordinate system, the initial set of atlases is propagated to all images through a succession of multi atlas segmentation steps. This breaks the problem of registering images that are very dissimilar down into a problem of registering a series of images that are similar. At the same time it allows the potentially large deformation between the images to be modeled as a sequence of several smaller deformations.

2.2 Proposed System

In present methods, further anatomical structure may have an effect on the performance of the selection of atlases. Such as, when segmenting the prostate from MR images detected by red curve shown in Fig.2, the existing manifold ranking methods are normally distracted by the anatomical structure. Proposed system is based on the idea to use label image constrain on the manifold projection to reduce the influence of surrounding structures and preserve the neighborhood structure as shown in Fig.3.

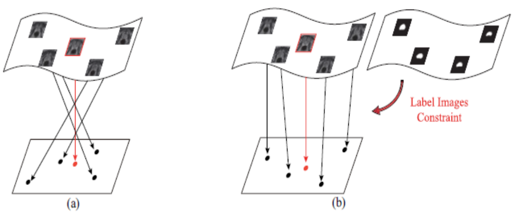

Fig.3.(a) Misleading manifold projection due to the influence of other anatomical structures. (b) Manifold projection constrained by the label images to reduce the influence and preserve the neighborhood structure.

When learning the manifold ranking the region of interest information from the label images is exploited together with the raw images. The intrinsic similarity between the target regions can be exposed in the lower-dimensional manifold space due to the constraint. In this space, the selected atlases are closer to the test image in terms of the regions of interest, and then the final fused template can improve the performance of the segmentation.

The main contribution in this paper is a new manifold ranking method is designed by taking information about the label image into consideration for atlas selection on a lower dimensional manifold space for the purpose of image segmentation, and this has been ignored by other existing methods. Manifold ranking technique is used to find the similarities in the training and testing image. The weights in the atlas combination are calculated by solving a difficulty in reconstruction of the data points of the manifold space.

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III. SCHEME OF IMPLEMENTATION

The block diagram of the label image constrained atlas selection method is shown in Fig.4. The proposed system consists of three main steps: transformation, selection and combination. The different raw MR images of atlases within the same dynamic range is done using normalization step. After normalization, the next stage is registration that each raw image of atlases maps to the test image. In transformation stage each atlas is warped to the test image, generating the deformed atlas. The next stage is atlas selection. The atlas selection method should measure the similarity between only the regions of interest across images. Thus, manifold ranking should not only preserve the neighborhood of the original manifold of raw images, but also consider the intrinsic similarity between the regions of interest. Final step of system is segmentation.

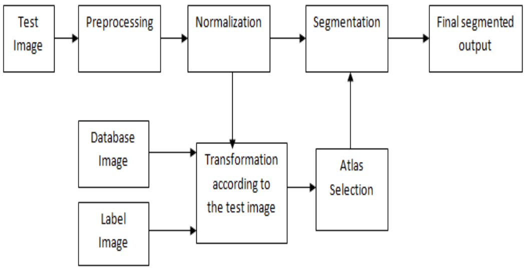

Fig.4. Overall workflow of a system

Preprocessing – As the original image may contain the noise, the preprocessing is used to remove the unwanted noise in the image. The test image is applied to the preprocessing step so as to make image clear. In this paper we apply median filtering to reduce the noise factor and improve the SNR i.e. signal to noise ratio. We also calculate MSE and PSNR for various test images.

Normalization- Normalization of pixel intensity of MR image into specific range is necessary so as to bring various raw images of atlases within the same dynamic range. It is usually to bring the image, or other type of signal, into a range that is more familiar or normal to the senses, hence the term normalization. Input to this step is the filtered image and output is the normalized image which is calculated by computing mean and standard deviation of the filtered image.

Transformation- After image normalization, each normalized raw image of atlases is aligned to the normalized test image. Image transformation means the adjustment of tilt present in input image. In this step, the orientation of training image is corrected according to the testing image. It means that orientation correction is done by rotating the training images in clockwise or anticlockwise direction in measures of degree.

