# A NOVEL SEGMENTATION TECHNIQUE FOR MRI BRAIN TUMOR IMAGES

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**ABSTRACT -** Brain tumor is among the most frequent cancers and its mortality rate is very high. In the brain tumor segmentation problem, we are asked to distinguish tumor tissues such as edema and active tumor from normal brain tissues such as gray matter, white matter and the cerebrospinal fluid. A novel automated framework is proposed in this paper to address the significant but challenging task of multi-label brain tumor segmentation. Kernel sparse representation, which produces discriminative sparse codes to represent features in a high-dimensional feature space, is the key component of the proposed framework.

**Index Terms - Feature selection, classification, brain tumor segmentation, SVM, MKL**

## 1. INTRODUCTION

Brain tumor is among the most frequent cancers and its mortality rate is very high. In the brain tumor segmentation problem, we are asked to distinguish tumor tissues such as edema and active tumor from normal brain tissues such as gray matter, white matter and the cerebrospinal fluid. Magnetic Resonance Imaging (MRI) is the common technique for brain tumor diagnostic [1] [2] [3]. MRI is distinguished from other techniques by its sensitivity to contrast. The existence of several MRI acquisition protocols allows to produce several types of images representing the same object (the brain). The different image sequences provide complement but redundant information. With a massive amount of brain images for each patient, the segmentation of brain tumor should be fast and accurate. Brain tumor shapes, appearances and locations are extremely heterogeneous and the brain tumor segmentation segmentation task stills a serious challenge.

In the literature, numerous features can be extracted to describe the brain tumor texture in MR images. These features can be classified into different categories. We distinguish for example statistic measures, intensity based features, texture based features, grey levels, probability based features, wavelets, etc. With this diversity of features, a feature selection step implemented separately is often necessary to eliminate the redundancy and to select the most useful features using a discrimination power criteria [16] or a class separability criteria [17].

In Multiple Kernel Learning (MKL) [18], the classification and the feature selection are done in the same optimization problem. The idea of the MKL is to select one or more kernel functions to each feature. For each of these functions, a positive weight can be associated. This weight reflects the importance of the corresponding kernel (feature) in the classification. The kernel weight increases if the corresponding kernel (feature) is judged informative and decreases if it is judged less informative. A sparse constraint is applied on the kernel weights to force some of them to be equal to zero. The corresponding features are considered as non-informative features and are not computed during the test step.

In this paper, we present a brain tumor segmentation method from MRI multi-sequence. The proposed method is based on classification and uses a MKL algorithm to exploit the diversity and the complementarity of the data supplied by the different images. From all types of images, we compute a large set of features from a small number of voxels selected by an expert to build a training feature base. In the learning step, the most informative features from the feature base are selected.

In the test step, only the selected features are computed and used to segment tumor and edema. A post-processing step is added to enhance segmentation result.

## 2. LITERATURE SURVEY

Stefan Bauer, Roland Wiest et al (2013) proposed. A survey of MRI-based medical image analysis for brain tumor studies. This paper present a framework for MRI-based medical image analysis for brain tumor studies is gaining attention in recent times due to an increased need for efficient and objective evaluation of large amounts of data. While the pioneering approaches applying automated methods for the analysis of brain tumor images date back almost two decades, the current methods are becoming more mature and coming closer to routine clinical application. This review aims to provide a comprehensive overview by giving a brief introduction to brain tumors and imaging of brain tumors first. Then, we review the state of the art in segmentation, registration and modeling related to tumor-bearing brain images with a focus on gliomas.

The objective in the segmentation is outlining the tumor including its sub compartments and surrounding tissues, while the main challenge in registration and modeling is the handling of morphological changes caused by the tumor. The qualities of different approaches are discussed with a focus on methods that can be applied on standard clinical imaging protocols. Finally, a critical assessment of the current state is performed and future developments and trends are addressed, giving special attention to recent developments in radiological tumor assessment guidelines.

Nelly Gordillo, Eduard Montseny et al (2013) proposed Magnetic Resonance Imaging. This paper present a framework for Brain tumor segmentation consists of separating the different tumor tissues (solid or active tumor, edema, and necrosis) from normal brain tissues: gray matter (GM), white matter (WM), and cerebrospinal fluid (CSF). In brain tumor studies, the existence of abnormal tissues may be easily detectable most of the time. However, accurate and reproducible segmentation and characterization of abnormalities are not straight forward.

In the past, many researchers in the field of medical imaging and soft computing have made significant survey in the field of brain tumor segmentation. Both semiautomatic and fully automatic methods have been proposed. Clinical acceptance of segmentation techniques has depended on the simplicity of the segmentation, and the degree of user supervision. Interactive or semiautomatic methods are likely to remain dominant in practice for some time, especially in these applications where erroneous interpretations are unacceptable. This article presents an overview of the most relevant brain tumor segmentation methods, conducted after the acquisition of the image. Given the advantages of magnetic resonance imaging over other diagnostic imaging, this survey is focused on MRI brain tumor segmentation. Semiautomatic and fully automatic techniques are emphasized.

