International Journal of Computer (IJC)
ISSN 2307-4523 (Print & Online)

http://ijcjournal.org/

Stationary Wavelet Transform(SWT) Based MRI Images Enhancement and Brain Tumor Segmentation

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Abstract

Brain tumor is the anomalous growing of Brain cancer cells. Because of its complex structure, brain tumor segmentation and identification are very difficult tasks in medical field. As with MR image processing, MR images are particularly sensitive to noise, resulting in errors in image acquisition and transmission such as Gaussian noise and impulse noise, etc. MRI image is filtered with Median filter and Wiener filter simultaneously to improve the MR image The Stationary Wavelet Transform (SWT) is then used to combine both Median and Wiener filter results. After preprocessing, Adaptive K-means clustering is used for image segmentation. In the post processing step, morphological operation and Median filter are used to get better segmentation results. This method is applied to the BRATS-2015 dataset, which consists of multi-sequence MRI data available to the public from patients with brain tumors. The well-known, based line methods are compared for comparing the proposed system. Mean Square Error (MSE) and Peak Signal Noise Ratio (PSNR) are used in evaluation of the enhancement. For testing tumor segmentation measures, True Positive Rate (TPR), True Negative Rate (TNR), Accuracy, and Jaccard Similarity Index are used. Compared with dependent line methods and state of the art, this system performs well, especially for the entire tumor area.

Keywords: Stationary Wavelet Transform; Adaptive K-means Clustering; BRATS.

1. Introduction

Many physicians, particularly therapists, need both spatial and spectral data mainly in the field of medicine for stages such as research, disease tracking, and evaluation of existing problems and also for the treatment of these problems using a single image modality.

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If we require high spectral and spatial information in an image from two separate image modalities, image fusion becomes very important. There are two fields that are used to focus multi-focus images, the first being spatial domain and the next being transform domain. Spatial domain method works on pixels directly and fuses images using linear or non-linear methods. Spatial scope restricts image blurring and the loss of fine detail. The methods for transform domain are applied to address the constraint of the spatial domain. Images are divided into frequency components in this domain, and then these decomposed components are fused to produce the new improved final fused image. A wavelet transform method is the perfect transforming tool for multi-image fusion. All the method of transforming a domain has three phases for image fusion [1]. Firstly, there is a decomposition of images. Firstly, a fusion rule fuses sub-bands of decomposed images and the last fused sub-bands are recovered using the inverse transform process. Discrete Wavelet Transform is commonly used to combine the images, but has many drawbacks, such as weak directionality, not a time-invariant transformation. For image fusion Stationary wavelet transformation is introduced to address these limitations. SWT has very little processing power. Different filters are used to enhance the quality of fused image. In this paper, we proposed a noise filtering approach and modified SWT fusion technique to improve the contrast and fused image quality. The paper is structured as follows: In Section I, related works are described. In section III, the Background Theory of proposed system is presented. In section III, the proposed the architecture of system and modified SWT fusion rules are described. In section IV, the Experiment results of the proposed Algorithm are shown. And in Section V, conclusion of the research work is presented.

