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SEGMENTATION BASED ON ENHANCED MORPHOLOGICAL WATERSHED ALGORITHM

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Abstract: Medical imaging and analysis, one of the predominant fields in medical industry, is the art of using automated techniques to manipulate an image. The techniques of medical image concentrate on improving the quality of an image and extracting useful information from the image for better understanding. Image segmentation and enhancement is one of the central research themes in medical image analysis and with the increasing number of imaging analysis and imaging studies, the necessity for automated medical image segmentation methods are expanding. The present research work focus on segmentation that combines neural network with Watershed algorithm modified to use automatic optimal threshold selection algorithm. The problem of oversegmentation is solved by using preprocessing technique. Experimental results prove that the proposed method is efficient in segmenting medical images.

Keywords: Guassian Filter, Neural Network,Medical Image Segmentation, Multiscale Morphology, Projection Distance Minimization, Watershed Algorithm,.

INTRODUCTION

Recent advances in medical imaging with significant contributions from electrical, computer engineering, medical physics, chemistry, and computer science have witnessed a revolutionary growth in diagnostic radiology. Revolutionary improvements in engineering and computing technologies have made it possible to acquire high-resolution multidimensional images of complex organs, to analyze structural and functional information of human physiology for computer-assisted diagnosis, treatment evaluation, and intervention [14].

Medical imaging and analysis, one of the predominant fields in medical industry, is the art of using automated techniques to manipulate an image. The techniques of medical image concentrate on improving the quality of an image and extracting useful information from the image for better understanding. Different techniques are being used for this purpose. Examples include enhancement, denoising, classification, feature extraction and segmentation. Out of this, image enhancement and segmentation are two techniques which are more frequently used.

Due to overwhelming amount of data generated to by medical equipments, manual analysis/interpretation of images is not straightforward and is often complicated. For this reason, automatic or semi-automatic techniques of computer-aided image analysis are necessary.

Image segmentation is a prerequisite in many medical image processing systems, such as pattern recognition, image retrieval and small surveillance. The result of segmentation is mainly used for image content understanding and visual object recognition [20] through the identification of region of interest. The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze [19]. Image segmentation is used to locate objects and boundaries (lines, curves, etc.) in images and assigns a label to every pixel in an image such that pixels with the same label share certain visual characteristics. In medical imaging, the aim is to separate different parts of the anatomy, which is proving to be very challenging with the overwhelming number of visual patterns in an image. Thus, image segmentation has been, and still is, a relevant research area in Computer Vision. Eventhough, several hundreds of segmentation algorithms have been proposed for natural images in the last 30 years, it is still evasive in medical domain.

A multiscale morphological watershed segmentation algorithm that combines neural network and automatic optimal threshold selection is proposed in this paper. The main goal of the proposed system is to preserve the edges that represent the image boundaries and perform efficient segmentation.

The paper is organized as below. Section 1 provided a brief introduction to the segmentation problem. Section 2 reviews work done in medical image segmentation domain. Section 3 discusses the working of watershed algorithm. Section 4 explains the proposed system, while Section 5 presents the experimental results. Section 6 concludes the work.

REVIEW OF LITERATURE

Segmentation, a subtask in image processing, dates back over 40 years, with applications in many areas other than computer vision. Image segmentation algorithms play a vital role in numerous biomedical imaging applications such as the quantification of tissue volumes [12], diagnosis [21], localization of pathology [26], study of anatomical structure [24], treatment planning [8], partial volume correction of functional imaging data [16], and computer integrated surgery [1]. Recently there has been a considerable amount of work on image segmentation, particularly for medical images ([7], [23], [25]).

Watershed based image segmentation is an area that is becoming popular in recent years. Watershed segmentation is a morphological based method of image segmentation. The gradient magnitude of an image is considered as a topographic surface for the watershed transformation. Watershed lines can be found by different ways. The complete division of the image through watershed transformation relies mostly on a good estimation of image gradients. The result of the watershed transform is degraded by the background noise and produces the over-segmentation. Also, under segmentation is produced by low-contrast edges generate small magnitude gradients, causing distinct regions to be erroneously merged.