El-Sayed A. El-Dahshan, Heba M. Mohsen et al (2014) proposed Computer-aided diagnosis of human brain tumor through MRI: A survey and a new algorithm. This paper present a framework for Computer-aided detection/diagnosis (CAD) systems can enhance the diagnostic capabilities of physicians and reduce the time required for accurate diagnosis. The objective of this paper is to review the recent published segmentation and classification techniques and their state-of-the-art for the human brain magnetic resonance images (MRI). The review reveals the CAD systems of human brain MRI images are still an open problem. In the light of this review we proposed a hybrid intelligent machine learning technique for computer-aided detection system for automatic detection of brain tumor through magnetic resonance images. The proposed technique is based on the following computational methods; the feedback pulse-coupled neural network for image segmentation, the discrete wavelet transform for features extraction, the principal component analysis for reducing the dimensionality of the wavelet coefficients, and the feed forward back-propagation neural network to classify inputs into normal or abnormal.

The experiments were carried out on 101 images consisting of 14 normal and 87 abnormal (malignant and benign tumors) from a real human brain MRI dataset. The classification accuracy on both training and test images is 99% which was significantly good. Moreover, the proposed technique demonstrates its effectiveness compared with the other machine learning recently published techniques. The results revealed that the proposed hybrid approach is accurate and fast and robust. Finally, possible future directions are suggested.

Naouel Boughattas, Maxime Berar et al (2016) proposed A Re-Learning Based Post-Processing Step for Brain Tumor Segmentation from Multi-Sequence Images. This paper present a framework for a brain tumor segmentation method from multi-spectral MRI images. The method is based on classification and uses Multiple Kernel Learning (MKL) which jointly selects one or more kernels associated to each feature and trains SVM (Support Vector Machine). First, a large set of features based on wavelet decomposition is computed on a small number of voxels for all types of images. The most significant features from the feature base are then selected and a classifier is then learned. The images are segmented using the trained classifier on the selected features. In our framework, a second step called re-learning is added. It consists in training again a classifier from a reduced part of the training set located around the segmented tumor in the first step.

A fusion of both segmentation procures the final results. Our algorithm was tested on the real data provided by the challenge of Brats 2012. This dataset includes 20 high-grade glioma patients and 10 low-grade glioma patients. For each patient, T1, T2, FLAIR, and post-

Gadolinium T1 MR Images are available. The results show good performances of our method. Brain tumor is among the most frequent cancers and its mortality rate is very high. The most aggressive forms of the disease, classified as HG gliomas (High-Grade gliomas), possess a two years survival mean rate and even less than two years and require an immediate treatment.

Mahshid Farzinfar, Eam Khwang Teoh et al (2011) proposed A Joint Shape Evolution Approach to Medical Image Segmentation Using Expectation–Maximization Algorithm. This paper present a framework for an expectation–maximization (EM)-based curve evolution algorithm for segmentation of magnetic resonance brain images. In the proposed algorithm, the evolution curve is constrained not only by a shape-based statistical model but also by a hidden variable model from image observation. The hidden variable model herein is defined by the local voxel labeling, which is unknown and estimated by the expected likelihood function derived from the image data and prior anatomical knowledge.

In the M-step, the shapes of the structures are estimated jointly by encoding the hidden variable model and the statistical prior model obtained from the training stage. In the E-step, the expected observation likelihood and the prior distribution of the hidden variables are estimated. In experiments, the proposed automatic segmentation algorithm is applied to multiple gray nuclei structures such as caudate, putamens and thalamus of three-dimensional magnetic resonance imaging in volunteers and patients. As for the robustness and accuracy of the segmentation algorithm, the results of the proposed EM-joint shape-based algorithm outperformed those obtained using the statistical shape model-based techniques in the same framework and a current state-of-the-art region competition level set method.

Tong Zhang, Yong Xia et al (2014) proposed Hidden Markov random field model based brain MR image segmentation using clonal selection algorithm and Markov chain Monte Carlo method. This paper present a framework for the hidden Markov random field (HMRF) model has been widely used in image segmentation, as it provides a spatially constrained clustering scheme on two sets of random variables. However, in many HMRF-based segmentation approaches, both the latent class labels and statistical parameters have been estimated by deterministic techniques, which usually lead to local convergence and less accurate segmentation. In this paper, we incorporate the immune inspired clonal selection algorithm (CSA) and Marko chain Monte Carlo (MCMC) method into HMRF model estimation, and thus propose the HMRF–CSA algorithm for brain MR image segmentation.

Our algorithm employs a three-step iterative process that consists of MCMC-based class labels estimation, bias field correction and CSA-based statistical parameter estimation. Since both the MCMC and CSA are global optimization techniques, the proposed algorithm has the potential to overcome the drawback of traditional HMRF-based segmentation approaches. We com-pared our algorithm to the state-of-the-art GA–EM algorithm, deformable co segmentation algorithm, the segmentation routines in the widely-used statistical parametric mapping (SPM) software package and the FMRIB software library (FSL) on both simulated and clinical brain MR images. Our results show that the proposed HMRF–CSA algorithm is robust to image artifacts and can differentiate major brain structures more accurately than other three algorithms.

## 3. CONCLUSION

We presented a brain tumor segmentation method from multi-sequence images. The method takes place in three stages; a learning step, a classification step and a post processing step. The method uses a multiple kernel learning algorithm allowing to do the feature selection and the classification in a unique optimization problem. It consists of selecting the features that optimize the classification. Results show good performance of our method. In future work, we intend to enrich our feature base by adding other classic and new features.

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