International Journal of Research
Available at https://edupediapublications.org/journals
e-ISSN: 2348-6848
p-ISSN: 2348-795X
Volume 05 Issue 12
April 2018

High Efficiency Brain MRI Segmentation for 3D Printing Applications

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Abstract: Histogram equalization (HE) is widely used for contrast enhancement in digital images. For improving the contrast in digital images, Histogram Equalization (HE) is one of the common methods used for contrast enhancement. But, this technique is not well suited for its implementation in consumer electronics, as this method will introduce visual deterioration such as saturation effect. To overcome this weakness the solution is to preserve the mean brightness of the input image inside the output image. In this paper there is a Recursively Separated and Mean separate Histogram Equalization (RSMHE) and Brightness Preserving Dynamic Histogram Equalization (BPDHE). The essential idea of RSMHE is to segment an input histogram into two or more sub-histograms recursively to modify the sub-histograms by means of a weighting process based on a normalized power law function. We show that compared to other existent methods, RSMHE preserves the image brightness more accurately and produces images with better contrast enhancement. It will enhance the image without severe side effects, and at the same time maintain input mean brightness. Comparison is done on the basis of different parameters like Image Brightness Mean (IBM), Image Contrast Standard Deviation (ICSD) and Peak Signal to Noise Ratio (PSNR).

Index Terms: Fuzzy sets, image enhancement, image processing, Brightness Preserving Dynamic Histogram Equalization (BPDHE), RMSHE

I. INTRODUCTION

Image processing has a wide and area in demand. Image processing has various applications which are used in various fields such as medical images, satellite images and also in industrial applications. Images act as the single most significant role in human perception. The techniques such as Digital Image Processing are utilized to magnify the variation for simpler interpretation of X-rays in medicine. An assured and effortless test is Magnetic resonance imaging (MRI) of the brain that utilizes a magnetic field and radio waves which is to provide in depth images of the brain and the brain stem.

These images of high-resolution are utilized to produce entire anatomical information for observing human brain maturity and discover abnormalities.

The advent of data-driven medicine and modern computing power has enabled patient-specific diagnosis and treatment based on medical imaging data. However, the primary bottleneck in this workflow remains the ability to efficiently segment medical imaging data for use in simulation, modeling, and statistical analysis. Manual image segmentation for a single CT or MRI scan is a laborious process, often requiring expensive, specialized software and many hours of work to segment a single image sequence. As an image processing problem, medical image segmentation also poses many significant challenges due to noisy data, low contrast images, and large variations between patients.

For applications in neurosurgery and neurology, advances in finite element modeling and additive manufacturing (3D printing) have made possible the accurate simulation and construction of patient-specific brain models and analogues. However, generating finite element meshes or surface models for 3D printing requires the effective segmentation of brain MRI images. Brain MRI images are particularly difficult to segment due to the low level of contrast between the brain tissue, surrounding tissue, and cerebrospinal fluid. The goal of this project is to create an image processing algorithm that can effectively segment brain MRI data. We focus on segmenting for 3D printing applications specifically for created patient specific brain analogues because this area remains less developed.

In this paper we review the most popular methods commonly used for brain MRI segmentation. We highlight differences between them and discuss their capabilities, advantages, and limitations. To introduce the reader to the complexity of the brain MRI segmentation problem and address its challenges, we first introduce the basic concepts of image segmentation. This includes defining 2D and 3D images, describing an image segmentation problem and image features, and introducing MRI intensity distributions of the brain tissue. Then, we explain different MRI pre-processing steps including image registration, bias field correction, and removal of non-brain tissue. Finally, after reviewing different brain MRI segmentation methods, we discuss the validation problem in brain MRI segmentation.