Bieniek and Moga [3] present an algorithm based on connected components. Li *et al*. [13] proposed an improved image segmentation approach based on level set and mathematical morphology. Hamarneh and Li [5] have proposed a method using prior shape and appearance knowledge to improve the segmentation results. Other researchers also proposed different method to remedy the problem of watershed. This study attempted to solve the over segmentation and sensitivity to noise. The segmentation stage is an automatic iterative procedure and consists of four steps: classical watershed transformation, improved k-means clustering, shape alignment, and refinement. The issues of watershed are remedied by this method, as over segmentation problem is handled by clustering and noise effect can be removed by mean intensity of each segment. The limitation of k-mean clustering algorithm affects the proposed methods result and a failure case is reported.

In order to reduce the deficiencies of watershed, many preprocessing techniques are proposed by the different researchers. For example, [6] present a robust watershed segmentation using wavelets where wavelets technique is used to denoise the image.

From the literature survey, it was found that most of the techniques previously proposed consider only the over segmentation problem. The under segmentation problem is not yet addressed by most of the researchers. This paper focuses on both the problems along with the sensitivity to noise problem.

WATERSHED ALGORITHM

Watershed segmentation is a predominant segmentation scheme with several advantages. It ensures the closed region boundaries and gives solid results. It is a way of automatically separating or cutting apart particles that touch. The watershed algorithm uses concepts from mathematical morphology [4] to partition images into homogeneous regions [22]. The general process of the conventional watershed algorithm consists of five steps during medical image segmentation as given in Figure 1.

A segmentation technique for natural images was proposed by [17]. This model is referred to as NK model in this paper. To improve the conventional watershed model, the NK model converts the RGB color space into HSV color space, so that the color contrast gradient can be found easily. A multiscale morphological gradient was also used to calculate the intensity of the image. These two values are multiplied and markers are extracted from this composite gradient image using a thresholding technique.

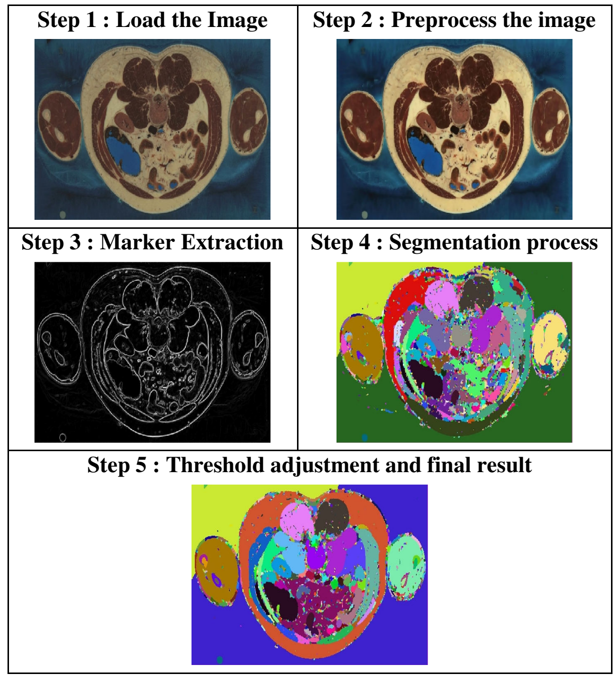


Figure 1 : Watershed Segmentation Algorithm

Careful analysis of this system identified two major drawbacks, (i) Sensitivity to noise and (ii) Over and under segmentation. The NK Model is sensitive to noise in the input image. The segmentation result was heavily dependent on the smoothness of the data and presence of noise often was identified as a separate region. The second problem identified was that the result was often cluttered with more number of segments than it should have.

The NK model is enhanced in the present research work to overcome these two problems. The first problem can be solved by introducing a preprocessing step that reduce the noise in the input image and at the same time, preserve the features that represent the image boundaries.

On deeper analysis, it was found that over segmentation problem can sometimes be solved by the correct usage of the threshold value, which was user defined in the NK model. The over segmentation result shows that the selection of threshold is very important. Choosing a very low value results in important regions merged together and a high value results in numerous number of small regions, resulting in over segmentation (Figure 2).

The over segmentation problem can be solved by using an optimal threshold value. A method to automatically calculate this optimal threshold value was proposed by [2] and is used in the present work to improve the NK model.

