



A NON LINEAR TEAGER APPROCH TO TUMOR IDENTIFICATION IN MAGNETIC RESONANCE IMAGING

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ABSTRACT

Brain tumors are the leading cause of the cancer death. Brain tumor is affected by uncontrolled and abnormal growth of cells in spinal canal or brain. Brain tumor detection is the most challenging and essential task in medical-image applications. Brain image analysis is a complex, difficult and time-consuming task to detect the malignant brain tumors. Artificial intelligence-based brain tumor classification plays essential role in medical diagnosis. Automated deep learning approach is employed for efficient tumor detection to automatically learn relevant characteristics and complex relationships. Different researchers carried out their research on brain tumor detection. Magnetic resonance images (MRI) is significant in medical diagnosis as it provides detailed information related to anatomical structures as well as abnormal tissues of the body for treatment planning. The current medical imaging research is still a very difficult task to diagnosis the disease perfectly. Since the developed imaging system has more error for exact analysis. In order to overcome such issues, Regressive Nonlinear Teager Filter based MAP Estimated Relevance Vector Image Segmentation (RNTF-MAPRVIS) Method is developed for processing the brain MRI images with higher accuracy and minimum time. The numbers of brain MRI images are collected from the database. The RNTF-MAPRVIS method performs two major processes with medical images, namely preprocessing and segmentation. Initially, the Regressive Nonlinear Teager Filter process is used to remove the noisy pixels from the image. The designed filter analyzes the relationship of an image pixel to obtain super-resolution brain MR image through the

warping and interpolation. After preprocessing, MAP estimated Relevance Vector Machine based image segmentation process is carried out to segment the input preprocessed image for finding as normal or abnormal. In RNTF-RVIS Method, Relevance Vector Machine constructs the hyperplane uses Maximum a Posteriori that segments the images based on the similarity between the extracted features and testing features. After performing the segmentation, the input image is said as normal or abnormal.

Keywords: Magnetic resonance images (MRI), preprocessing, Regressive Nonlinear Teager Filter, Maximum a Posteriori, Relevance Vector Machine Image Segmentation

1. INTRODUCTION

Magnetic resonance imaging (MRI) is a more efficient imaging method and efficient diagnostic tool in medical applications to analyze the information of internal body parts. MRI images are affected by the noise during collection and it minimizes the quality of the images. The removal of the noisy image without corrupting the original images is essential for exact analysis. Therefore, the noise reduction technique is essential for the medical image in the medical field. In addition, image segmentation plays a major role in image processing in order to represent an image in a simply analyzable way without difficulty. Several image processing techniques have been introduced for filtering and segmentation. However, accurate analysis was not performed. In order to improve performance, machine learning techniques are used in the proposed work.

A small kernels two-path convolutional neural network and random forests (SK-TPCNN+RF) was introduced in [1] for processing the MRI images to segment the brain tumors. But, the performance of peak to signal ratio was not improved. A modified level set method was developed in [2] for brain tumor segmentation and removing the noise. Though the PSNR was improved, it failed to improve the segmentation accuracy of the abnormal brain and normal MRI brain images.

A clustering algorithm integrated with morphological operations was developed in [3] to segment the brain tumors images. But the performance of segmentation time was not minimized. A multicascaded convolutional neural network (MCCNN) was introduced in [4] for segmenting the brain tumor images. Though the model has less computation time, the performance of the peak signal to noise ratio remained unsolved. In [5], a multi-modality aggregation network (MMAN) was presented to extract multi-scale features of the brain for improving the segmentation accuracy. But it failed to use the accurate filtering technique for noise removal.

A fully convolutional neural network was developed in [6] for segmenting the brain tumors images. Though the designed model improves the segmentation, the time consumption was not minimized. A Markov multiple feature random fields (MMFRF) method was designed in [7] to segment the brain MR image. The method failed to minimize the artifacts of the images.

A Wiener filtering technique was introduced in [8] for noise reduction to classify the brain images using random subspace ensemble classifier. The designed technique failed to analyze the performance of the image quality through the peak signal to noise ratio.

