Review Article

Multi Label Health image Segmentation Model of MRI Using SVM Algorithm: A Review

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ABSTRACT

Currently, MRI has been widely applied in diagnosis of a variety of diseases. It can reduce susceptibility artifact and cardiovascular beat artifact arising from the air-tissue interface when diagnosing lung diseases. MRI is characterized by multiple-layer and multiple-sequence imaging and intensified signals. It can also reflect the number of capillaries and blood perfusion parameter values of benign and malignant lung nodules. Magnetic Resonance Imaging (MRI) images processed by a Support Vector Machine (SVM) algorithm-based model in diagnosis. The SVM algorithm was constrained by a self-paced regularization item and gradient value to establish the MRI image segmentation model (SVM-B) for brain. The study of the brain and its connection to human activities has been of interest to scientists for centuries. However, it is only in recent years that medical imaging methods have been developed to allow a visualization of the brain. Magnetic Resonance Imaging (MRI) is such a technique that provides a non-invasive way to view the structure of the brain. Functional MRI (fMRI) is a special type of MRI, measuring the neural activity in human brain. The aim of this dissertation is to apply machine learning methods to functional and anatomical MRI data to study the connection between brain regions and their functions. A standard MRI study produces massive amount of noisy data with strong spatial-temporal correlation. Existing methods include a model-based approach, which assumes spatial-temporal independence, and a data-driven method which fails to exploit the experimental design. In this work we propose a SVM and Random Forest process model to incorporate the temporal correlation through a model-based approach. We validate the method on simulated data and compare the results to other methods through real data analysis. Magnetic resonance imaging (MRI) technique is used for the study of the human brain. In this research work, classification techniques based on Support Vector Machines (SVM) are proposed and applied to brain image classification. The time it takes for the protons to realign with the magnetic field, as well as the amount of energy released, changes depending on the environment and the chemical nature of the molecules. Physicians are able to tell the difference between various types of tissues based on these magnetic properties. To obtain an MRI image, a patient is placed inside a large magnet and must remain very still during the imaging process in order not to blur the image. Contrast agents (often containing the element Gadolinium) may be given to a patient intravenously before or during the MRI to increase the speed at which protons realign with the magnetic field. The faster the protons realign, the brighter the image.

KEYWORDS

MRI, SVM, classification, convolutional neural network, discrete wavelet transform, Image segmentation

1. INTRODUCTION

In medical imaging technology, a number of complementary diagnostic tools such as x-ray computer tomography (CT), magnetic resonance imaging (MRI) and position emission tomography (PET) are available. Magnetic resonance imaging (MRI) is an important diagnostic imaging technique for the early detection of abnormal changes in tissues and organs. Its unique advantage over other modalities is that it can provide multispectral images of tissues with a variety of contrasts based on the three MR parameters ρ, T1, and T2.

Therefore, majority of research in medical image concerns MR images Magnetic resonance imaging (MRI) relies upon the inherent magnetic properties of human tissue and the ability to use these properties to produce tissue contrast. MRI is a type of diagnostic test that can create detailed images of nearly every structure and organ inside the body. MRI uses magnets and radio waves to produce images on a computer. MRI does not use ionizing radiation. Images produced by an MRI scan can show organs, bones, muscles and blood vessels. The brain is the most complex organ in the human body with billions of nerve cells. It controls every aspect of our daily lives, such as perception and cognition, movement and regulation, memory and thoughts. For centuries, scientists and philosophers have tried to unravel the complex networks of the brain and its connection to human activities.

In the 17th century, people discovered that various areas of the brain had specific functions. Since then understanding the functional regions of the brain becomes a major research area and presents great challenges to the neuroscientists.

Before the brain imaging techniques, the studies of the brain function were mainly down by the stimulation of animal brains using electrical currents or the observation of the patients with neurological disorders. However, the results showed many in consistencies and very limited regions could be identified using these methods.

Modern imaging techniques brought a technological breakthrough to the neuroscience, leading to a wave of innovation and enthusiasm in brain studies. These brain-imaging methods provide a direct visualization of the structure of the brain, making the studies of living healthy subjects possible. Among them Magnetic Resonance Imaging (MRI) has dominated the neuroscience literature for the current decade because of its high temporal and spatial resolution.

Functional MRI (fMRI) is a special type of MRI. A typical fMRI experiment involves presenting a sequence of stimuli to the subjects while recording the subject's neural activities. It produces a series of scans during one session with temporal resolution varying from 500 ms to 3s. fMRI is particularly useful in cognitive neuro science research. The fMRI analysis finds the relation between the neural activities and the time course of stimuli. Usually, the main goal of the fMRI analysis is to identify the regions that respond to the stimuli, connecting the regions to the functions.