2. Related Work

Medical images are acquired from various modalities and different types of equipment which convey different information. Single image may not provide enough information to examine for diagnostic purposes. This involves the use and integration of different images obtained from different techniques. Image fusion incorporates complementary knowledge based on specific rules from various modalities to provide an improved visual image of a scenario appropriate for further processing [2]. Oumaima El Mansouri et.al proposed a new fusion approach for magnetic resonance imaging (MRI) and ultrasound (US) data incorporating two reverse problems: MRI reconstruction using super-resolution and U.S. image de-speckling, using an unknown polynomial feature model that relates the two modes. They illustrated the accuracy of the suggested fusion algorithm, using synthetic data, through quantitative and qualitative evaluation. The resulting fused image is considered in contrast with the native MRI and US images [3] to have an improved signal to noise ratio and spatial resolution. This paper was researching a new method of fusion for photos from MR and US. The recommended method was able to rebuild an image enclosing information from both images by resolving an inverse super-resolution problem for magnetic resonance images and an ultrasound image de-speckling problem. Using correct statistical models and a polynomial relationship between the images of awareness, these two problems were solved jointly. Results obtained on simulated images obviously demonstrate the benefit of integrating the information provided by these two modalities, rather than using it separately. The new pixel level fusion technique was suggested by A. Min and his colleagues on the findings of Median filter and Wiener filter. They suggested the results fusion approach for improving the picture and integrating adaptive clustering k-means with morphological activity for segmentation of tumors. All experimental results will be experienced on multimodal BRATS images from Benchmark Brain Tumor Segmentation dataset. There are two sections primarily in this article. First part is improvement of the MRI image and second part is segmentation of the tumors. The proposed method of enhancement is compared in the first part with Median filter and Wiener filter. In the second part the results of the proposed segmentation are compared with the results of the base line segmentation methods [4]. The paper suggests state-of - the-art strategies for tumor detection using the Watershed Dynamic Angle Projection-Convolution Neural Network (WDAPP-CNN). The tumor area is precisely segmented by the Watershed algorithm. The proposed segmentation and classification of brain tumors is implemented via the features of the Water Shed Algorithm (WSA), Dynamic Angle Projection Pattern and these features are categorized using CNN. The value of the Watershed segmentation algorithm is that it efficiently extracts the tumor regions for proficient extraction of the DAPP function. The DAPP extracts the texture features from the segmented tumor areas, and obtains histogram features. Such feature vectors are added to the classifier input for CNN that performs the classification. For the proficient diagnosis of brain tumor, segmentation and classification of the MRI brain image is needed. The experimental results are implemented via the BRATS database [5]. Minal Padlia et.al, proposed from the complex T2-weighted brain MRI image a fractional sobel mask and watershed transform dependent tumor segmentation scheme. The maxima image of the regional production is taken as an internal marker. Distance transformation based watershed transformation is performed on regional maxima image; the ridge lines of the watershed are used as external markers. Over watershed transformation segmentation problem is primarily regulated by internal and external markers derivative from morphological characteristics (localized regional maxima) and distance-based watershed transformation (separates regions created from internal markers) ridge lines, respectively. Fractional order sobel mask generates sharper gradient magnitude image, as this mask improves the specifics of the medium frequency texture and is less noise sensitive [6].

3. Background Theory

In this paper, Stationary Wavelet Transform (SWT) is used to fuse the results of Median Filter and Wiener filter to enhance the quality of MRI images. Adaptive K-means clustering is used to segment brain tumors from MRI images. As finally step, Morphological Operation and Median filter are used to get exact tumor segmentation results.

3.1. Median Filter

Gaussian noise and Impulse noise are famous noises that are spreading in images of MR magnitude and are inescapable. It's affected by malfunctioning pixels in camera sensors, defective hardware memory locations, or a noisy channel transmission. It is independent forever and uncorrelated to the image and pixels of MR. Median filter is popular method for eliminating this noise. Median filtering is related to using an average filter in that each pixel is set to an average of the pixel values in the corresponding input pixel neighborhood. Therefore, median filtering is well capable of removing this outlier without raising the picture sharpness. The formulation of Median filter is shown as below:

$$f(x, y) = median\ \{g(s, t)\} \qquad (1)$$

Where, S_{xy} is the set of coordinate in a rectangular sub MR image window which has center at (x,y). f(x,y) is the restored image and g(s,t) is corrupted and calculated area under the S_{xy} .

3.2. Wiener Filter

During processing Gaussian noise in MR images occurs. Unique of the oldest and best known methods to updating linear images is the Wiener filtering or adaptive filtering. Thanks to the Wiener filter linear movement, the most effective technique for removing noise in images is. The main improvement is that a short time of measurement finds a solution and it is intended to reduce the amount of noise in the picture. The restored image is calculated as follows:

$$f'(x,y) = \mu + \frac{\sigma^2 - \nu^2}{\sigma^2}\left(f(x,y) - \mu\right) \qquad (2)$$

where, μ is local mean of each pixel, σ^2 means local variance of each pixel, ν^2 is noise variance, $f(x,y)$is original degraded image, $f'(x,y)$ refers the restored image.