A texture feature and kernel sparse coding method was developed in [9] for automatic brain tumor segmentation with minimum computation cost. The developed method failed to improve the segmentation performance. Random forests combined with an active contour model was introduced in [10] for the automated segmentation of the MR images. The feature learning was not improved to obtain higher segmentation accuracy.

1.1 Proposal contribution

The major issues reviewed by the above-said literature are overcome by introducing a novel method called RNTF-MAPRVIS. The overall contribution of the proposed RNTF-MAPRVIS method is summarized as follows,

- ◆ To improve the peak signal to noise ratio, RNTF-MAPRVIS uses the regressive nonlinear Teager filtering technique. The machine learning technique called regression is used for analyzing the adjacent pixels. Followed by, the warping and interpolation of the image sequence are measured for digitally manipulating an image and correcting the image distortion. Finally, the median denoising is performed to remove the noisy pixels.
- ◆ To improve the segmentation accuracy, MAP estimated relevance vector machine is applied in the RNTF-MAPRVIS method. The relevance vector machine constructs the hyperplane to segment the input preprocessed images into the normal or abnormal by measuring the similarity between the features. The extracted features are highly correlated with the disease testing feature, and then the images have a higher probability for classified into an abnormal.

1.2 Outline of the paper

The outline of the paper is organized into five different sections. Section 2 discusses the literature review using MRI imaging techniques. Section 3 briefly describes the proposed RNTF-MAPRVIS method for MRI image processing. Finally, section 4 concludes the paper.

2. LITERATURE REVIEW

A Berkeley wavelet transformation (BWT) based tumor segmentation was introduced in [11] to enhance the performance and minimize the complexity. But it failed to improve the accuracy of the classification of the tumor as normal or abnormal. A deep convolutional neural network (CNN) was developed in [12] to classify the brain tumors from the MRIs. But the designed model failed to perform the denoising to enhance the image contrast. An adaptive differential evolution algorithm was designed in [13] for MRI brain image segmentation. However, the algorithm failed to make it less sensitive to noise.

A fully convolutional neural network (CNNs) was developed in [14] to improve the accurate brain tissue segmentation. The segmentation time was minimized but the model failed to analyze the pixels for improving the image contrast by removing the noisy pixels. A 3D supervoxel based learning model was designed in [15] for segmentation of tumor from the multimodal MRI brain images. But the more detailed segmentation of tumor tissue was not performed.

A possibilistic fuzzy c-means (FCM) method was introduced in [16] Based on a similarity to enhance the segmentation performance for MRI brain images. The method minimizes the error rate but the performance of segmentation time was not minimized.

Deep learning with a convolutional neural network was introduced in [20] for image segmentation with higher accuracy. The designed method preprocessing the images but the peak signal to noise ratio was not improved. The major issues of the existing reviews are overcome by introducing a new technique called CWFE-BAC technique. The description

of RNTF-MAPRVIS Method with the neat diagram is explained in the next section.

3. Methodology

In medical image processing, the MRI image produces high-quality representations of the parts in the human body. The MRI image analysis is a very important process for providing the proper treatment at the right stage for the infected individual. In general, there are various imaging modalities utilized for capturing the images of the organs in the body such as Ultrasound imaging, computed tomography (CT) and X-RAY radiography, magnetic resonance imaging (MRI), and so on. Among them, MRI is an accurate medical diagnostic instrument to provide accurate images for diagnosing the illness. In addition, the various image processing techniques with MRI is very hard for accurate diagnostic. Therefore, an efficient machine learning technique based segmentation is required to improve the MRI image processing. The new machine learning-based segmentation method called RNTF-MAPRVIS is introduced with two processing steps such as preprocessing and segmentation. The architecture with these two processes of the RNTF-MAPRVIS method is shown in figure 1.