Training Database Creation- The input to this step is multiple MRI images. Then the normalization of each of this image is performed. Then the prostate region in these images is detected manually by experts first. And the segmented label image is saved in a database. Now these images are used for automatic segmentation of number of testing images.

Atlas Selection – For atlas selection manifold ranking method is used. In this the weights are assigned to testing image and training images so as to find the similarities between testing and training images. This is shown in Fig.5, in which the middle image is the test image surrounded by the multiple testing images where weights are assigned to each link between test image and testing images. Atlas with more weight i.e. with more similarity will be selected for segmentation.

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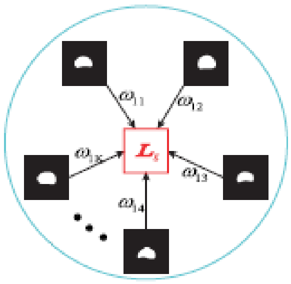

Fig.5. Manifold ranking on lower dimensional subspace

Segmentation- This is the final step of the process where the segmentation of testing image according to selected atlases is done. After that we will get to know whether the prostate cancer is present or not.

However we can further improve the system performance by extracting additional features such as area of pixels, perimeter and eccentricity, etc. which is useful for further classification such as cancer stage detection.

IV. EXPERIMENTAL RESULTS

For experiment, we used Matlab 2013 software. Firstly we created the training database by doing manual segmentation which is useful for automatic segmentation of test image. The preprocessing step is done on the test image to remove noise and to improve SNR. It will also measure the MSE and PSNR values. After that normalization is done using mean and standard deviation value. Next step is transformation where tilt is adjusted. From the various database images we selected the two atlases which find the similarity with the test image.

V. FUTURE WORK

From the selected atlases the segmentation is performed by superimposing the atlases on the original test image and final result of segmentation of prostate is obtained. Further we can find the additional features as area of pixels, perimeter as well as eccentricity in the segmented image so as we will get to know at what stage the cancer is i.e. cancer stage detection.

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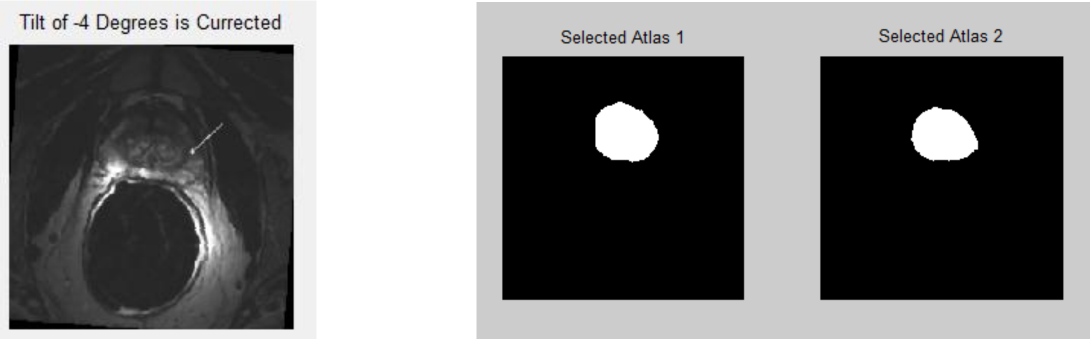

Fig.6. Results of Experimen

VI. CONCLUSION

In this paper, we will propose a novel manifold learning based atlas selection method and a new weight computation algorithm for atlas combination in multiatlas based segmentation. For atlas selection we use manifold ranking method which uses the label image constrain on the manifold subspace so as to reduce the effect of surrounding anatomical structure. The manifold ranking method helps to find the intrinsic similarities across the region in which we are interested. The weight computation in atlas combination step is done for combining the selected label image for the final segmentation process from which we get the result of prostate cancer detection.

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BIOGRAPHIES

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