Structural or anatomical MRI, in general, is used for viewing the structure of the brain. Unlike fMRI, structural MRI acquires only one scan of each subject with high spatial resolution. It provides a good contrast between different tissues, especially useful for detecting small anatomical changes in the brain. It is known that then euro degenerative diseases will cause loss of the gray matter, which can be discovered by comparing the structural images between the patients and healthy controls. As a result, structural MRI not only becomes popular in brain research but also shows promising results in clinical diagnosis.

About MRI:

MRI provides a non-invasive way to study the neural activities in human brain with MRI. It works by detecting the changes in blood oxygenation level that occur in response to the local neural activities. Active neurons consume oxygen. Increases in the local neuronal activities lead to an increase in the local blood flow, carrying more oxygen to the regions with increased activities Roy and Sherrington (1890). Oxygen is delivered by haemoglobin in blood cells, which is diamagnetic when oxygenated but paramagnetic when deoxygenated. The small difference in magnetic properties leads to a stronger fMRI signals. Since the blood oxygenation level changes according to the regional neural activities, it can be measured as an indicator of brain activities.

When neuronal activity increases there is an increased demand for oxygen and the local response is an increase in blood flow. This local increase is known as blood oxygenation level dependent (BOLD) signal during a typically fMRI experiment, subjects are asked to perform a certain task while been scanned repeatedly, giving a series of 3D images. Each voxel in the image is represented by a time series of the signal. Usually the main goal of fMRI analysis is to find the area of the brain activated by the task during the experiment.

The most intuitive solution is to compute the correlation between the recorded signals and the time course of the stimuli and pick the voxels with the highest correlation scores. However brain is a complex network and there are many sources of noises contributing to the signals. The actual analysis is a more sophisticated process than simply computing the correlation scores.

Fig-1 MRI Machine

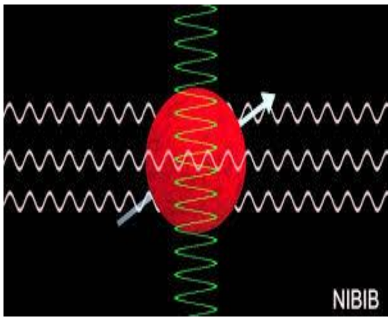

Fig-2 X-rays

A form of high energy electromagnetic radiation that can pass through most objects, including the body. X-rays travel through the body and strike an x-ray detector (such as radiographic film, or a digital x-ray detector) on the other side of the patient, forming an image that represents the "shadows" of objects inside the body.

MRIs employ powerful magnets, which produce a strong magnetic field that forces protons in the body to align with that field. When a radiofrequency current is then pulsed through the patient, the protons are stimulated, and spin out of equilibrium, straining against the pull of the magnetic field. When the radiofrequency field is turned off, the MRI sensors are able to detect the energy released as the protons realign with the magnetic field. The time it takes for the protons to realign with the magnetic field, as well as the amount of energy released, changes depending on the environment and the chemical nature of the molecules. Physicians are able to tell the difference between various types of tissues based on these magnetic properties.

In medicine and biotechnology, sensors are tools that detect specific biological, chemical, or physical processes and then transmit or report this data. Some sensors work outside the body while others are designed to be implanted within the body. Sensors help health care providers and patients monitor health conditions. Sensors are also used to monitor the safety of medicines, foods and other environmental substances we may encounter.

Structural MRI:

MRI (structural MRI or anatomical MRI) uses the phenomena of Nuclear Magnetic Resonance of the nuclei of the hydrogen atom within water. It provides anon-invasive way to visualize the brain. The advantage of MRI over other brain imaging techniques is its superior spatial resolution, providing a detailed map of the brain. Structural MRI has become a powerful tool in both brain research and clinical neurology. The usual structural MRI experiments scan two groups of different subjects, such as patients vs healthy controls. The main goal of structural MRI studies is to identify the regional changes in the brain that are caused by certain conditions.