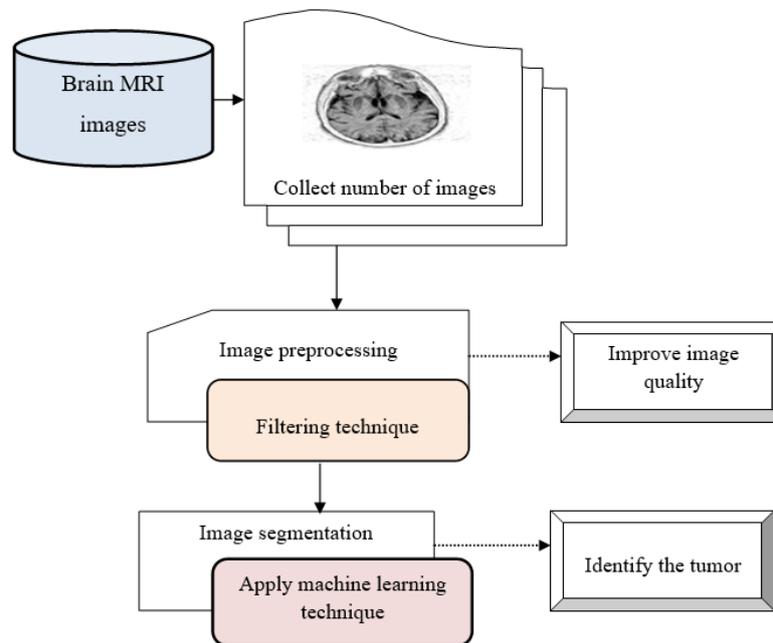


Figure 1 architecture diagram of proposed RNTF-MAPRVIS method

Figure 1 shows the architecture diagram of proposed RNTF-MAPRVIS method is to automatically detect the tumor from the MRI images. Initially, image acquisition is carried out where the number of brain images $bi_1, bi_2, bi_3, \dots, bi_n$ are collected from the MRI

image database. Followed by, preprocessing is done by applying the Regressive Nonlinear Teager Filter to remove the noise artifacts from the images resulting in the quality of image gets improved and minimize the tumor detection time. Finally, the machine learning technique

called MAP estimated Relevance Vector Machine is applied to segment the images based on the pixel based feature extraction. The segmentation results are used for identifying the given input images as normal or malignant. The machine learning technique effectively identifies the tumor in the brain MRI images with higher accuracy. The detailed explanation of the above said two processes are described in the following subsections.

3.1 Regressive Nonlinear Teager Filter based image preprocessing

In the proposed RNTF-MAPRVIS method, initially, the input MRI brain images are pre-processed in order to remove the noise

artifacts before the segmentation. The MRI image generally comprises distortion and artifacts. For computer-aided segmentation, the distortion and artifacts must be removed. Therefore, the RNTF-MAPRVIS method uses the regressive nonlinear Teager filtering technique to enhance image quality. The regression is the machine learning technique used for analyzing the pixels in the given input MRI images and removing the noisy pixels using Nonlinear Teager filter. The Nonlinear Teager filter is a denoising technique used to obtain the super-resolution image and suppress the noise. The block diagram of the Regressive Nonlinear Teager Filtering is shown in figure 2.