II. LITERATURE REVIEW

Several methods of image segmentation have been proposed, which can be roughly divided into statistical techniques and partial differential equation-based techniques. The most popular statistical technique is fuzzy c-means classification, since it can effectively segment the image into separate classes of signal. Other statistical techniques are more advanced and computationally intensive, such as convolutional neural networks. For partial differential equation methods, there are many models based on energy minimization and level set methods. One of the most effective partial differential equation-based techniques is active contour models, which fit a spline with minimal energy to the image contours. There are also many deterministic models of edge detection based on wavelet transform or other transform methods. Wavelet-based methods work by taking the discrete wavelet transform of the image and combining these to find the edges in the image, while energy minimization methods treat the edge contour as a flexible plate and seek to minimize its energy.

The algorithm presented here employs a novel method of complementing iterated active contour segmentation with nonlinear filtering and then post-processing with statistical techniques to produce an improved final segmentation result. While has shown that active contours in conjunction with wavelet-based edge detection can be effective for image segmentation, little work has been done on active contours in conjunction with nonlinear filters. The algorithm is designed specifically for brain MRI segmentation, and exploits the geometric properties of the brain to improve the convergence properties.

III. PROPOSED SYSTEM

A. Brain Image Enhancement

Enhancement is the modification of an image to correct affect on the observer. The determination of the image can be given by preprocessing techniques is image enhancement. The techniques such as Image Enhancement are utilized for improving the quality of an image or appearance for the observation of human. The processed image is more appropriate than the original image for a particular application. The most part of the technique is used, due to its simplicity and relatively better performance on images.

MRI of the brain can be beneficial in determine problems like dizziness, weakness, persistent headaches and blurry vision or seizures, and it can help to recognize specific chronic diseases of the nervous system like multiple sclerosis. Magnetic resonance imaging (MRI) system is a popular tool in the field of medicine for the study of human anatomy, segmentation to aid pathology. Quality evaluation is required at the acquisition and post acquisition stages of an imaging workflow. Quality evaluation assesses the integrity of information contained in images to ensure that they are of acceptable quality before post-acquisition processing and analysis. Image quality evaluation is one of the basic criteria for the performance evaluation of MRI system devices at the acquisition stage and the performance evaluation of automated image analysis systems at the post-acquisition stage.

An example of the post-acquisition utility of brain MRI images is in clinical research organization (CRO) that manages the clinical trials of drugs for the treatment and monitoring of multiple sclerosis and Alzheimer's diseases. Daily clinical research organizations receive large volumes of MRI data acquired from several clinical trial sites around the globe.

However, subjective evaluation by human observers will be grossly inefficient in real-world scenarios such as the CRO where large volumes of brain MRI images are evaluated before processing by automated image analysis systems. Some quality evaluation task requires the consent of other trained readers because the human eyes do not possess clearly defined quality index threshold for distinguishing a good quality image from a poor quality image. Often it is difficult for trained MRI readers to arrive at a consensus for images that are perceived to lie on the borderline between acceptable and unacceptable quality. The consequence is high intra-reader and interreader variability, and the task of quality evaluation becomes cumbersome.

Most brain MRI quality assessment method focus on the acquisition stage of the imaging workflow. Quality evaluation methods at the acquisition stage involves modifying the design of system hardware, optimizing acquisition parameters and the implementation of under sampling and constrained reconstruction schemes to reduce acquisition time and generate high quality images. One of the few contributions in the literature proposed SNR as a quality metric within an automated quality control system. The authors in adopt artifactual voxels and noise level as the two quality attributes to measure image quality. The report applies analysis of variance (ANOVA) algorithm to assess the variation of several quality measures with different levels of distortions.

A. Active Contour Model: There currently exist two main neuro mechanical models. The first is based on minimizing the distance between functionally-related neurons, and the other on minimizing the folding energy of cortical tissue. The former hypothesis disagrees with dissection experiments, but is more in-line with the material properties of the brain. The latter model does not match material properties of the brain, but does agree well with dissection experiments.