2. LITERATURE SURVEY

P. Maji, M. K. Kundu and B. Chanda et.al, During MR imaging, the image of the object may get de- formed due to the slope between the MR probe and the object. It is in general undesirable, particularly for 3D imaging. In this paper we propose a novel method to reconstruct the underformed image of the object by measuring the deformation at the time of the MR scan. The image registration technique coupled with genetic algorithm is used to predict the deformation of the object. The inverse of this deformation is then applied to the image, generating the image that would have been seen had there been no slope with the probe. The proposed algorithm has been tested on a set of brain MR images and shown to remove the deformation and so give improved 3D reconstructions.[1]

Zhang, Y.; Dong, Z.; Wu, L.; Wang, S **et.al,** In this paper, a model based on discrete wavelet transform and convolutional neural network for brain MR image classification has been proposed. The proposed model is comprised of three main stages, namely preprocessing, feature extraction, and classification. In the preprocessing, the median filter has been applied to remove salt-and-pepper noise from the brain MRI images. In the discrete wavelet transform, discrete Harr wavelet transform has been used. In the proposed model, 3-level Harr wavelet decomposition has been applied on the images to remove low-level detail and reduce the size of the images. Next, the convolutional neural network has been used for classifying the brain MR images into normal and abnormal. The convolutional neural network is also a prevalent classification method and has been widely used in different areas. In this study, the convolutional neural network has been used for brain MRI classification. The proposed methodology has been applied to the standard dataset, and for performance evaluation, we have used different performance evaluation measures. The results indicate that the proposed method provides good results with 99% accuracy. The proposed method results are then presented for comparison with some state-of-the-art algorithms where simply the proposed method outperforms the counterpart algorithms. The proposed model has been developed to be used for practical applications.[5]

N. Varuna Shree and T. N. R. Kumar **et.al,** Analysing and processing of MRI brain tumor images are the most challenging and upcoming field. Magnetic resonance imaging (MRI) is an advanced medical imaging technique used to produce high-quality images of the parts contained in the human body and it is very important process for deciding the correct therapy at right stage for tumor-infected individual. Many techniques have been proposed for classification of brain tumors in MR images such as fuzzy clustering means (FCM), support vector machine (SVM), artificial neural network (ANN), knowledge-based techniques, and expectation-maximization (EM) algorithm technique which are some of the popular techniques used for region based segmentation and so to extract the important information from the medical imaging modalities.[6]

Bahadure al. proposed BWT and SVM techniques image analysis for MRI-based brain tumor 3detection and classification. In this method, accuracy of 95% was achieved using skull stripping which eliminated all no brain tissues for the detection purpose.Joseph et al proposed segmentation of MRI brain images using Kmeans clustering algorithm along with morphological filtering for the detection of tumor images. The automated brain tumor classification of MRI images using support vector machine was proposed by Alfonse and Salem. The accuracy of a classifier was improved using fast Fourier transform for the extraction of features and minimal redundancy maximal relevance technique was used for reduction of features. The accuracy obtained from this proposed work was 98%.

3. METHODOLOGY AND WORK DESCRIPTION

This describes the materials, the source from which the brain image data collected and the algorithms for brain MRI segmentation and feature extraction. The methodology proposed includes application on brain MRI images of [256×256, 512×512] pixel size on dataset. It is converted into grey scale for further enhancement. The following discussion deals with implementation of algorithm.

a. Pre-processing

The pre-processing step improves the standard of the brain MR images and makes these images suited for future processing by clinical experts or imaging modalities. It also helps in improving parameters of MR images. The parameters includes improvement in signal-to-noise ratio, enhancement in visual appearance of MR images, the removal of irrelevant noise and background of undesired parts, smoothing regions of inner part, maintaining relevant edges.

Segmentation

The segmentation is a process where the image is partitioned into different regions. Let an entire region of image be represented by S. Segmentation process can be viewed as partition of S into p sub-regions like S1, S2, S3, …Sp. Certain conditions has to satisfied such as the segmentation must be intact; that is each and every pixel should be within the region, every points in the regions should be connected in some sense, regions should be disjoint, etc.

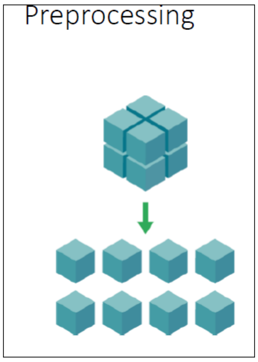

Fig-3 3D image Pre processing

Region Growing

Region growing is grouping of pixels or sub-regions into larger regions based on certain criteria. The main aim was to select a 'seed' points and attach each of these seed to those neighboring pixels having identical properties to grow region. A set of seeds was taken as input within the image and marked the objects to be segmented. The region grows iteratively by estimating all unallocated neighbouring pixels of the region. The similarity was the measure of difference between pixel's intensity value and the region's mean, δ. The pixel with the smallest difference measured this way was allocated to the respective region. This was continued until all pixels were allocated to a region. Seeded region growing requires seeds as additional input. The results depend on the selection of seeds. The measurement was based on mean value of the pixel intensity. The image gets segmented; this image was used to identify the desired tumor region.