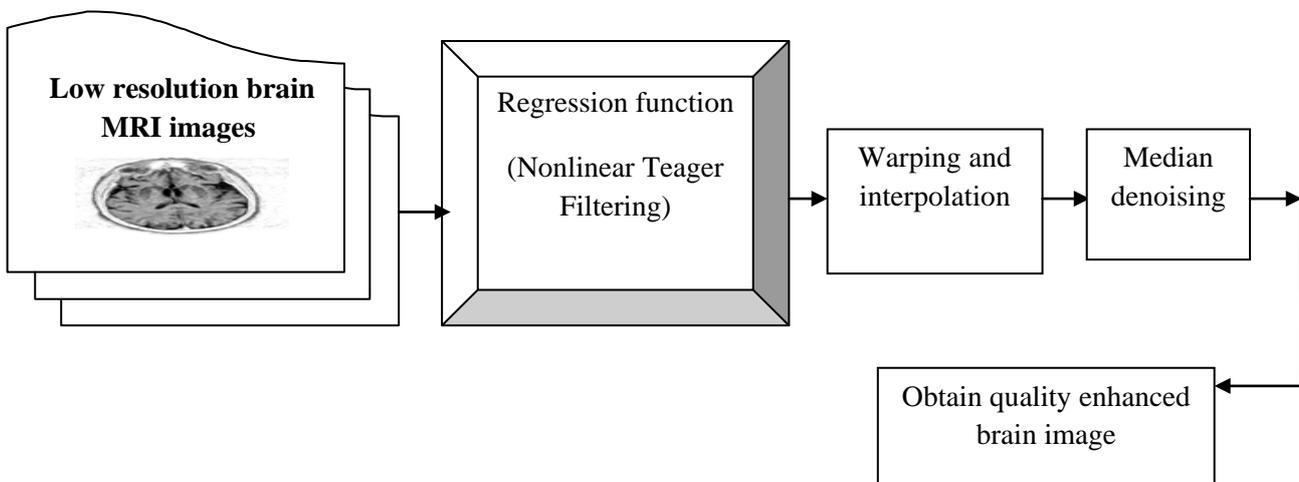


Figure 2 block diagram of the Regressive Nonlinear Teager Filter

Figure 2 shows the block diagram of the regression-based filtering technique to evaluate the pixels from the input MRI images. Let us consider the number of MRI images collected from the brain database.

$$bi_1, bi_2, bi_3, \dots, bi_n \in DB \quad (1)$$

From (1), $bi_1, bi_2, bi_3, \dots, bi_n$ denotes a number of Brain MRI images collected from the database DB . After collecting the images, the pixels analysis is done by applying the regression function and Improve the image quality using Nonlinear Teager Filter. For any brain MRI image, the Teager filter is applied to measure the pixel relationship as follows,

$$p_{ij} = 3p^2(i, j) - 0.5 * p(i + 1, j + 1) p(i - 1, j - 1) - 0.5 p(i + 1, j - 1) p(i - 1, j + 1) - p(i + 1, j) p(i - 1, j) - p(i, j + 1) p(i, j - 1) \quad (2)$$

Where, p_{ij} denotes a pixel of the input images, (i, j) denotes a horizontal (i.e. row) and vertical (i.e. column) translation. Each image

pixels are represented in the 3×3 windows with the rows and columns. $i + 1, j + 1, i - 1, j - 1$ represents the neighboring pixels in the window. Then the filter highlights the edges and suppresses the noise. Then the images are warped and interpolated as follows,

$$w(i, j) = I \left(\sum_{i=1}^n \sum_{j=1}^m A_b p_{ij} \right) \quad (3)$$

Where, $w(i, j)$ denotes a output of the warping and interpolation with the pixels, I denotes a non linear interpolation function used to make a images into smooth, A_b is the warp matrix for each low resolution image, p_{ij} is the pixels of the image. Image warping is used for digitally manipulating the image and correcting the image distortion. Then the normalization is applied for ordering the range of pixel intensity values from minimum to maximum.

$$w_{ij} = \frac{w(i, j) - \min(w(i, j))}{\max(w(i, j)) - \min(w(i, j))} \quad (4)$$

Where, w_{ij} is the normalized output of the pixels (i, j) using warped and interpolation, min and max denotes a minimum and maximum value of output of the warped and interpolation with pixel intensity $w(i, j)$. After the normalization, images are then applied to median denoising for smoothing the artifacts due to the reconstruction process and obtaining the final super resolutions image. The mathematical formula for mediandenoising are explained as follows,

$$f(x) = med\{w_{ij}\} \quad (5)$$

In the above equation (5), ' $f(x)$ ' denotes an output of the median denoising and Med denotes a median, w_{ij} denotes a normalized value of the pixels (i, j) using warped and interpolation. The median process is applied in the entire pixel and accordingly, the median value removes the noisy pixels in the window. This helps to improve the image quality for identifying the brain tumor in the given images.

