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MRI Image Processing with Intelligence: Step towards Computer Aided Diagnostic (CAD) in Healthcare Systems

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Abstract—Diagnostic imaging is a critical tool in healthcare sector. There are various modalities such as Magnetic resonance imaging (MRI), computed tomography (CT), digital mammography, and others, to provide an insight of subject's body, noninvasively in order to facilitate stakeholders to take decision in diagnosis. Additionally, in medical research, these technologies has been playing centre role in most of the health care studies and experiments. Being a critical component in imaging systems, MRI system has been active area for researchers in computational intelligence and image processing. Due to advances in computing hardware and its easy availability, the performance of MRI system has been improved dramatically since its inception and is able to provide fast imaging, better resolution, immunity to artefacts and cheaper cost. One of the most important problems in image processing and analysis is segmentation and same is true for biomedical imaging. Various approaches has been reported in literature for segmentation of brain, where main objective is separating the pixels associated with different types of tissues like white matter (WM), gray matter (GM) and cerebrospinal fluid (CSF). In this paper, we review the methodologies of MRI segmentation that can be used in various diagnostics such as fMRI (Functional MRI), CMRI (cardiac MRI) and MRA (Magnetic Resonance Angiography). We will also present the different techniques of computational intelligence to be efficiently used in MRI segmentation.

1. Introduction

Diagnostic imaging is a critical tool in healthcare sector. There are various modalities such as Magnetic resonance imaging (MRI), computed tomography (CT), digital mammography, and others, to provide an insight of subject's body, noninvasively in order to facilitate stakeholders to take decision in diagnosis. Additionally, in medical research, these technologies has been playing centre role in most of the health care studies and experiments. Being a critical component in imaging systems, MRI system has been active area for researchers in computational intelligence and image processing. The high contrast sensitivity to soft tissues differences and the inherent safety to the patient resulting from the use of non-ionizing radiation have been key reasons, why MRI has replaced many CT and projection radiography methods. Magnetic resonance imaging (MRI) uses two natural forces – a magnetic field and radio frequency pulses to enable non-invasive, high resolution, three dimensional images of the body's internal structure. The local magnetic resonance signal which has a information of the body tissue, is produced as a result of the interaction of the particular pulse sequence parameter with local tissue properties.

Due to advances in computing hardware and its easy availability, the performance of MRI system has been improved dramatically since its invention in early 70's and is evolved to provide fast imaging, better resolution, immunity to artefacts and cheaper cost. Magnetic resonance imaging is also applied to study the behaviour of cells and how they react with disease and treatment. Subatomic particles (electron, proton and neutron) can be imagined as spinning on their axes.

Various approaches has been reported in literature for segmentation of brain, where main objective is separating the pixels associated with different types of tissues like white matter, gray matter and cerebrospinal fluid (CSF). Of these, semi-automated methods that employ only sequence of image processing techniques are not preferred because they rely heavily on human interaction for accurate and reliable segmentation. Fully automated methods, on the other hand, are free from any human interference and can segment the brain with high precision by using computational intelligence in association with image processing algorithms. In this paper, we review the methodologies of MRI segmentation that can be used in various diagnostics such as fMRI (Functional MRI), CMRI (cardiac MRI) and MRA (Magnetic Resonance Angiography). We will also present the different techniques of computational intelligence to be efficiently used in MRI segmentation.

The remaining part of the paper is organised as follows. In section II, we describe how MRI can be used in different diagnostic situations. The survey of important segmentation methods involved in MRI images has been presented in section III. In section IV, we have discussed about possible computational intelligence that can be included in segmentation algorithms. Finally, paper is concluded with highlighting the need of reliable application of MRI images and automated software's in healthcare systems.

Diagnostics using MRI

Use of medical images acquired from imaging modalities is the once of the important step towards the medical diagnostic and treatment. The tasks such as identification of diseases, surgical planning, medical reference, research and training are heavily rely on the analysis and findings from MRI images. In general, the observations associated with images may involve measurements of the biological parameters, such as density of particular type/s of tissues. Therefore, effective and meaningful analysis and classification of these images are vital. The annotation of MRI images representing subject's anatomical structure is conventionally done manually. However, manual annotation suffers from limited knowledge of annotator, inconsistency, time consuming. The solution to overcome this problem is to use of automated software to analyse the biological parameters or diagnostic parameters of interests without human interaction. In today's interconnected world, computerised automated annotation can be used in collaborative manner to include the medical expert's advice without having him/her physically present in place. The high quality expertise can be seamlessly acquired across the globe at reduced cost. Thus, segmentation of various tissues in anatomical structure appears in given MRI image is an important issue in computer aided diagnostic and healthcare systems.

