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**Research Article**

# A Combination of Restoration, Enhancement and Skull Stripping for Brain MRI

[1]S. Madhukumar and [2]N. Santhiyakumari
[1]Department of Electronics and Communication Engineering, St. Joseph's College of Engineering and Technology, Palai, Kottayam,
[2]Department of Electronics and Communication Engineering, Knowledge Institute of Technology, Salem, India

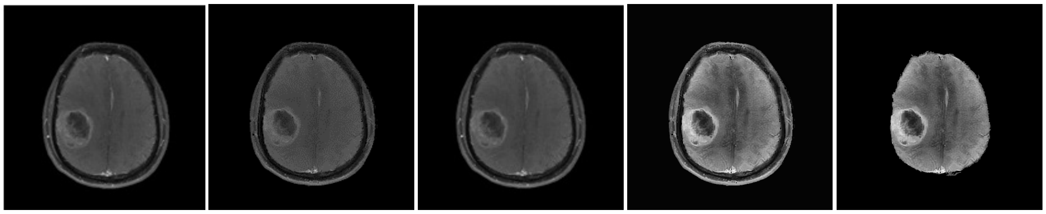
**Abstract:** The preprocessing steps have substantial influence on the accuracy of segmentation and classification of lesions. The background on the image grid, behind the brain structures in the MRI images may not be always homogeneous. The edges or sharp pixel intensity transitions present in the back ground may get preserved during edge sensitive noise restoration and highlighted during contrast enhancement. If conventional noise restoration methods as Gaussian Kernels are adopted, the weak edges of lesions and structures get smoothened. Similarly, common contrast enhancement schemes like Global/Local histogram equalization either over saturate the image or degrade the textural, intensity and geometrical features of the image above tolerable limit. This study proposes a novel combination of preprocessing methods which is exclusively suitable for MR images carrying weak edges. The proposed combination of preprocessing comprises back ground elimination, restoration with bilateral filter, enhancement with Contrast Limited Adaptive Histogram Equalization (CLAHE) and skull stripping. Back ground elimination and skull stripping are performed by multiplying the original image and contrast enhanced image respectively with a multiplication mask. Multiplication mask for background elimination is generated by gradient based thresholding and a series of morphological operations and the multiplication mask for skull stripping is generated via adaptive Otzu's thresholding. MR images of tumor edema complex are used for testing the proposed strategy. The method is experimented in Matlab®. Qualitative inspection of the skull stripped images reveals that the weak edges of tumor-focus and perifocal edema are well preserved, inhomogeneity in the uniform regions is suppressed, CLAHE do not alter the textural intensity and geometrical image features and the brain region is accurately extracted.

**Keywords:** Bilateral filter, contrast limited adaptive histogram equalization, glioblastoma multiforme, otzu's threshold, preprocessing

## INTRODUCTION

The term 'preprocessing' when used in connection with medical images refers to restoration and contrast enhancement. Contrast enhancement in medical imaging is nothing but improving the pixel intensity difference between different morphological structures so that visual distinction between these structures or their automated segmentation is easy. Sharp pixel intensity transitions in the homogenous tissue structures which causes unpleasant visual impact is 'noise'. Traditional mean filters, median filters and Gaussian kernels degrade the contrast between the morphological structures and smoothen edges between the morphologies (Wang *et al*., 2006). Similarly, for enhancing contrast, there are traditional methods like contrast stretching, (Jagatheeswari *et al*., 2009; Umamaheswari and Radhamani, 2012) contrast transformation (Hossain *et al*., 2010) and histogram equalization. Contrast stretching is not applicable if the raw image itself is spread over the possible full intensity range. Devising a mapping function which equally suits multiple images is difficult in contrast transformation. Generally, histogram equalization saturates the image beyond tolerable limits. Though edge sensitive restoration methods like non-local means filter (Lu *et al*., 2012), anisotropic diffusion filter (Sameh Arif *et al*., 2011) and bilateral filters are available, operational parameters has to be selected carefully. Otherwise the outcome may become even worse than the raw image. Even for the most widely accepted contrast enhancement scheme CLAHE, the operational parameters like tile size, clip-limit, distribution etc. can be fixed empirically, from qualitative evaluation of the equalized images. Formulating the right combination of the restoration and enhancement schemes and the selection of their operational parameters are quite critical, in specific