Figure 2 : Original Image and Over Segmentation Resul

OPTIMAL THRESHOLD SELECTION METHOD

In traditional segmentation systems, threshold selection is based on the local data available within the image. In the optimal threshold algorithm presented here, the projected data is used instead of the local image data. This is performed by using a measurement called Projection Distance Minimization (PDM) method, which is used to minimize the distance between the forward projection of the segmented image and the measured projection data and by using these values, the thresholds are computed. The procedure is explained below.

Let an image be represented on a rectangular grid of width ‘w’ and height ‘h’, then the total number of pixels is given by n = wh. The image $x \in R^n$, which is to be segmented is a reconstruction of some physical object, of which projections were acquired. Let ‘m’ denote the total number of measured detector values (for all angles) and let $p \in R^m$ denote the measured data. The physical projection process can be modeled as a linear operator ‘W’ that maps the image x (representing the object) to the vector p of measured data (Equation 1).

$$Wx = p \qquad (1)$$

For parallel projection data, the operator ‘W’ is a discretized version of the well-known Radon transform, which is represented as a m x n matrix. For each projection angle, every pixel i will only project onto a few detector pixels, so the matrix W is very sparse. The matrix representation of the projection operator is commonly used in algebraic reconstruction algorithms.

The main motivation of using thresholding in general, is that pixels representing the same “material” in the scanned object should have approximately the same color values. The optimal threshold value is obtained by assigned a real-valued grey level to each of the segmentation classes. Using these grey levels, the projections of the segmented image are then computed. The computed forward projections are compared to the measured projection data, which provides a measure for the quality of the segmentation (along with the chosen grey levels). This quality measure can also be used for other segmentation techniques than thresholding. Determination of grey levels for each of the segmentation classes of a segmented image is given below.

Consider a segmentation of an image into ‘l ’ classes as a partition of the set of pixels, consisting of ‘l ’ subsets. Let $S = \{S_1, \ldots, S_l\}$ be a partition of $\{1, \ldots n\}$. Each set is labeled by its index t: St. Each pixel j is contained in exactly one set $St \subset S$, denoted by $s(j) \in \{1, \ldots l\}$. To each set St, a grey level $\rho_t \in R$ is assigned, which induces an assignment of grey levels to the pixels $1 \le j \le n$, where pixel j is assigned the grey level $\rho_{s(j)}$. Let $\rho = (\rho_t) \in R^l$ represent the vector of gray levels of the segmented image and define

$$r_s(\rho) = (\rho_{s(1)}, \ldots, \rho_{s(n)})^T \qquad (1)$$

where the symbol T denotes transposition. The vector $rS(\rho) \in R^n$ contains, for each pixel j, the corresponding grey level of that pixel. The goal is to determine “optimal” grey values ρ for the given partition S. The quality of a vector ρ is determined by computing the projections of the segmented image, using the grey levels from p, and comparing the computed projections to the measured projections p. The optimal threshold procedure is given in Figure 3.

```
τ := τ0;   For i = 1,...,m:   Si := {1 ≤ j ≤ n : τi−1 < xj ≤ τi};
For i = 1,...,m:   compute ai, ci and Qi;
Compute c̄ and Q̄;
stepsize := initial stepsize;
while stepsize > min_stepsize do
begin
  begin
    For all thresholds i = 1,...,ℓ − 1, compute the minimal projection distance that can be
    obtained if τi is either increased or decreased by stepsize, considering only cases
    where τ1 < ... < τℓ−1;
    if (an improved projection distance was found w.r.t. the current thresholds τ) then
    begin
      update the threshold τi for which the minimal projection distance was obtained by
      adding (or subtracting) stepsize;
      Update the variables ai, ci and Qi accordingly, for all affected i = 1,...,n;
    end
    else
      stepsize := stepsize×F;
  end
end
```

Figure 3 : Optimal threshold selection algorithm

PROPOSED SEGMENTATION ALGORITHM

Mathematically, image segmentation is defined as the partitioning of an image into non-overlapping, constituent regions which are homogeneous with respect to some characteristic such as intensity or texture. If the domain of the image is given by I, then the segmentation problem is to determine the sets $S_k \subset I$ whose union is the entire image I. Thus, the sets that make up a segmentation must satisfy

$$I = \bigcup_{k=1}^{k} S_k \qquad (2)$$

where $S_k \cap S_j = \phi$ for $k \neq j$., and each S_k is connected. Ideally, a segmentation method finds those sets that correspond to distinct anatomical structures or region of interest in the image.

