3T MRI Multi-Modality for Segmenting Hippocampal Subfield

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Abstract-*In the functioning of human brain, hippocampal subfields play a vital role (Bankman, 2009). However, segmentation of hippocampal fields has in most cases been hindered by problems of low resolution and bad image quality of 3T MR (Beichel et al., 2006). The use of 3T multi-modality MR images can be used to improve the segmentation performance of the sub-fields. The process basically involves extraction of both appearance and structural features from MR images and also the patterns of connectivity of the resting state fMRI (Cong et al., 2016). The first stage involves training Random Forest classifiers, second stage involves testing of classifiers extracted in order to predict segmentation of the hippocampal fields (Costaridou, 2005). It is shown that the proposed multi-modality is better in performance in segmentation in comparison to one modality.*

I. INTRODUCTION

Dexterity in human body is such a vital element which cannot be ignored. Bankman (2009) affirms that hippocampal is an essential structure useful in encoding and retrieval of information. If we are able to understand the structure and its components, it becomes easy to control health conditions associated with unhealthy hippocampus (Giuliano et al., 2017). Traditional neural scientists went ahead and tried to understand the entire structure. The effort yielded futile results because it became a bit complex. Segmentation is the only way to get full information which can be helpful in diagnosing neural related diseases (Hillman & Goldsmith, 2011). This traditional method of examining the entire structure is replaced by a current one, which seeks to deconstruct the process into smaller units of observation. What makes segmentation an important trend is because change of hippocampal volume can be a good indication of a neurological disease? Subfields are valuable in directing the possible areas of disease origination (Marizzoni et al., 2015)

II. LITERATURE REVIEW

Many applications for segmentation have been brought forward. However, most of them are manual. This means that they would require an expert to operate and would also lead to time wastage (Santos et al., 2017). Although automatic is the solution to this problem, it has its own hurdles as well. One is the problem of resolution and low signal which is unable to succinctly give identifiable features. To solve this problem associated with automatic segmentation, two strategies were proposed (Sherrow, 2007). One is performing multiple scans to increase the chances of reliability. Additionally, dedication of scan protocols would give more accuracy.

Moreover, images produced by the current method appear less bumpy. This is an advantage to the radiologist since he or she is able to deconstruct and identify areas of interest. Applying the method in the current form of diagnoses would give the medical practitioners a more elaborate manner to address certain complication which could not be established through traditional methods (Witharana et al., 2016). From the dataset of results obtained from the multimodality images, it is possible to compare the information and improve segmentation. Also, automatic method will be able to compare both appearance and features embracing the new move is the right away to go (Winterburn et al., 2015).

Notably, the previous paragraphs indicate that there are two broad sections of segmenting the hippocampus. Basically, the automatic one performs better by far compared to the novice second rater. Training for the second rater takes a little bit longer time as opposed to automatic (Wolf et al.,2015). With the discovery of automatic segmentations time can be considerably reduced to increase the level of accuracy (Wu et al., 2016). It has to be remembered that the effectiveness of any diagnosis or research work is actualized by the rate at which studies are accomplished. If one structure is studied for a long time due to inefficient methods, it not only affects the output but also impedes the validity of data (Bankman, 2009). This underlines the importance of automation, since it handles large data set in areas where manual could be prohibitive.