Active contour models seek to minimize the energy norm of the contour. Since cortical folding will naturally also seek the locally minimal energy state, there is an inherent connection between active contours and cortical folding. Because parameterizing a contour becomes very computationally difficult due to possible topological changes in the contour as it evolves between iterations, we instead employ a level set approach and treat the contour as the zero level set of higher dimension function.

This particular active contour model was chosen because it is not dependent on a large edge gradient. Due to the low contrast between gray matter and cerebrospinal fluid, the edges in brain MRI will have a low gradient, so an edge-free model is ideal for brain MRI segmentation.

B. Brain Geometry: Because the brain is a three dimensional function, we can also treat each individual slice of the brain as a level set. This property (approximately) holds for all brain slices, so we can exploit this property for efficiently segmenting the brain. That is, if we manually segment, we can propagate the convex hull of each successive slice to remove unwanted features outside as well as provide an accurate initial value for the active contour segmentation, which in turn accelerates the convergence.

C. Image Segmentation Algorithm: The goal of image segmentation is to divide an image into a set of semantically meaningful, homogeneous, and nonoverlapping regions of similar attributes such as intensity, depth, color, or texture. The segmentation result is either an image of labels identifying each homogeneous region or a set of contours which describe the region boundaries.

Fundamental components of structural brain MRI analysis include the classification of MRI data into specific tissue types and the identification and description of specific anatomical structures. Classification means to assign to each element in the image a tissue class, where the classes are defined in advance. The problems of segmentation and classification are interlinked because segmentation implies a classification, while a classifier implicitly segments an image. In the case of brain MRI, image elements are typically classified into three main tissue types: white matter (WM), gray matter (GM), and cerebrospinal fluid (CSF). The segmentation results are further used in different applications such as for analyzing anatomical structures, for studying pathological regions, for surgical planning, and for visualization.

Image segmentation can be performed on 2D images, sequences of 2D images, or 3D volumetric imagery. Most of the image segmentation research has focused on 2D images. If the data is defined in 3D space (e.g., obtained from a series of MRI images), then typically each image "slice" is segmented individually in a "slice-by-slice" manner. This type of segmenting 3D image volumes often requires a post-processing step to connect segmented 2D slices into a 3D volume or a continuous surface. Furthermore, the resulting segmentation can contain inconsistencies and non-smooth surface due to omitting important anatomical information in 3D space. Therefore, the development of 3D segmentation algorithms is desired for more accurate segmentation of volumetric imagery.

The main difference between 2D and 3D image segmentation is in the processing elements, pixels/ voxels, respectively, and their 2D or 3D neighbourhoods over which image features are calculated. In practice, 2D image segmentation methods can be extended to 3D space.

The proposed algorithm uses the active contour model. In this algorithm, we combine gamma filtering with iterated active contour segmentation to improve the final segmentation result. Additionally, the algorithm employs statistical techniques to further remove unwanted background features and morphological post-processing to improve the 3D printing properties. The goal is to create a robust brain MRI segmentation system by combining these techniques.

Recursive mean-separate histogram equalization (RMSHE) method: In Recursive mean-separate histogram equalization (RMSHE) method, instead of decomposing the image only once, it is proposed to perform image decomposition recursively, up to a scale r, generating 2r sub-images. After that, each one of these sub-images is independently enhanced using the Histogram Equalization (HE) method. When r = 0 (no sub-images are generated) and r =1, the RMSHE method is equivalent to the HE and BBHE methods, respectively. In this method, the preservation of the output image increases as r (separation level) increases.

Brightness Preserving Dynamic Histogram Equalization (BPDHE): In BPDHE method the original image is decomposed into multiple sub images according to their local maxima, then the dynamic histogram equalization is applied to each sub image and finally, the sub images are combined. It divides the histogram based on the local maxima. It produces the output image with the mean intensity almost equal to the mean intensity of the input, thus fulfils the requirement of maintaining the mean brightness of the image. This method smoothes the input histograms with one dimensional Gaussian filter, and then partitions the smoothed histogram based on its local maxima. After that it assigns new dynamic range to each partition. Then, the histogram equalization process is applied independently to these partitions, based on this new dynamic range and the output image is normalized to the input mean brightness.