The block diagram of the base system is given in Figure 4. Initially, a color space transformation from RGB to HSV takes place to establish the color contrast gradient image. The intensity image of the input image is constructed from which the multiscale morphological gradient of the intensity channel is constructed. Morphological operators are used at this stage to smoothen or bring in uniformity of intensity over the intensity image. This multiscale morpholocal gradient of the intensity channel of the original image and the color contrast gradient image are multiplied to obtain a composite color gradient image, from which the markers are extracted. These markers are fed as input to the watershed algorithm. The watershed algorithm is modified to use Hill-climbing approach to identify neighborhood pixels to form similar regions and group them into labels. The steps involved are explained in detail below.

Step 1 : RGB - HSV Conversion

The main purpose of the base system is to segment an image into visually distinct colors, which the HSV system prefers. In order to that, as a first step, a medical color image is transformed from RGB colour space to HSV color space.

Step 2 : Preprocessing
A Gaussian Filter was used to remove noise introduced in the MRI images. Preprocessing was offered as an optional choice, which was applied by the user only when need arises.

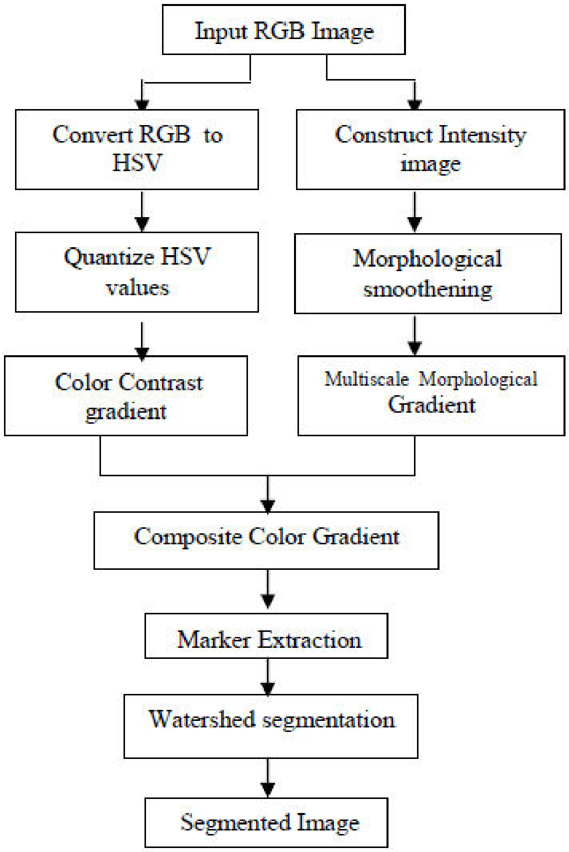


Figure 4 : Block Diagram of the Base System

Step 3 : Quantization
For the purpose of human perception and simplifying the image, the HSV values are uniformly quantized into (37, 5, 9) levels respectively. The five levels of saturation represent five grade of chroma: achromatic, nearly achromatic, low achromatic, middling chromatic, and highly chromatic. The range of quantized saturation is from 0 to 4. In the achromatic level, the saturation value is equal to zero and there is no perceived color. In the nearly achromatic level, the color is perceived as an achromatic color even if a color has a hue component. In the above situation, the perceptual contrast depended on the brightness. In low or middle chromatic level, the number of perceptible colors is still slightly less than in highly chromatic level. In these situations, the perceptual contrast depended on hue mainly.
The HVS can distinguish colors like red, green, blue, yellow and mixed colors such as orange effectively. In order to tone down the image from step 1 into a set of colors that HVS can distinguish, a quantization step is performed. The named colors will be in non-uniform quantized position of the hue plane and it is difficult to measure the distance of two colors. To reduce this variation, quantization process is intended for calculating color contrast. The original hue plane is divided into 37 levels. The levels of value are quantized to 9 levels and saturation into 5 levels based on the following set of equations. Finally, the (qH, qS, qV) are all integer values representing the quantized (H, S, V). The process is shown below :