3.3. Stationary Wavelet Transform (SWT)

In Undecimated Wavelet Transform or stationary wavelet Transform (SWT) the signal is represented with same number of wavelet coefficients by neglecting the decimation process after convolution. SWT does not used down sampling techniques in image decomposition and reconstruction. Therefore, the sub-band of SWT will have the same size. This point is difference between DWT and SWT. SWT was planned to overcome the lack of DWT (Discrete Wavelet Transform) translation-invariance. SWT needs more calculation and calls for greater memory, allows for improved de-noise efficiency and better edge detection capability. SWT perform better in denoising, edge detecting, and image fusion and break down point detection. SWT transforms the original image into four parts which can be labeled as LL1, LH1, HL1& HH1.

3.4. Adaptive K-means Clustering

Clustering is the function of grouping a collection of objects so that objects in the same category (referred to as a cluster). A standard clustering technique is based on K-means, so that the data is divided into K clusters. The disadvantage of the clustering approach is to assign the user the initial point and the control number for iteration. The adaptive clustering of K-means was resolved with the drawback of K-means Clustering. This algorithm is based on calculating distance between a given entity and a cluster. The distance between the pixels is determined using the Euclidean distance. It starts with the selection of K elements from the input data. It takes as the initial seed point the mean value from the pixels of the MR image. It can find the optimal stage of stop iteration and produce the satisfied results from the MR image.

3.5. Morphological Operation

Morphological operation often takes as input and in combination with the use of a switch a binary image and structural element (intersection, union, inclusion, and complement). It is also possible to use these methods to find specific paths in the image. In this system, morphological methods of closing and opening are employed.

4. Proposed System and Methods

The proposed system accepts MRI image and this image are converted to Grayscale image. Then image size 240 X 240 is used in this system. After finished the above steps, the grayscale image is filtered and removed noise by using Median filter and Wiener filter. Stationary Wavelet Transform (MSWT) is used to fuse the results of Median filter and Winer filter. Adaptive K-means clustering is used to segment the tumor area. Morphological operation and Median filter are used to get the better results.

4.1. MRI images Enhancement

The modified Stationary Wavelet Transform is the main contribution of the research. SWT accepts the MRI image and it decomposes the MRI image to four subbands. They are Approximation (A), Vertical (V), Horizontal (H) and Diagonal (D). In this paper, SWT used two- level decomposition. Thus, the image that filtered with Wiener filter is decomposed to two- level decomposition. For this image, A1L1 (Approximation), V1L1 (Vertical), H1L1 (Horizontal) and D1L1 (Diagonal) are one level decomposition. And then, A1L1 is decomposed to get two-level decomposition. Thus, A1L2, V1L2, H1L2 and D1L2 are subbands of two-level decomposition. The rest image that filtered with Median filter is also performed same above process. The system gets four subbands (A2L1, V2L1, H2L1, D2L1) for one level-decomposition and four subbands (A2L2, V2L2, H2L2, D2L2) for two-level decomposition. After finished the decomposition both of two images (Wiener image and Median image), the proposed fusion rules are used to fuse on each level decomposition subbands respectively. Fusion rules are applied on each subband according to Figure (1) and Figure (2).

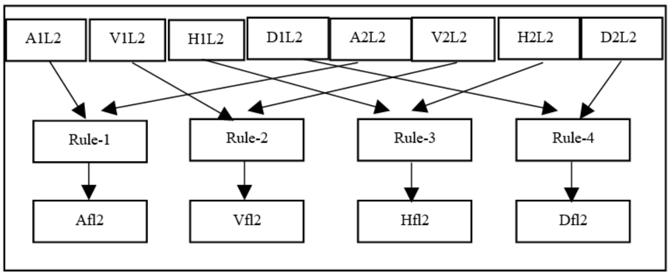

Figure 1: Level 2 Fusion on SWT Decompositon

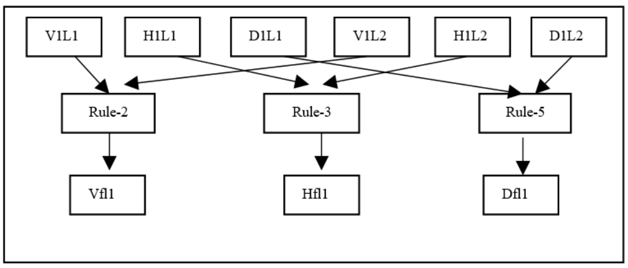

Figure 2: Level 1 Fusion on SWT Decompositon

The system proposed the fusion rules on Stationary wavelet transform. The approximation coefficients of A1L2 and A2L2 are fused with Rule-1. V1L2 and V2L2 are fused with Rule-2, H1L2 and H2L2 are fused with Rule-3 and D1L2 and D2L2 are fused with Rule-4 respectively. The proposed rules are described as follow:

Rule1:

$$\text{if } S1_{(\text{coefficient})} >= S2_{(\text{coefficient})} \tag{3}$$

$$F\,A = S1_{(\text{coefficient})}$$

Else

$$F\,A = S2_{(\text{coefficient})}$$

Where, $S1_{(\text{coefficient})}$ is modified approximation coefficients of Wiener image and $S2_{(\text{coefficient})}$ is modified approximation coefficients of Median image. F A refers to fusion the approximation coefficients. $S1_{(\text{coefficient})}$ and $S2_{(\text{coefficient})}$ are modified with the following (4).

$$S = ((Smax - Smin)/(rmax - rmin))(r - rmin) + Smin \tag{4}$$

$$S_{max} = \frac{\sum_{i=1}^{M\times N} ri}{M\times N} \tag{5}$$

Where, S is Modified coefficient of Output, S_{max} is Maximum coefficient of Output, S_{min} is Minimum coefficient of Output, r is coefficients of Approximation, r_{min} is Minimum coefficient of Approximation and r_{max} is Maximum coefficient of Approximation.

Rule-2:

$$FV = max\,(V1, V2) \tag{6}$$

Where, FV is fusion coefficients of Vertical, V1 is vertical coefficients of Wiener image and V2 is vertical coefficients of Median image.

Rule-3:

$$FH = max\,(H1, H2) \tag{7}$$

Where, FH is fusion coefficients of Horizontal, H1 is horizontal coefficients of Wiener image and H2 is horizontal coefficients of Median image.

Rule-4:

$$FD = max\,(D1, D2) \tag{8}$$

Rule-5:

$$FD = min\ (D1, D2) \quad (9)$$

Where, FD is fusion coefficients of Diagonal, D1 is diagonal coefficients of Wiener image and D2 is diagonal coefficients of Median image. After fusion each of subbands and each level, Inverse Stationary wavelet transform (ISWT) is used to get the reconstructed image or enhanced image. The process of ISWT is presented in Figure (3).

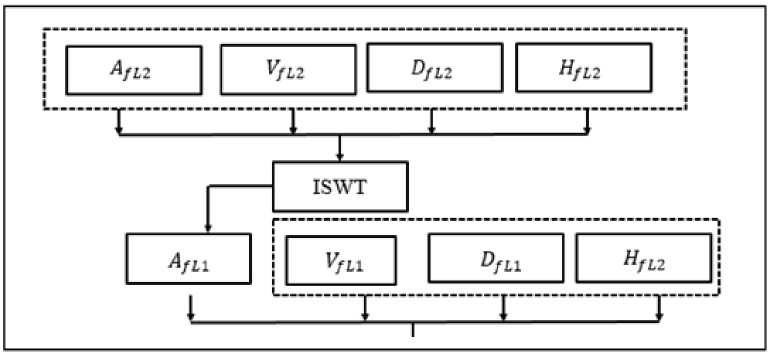

Figure 3: Reconstruction with ISWT

4.2. MRI images Segmentation

In this paper, adaptive K-means clustering, morphological operation and Median filter are used in MRI image segmentation. After the MRI image enhanced by using modified stationary wavelet transform, the system receives this enhanced image and it is segmented with adaptive K-means clustering. Then, morphological operation and Median filter are used to get exact shape and size of tumors. In morphological operation, opening and closing operators is used. The string length value of closing is [1 1 1 1 1 1 1 1 1 1 1 1] and opening is [1; 1; 1; 1; 1; 1]. Median filter used [5X5] window size.