IV. RESULTS

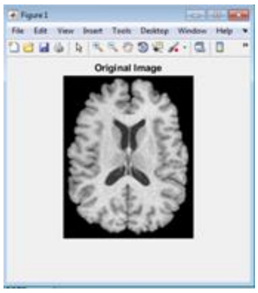

Fig 1. Original Image

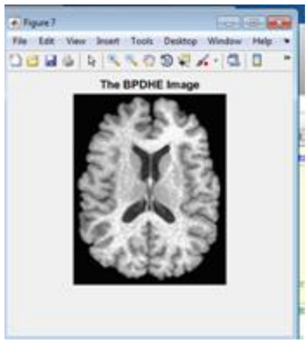

Fig 2. BPDHE Image

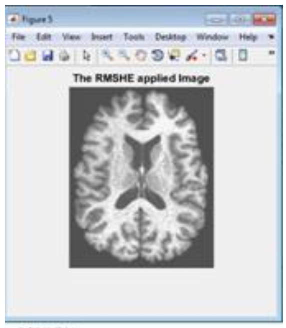

Fig 3. RMSHE Image

V. CONCLUSION

This paper has presented an algorithm for contrast enhancement of digital images. In general, it is observed that contrast enhancement and high PSNR are two conflicting requirements. The performances of various algorithms are compared according to three parameters namely, Image Brightness Mean, Image Contrast-Standard Deviation and PSNR. It is observed that RMSHE algorithm produces the best image contrast enhancement producing good image contrast enhancement. The experiments showed that BPDHE and RMSHE are well suited for preserving the brightness of the processed image (in relation to the original one) and yield images with natural appearance, at the cost of contrast enhancement. However, where the main objective is to enhance the contrast of the image and preserve its brightness, thus RMSHE is the best method among those considered in the present study.

VI. REFERENCES

[1] M. A. Balafar, A. R. Ramli, M. I. Saripan, and S. Mashohor, "Review of brain MRI image segmentation methods," Artificial Intelligence Review, vol. 33, no. 3, pp. 261–274, January 2010.

[2] M. B. Panzer, B. S. Myers, B. P. Capehart, and C. R. Bass, "Development of a finite element model for blast brain injury and the effects of CSF cavitation," Annals of Biomedical Engineering, vol. 40, no. 7, pp. 1530–1544, February 2012.

[3] M. Balafar, A. Ramli, M. Saripan, R. Mahmud, and S. Mashohor, "Medical image segmentation using fuzzy c-mean (fcm) and dominant grey levels of image," in Visual Information Engineering, 2008. VIE 2008. 5th International Conference on, July 2008, pp. 314–317.

[4] M. Rostami, J. Ghasemi, and R. Ghaderi, "Neural network for enhancement of fcm based brain mri segmentation," in Fuzzy Systems (IFSC), 2013 13th Iranian Conference on, Aug 2013, pp. 1–4.

[5] S. Khare, N. Gupta, and V. Srivastava, "Optimization technique, curve fitting and machine learning used to detect brain tumor in mri," in Computer Communication and Systems, 2014 International Conference on, Feb 2014, pp. 254–259.

[6] M. Kass, A. Witkin, and D. Terzopoulos, "Snakes: Active contour models," International Journal of Computer Vision, vol. 1, no. 4, pp. 321–331, 1988.

[7] S. W. Yoon, H. S. Shin, S. D. Min, and M. Lee, "Medical endoscopic image segmentation with multi-resolution deformation," in 2007 9th International Conference on e- Health Networking, Application and Services. Institute of Electrical & Electronics Engineers (IEEE), June 2007.