IMPLEMENTATION OF DIFFERENTIAL EVOLUTION ALGORITHM TO PERFORM IMAGE FUSION FOR IDENTIFYING BRAIN TUMOR

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ABSTRACT

Automated mechanization for curing a disease is a reliable and protuberant method. A disease in brain can be detected by Magnetic Resonance Imaging (MRI). In this context, image fusion is a method for creating an image by merging pertinent data from 2 or more images. The resultant image will be highly useful than the individual input images to retentive the vital characteristics of every image. Multiple image fusion is a significant method employed in image processing techniques. In this study, differential evolution (DE) algorithm-based image fusion has been performed with MRI and computed tomography (CT) images. The simulation works have been carried out to evaluate the different quality measurements of DE on image fusion.

KEYWORDS

De-speckling, Brain tumor detection, CT, DE, Image fusion, MRI.

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1. INTRODUCTION

Brain tumours is harmful to humans, due to the atypical availability of cells inside the brain. Brain function will be interrupted and be deadly. Benign and malignant tumors are frequently identified. Benign tumors are not as harmful as malignant tumors, because they can grow rapidly. Medical imaging methodologies such as MRI, CT, Ultrasound, X-ray etc. are employed to display the internal body parts for diagnosing (Rowden, 2019). Among them MRI is widely employed and it offers accurate brain images and cancer cells. So, brain tumor can be detected via MRI images. This study concentrates on detection of brain tumor through image fusion. Image fusion is a process of merging two or more images into a single compound image that contains the information of the source images without clamor. Multi-modular recuperative image fusion has been employed to recognize the wounds. In biomedical image processing image fusion has got more attention in the past decade (Daneshvar & Ghassemian, 2010; Wang, Li, & Tian, 2014). MRI and CT images held more practical information than biomedical images. The aim of image fusion is to obtain the information at each pixel without damaging the pixel associations of the particular image.

In this context, previously, a complex wavelet modification for image fusion has been proposed to attain the optimal combination using Lifting wavelet transform (LWT), Multiwavelet transform (MWT), Stationary wavelet transform (SWT) and spatial domain (Principal component analysis (PCA) approaches (Singh & Khare, 2014). Similarly, undecimated wavelet has been implemented, where the image is crumbled into two successive scrutinizing errands (Ellmauthaler *et al.*, 2013). An affable fusion technique using SWT and NSCT has been presented, where the input image is rotten by SWT and NSCT. The coefficients of SWT and NSCT are combined to form the fused image (Li & Liu, 2009). A new framework has been proposed where the images considered with SWT primarily and the overall textural topographies have been attained via gray level co-occurrence matrix (Singh & Khare, 2014; Huang *et al.*, 2014; Shi & Fang, 2007). Hence, a scheme for fusing MRI and CT images using DE based Debauchee's wavelet Transform (DE-DWT) has been attempted in this study.

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2. MATERIALS AND METHODS

As a part of image fusion, pre-handling of images have been performed using DE. DE has been employed to create the fission rubrics. The preprocessing steps involved in image fusion have been illustrated in Figure 1.

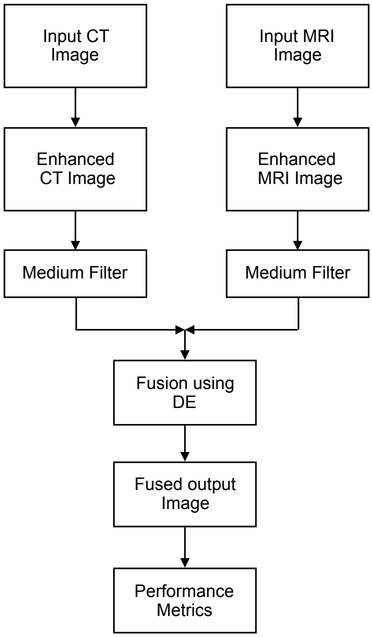

Figure 1. Flowchart of proposed approach.

Primarily, the informative source images such as CT and MRI images have been collected. Subsequently, the source images have been converted into dark scale and resized. The enhancement of quality of the images has been performed using imadjust order available in MATLAB simulation. Commotion dismissal has been carried out by using median channel. This is an excellent method in ejecting salt and pepper commotions of biomedical images. It happens due to the movement of antiquities.

Performance indices such as Mean Square Error (MSE), Peak Signal to Noise Ratio (PSNR), contrast and homogeneity have been estimated. The amount of clamor available in the image is denoted as PSNR. It is used to indicate the obtained fused image has tumbled-down or not. MSE value need to be low and PSNR value need to be high.

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$$MSE = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[(i,j) - K(i,j)]^2 \tag{1}$$

$$PSNR = 20\log_{10}\left(\frac{MAX}{\sqrt{MSE}}\right) \tag{2}$$

Contrast reinstates the data associated with the pixel with the adjacent pixel. It has been calculated as follows.

$$Contrast = \sum (i-j)2 \times P(i,j) \tag{3}$$

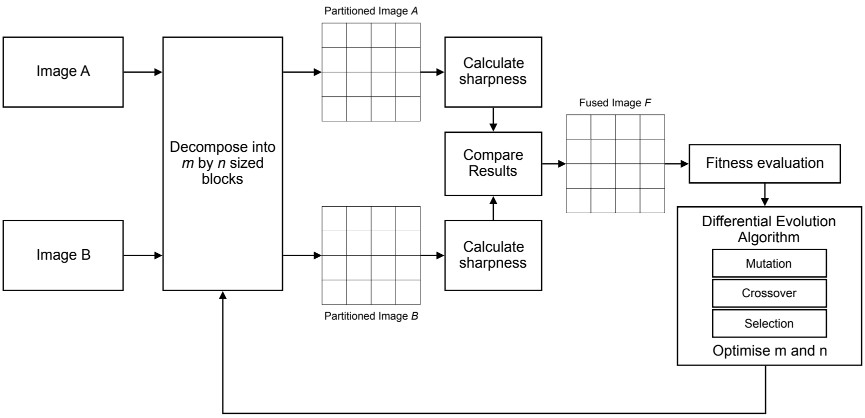

Figure 2. Flowchart for image fusion using DE.