The possible extended applications for the segmentation methods using images processing are described below:

Diagnosis System

General objectives of diagnosis system using MRI image processing can be:

- localizing the objects of interest, i.e. different organs
- taking the measurements of the extracted objects, e.g. tumours in the Image
- interpreting the objects for diagnosis

Functional MRI (fMRI)

The brain functioning needs continuous supply of glucose and oxygen, which are supplied by CBF. Several studies and experiments indicated that within the brain, there are heterogeneous distributions of blood, with grey matter receiving several times more flow per gram of tissue than white matter [1]. This distribution in terms of CBF (cerebral blood flow) which is the rate of delivery of a particular mass of tissues and oxygen metabolism has resulted into blood oxygenation. The magnetic resonance (MR) signal is sensitive to this change because deoxyhemoglobin (dHb) is paramagnetic and the presence of dHb reduces the MR signal at rest. During activity in brain, MR signal will increase slightly. This MR signal increase during brain activation has now been measured during wide range of sensory, motor and cognitive tasks due to change in blood oxygenation. Thus, functional MRI measures blood–oxygenated-level– dependent (BOLD) signal changes caused by regional hemodynamic adjustments in response to changes in neuronal activity. The statistical analysis of blood oxygen level dependent (BOLD) is a critical part of the brain mapping with functional magnetic resonance imaging . Aim of such analysis is to produce an image identifying the region which shows significant signal change in response to the task.

Cardiac MRI (CMRI)

An investigation of biomechanical processes in normal and abnormal heart muscle are vital to understand the cardiovascular disease and therapeutic interventions on ventricular performance. To identify the abnormal motion of of heart in diseases associated with heart itself and lung, there should be straightforward dynamic model of normal motion of the heart during normal functioning. In order to measure, myocardial strain or modelling wall motion, for clinical assessment, it crucial to localize the same point of heart surface on two images acquired at different parts of cardiac cycle. Two most common techniques used in MRI to measure myocardial motion are myocardial tagging and myocardial velocity mapping.

2. Segmentation Methods

One of the most important problems in image processing and analysis is segmentation. Various approaches have been reported in literature for segmentation of brain MRI images, where main objective is separating the pixels associated with different types of tissues like white matter, gray matter and cerebral fluid (CBF) as shown in figure 1. There are two ways to handle the segmentation in anatomical images. Semi-automated methods, that employ only sequence of image processing techniques, are not preferred because they rely heavily on human interaction for precise and reliable segmentation. Fully automated methods, on the other hand, are free from any human interference and can segment the brain with high precision by using computational intelligence in association with image processing algorithms. Thus, automated MRI segmentation has great importance in research and clinical applications.

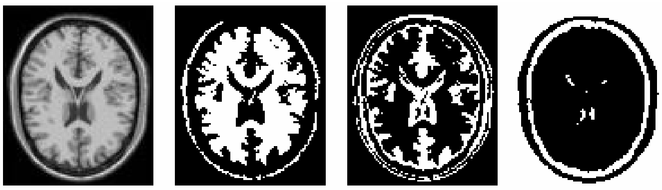

Fig. 1. From left to Right, 1)MRI Image, 2)WM , 3) GM and 4) CSF

In following discussion, we have surveyed the segmentation techniques to be applied for MRI brain images. In next section, we reported segmentation techniques exclusively based on computational intelligence approach.

In one of the model based approach presented in [2], uses contour model to match with input image at required landmarks using wavelet features. The segment obtained from this step is passed through the posterior probability model to further refine the results and to reduce the errors.

Most of the MRI images suffer from the non-uniformity in the pixels intensities even though they represent the same type of tissue type. This in-homogeneity becomes very serious obstacle in segmentation process, especially, if it is intensity based. In one of the useful paper [4], parametric bias is estimated to use it in polynomial approach for histogram adjustment to facilitate the segmentation algorithm. One of the classical methods, watershed algorithm, have been used for segmentation in [5]. The gray-level morphology operation based segmentation of MRI images is presented in [6].