**Corresponding Author:** S. Madhukumar, Department of Electronics and Communication Engineering, St. Joseph's College of Engineering and Technology, Palai, Kottayam, India



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

Fig. 1: The images after each step of pre-processing; (a): Original image; (b): Background eliminated image; (c): Restored image after bilateral filtering; (d): Contrast enhanced image after CLAHE and (e): skull stripped image

medical applications as the intensity and texture of the image has certain diagnostic meaning.

Intensity transients and intensity in homogeneity are usually present in the background of MR images as evident in Fig. 1a. These intensity transitions in the background and the noise present in the morphological structures may interfere with the performance of the edge based segmentation schemes. Moreover, the contrast of the image would not be enough to allow an accurate segmentation of the Region of Interest (ROI). The structures and tissue classes other than the brain region, like skull and scalp, increases the number of tissue classes in the whole image. Segmentation methods like, K-Means (Chen *et al*., 2008) and Expectation Maximization (EM) (Carson *et al*., 2002), yield better outcomes when the number of tissue classes in the image of interest is less.

This study proposes a combination of background elimination, noise restoration, enhancement and skull stripping for MR images. The optimum operational parameters of CLAHE and bilateral filter are used which are fixed through qualitative inspection of the processed MR images. In fact operational parameters of enhancement methods like CLAHE and restoration methods like bilateral, anisotropic and non-local means filters can be fixed only empirically. But the choice operational parameters may be distinct for different classes of images.

The forthcoming discussions comprise mathematics of background removal, restoration, enhancement and skull stripping followed by qualitative evaluation of the preprocessed MR images.

## MATERIALS AND METHODS

Axial Plane T1 contrast enhanced (Series: AX T1 SE FS+C, Spin Echo Sequence (SE)) MR images (courtesy: Hind Labs, Govt. Medical College Kottayam, Kerala) are selected for the experimental evaluation of the proposed method. The specification of MR equipment is; Manufacturer: GE Medical Systems, Model Name: SignaHDxt, Acquisition Type: 2D and 1.5T field strength. The proposed preprocessing is experimented inMatlab®. Figure 2 illustrates the hierarchy of steps involved in preprocessing. Background elimination was accomplished by multiplying the original MR image with a binary multiplication mask. Towards the construction of this multiplication mask, binary edge map of the raw MR image is generated through gradient based threshold (Yazid and Arof, 2013). The multiplication mask is constructed from this edge map through a series of morphological operations. The series of morphological operations include, dilation, hole filling, border clearing and erosion. In gradient based threshold, the gradient is computed with Sobel mask (Jähne *et al*., 1999).

The magnitude gradient is computed from gradient along horizontal and vertical directions (Gonzalez and Woods, 1992; Acharya and Ray, 2005).

The gradient along x-direction:

$$g_x = \frac{\partial f(x,y)}{\partial x} \tag{1}$$

The gradient along y-direction:

$$g_y = \frac{\partial f(x,y)}{\partial y} \tag{2}$$

The gradient magnitude:

$$G(x, y) = \sqrt{g_x^2 + g_y^2} \tag{3}$$

Edge image generated from gradient based threshold:

$$\hat{f}(x, y) = \begin{cases} 1 & \text{if } G(x,y) \geq G_T \\ 0 & \text{else} \end{cases} \tag{4}$$

where, $G_T$ is the adaptive gradient threshold. For dilation of the traced edges, horizontal and vertical structuring elements or strel objects with three neighbours or length 3 are used. Erosion is performed with a diamond strel object having five neighbours or with a length one neighbours or length 3 are used. Erosion is performed with a diamond strel object having five neighbours or with a length one.