- H [0 , 360]; qH[0, 3 6] , $qH = \begin{cases} 0 & \text{if } H = 0, \text{No Hue} \\ ((H-5)/(10+1))(\text{Mod}\,36) & \end{cases}$
- S [0,1] ; qS [0 ,4] and qS = S * 100 / 25
- V [0, 255] ; qV [0, 8] and qV = V / 3 2

Step 4 : Color Contrast Gradient
The difference of Hue, Saturation and value are constructed by considering the eight neighbors of each pixel in the quantized HSV image. From the circular relationship of hue, the maximal difference of hue between two pixels is defined as 18, and the distance between level 36 and level 1 is equal to 1. Consequently the maximal distance between two pixels is 18 + 4 + 8 = 30. The perceptible colors vary with different chromatic condition and two colors are perceptibly different when the difference of their quantized hue level is more than three in a highly chromatic situation. Moreover, in the HSV color space, saturation represents the degree how much white element is mixed to a pure color. In human perception, saturation often reflects the intensity of lightness, and the brightness is more perceptible than hue in the achromatic and nearly achromatic situation. Therefore, saturation plays a critical role in color contrast measurement and is a criterion to determine how much the difference of quantized hue (qH) to settle one degree of hue and brightness contrast when in the different chromatic condition.
The gradient of the image, GRAD, is calculated using Equation (3).

$$GRAD = Crt\_Vx * wtv + 2 * Crt\_Hx * wth \qquad (3)$$

where, Crt_V and Crt_H are the difference matrices of brightness and hue of pixel (i,j) related to its eight neighbors, wtv and wth are the related horizontal and vertical saturation level weight matrices.

The Color Contrast Gradient (CCG) of each pixel is calculated as the maximum of GRAD obtained above (Equation 4).

$$CCG_{i,j} = MAX\,(GRAD) \qquad (4)$$

Finally the gradients are normalized to be in the range from 0 to 10 and a normalized color contrast gradient (NCCG) is given as Equation (5).

$$NCCG_{i,j} = 10[CCG_{i,j} / MAX(CCG_{i,j})] \qquad (5)$$

Step 5 : Multiscale Morphological Gradient
The intensity channel of original image is smoothened to keep the interior of the objects and to preserve the boundary of the objects. The objects to be smoothened are subjected to a group of morphological operators. The basic morphological operators involved in this phase are listed below.
In the morphological analysis, a 2-D image is defined as a subset of the 2-D Euclidean space RxR or its digitized equivalent ZxZ. The base system considers only intensity images, which is defined as subsets of ZxZ. The two most fundamental morphological operations are dilation and erosion. Dilation of the image, ‘f’ by ‘B’ expands the image, while the erosion of ‘f’ by ‘B’ shrinks the image. They are

defined respectively in Equations (6) and (7), with f and B in the set ZxZ as

$$f \oplus B = \{X / (B)x \cap f \neq \varphi\} \quad (6)$$

$$f \, \theta \, B = \{x / (B)x \subseteq f \neq \varphi\} \quad (7)$$

Opening of the binary image f by the 4 or 8 connected structuring element B denoted as $f \circ B$, is defined as

$$f \circ B = (f \, \theta \, B) \oplus B \quad (8)$$

Closing of the binary image f by the 4 or 8 connected structuring element B denoted as $f \bullet B$, is defined as

$$f \bullet B = (f \oplus B) \, \theta \, B \quad (9)$$

The local color variation in the image is thus given by the morphological gradient. A gradient helps detecting ramp edges and avoids thickening and merging of edges providing edge-enhancements. The gradient image, G(f), is morphologically obtained by subtracting the eroded image, $\varepsilon(f)$ from its dilated version, $\partial(f)$. A multiscale gradient, MG(f) is the average of morphological gradients taken for different scales of the structure element, B_i, where B_i is a SE of size (2_{i+1}) x (2_{i+1}) ([9], [10], [11]).

