Image Pre-processing and Feature Extraction Techniques for Magnetic Resonance Brain Image Analysis

D. Jude Hemanth and J. Anitha

Department of ECE, Karunya University, Coimbatore, India
{jude_hemanth,rajivee1}@rediffmail.com

Abstract. Image pre-processing and feature extraction techniques are mandatory for any image based applications. The accuracy and convergence rate of such techniques must be significantly high in order to ensure the success of the subsequent steps. But, most of the time, the significance of these techniques remain unnoticed which results in inferior results. In this work, the importance of such approaches is highlighted in the context of Magnetic Resonance (MR) brain image classification and segmentation. In this work, suitable pre-processing techniques are developed to remove the skull portion surrounding the brain tissues. Also, texture based feature extraction techniques are also illustrated in this paper. The experimental results are analyzed in terms of segmentation efficiency for pre-processing and distance measure for feature extraction techniques. The convergence rate of these approaches is also discussed in this work. Experimental results show promising results for the proposed approaches.

Keywords: Pre-processing, MR brain images, feature extraction, segmentation efficiency and convergence rate.

1 Introduction

Generally, real-time images collected from scan centre and simulated images collected from publicly available database are used for image classification and segmentation. These are raw images which are unsuitable for analysis due to the various types of noises present in the images. Hence, suitable pre-processing methodologies must be used to enhance the quality of the images. Literature survey reveals the availability of several pre-processing and feature extraction techniques for MR brain image analysis. The raw MR images normally consist of many artifacts such as intensity inhomogenities, extra cranial tissues, etc. which reduces the overall accuracy. Several researches are reported in the literature to minimize the effects of artifacts in the MR images. An analysis on filtering techniques such as Gabor & QMF filters for noise reduction is performed by Nicu et al (2000).

Fuzzy connectedness based intensity non uniformity correction has been implemented by Yongxin et al (2006). A sequential approach with fuzzy connectedness, atlas registration and bias field correction is used in this approach. The conclusions revealed that the proposed technique can be used only if the intensity variations between the images are of a limited range. Marianne et al (2006) have

T.-h. Kim et al. (Eds.): FGCN/DCA 2012, CCIS 350, pp. 349–356, 2012.

minimized the effects of inter-slice intensity variation with the weighted least square estimation method. The selection of weights for the least square method is the major disadvantage of this approach. Bo et al (2008) have proposed the noise removal technique using wavelets and curvelets.

Hybrid approaches involving Variance Stabilizing Transform (VST) are also used in this work. But this technique is applicable for images with Poisson noise. Tracking algorithm based de-noising technique is performed by Jaya et al (2009). Since the seed point for tracking is random in nature, this technique is not much efficient. A contrast agent accumulation model based contrast enhancement is implemented by Marcel et al (2009). This improves only the contrast of the image and the unwanted tissues are not eliminated. Rajeev et al (2009) have used the wiener filtering technique for noise removal in MR brain images. Apart from noise removal, several other pre-processing steps are also reported in the literature. This includes image format conversion, image type conversion etc. Rajeev et al (2009) also have used the combination of three modalities of MR images for further processing. All the above mentioned techniques remove only specific artifacts which is not sufficient for high classification accuracy and segmentation efficiency.

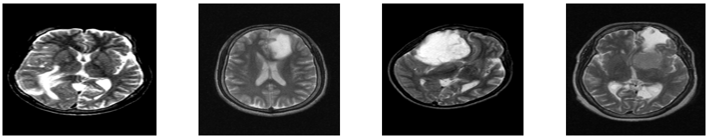
The next step in the automated diagnosis process is feature extraction. Feature extraction is the technique of extracting specific features from the pre-processed images of different abnormal categories in such a way that the within - class similarity is maximized and between - class similarity is minimized. Earlier research works report many feature extraction techniques employed for medical image processing. Arivazhagan et al (2003) have used 2D wavelet transform based textural features for classification. In this report, initially basic statistical features are used and then co-occurrence based textural features are used to improve the accuracy. But the effects of usage of different wavelets are not dealt in the report. A comparison of 2D wavelet transform based textural features and 3D wavelet transform based textural features is performed by Kourosh et al (2004). This work concluded that the combination of 2D and 3D wavelet based textural features yield better results than the 2D wavelet features. Hiremath et al (2006) have presented a feature extraction technique using the complimentary wavelet transformed image. The report claimed that the features extracted from all the four sub-bands are more efficient than the features from the only the approximation sub-band. All these techniques used the basic Discrete Wavelet Transform (DWT) which does not yield superior results.