Another paper [7] based of model based approach, describes the approach to build the shape model by using training examples of images where shape counter points are marked. This approach is based on "Procrustes" analysis and outlier shapes from training examples are discarded. Flexible matching method is proposed in this paper to find the shape counters in problem image. This approach considers the effect of pose, scale and nonlinear shape differences. In one of the segmentation technique depicted in [21], spherical wavelet transform has been used to achieve the multi-scale shape representation. It is also shown that this method outperforms the active shape model algorithm as it is more successful in capturing finer shape details.

An automatic left ventricle (LV) segmentation algorithm is presented for quantification of cardiac output and myocardial mass in clinical practice [27]. The LV endocardium is first segmented using region growth with iterative thresholding by detecting the effusion into the surrounding myocardium and tissues. Then the epicardium is extracted using the active contour model guided by the endocardial border and the myocardial signal information estimated by iterative thresholding. This iterative thresholding and active contour model with adaptation (ITHACA) algorithm was compared to manual tracing used in clinical practice and the commercial MASS Analysis software (General Electric) in 38 patients, with Institutional Review Board (IRB) approval.

An interesting approach depicted in [8] has used the information fusion approach. The information is obtained from image as well as expert's knowledge. This information is in the form of morphology, topology and constitution of tissue. This approach was supplemented by fuzzy logic. In diagnostic application point of view, separating or segmenting healthy tissue and tumour is crucial task. This task can be achieved by segmentation method presented in [9], which is based on probabilistic approach, expectation maximization (EM) algorithm. Another work on probabilistic approach has been presented in [10], where variant of EM algorithm is employed.

Another pre-processing approach to remove the in-homogeneity, anisotropic diffusion has been reported in [11]. This pre-processing is followed by fuzzy c-means segmentation.

In most systems, the features and its application is coded in the system on the basis of prior knowledge of the domain expert. However, an attempt has been done in the [13], to decide the features and its application of logic for classifier from the sample image and its corresponding ideal segmented image. This learning process is used for segmenting other sample images. This learning process is basically aimed at three elements: 1) the feature associated with the pixel under consideration, 2) the relationship of this pixel and surrounding pixels, and 3) feature calculations for different size of windows. The author has claimed in this work that learning can be accomplished using only single pair of sample image and its ideal segmented image.

The PCA and ICA have been used to model the variants of primary shapes and applying it for pattern recognition problems. There has been study to use PCA and ICA combinely to segment the MRI images in [14]. Similarly, SVM and Radial Basis Function (RBF) based Adaboost method have been applied to MRI image for white matter lesion in one of the work presented in [15] and it is found that Adaboost method is faster than SVM method.

An adaptive mean shift has been a powerful algorithm for segmentation and is used in segmentation of MRI brain images in work reported in [17 , 18].

A novel method for simultaneous segmentation and registration is presented in [23]. This algorithm can be carried out by a statistical modelling framework. First, the authors segment the medical volume data using the geometric active model with level set theory and then extract the region of an object from a given volume data. Second, they use a hidden Markov model and the conditional likelihood function to statistically model a problem that aligns the extracted object with other volume data.

The detection of cartilage loss due to disease progression in Osteoarthritis remains a challenging problem. The sensitivity of detection from 3D MR images can be improved significantly by focusing on regions of 'at risk' cartilage defined consistently across subjects and time-points. These regions in a frame of reference are defined based on the bones, which require that the bone surfaces are segmented in each image, and that anatomical correspondence is established between these surfaces. Previous results has shown that this can be achieved automatically using surface-based Active Appearance Models (AAMs) of the bones. In [28], a method for refining the segmentations and correspondences by building a volumetric appearance model using the minimum message length principle is described.

Brain structural volumes can be used for automatically classifying subjects into categories like controls and patients. One of the recent papers [29] aims to automatically separate patients with temporal lobe epilepsy (TLE) with and without hippocampal atrophy on MRI, pTLE and nTLE, from controls, and determine the epileptogenic side.

3. Computational Intelligence in MRI Segmentation

Additionally, advances in computational intelligence, machine learning has made researchers to explore the new techniques for meaningful segmentation. It will be interesting to note the effectiveness of methods based on computational intelligence over the earlier methods. We expect to have more reliability, accuracy over classical methods. The generalized framework system for the application based on MRI segmentation is shown in figure 2.