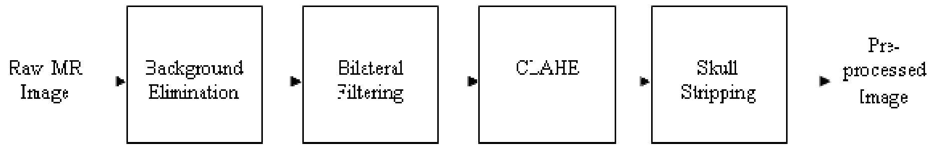



Fig. 2: Steps involved in pre-processing

Conventional spatial filter kernels may smooth the weak edges present between morphological structures. Bilateral filtering is a technique to smooth homogeneous regions of images while preserving the edges. In bilateral filtering, each pixel intensity is replaced by a weighted average of its neighbouring intensities. The mathematical concept of bilateral filter (Tomasi and Manduchi, 1998) is the corrupted signal $\underline{Y}$ is the sum of noise $\underline{V}$ and the uncorrupted signal $\underline{X}$:

$$\underline{Y} = \underline{X} + \underline{V} \tag{5}$$

The bilateral filter approximates a weighted average of pixels in the given image $\underline{Y}$:

$$\hat{X}[k] = \frac{\sum_{n=-N}^{N} W[k,n]Y[k-n]}{\sum_{n=-N}^{N} W[k,n]} \quad -N \le n \le N \tag{6}$$

In (6) restored intensity is the normalized weighted average of a neighbourhood of [2N+1] samples around the $k^{th}$ sample. The weights W [k, n] are computed based on the content of the neighbourhood. For the center sample X[k], the weight W[k, n] is computed from the following two factors:

$$W_s[k,n]=\exp\left\{-\frac{d^2\{[k],[k-n]\}}{2\sigma_S^2}\right\}=\exp\left\{-\frac{n^2}{2\sigma_S^2}\right\} \tag{7}$$

$$W_g[k,n]=\exp\left\{-\frac{d^2\{Y[k],Y[k-n]\}}{2\sigma_R^2}\right\}=\exp\left\{-\frac{\left[Y[k]-Y[k-n]\right]^2}{2\sigma_R^2}\right\} \tag{8}$$

where, $\sigma_S^2$ and $\sigma_R^2$ are the variance of the Gaussian functions which form, the kernel of spatial and radio metric weight factors, respectively.

The final weight is the product of spatial and radio metric weight factors:

$$W[k,n]=W_s[k,n]W_R[k,n] \tag{9}$$

For the bilateral filter, optimum window size of 11*11, variance of the spatial weight factor Gaussian kernel = 10 and variance of the radiometric weight factor Gaussian kernel = 1.3 are opted through trial and error. Usually, the contrast between the brain structures and ROI may be poor so that contouring the ROI is difficult. For example, in the MR images used to test the proposed preprocessing, the GBM-focus and the perifocaledema exhibit fairly close intensities. The contrast between the brain structures and edema is also poor as evident in Fig. 1. Even though schemes like Histogram Equalization (HE) can be employed to enhance the contrast, HE either over enhances the noise or saturates the image. In HE, the degree of contrast enhancement is determined by the slope of the mapping function, which transforms the original intensity into contrast enhanced intensity. Hence, the enhancement of noise can be managed by manipulating the slope of the mapping function. In HE, the contrast enhanced intensity '$S_k$' is directly proportional to the cumulative probability density. The slope of the mapping function at any point is proportional to the height of the histogram at the corresponding intensity as apparent in (10). So that limiting the slope of the mapping function is equivalent to clipping the height of the histogram:

$$S_k=\frac{(L-1)}{MN}\sum_{j=0}^{k} n_j \quad k=0,1,2,\ldots,L-1 \tag{10}$$

where,

L = The maximum possible intensity, say 255 in a uint8 image
M*N = The total number of pixels
$n_j$ = The probability of occurrence of the $j^{th}$ intensity