An improved version based on wavelet packet decomposition is implemented by Hiremath et al (2006). The results revealed that the packet decomposition technique is more efficient than the DWT technique. Apart from extracting the features from the whole image, features are also extracted from local regions which are used for image segmentation applications. One such work is reported by Ryszard (2007). Pantelis et al (2007) have described a novel feature set which comprises the features such as short run emphasis, run length non-uniformity, etc. which are based on run length matrices. The drawback of this work is the low classification accuracy which shows that these features do not guarantee superior results. Ke et al (2008) have explored the merits of wavelet features for image classification. The technique of dimensionality reduction based on sub band grouping and selection have also been implemented in this work. A comparative analysis with the conventional algorithms is presented in this report.

In this work, emphasis is given to remove the extra-cranial (skull) tissues which often interfere with the brain tissues leading to the performance reduction of the system. Suitable morphology based techniques are used to remove the skull tissues. Next, an extensive feature set is extracted from these images and supplied as input to the automated system. The characteristics of the input images are reflected by these features which are necessary to enhance the efficiency of the system. These feature extraction techniques are performed in a different manner for the classification and segmentation techniques.

2 Brain Image Database

The image database used in this work is collected from M/s. Devaki scan centre in Madurai, Tamilnadu, India. The total number of images is 540 with representations from four categories such as Meningioma, Glioma, Metastase and Astrocytoma. The images are further categorized into training dataset and testing dataset. The images are gray level images with intensity value ranges from (0 to 255). These images are used for both classification and segmentation applications. Some samples of the MRI database have been displayed in Figure 1.



(a) (b) (c) (d)

Fig. 1. Sample data set: (a) Metastase (b) Glioma (c) Astrocytoma (d) Meningioma

The ground truth tumor image is also available for all the 540 images. These ground truth are used as reference for the tumor segmentation applications.

3 Image Pre-processing

The raw images collected from the scan centre and the websites are not suitable for direct processing due to the various noises present in these images. In this work, emphasis is laid on the removal of extra-cranial (skull) tissues which often interfere with the brain tissues. The presence of these skull tissues has reduced the perofrmance of the automated system. Hence, suitable morphology based techniques are devised in this work to eliminate these extra-cranial tissues.

3.1 Framework of the Proposed Technique

The various steps followed in the extra-cranial tissue extraction are shown in this section. Different sequential steps with different parameters are implemented in this work to eliminate the skull tissues which are usually surrounding the brain tissues.

The procedual flow of this algorithm is detailed in the following three steps.

Step 1: Generation of mask
The first step after reading the image is the generation of a mask. Two basic morphological operations namely erosion and filling are used in this work to generate the mask.

a) Erosion:

The main function of this operation is to remove the pixels on object boundaries. The rule given below defines the operation of the erosion operation. “If every pixel in the input pixel's neighborhood is on, the output pixel is on. Otherwise, the output pixel is off”. A specified neighborhood is used in this operation. The neighborhood for an erosion operation can be of arbitrary shape and size. The neighborhood is represented by a structuring element, which is a matrix consisting of only 0's and 1's. The shape of the structuring element used in this work is “ball” and the size of the structuring element is 5-by-5.

b) Gray to binary image conversion:

A suitable threshold (40-50) is selected and the pixels above the threshold value are made equal to 255 and the pixels below the threshold value are made equal to 0. These thresholds are selected based on trial and error method.

c) Connected component analysis:

It is a process that "fills" a region of interest by interpolating the pixel values from the borders of the region. This process can be used to make objects in an image seem to disappear as they are replaced with values that blend in with the background area. This function is useful for removal of extraneous details or artifacts. The resultant image yields the mask for the corresponding input image.

Step 2: Logical conversion of the mask

The indices of the binary mask image are changed from (0-255) to (0-1).

Step 3: Masking

The original input image is masked with the binary mask. The masking is achieved by performing the multiplying operation between the original image and the mask. The resultant image is free from the extra-cranial tissues which is evident from the output images.

4 Feature Extraction

The purpose of feature extraction is to reduce the original data set by measuring certain properties or features that distinguish one input pattern from another pattern. The extracted feature should provide the characteristics of the input type to the classifier by considering the description of the relevant properties of the image into a feature space. Eight different textural features are used in this work for image analysis. But, these features are estimated in a different manner for the classification and segmentation applications. Since image classification is performed between images, the features are estimated from the whole image. On the other hand, image segmentation is performed within the image and hence the features are estimated for each pixel. A neighborhood window of size 3×3 is chosen with the center pixel being the pixel of interest. The procedure is repeated for all the pixels to estimate the features.

In this work, eight textural features such as angular second moment, contrast, correlation, variance, entropy, Inverse Difference Moment, skewness and kurtosis are used for image classification and segmentation. The textural features are extracted from the pre-processed image which guarantees high success rate for the subsequent steps. The features used in this work are estimated from the following formulae.