Step 6 : Composite Color Gradient Image

Composite Color gradient is obtained by multiplying both color contrast image NCCG and multiscale morphological gradient image MG(f).

Step 7 : Marker Extraction

The conventional Watershed segmentation algorithm applied directly to the composite color gradient image can cause oversegmentation due to serious noise patches or other image irregularities. This problem is overcome by the use of Markers. The main goal of using markers is to detect the presence of homogeneous regions from the image by a thresholding technique. They spatially locate object and background, ensures to keep up the interior of the object as a whole. The thresholding method used was explained in the previous section (Section 4).

The Markers are connected components belonging to an image. Two types of markers are used, namely, internal and external markers. The internal markers are inside each of the objects of interest (gradient value less than computed optimal threshold) and external markers (gradient value greater than computed optimal threshold) are contained within the background. Thus, the composite color gradient image is thresholded to extract the markers.

The resulting marker image M(f) is a binary image such that a pixel is a marker (to be black) if it belongs to a homogeneous region, a pixel will be white if it does not belongs to homogeneous regions. Thus, the marker image contains a set of black pixels (markers), which denote the core regions, and a set of white pixels remaining unassigned to any regions.

Step 8 : Watershed Transform and Segmentation

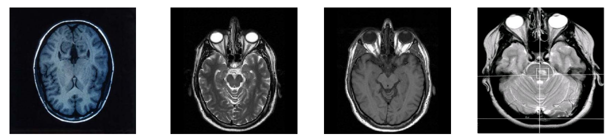
A fast watershed transform based on Hill Climbing technique [18] is proposed. Since marker extracted composite color gradient image is given as input to the Hill Climbing technique, number of local minima is reduced and better segmentation result is obtained. The complexity of the algorithm has been reduced by doing away with multiplication normally required to form a lower complete image in an intermediate step of the overall segmentation process. Its moderate complexity makes it amenable to dedicated hardware implementation.

EXPERIMENTAL RESULTS

The proposed system was tested using an experimental set consisting of brain MR images of 256 x 256 size. The system was developed using MATLAB 7.3 and was tested on Pentium IV system with 512 MB RAM. The experimental results are discussed under 5 headings :

(i) Effect of preprocessing on segmentation
(ii) Segmentation Result
(iii) Number of clusters
(iv) Edge detection performance on segmentation results
(v) Time Taken for Segmentation

Several test images were used during experimentation and the result of four sample images are projected in this srction. The four test images are shown in Figure 5



Brain-1 **Brain-2** **Brain-3** **Brain-4**

Figure 5 : Sample Test Images

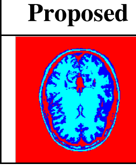
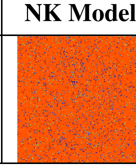
A. Effect of preprocessing on segmentation

As the base system performance on segmentation was affected by the noise present in the original image. Experiments were conducted with noisy images to judge the performance on segmentation result was tested with respect to noisy image. 20% Guassian noise was added to all the original images to create noisy images. Figure 6 shows the original image, noisy image and segmentation result.

It can be seen that the base system performance degrades with the introduction of noise in the medical image, while the proposed system performance is stabilized with or without noise. Moreover, the introduction of noise, the base system arises a under segmentation scenario and it is, in most of the cases, results in only two regions. While in the normal scenario (that is, images without noise), in some cases, the base model performs an over segmentation. This is very clearly evident with Brain1 and Brain 4 images.

B. Segmentation Result

The main objective of this research work is to develop a novel algorithm for segmenting medical images. As each medical image have different characteristics, using the same segmentation technique for all types of images is impossible. The present method is developed for MRI image, but the same can be tested for other images also. Figure 7 shows the result of segmentation on the test images.