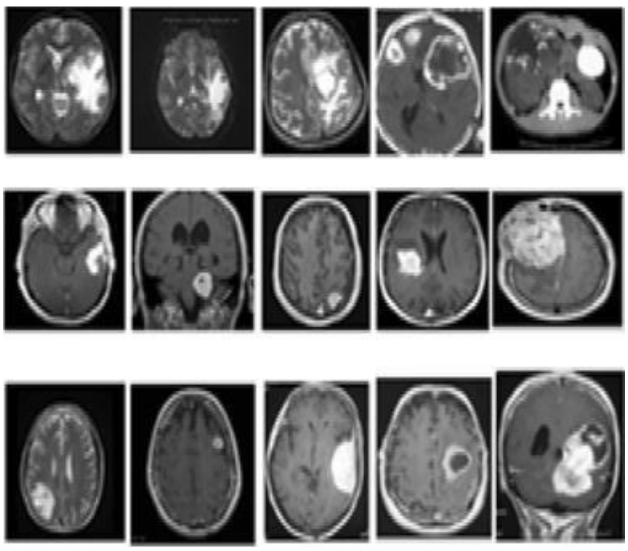

Fig-4 MRI Image

b. Morphological Operation

Morphology deals with study of shapes and boundary area extraction from brain tumor images. Morphological operation is rearranging the order of pixel values. It operates on structuring element and input images. Structuring elements are attributes that probes a features of interest. The basic operations used here are dilation and erosion. Dilation operation adds the pixels to boundary region, while erosion removes the pixels from the boundary region of the objects. These operations were carried out based on the structuring elements. Dilation chooses highest value by comparing all pixel values in neighbourhood of input image described by structuring element, whereas erosion chooses the lowest value by comparing all the pixel values in the neighbourhood of the input image.

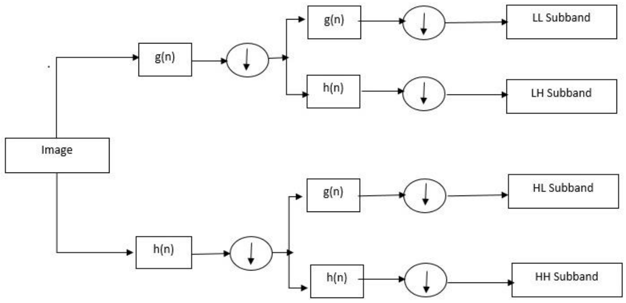

Fig-5. Feature Extraction

c. Feature Extraction

In this paper, the feature extraction of MRI images is obtained using the discrete wavelet transform (DWT) domain sub-images. The wavelet is a powerful mathematical tool for feature extraction, and has been Excessive features increase the computation time and memory storage which sometimes causes some complications in the classification process (the curse of dimensionality), and so it's required to reduce the number of features. The principal component analysis (PCA) is the most well-known used subspace projection technique as it provides suboptimal solution with a low computational cost and computational complexity. PCA is an efficient strategy for transforming the existing input features of a data set consisting of a large number of interrelated variables into a new lower-dimension feature space while retaining most of the variations. The basic scheme of DWT decomposition and its application to MR images is shown in Fig-4. Where the functions h(n) and g(n) represent the coefficients of the high-pass and low-pass filters, respectively. As a result, there are four sub-band (LL, LH, HH, HL) images at each scale. The LL sub-band can be regarded as the approximation component of the image, while the LH, HL, HH sub-bands can be regarded as the detailed components of the image. For feature extraction, only the sub-band LL is used for DWT decomposition at next scale. Also, the LL sub-band at last level is used as output feature vector. In our algorithm, a two level decomposition via Haar wavelet was utilized to extract features.

4. CONCLUSION AND FUTURE SCOPE

In this research work the categorization of brain MRI images is performed. As found during the research survey related to the classification of brain MRI, almost all the previous techniques follow the process of feature reduction i.e.

dimensionality reduction technique has been applied. But while working in this research effort the stage of the feature reduction has been omitted. It has been analysed that the selection of optimal features diminishes the probability of implementation of the feature reduction techniques. In this whole procedure training of the Random Forest has been originated as the most crucial and dependent issue for the performance parameter. Amplifies the input parameter for the Random Forest affects the estimation of the performance of the classification.

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