Angular Second Moment (ASM):
The summation of the squares of gray levels of the image is known as angular second moment. It is also named as energy (or) uniformity. The energy is usually high when the intensity values are unequal.

$$f_1 = \sum_i \sum_j \{p(i,j)\}^2 \tag{1}$$

where $p(i,j)$ represents the input image.

Contrast:
The local contrast of an image is measured by this feature. It is expected to be low if the intensity values of the pixel are similar.

$$f_2 = \sum_{n=0}^{N_{g-1}} n^2 \left\{ \sum_{i=1}^{N_g} \sum_{j=1}^{N_g} p(i,j) \right\} \tag{2}$$

where N_g is the number of gray levels in the original image.

Correlation:
The linear dependency of grey levels on the neighboring pixels is represented by the correlation feature. The statistical relationship between the two variables is denoted by this feature.

$$f_3 = \frac{\sum_i \sum_j (ij) p(i,j) - \mu_x \mu_y}{\sigma_x \sigma_y} \tag{3}$$

where $\mu_x, \mu_y, \sigma_x, \sigma_y$ are the means and standard deviations of the input image in the row-wise and column-wise order.

Variance:
Variance is a measure of the dispersion of the values around the mean. The variance can also be defined as the measure of how far the gray values are spread out in the input image.

$$f_4 = \sum_i \sum_j (i - \mu)^2 p(i,j). \tag{4}$$

where μ is the mean of the whole image.

Inverse Difference Moment (IDM):
The details of the smoothness of the image are defined by the Inverse difference moment. The IDM is expected to be high if the gray levels of the pixel are similar.

$$f_5 = \sum_i \sum_j \frac{1}{1+(i-j)^2} p(i,j). \tag{5}$$

Entropy:

The randomness of a gray level distribution is denoted by entropy. The entropy is expected to be high if the gray levels are distributed randomly throughout the image.

$$f_6 = -\sum_i \sum_j p(i,j)\log(p(i,j)). \tag{6}$$

Skewness:

The measure of symmetry is given by this textural feature. This value can be either negative or positive. The value is usually zero if the image is exactly symmetrical.

$$f_7 = \frac{1}{\sigma^3} \sum_i \sum_j (p(i,j)-\mu)^3 \tag{7}$$

Kurtosis:

Kurtosis is a measure of whether the data are peaked or flat relative to the normal distribution.

$$f_8 = \frac{1}{\sigma^4} \sum_i \sum_j (p(i,j)-\mu)^4 - 3 \tag{8}$$

These features are commonly used for brain image analysis. These features are specifically found to be superior for image classification and segmentation applications.

5 Experimental Results and Discussions

The algorithms are implemented using MATLAB software with the processor speed of 1.66GHz and 1GB RAM. Sample results of the various stages of skull removal technique for the real-time dataset are shown in Figure 2.

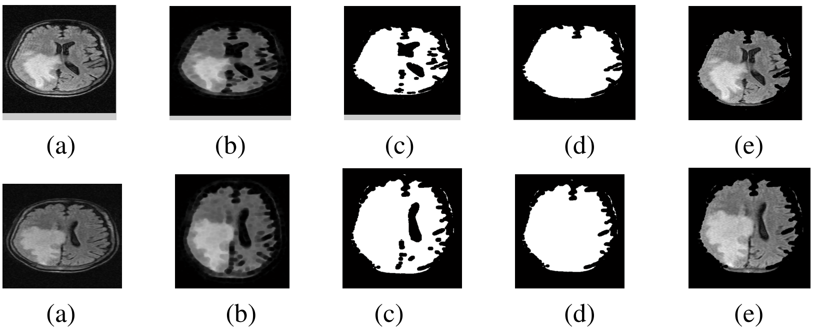


Fig. 2. Sample pre-processed images: (a) Input images, (b) Eroded images, (c) Binary images, (d) Images after connected component analysis, (e) Masked images

An analysis of the above results has clearly revealed the success rate of the pre-processing technique in removing the skull tissues. The difference is visible in Figure 2 (e). A quantitative analysis on these results is shown in Table 1.

Table 1. Quantitative analysis of image pre-processing technique

Image type	No. of ground truth skull pixels	No. of skull pixels removed by the technique	Segmentation efficiency (%)
Real-time images	4990	4878	98

The average values are shown in the results since there is a slight deviation in the number of skull pixels removed in each input images. The robustness of this technique is also revealed since this method is applicable for the simulated images and the real-time images. The convergence rate of this method is only 0.47 CPU seconds which is very much significant for real-time applications.