Input: Brain MRI image DB , Number of brain images $bi_1, bi_2, bi_3, \dots, bi_n$

Output: Improve the image quality

Begin

1. **For each** input image (bi_i)
2. Analyze the pixels p_{ij}
3. Perform warped and interpolation of the pixels $w(i, j)$
4. Normalize the pixels w_{ij}
5. Remove noisy pixels by applying $f(x) = med\{w_{ij}\}$
6. Obtain quality enhanced image
7. **End for**

End

Algorithm 1 Regressive Nonlinear Teager Filter based preprocessing

Algorithm 1 describes the filtering based preprocessing algorithm to remove the noise artifacts and smooth the images. The input pixels and their neighboring pixels are analyzed for identifying the noisy pixels in images. The Regressive Nonlinear Teager Filter uses the median denoising. The median value removes the noisy pixels in the image resulting in obtains high-resolution images. This, in turn, improves the image quality as well as improves the peak signal to noise ratio.

3.2 MAP estimated Relevance Vector Machine based Image Segmentation

After preprocessing, the RNTF-MAPRVIS method performs the image segmentation to identify the tumor as normal or abnormal using MAP estimated Relevance Vector Machine. The image segmentation is considered as a classification task. A Relevance Vector Machine (RVM) is a machine learning technique that uses Maximum a Posteriori (MAP) for probabilistic classification. Maximum a Posteriori is used for identifying the maximum correlation between the features. Initially, the MR parameters (i.e. pixel-level features) such as size, shape, texture, color, area, length are extracted from the preprocessed

images. Then the tumor is characterized as normal (having no tumor) or abnormal (having tumor) with the extracted feature from the Region of Interest (ROI).

The MAP estimated Relevance Vector Machine considered as a set of training samples ' $\{(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)\}$ ' where ' x_i ' indicates an input preprocessed images and ' y_i ' refers to the output (classification result) $y_i \in \{0, 1\}$. Relevance Vector Machine uses optimal hyperplane for classifying the images. The hyperplane is a decision boundary between the two classes. The Relevance Vector classifies the images on either side of the decision boundary.

$$D_b \rightarrow \vartheta \cdot br_i + d = 0 \quad (6)$$

Where, D_b represents a decision boundary, ϑ is the normal weight vector to training samples (i.e. images), d denotes a bias. The two marginal hyperplanes are selected as lower and upper side of the decision boundary.

$$M_1 \rightarrow \vartheta \cdot br_i + d > 0 \quad i.e. \ ' + 1 ' \quad (7)$$

$$M_2 \rightarrow \vartheta \cdot br_i + d < 0 \quad i.e. \ ' - 1 ' \quad (8)$$

Where, M_1, M_2 are the lower and upper marginal hyperplanes to classify the brain images into above and below the boundary. The relevance vector machine uses the kernel function to obtain the final classification.

$$y = \text{sign} \sum \vartheta_i k(f_i, f_t) \quad (9)$$

In (9) y denotes a predicted classification results, ϑ_i denotes a weights of the training images, k denotes a kernel function that measures the similarity between any pair of features i.e. extracted features (f_i) and testing features (f_t), 'sign' determines whether the classification output either positive (+1) or negative (-1). The hyperplane measures the similarity between extracted features and testing features using maximum probability for classifying the images into any of the two classes.

$$\mu_{\text{map}}(y_i | br_1, br_2, br_3, \dots, br_n) = \text{arg max } p(br_i | y_i) \quad (10)$$

$$p(br_i | y_i) = \exp\left(-\frac{\|f_i - f_t\|^2}{2\sigma^2}\right) \quad (11)$$

In (10), (11), μ_{map} is the maximum probability function, arg max represents an argument of a maximum function using MAP rule, $p(br_i | y_i)$ is the classification probability. Gaussian kernel function is used for measuring the similarity between the features, f denotes a extracted features, f_t denotes a testing disease features, $\|f_i - f_t\|^2$ denotes a squared distance between the extracted features and testing disease features, σ denotes a deviation. The squared distance is used to measure the similarity of the features. If the distance is minimized, the two features are highly correlated. Based on the MAP estimated relevance vector, the features with higher similarity have a maximum probability belongs to the class '-1' i.e. images are classified as malignant. Otherwise, it has a maximum probability belongs to the classes '+1' i.e. image is classified as normal.