Table 1. Best parameters of DE.

Parameter	Value
Number of population	100
Maximum generation	100
Crossover probability	0.5
Scaling factor	0.9

Homogeneity has been used to estimate the intimacy of components availed in gray level concurrence matrix (GLCM).

3. DIFFERENTIAL EVOLUTION ALGORITHM

Price and Storn introduced DE as a population-based stochastic direct search technique. The implementation procedure of DE has been adopted from Aslantas and Toprak (2014).

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The steps involved in DE based image fusion have been illustrated in Figure 2. The best control parameters for DE have been provided in Table 1.

The performance indices such as MSE, PSNR, Contrast, Entropy and Homogeneity have been presented in Table 2.

Table 2. Performance indices of DE on image fusion.

SET	MSE	PSNR	Entropy	Contrast	Homogeneity
1	12447	5.4875	10.1457	0	1
2	10253	6.0248	11.2488	0	1
3	17305	8.1027	12.5761	0	1

4. RESULTS AND DISCUSSIONS

MRI and CT images have been fused together using DE. The ultimate objective of image fusion is to acme the valuable data from various input images. The adaptive fuzzy clustering rule has been employed to fragment the region of interest (ROI) to isolate the tumor from the resultant fused image. It will group the various grade intensity segments of the fused image. The segments with huge grade intensity are marked as the tumor, and they have been isolated using thresholding method (Chabira, Skanderi, & Aichouche, 2013).

Figures 3 (a), (b), (c) and (d) provide the information about the CT and MRI images which are processed for fusion. Figures 3 (a) and (b) displays the gray scale CT and MRI images respectively. Figures 3 (c) and (d) demonstrate the median filtered CT and MRI images respectively. DE-DWT has been involved in the fusing mechanism. Using the fusing rules, fusing rules, the input images have been combined. Diverse levels have been fixed to decide clamor data adversity in the image. Figures 4 (a) and (b) demonstrate decomposed CT and MRI images. Figure 5 illustrates the resultant fused image with decent idiosyncratic enrichment. By following the DE-DST rule, least value of CT is combined with the least level decomposed MRI image to form the fused image.

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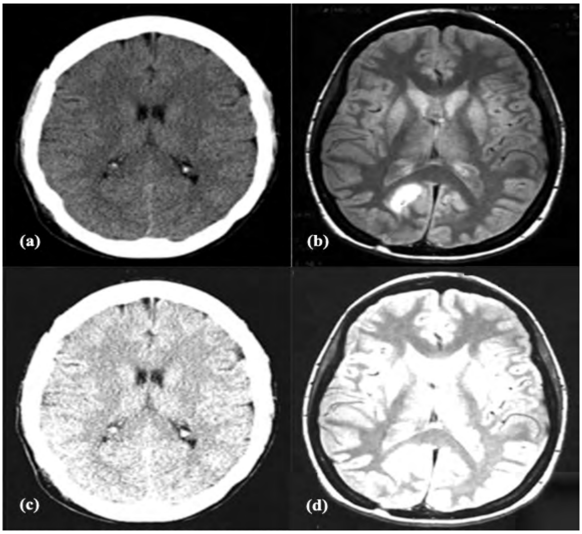

Figure 3. (a) Gray scale CT image (b) Gray scale MRI image (c) Median filtered CT image (d) Median filtered MRI images.

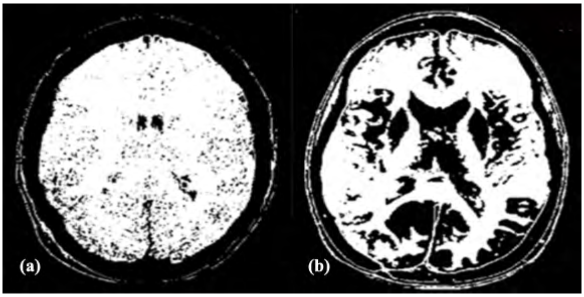

Figure 4. (a) Decomposed CT image (b) Decomposed MRI image.

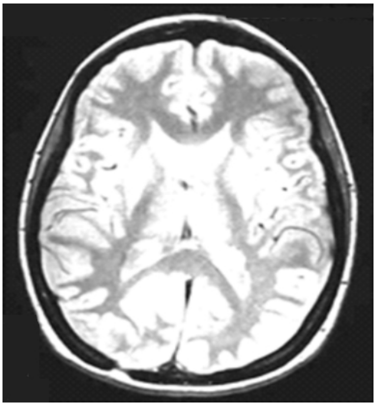

Figure 5. Resultant fused image.

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5. CONCLUSION

A typical muscles grown in brain disturb brain activities and that is referred as brain tumor. Biomedical image processing aims to recognize precise data through images with minimum error. Detection of brain tumor via MRI images is not easy due to the intricacy of brain. A pixel based image fusion procedure using DE-DWT has been proposed in this study. The simulations have been carried out with CT and MRI images. The performance indices such as entropy, MSE, PSNR, contrast and homogeneity imply the effectiveness of the proposed DE-DWT approach.

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