The textural features mentioned above are also calculated using the MATLAB software. These features are calculated separately for the image classification and segmentation process. The size of the feature set for the image classification is 1×8 for an image of any input size. These features are estimated for all the four categories and are tabulated in Table 2.

Table 2. Feature extraction results for image classification

Features	Metastase	Meningioma	Glioma	Astrocytoma
ASM	1.0022e+009	223000562	604422466	384652269
Contrast	8763781	2177178	6457236	3700147
Correlation	3.2290e+005	2.0014e+005	4.2467e+005	1.6320e+005
Variance	4.5537e+011	2.3593e+010	3.8371e+011	2.1467e+011
IDM	6.5249e+004	3.7115e+004	4.2941e+004	2.1614e+004
Skewness	3.1741e+010	8.5147e+009	1.3335e+010	2.8693e+010
Entropy	3.9759e+007	9.5895e+006	2.7925e+007	1.6630e+007
Kurtosis	5.5761e+012	1.3690e+012	2.7647e+012	4.7109e+012

The features extracted using this method is highly efficient which is validated from the experimental results. The distance measure of these feature values within the class is very minimum for any individual feature and maximum between the classes. Thus, this work has suggested suitable methodologies for image pre-processing and feature extraction for MR brain image analysis.

6 Conclusion

The significance of pre-processing and feature extraction methodologies is verified in this work. The accuracy level is significantly high for the proposed techniques. The time requirement is also significantly low which suggests the feasible nature of these techniques. Thus, these approaches can be used for practical medical applications where the accuracy and convergence rate are extremely important.

Acknowledgment. The authors wish to thank M/s. Devaki Scan Centre for their help regarding database collection and validation.

References

1. Nicu, S., Michael, S.L.: Wavelet based texture classification. In: 15th International Conference on Pattern Recognition, vol. 3, pp. 3959–3962 (2000)
2. Yongxin, Z., Jing, B.: Atlas based fuzzy connectedness segmentation and intensity non-uniformity correction applied to brain MRI. IEEE Transactions on Biomedical Engineering 54(1), 122–129 (2006)
3. Marianne, M., Russell, G., Jorg, S., Albert, M., Mark, S.: Learning a classification based glioma growth model using MRI data. Journal of Computers 1(7), 21–31 (2006)
4. Bo, Z., Jalal, M.F., Jean-Luc, S.: Wavelets, ridgelets and curvelets for Poisson noise removal. IEEE Transactions on Image Processing 17(7), 1093–1108 (2008)
5. Jaya, J., Thanushkodi, K.: Implementation of classification system for medical images. European Journal of Scientific Research 53(4), 561–569 (2011)
6. Marcel, P., Elizabeth, B., Guido, G.: Simulation of brain tumors in MR images for evaluation of segmentation efficacy. Medical Image Analysis 13, 297–311 (2009)
7. Rajeev, R., Sanjay, S., Sharma, S.K.: Brain tumor detection based on multi-parameter MR image analysis. Graphics, Vision and Image Processing Journal 9(3), 9–17 (2009)
8. Rajeev, R., Sanjay, S., Sharma, S.K.: Multiparamter segmentation and quantization of brain tumor from MR images. Indian Journal of Science and Technology 2(2), 11–15 (2009)
9. Arivazhagan, S., Ganesan, L.: Texture classification using wavelet transform. Pattern Recognition Letters 24, 1513–1521 (2003)
10. Kourosh, J.K., Hamid, S., Kost, E., Suresh, P.: Comparison of 2D and 3D wavelet features for TLE lateralization. In: Proceedings of SPIE, vol. 5369, pp. 593–601 (2004)
11. Hiremath, P.S., Shivashankar, S.: Texture classification using wavelet packet decomposition. Graphics, Vision and Image Processing Journal 6(2), 77–80 (2006)
12. Ryszard, S.C.: Image feature extraction techniques and their applications for CBIR and biometrics system. International Journal of Biology and Biomedical Engineering 1(1), 6–16 (2007)
13. Georgiadis, P., Cavouras, D., Kalatzis, I., Daskalakis, A., Kagadis, G.C., Sifaki, K., Malamas, M., Nikiforidis, G.C., Solomou, E.: Non-linear Least Squares Features Transformation for Improving the Performance of Probabilistic Neural Networks in Classifying Human Brain Tumors on MRI. In: Gervasi, O., Gavrilova, M.L. (eds.) ICCSA 2007, Part III. LNCS, vol. 4707, pp. 239–247. Springer, Heidelberg (2007)
14. Ke, H., Selin, A.: Wavelet feature selection for image classification. IEEE Transactions on Image Processing 17(9), 1709–1720 (2008)