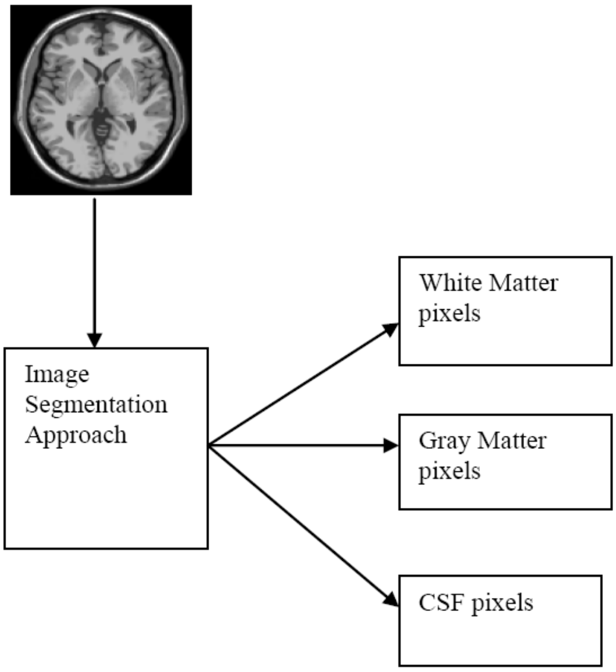

Fig. 2: MRI segmentation system

In an interesting paper [3], coarse to fine expert system composed of rules/knowledge predicates is used to identify the WM, GM and CSF pixels. The rules are extracted from T1, T1 and proton density based MRI images. In one of the useful paper [12], the segmentation is achieved by edge detection based on domain expert system made up of fuzzy logic and semantic knowledge. Improvement and flexibility of these methods shows the importance of soft computing in medical healthcare system.

In another segmentation work [16], based on computational intelligence, the RBF neural network applied and the number of hidden nodes and RBF parameters are optimized using genetic algorithm. The genetic algorithm can also be applied in the k-means clustering for optimization purpose and improvement of around 4 % over the fuzzy c-means method has been reported in [19].

Particle Swarm Optimization (PSO) is one of the latest computational approaches and has been applied many engineering applications. In [20], authors have applied PSO method to optimize the parameter of fuzzy c-means segmentation process. This technique has given an improved performance in noisy images. Another class of computational algorithm based on AntTree structure model has been applied in [22] and its performance compared with K mean and FCM algorithms and found to be superior in terms of speed, robustness and accuracy.

An automated system that extracts metabolic disease related features and subsequently classifies them for diagnostic purposes is introduced in [24]. The algorithm consists of two main components; the feature extraction, and the fuzzy classification. The DWI image features are extracted first; they constitute a feature vector length of twenty-two which will be the input to the fuzzy classifier. In the second part, the features are related to disease categories implementing fuzzy relations and membership functions.

An attempt has been made in [25] to determine the degree of malignancy of brain tumours using artificial intelligence. Significant shape-based boundary features and texture features are extracted from region of interests of tumour and fed to the classifier. In the classification block, input images are analyzed using two simple approaches (shape based and texture based). The ultimate classifier is an adaptive neuro-fuzzy classifier for uncertainty management appears due to the insufficient information of brain lesions. In the detection block, tumour blocks are identified and marked as second opinion of radiologists.

In [26], a segmentation method for brain MR images using an ant colony optimization (ACO) algorithm is proposed. This is a relatively new meta-heuristic algorithm and a successful paradigm of all the algorithms which take advantage of the insect's behaviour. It has been applied to solve many optimization problems with good discretion, parallel, robustness and positive feedback. As an advanced optimization algorithm, only recently, researchers began to apply ACO to image processing tasks. Hence, we segment the MR brain image using ant colony optimization algorithm.

Authors from [30] segregate the image based on levels of intensity, because diseased portion of the MRI image will have a different intensity value with that of a non diseased multimodal MRI image. They use entropy maximization to get the range of gray level of diseased cells of MRI image. The range is optimized using particle swarm optimization (PSO) algorithm and further fine tuned using the concept of variable mask in which the mask is incrementally applied on the region of interest. Depending on the similarity of the neighbourhood pixels the mask is incremented.

4. Conclusion

Various approaches has been reported in literature for segmentation of brain, where main objective is separating the pixels associated with different types of tissues like white matter, gray matter and cerebrospinal fluid (CSF). In this paper, we review the methodologies of MRI segmentation that can be used in various diagnostics such as fMRI (Functional MRI), CMRI (cardiac MRI) and MRA (Magnetic Resonance Angiography). We will also present the different techniques of computational intelligence to be efficiently used in MRI segmentation.

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