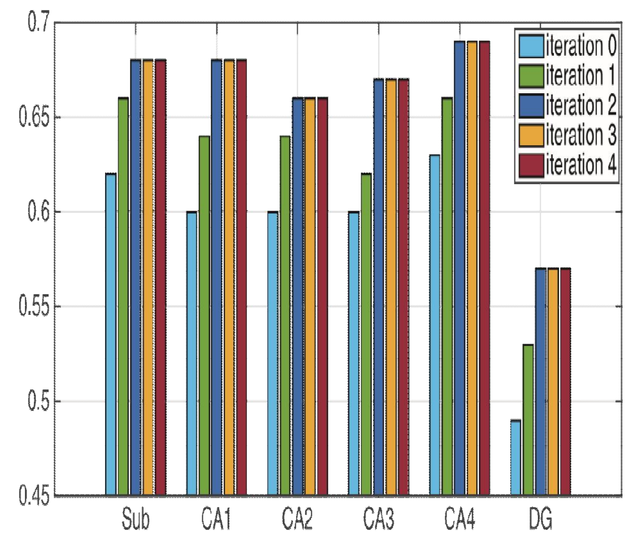
Consequently, any method is embraced depending on its reliability scale. For the current automatic method of segmenting the subfield, it was discovered that it has comparable higher accuracy. It is important to state here that any medical adventure focuses on accuracy and ability to identify every single lead information (Beichel et al., 2006). Settling on a method which is able to clearly show every characteristic of the organ under study remains paramount. The use of 3T MR has incorporated machine learning corrective recognition (Celebi, 2014). This is whereby the machine is used to show images with the description of every structure surrounding the primary organ of interest. Under the technological realm, it is regarded as artificial intelligence. The machine possesses capability to do tasks which manual procedures cannot afford to accomplish (Cong et al., 2016). With rapid changes in the medical field, it is expected that more sophisticated and efficient methods of analysis are underway.

III. PROPOSED SYSTEM

The resting state fMRI (3T rs-fMRI) achieves the objective of improving segmentation by capturing the various connectivity patterns in the subfields. Through this, the difference created by these patterns are applied to create separation of patches. This is possible even where the patterns are similar in appearance (Toennies, 2017). The functional connectivity which exists between the patches and their regions of reference is usually used as the basis of distinction. This simply implies that, once the difference in the patterns of connectivity has been established, then the patches can be viewed as different entities (Giuliano et al, 2017).To set out the segmentation process, four stages are very vital; firstly the preprocessing of data where generation of manual label and alignment based on other modality images is done. Secondly is the extraction of both the appearance and the relationship features which form the basis of capturing both the appearance and connectivity patterns. Appearance features are extracted from structural MRI while the relationship features are extracted from resting state fMRI (Marizzoni et al, 2011). Once the connectivity and appearance features have been extracted, they are then linked forming a forest classifier which is random and structured— the classifier for segmentation is therefore introduced. In the last step, the refinement of the segmentation is improved by the combination of the structured random forest and the auto-context frameworks.

IV. RESULTS

Experimentation forms an important part of the whole process. In this part two datasets are required and hippocampal subfields manually protracted by an expert radiologist. From this, segmentation performance is deduced from the dice ratio between the automatic segmentation and manual label. However, segmentation of the hippocampal subfields may have some differences due to the different protocols of partitioning. Subjectivity may also arise as various experts may delineate the boundaries in hippocampal differently. The method may also experience a limitation as few number of subjects are being handled, since the whole process is time consuming. The datasets are currently limited to health subjects. Using multi-modality method produces images which can be studied on all angles. It is possible to clearly identify various sections without much struggle. The radiologist finds it easy to study both posterior and anterior lobes, hence getting to guide them in their judgment. The figure below shows segmentation separation when using the new system, which makes it easy for study.



Subfieldsegmentationresults(meanDiceratio)atdifferentauto-contextiterations

The y axis represents the mean dice values and standard deviation while x axis represents the various hippocampal subfields.

V. CONCLUSION

It is the long tradition of inclining to traditional beliefs of past methods, which has continually impeded the positive growth in segmentation. Settling for multi-modality method of segmentation is the only way which can guarantee accuracy of information. The method compares with the available methods, which have not proven efficient in the task. Little has been researched on 3T MRI, but it sounds as the best solution. The move will assist greatly in establishing some of the neurological diseases early. Considering the high precision rate, immeasurable interest has been shifted to this process of segmentation. In the near future, it is expected that the manual methods will be faced off. Alternatively, both automatic and manual will be used corporately to supplement the accuracy levels. More research should be conducted.

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