CLAHE is an extension of the adaptive histogram equalization which improves contrast between morphologies and suppresses pixel intensity transitions in the homogeneous regions. In CLAHE (Karel, 1994), the image is divided into non-overlapping contextual region or tiles and the local histogram of the tile is computed. Prior to the estimation of the cumulative probability density and contrast enhanced intensity, histogram of each tile is clipped with respect to a user defined clip-limit. The clip-limit is a multiple of the average height of the histogram of the contextual region. Average height of the histogram is the ratio of total number of pixels present in the contextual region and the number of grey levels. In this respect, clip-limit is the product of the user-defined contrast factor, 'α' and average number of pixels falling in each histogram bin. For a contextual region of size 'M' rows and 'N' columns and L being the number of histogram bins, the clip-limit is given by:

$$n_T = \frac{\alpha MN}{L} \quad 0<\alpha \le 1 \tag{11}$$

The original height of the histogram of the contextual region is clipped with respect to the clip-limit $n_T$ such that:

$$h_k=\begin{cases} n_T & \text{if } n_k \geq n_T \\ n_k & \text{else} \end{cases} \quad k=1,2,\ldots\ldots L\text{-}1 \tag{12}$$

$n_k$ is the histogram of contextual region and:

$$\sum_{k=0}^{L-1} n_k = MN \tag{13}$$

Total number of clipped pixels:

$$n_c = MN - \sum_{k=0}^{L-1} h_k \tag{14}$$

To renormalize the histogram or to bring its area under the curve back to the original, the clipped pixels are redistributed back to the histogram bins. This redistribution can be uniform or distributing them into the bins with contents less than the clip-limit, in proportion to the number of pixels in the bin. Here, the clipped pixels are equally redistributed to all the histogram bins such that the bin content is less than the clip-limit. The number of clipped pixels to be redistributed to each histogram bin:

$$n_\mu = \frac{n_c}{L} = \frac{MN\text{-} \sum_{k=0}^{L-1} h_k}{L} \tag{15}$$

The clipped pixels are uniformly redistributed to all the histogram bins, provided the new histogram:

$$h_k=\begin{cases} n_T & \text{if } n_k + n_\mu \geq n_T \\ n_T+n_k & \text{else} \end{cases} \tag{16}$$

The number of undistributed pixels are again computed from (14-15) and the transformation (16) is repeated till all the clipped pixels get distributed uniformly to the histogram bins and the histogram grows back to the original area. The cumulative histogram of the contextual region is given by:

$$C_k = \frac{1}{MN}\sum_{j=0}^{k} h_j \tag{17}$$

Contrast of each tile is enhanced so that the histogram of the tile approximately matches with the histogram specified by the distribution parameter as uniform (flat), Rayleigh (bell-shaped) or exponential (curve shaped). The neighbouring tiles are combined using bilinear interpolation to eliminate artificially induced boundaries. The clip-limit and tile size opted here is 0.1 and 8*8, respectively and the distribution specified is uniform. This also was decided empirically, as the bilateral filter parameters. MR image after restoration and contrast enhancement is intensity threshold and connected components in the resulting binary image are labelled. As the intensity features of each MR image is different, an image adaptive threshold is computed using Otsu's method (Otsu, 1979). The mathematical way of estimating Otsu's threshold is as follows:

Let L is the maximum possible grey level in the histogram equalized MR image and the image contains grey levels, {0, 1, 2….L}. The normalized grey level histogram:

$$P_i = {n_i}/{N} \quad P_i \geq 0,\ \sum_{i=1}^{L} p_i = 1 \tag{18}$$

where, N is the total number of pixels in the MR image, $n_i$ is the number of occurrence of grey level 'i' and $p_i$ is its probability density function, given, i = { 0, 1, 2,…..L} and N = $\{n_1+n_2+....+n_L\}$. If the grey levels are assumed to be of two classes $C_0$ and $C_1$, separated by a threshold 'k', so that $C_0$ = 0, 1,…k} and $C_1$= {k+1…}, the probabilities of class occurrence:

$$\omega_0 = Pr(C_0) = \sum_{i=1}^{k} P_i = \omega(k) \tag{19}$$

$$\omega_1 = Pr(C_1) = \sum_{i=k+1}^{L} P_i = 1\text{-}\omega(k) \tag{20}$$

The mean grey level of classes:

$$\mu_0 = \sum_{i=1}^{k} i\,Pr\left({i}/{C_0}\right) = \sum_{i=1}^{k} {iP_i}/{\omega_0} = {\mu(k)}/{\omega(k)} \tag{21}$$