5. Experimental Results

In this research, BRATS-2015 brain tumor dataset is tested. In this dataset, T1c, T1, T2 and Flair sequences include. And then, 220 folders of High grade glioma (HGG), 54 folders of Low grade glioma and 110 folders of High grade glioma and Low grade glioma (HGG,LGG) contain in this dataset. For experimental results, there are two mainly parts in this paper. First part is the evaluation results of MRI image enhancement. For this evaluation, 40 flair images of HGG_LGG (Brats 2015) are used. In this portion, Mean Square Error (MSE) and Peak Signal Noise Ratio (PSNR) are used to evaluate and the proposed method is compared with Median filter and Winer filter. Second part is the evaluation results of MRI image segmentation. In this portion, True positive rate (TPR), True negative rate (TNR), Accuracy (A) and Jaccard similarity index are used to evaluate.

Table 1: Average Result of HGGLGG

Methods	MSE	PSNR (dB)
Median	35.5557	33.3925
Wiener	32.9356	33.2784
Proposed	15.2767	36.9693

In these experimental results, the methods that get minimum MSE value and maximum PSNR value are the best. Thus, the proposed preprocessing is the best in this comparing. For MRI image segmentation, the flair sequence of Brats 2015 dataset is used. In Brats 2015 dataset, there are four sequences. They are T1, T1c, Flair and T2. T1 describes the brain area. T1c describe the enhancing tumor area. T2 describes the core tumor area. Flair describes the whole tumor area. Therefore, Flair sequence is used in this experiment.

Table 2: Average Result of HGGLGG

Methods	TPR (%)	TNR (%)	Accuracy (%)	Jaccard
Proposed	90.8067	98.6602	98.3588	0.691
PSO	71.6429	98.9895	96.6874	0.599
Fuzzy C-means [7]	39.0222	99.3624	89.4423	0.365
K-means [7]	58.5538	98.1433	96.9151	0.494

Agreeing to the experimental results of Table (2), the proposed system got the satisfying results and it is better than other compared methods in HGG, LGG. The results of Otsu thresholding and Particle Swarm Optimization are almost the same. The rest methods do not get the reliable and satisfied results.

Table 3: Average Result of HGG

Methods	TPR (%)	TNR (%)	Accuracy (%)	Jaccard
Proposed	87.3049	98.8040	98.3204	0.674
PSO	53.3067	99.3846	93.9942	0.485
Fuzzy C-means [7]	35.3104	99.4774	88.8088	0.333
K-means [7]	57.2887	98.4245	97.0592	0.498

The experimental results of High-grade glioma are described in Table (3). According to the experimental results, the proposed method is better than other compared methods. In Table (4), the evaluation results of Low-grade glioma are presented. Low grade glioma is the step-1 and step-2 of malignant cancerous cell state. Therefore, LGG spreads cancerous cell slowly and it is difficult to segment. The proposed system's segmentation result is satisfying for medical image processing. Table (5) describes about the sensitivity comparison of Brats- 2015 dataset.

Table 4: Average Result of LGG

Methods	TPR (%)	TNR (%)	Accuracy (%)	Jaccard
Proposed	88.9234	98.7298	98.2878	0.689
PSO	65.7619	99.2766	95.2747	0.572
Fuzzy C-means [7]	47.1952	99.3862	91.9287	0.436
K-means [7]	62.1615	98.3716	97.271	0.516

Table 4: Average Result of TPR in 2015 Brats Dataset

Methods	HGG	LGG	HGG,LGG
Proposed	87.3049	88.9234	90.8067
Maier, O. and his colleagues [9]	-	85	-
Pereira, S. and his colleagues [10]	86	88	86

6. Conclusion

In this study, a model for the segmentation of Brain tumor is proposed and experiments are conducted on the 2015 benchmarking dataset. Manual segmentation in brain tumor is a time-consuming task. The proposed segmentation algorithm can reduce the time-consuming task. The proposed segmentation algorithm is easy to implement and requires no changes in any parameters because of unsupervised nature. It also provides good segmentation results. To improve the accuracy for the segmentation, the proposed preprocessing method can supply to the segmentation method well. The proposed segmentation algorithm is compared with the base-line methods. The segmentation results got satisfying. It can be concluded from the experimental results that the proposed system can be effectively used by patients and physicians to diagnose.

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