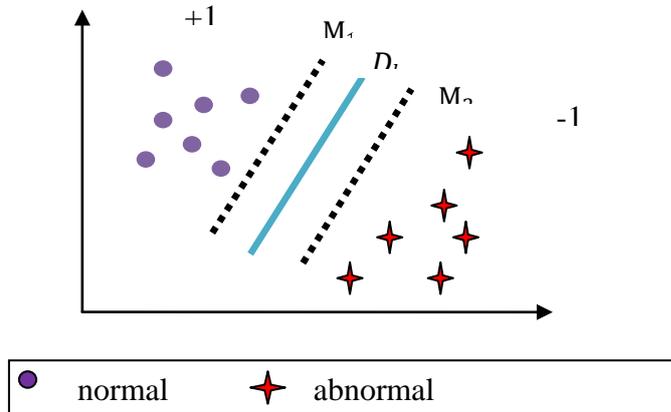


Figure 3 Map estimated relevance vector machine

Figure 3 shows the Map estimated relevance vector machine to classify the brain MRI images into the normal or abnormal. As shown in figure 3, the input preprocessed images are

segmented and the upper sides of the hyperplane are called as normal images whereas the lower labeled samples are abnormal images

Input: Preprocessed MRI brain images $br_1, br_2, br_3, \dots br_n$
Output: Improve segmentation accuracy
Begin

1. **for** each preprocessed br_i
2. Extract the features
3. Construct optimal hyperplane D_b
4. Find two marginal hyperplane M_1, M_2
5. The output of the classifier is $y = \text{sign} \sum \vartheta_i k(f_i, f'_i)$
6. Find maximum probability $\mu_{\text{map}}(y_i | br_1, br_2, br_3, \dots br_n)$
7. **If** (f_i, f_t) highly correlated
8. $y = -1$
9. Images is classified as 'abnormal'
10. **else**
11. $y = +1$
12. Images is classified as 'normal'
13. **end if**
14. Obtain classification results
15. **End for**

End

Algorithm 2 MAP estimated relevance vector classifier

Algorithm 2 describes the step by step process of MAP estimated relevance vector classifier for image segmentation. The preprocessed images are taken as input and extract the features from it. Then the relevance vector uses the hyperplane to measure the similarity between the extracted features and the disease testing features. The hyperplane acts as a decision boundary for identifying the similarity between the features. Based on the similarity, the images are categorized into either side of the hyperplane through the maximum probability estimation. If the two features are more similar, then the images have a higher probability for classifying the abnormal image. Otherwise, the images are classified as normal. As a result, the classification outcomes improve segmentation accuracy and minimize the false positive rate.

4. CONCLUSION

A novel method called RNTF-MAPRVIS is designed for processing the MRI brain images through the segmentation algorithm. The main goal of the RNTF-MAPRVIS method is to perform the preprocessing and segmentation for isolating the region of interest from its background. The regressive pixel analysis based filtering is applied to remove the noisy

pixels and enhance the image contrast for further processing. After preprocessing, the images are segmented by the classification. In this segmentation module, the preprocessed brain MRIs obtained, which is to be classified as a normal or abnormal through the separating the hyperplane. The relevance vector-based segmentation method is robust and precise. The experimental is conducted with the MRI brain image database. The proposed algorithm is compared with state-of-the-art approaches using different parameters such as peak signal to noise ratio, segmentation accuracy, false positive rate and segmentation time. From the results obtained, it is clearly noted that the proposed RNTF-MAPRVIS method offers better performance in the peak signal to noise ratio, segmentation accuracy, false positive rate and minimum time than the state-of-the-art methods.

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