$$\mu_1 = \sum_{i=k+1}^{L} i\,Pr(i/C_1) = \sum_{i=k+1}^{L} ip_i/\omega_1 = \frac{\mu_T\text{-}\mu(k)}{1\text{-}\omega(k)} \tag{22}$$

$$\omega(k) = \sum_{i=1}^{k} p_i \tag{23}$$

$$\mu(k) = \sum_{i=1}^{k} ip_i \tag{24}$$

where, ω(k) and μ(k) are the zeroth and first order cumulative moments of the histogram up to the $k^{th}$level, respectively:

$$\mu_T = \mu(L) = \sum_{i=1}^{L} ip_i \tag{25}$$

$\mu_T$ is the global mean of histogram equalized image:

$$\omega_0\,\mu_0 + \omega_1\,\mu_1 = \mu_T,\ \omega_0 + \omega_1 = 1,\ \forall\, k \tag{26}$$

The class variances are given by:

$$\sigma_0^2 = \sum_{i=1}^{k}\left(i\text{-}\mu_0\right)^2 Pr(i/C_0) = \sum_{i=1}^{k}\left(i\text{-}\mu_0\right)^2 P_i/\omega_0 \tag{27}$$

$$\sigma_1^2 = \sum_{i=k+1}^{L}\left(i\text{-}\mu_1\right)^2 Pr(i/C_1) = \sum_{i=k+1}^{k}\left(i\text{-}\mu_1\right)^2 P_i/\omega_1 \tag{28}$$

To evaluate the performance of the threshold 'k', the following discriminant criterion is used:

$$\lambda = \sigma_B^2/\sigma_w^2 \quad K = \sigma_T^2/\sigma_w^2 \quad \eta = \sigma_B^2/\sigma_w^2 \tag{29}$$

where λ, K and η are within class variance, between class variance and the variance of total grey levels, respectively:

$$\sigma_w^2 = \omega_0\sigma_0^2+\omega_1\sigma_1^2 \quad (30)$$

$$\sigma_B^2 =\omega_0\left(\mu_0-\mu_T\right)^2+\omega_1\left(\mu_1-\mu_T\right)^2= \omega_0\omega_1\left(\mu_1-\mu_0\right)^2 \quad (31)$$

The global variance of grey levels:

$$\sigma_T^2 = \sum_{i=1}^{L}\left(i-\mu_T\right)^2 P_i \quad (32)$$

At optimum threshold k, the object function (29) maximizes.

The discriminant criteria maximizing λ, K or η for k, are however, equivalent to one another; e.g., K= λ+1 and η= λ/(λ+1) in terms of λ because the following basic relation always holds:

$$\sigma_w^2 + \sigma_B^2 = \sigma_T^2 \quad (33)$$

$\sigma_w^{2,}$ and $\sigma_B^2$ are functions of threshold level k, but $\sigma_T^2$ is independent of k, $\sigma_w^2$ is based on the second order statistics, while $\sigma_B^2$ is based on the first order statistics.

Therefore, $\eta$ is the simplest measure with respect to k. Thus at the optimum threshold 'k', the object function $\eta$ maximises.

The optimal threshold 'k' which maximizes $\eta$ or equivalently maximizes $\sigma_B^2$, is selected through a sequential search using (23) and (24), or explicitly using (19)-(22):

$$\eta(k) = \sigma_B^2(k)/\sigma_T^2 \quad (34)$$

$$\sigma_B^2(k)=\frac{\left[\mu_T\omega_{(k)}-\mu_{(k)}\right]^2}{\omega_{(k)}\left[1-\omega_{(k)}\right]} \quad (35)$$

And the optimal threshold k is:

$$\sigma_B^2\left(k^*\right) = \max_{1\leq k<<L} \sigma_B^2(k) \quad (36)$$

The MR image is converted to binary image by thresholding it with respect to the optimum threshold 'k' as in (37):

$$\widehat{B}(x,y) = \begin{cases} 1, \text{ if } B(x,y) \geq k \\ 0, \text{ else} \end{cases} \quad (37)$$

where, B(x, y) is the MR image after back ground elimination, restoration and enhancement, the $\hat{B}(x,y)$ is the binary image generated via intensity threshold. The connected components in the binary image are labelled. Region properties, area and solidity of each labelled regions are estimated. Labelled region, presenting area above half of the maximum area are identified as high solidity regions. This high solidity labelled region, exhibiting highest area, corresponds to the brain region. A multiplication mask, similar to the mask used in background elimination was generated by hole-filling this 'high solidity-high area' region. The skull stripped image is:

$$U(x,y) = S(x,y)\times F(x,y) \quad (38)$$
$$x = \{1,2,3,\ldots\ldots M\} \text{ and } y = \{1,2,3,\ldots\ldots N\}$$

where, 'F' is the binary multiplication mask and 'S' is the MR image after background elimination, bilateral filtering and CLAHE.

## RESULTS AND DISCUSSION

The combination of pre-processing, background elimination, bilateral filtering, enhancement with CLAHE and skull stripping is experimentally proved to

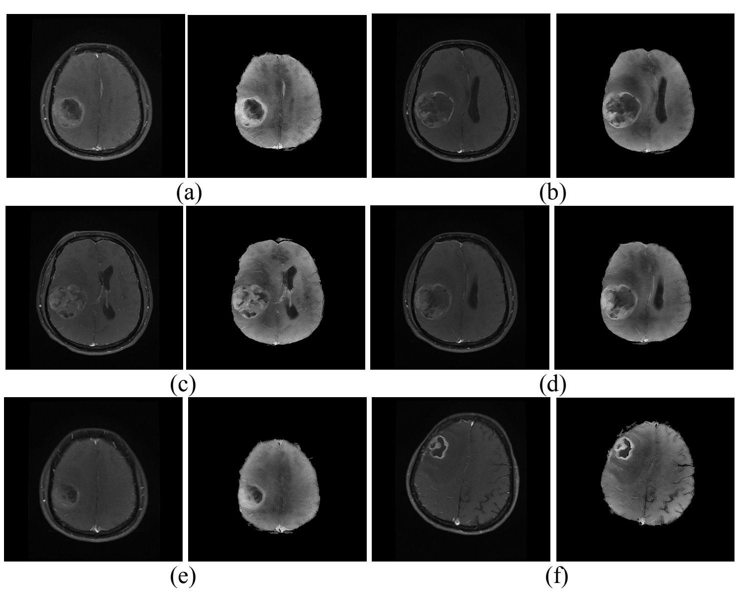


Fig. 3: Original image specimens and its pre-processed versions

be viable on Axial Plane T1 contrast enhanced MR images of Glioblstoma Multiforme-edema complex. Figure 1 demonstrates the images after each step of preprocessing. It is apparent from the Fig. 1a and b that the structures other than the morphologies are removed from the raw MR image after background elimination. Bilateral filtering well preserves the weak edges among the morphological structures while smoothening the noise inherent in homogeneous regions. It is obvious from the qualitative inspection of the contrast enhanced image that CLAHE has good noise suppression capabilities and the degree of contrast enhancement is sufficient to support characterization of tissue classes such that even primitive segmentation methods can yield accurate outcomes. As skull stripping accurately extracts the brain region, effectively eliminating skull and scalp, the number of tissue classes in the resultant image comes down and this would enhance the accuracy of segmentation, especially when K-means or EM are employed.

Six sets of raw MR images and the corresponding preprocessed images are illustarted in Fig. 3.

## CONCLUSION

A combination of background elimination, restoration, enhancement and skull stripping schemes were successfully demonstrated on axial plane T1 weighted MR images. The background elimination could remove structures other than morphology from the image grid. Edge sensitive bilateral filter could preserve the weak edges between the tumor-focus and the perifocaledema during smoothening. CLAHE exhibits good noise suppression capabilities and it is immune to saturation. The skull stripping methodology, adopted could extract the brain region perfectly. As the pre-processing steps proposed here are robust and adaptive, segmentation algorithms would yield better outcomes.

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