Noisy Image	**Proposed**	**NK Model**
Brain-1		

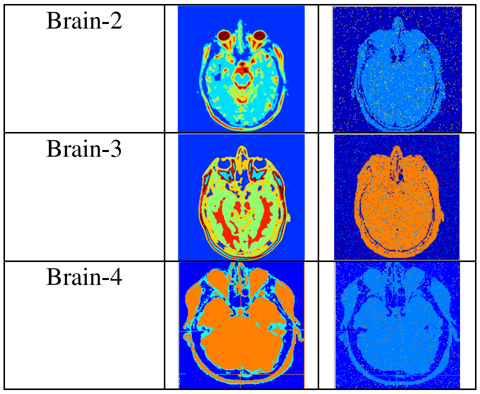


Figure 6 : Noisy Image and Segmentation Result

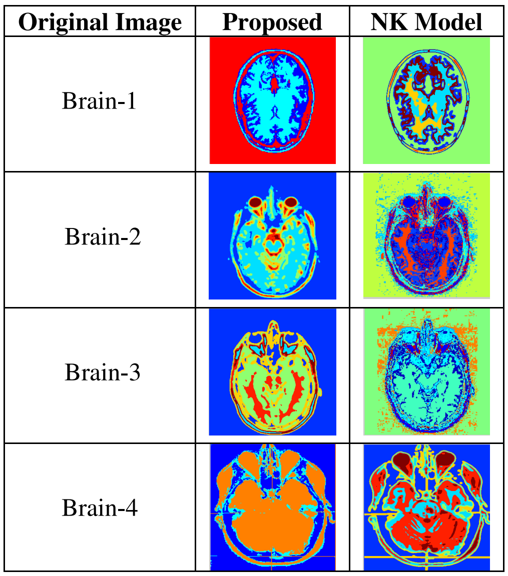


Figure 7 : Segmentation Result

For segmentation algorithm to be perfect, there should be clear distinction between the various regions of the image and the edges of these regions has to be identified unmistakably [15]. Supporting this theory, the proposed model segments the image in a more accurate fashion, by dividing it into more regions separating it using random colours. The edges of the image are more evident in the proposed model while the same cannot be held good for the base model, which clearly supports the argument that the segmentation process is more reliable and accurate in the proposed system.

C. Number of regions

The next quality metric chosen to judge the performance of the proposed segmentation system is the number of regions. Table 1 shows the number of clusters for normal, noisy images while applying the base segmentation algorithm and segmentation proposed algorithm.

TABLE 1 : NUMBER OF REGIONS

Image Name	Normal Image		Noisy Result	
	Proposed	Base	Proposed	Base
Brain01	4	7	4	2
Brain02	4	5	4	2
Brain03	5	3	5	2
Brain04	3	5	3	2

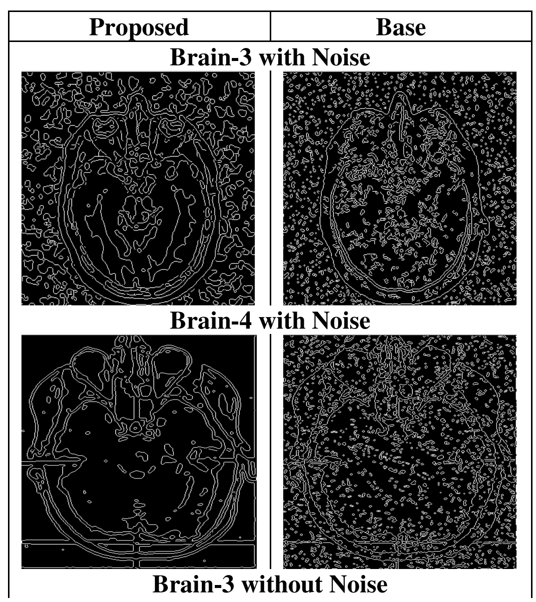
All these results stress the fact that the multi-scale morphological based watershed segmentation algorithm has been improved by the introduction of noise removal and optimal threshold value selection algorithm.
All these results prove that the performance of proposed system is better than the base model.

D. Edge Detection

Guiding image segmentation with edge information is an often employed strategy in low level computer vision and therefore a simple edge detection algorithm called Canny Edge Detection Algorithm was used to detect the edges. The results are projected for image 3 and 4 in Figure 8 for noise introduced and normal images. The same trend was observed with other images also.
From the visual results projected, it is clear that the proposed method is superior to the base model. In most of the cases, proposed method has retained edges of the medical image more efficiently than the base model. The performance, though slightly reduced, is still good in the proposed model.

E. Speed of Segmentation

Segmentation speed is the time taken by the algorithm to segment or divide the input image into regions. The time taken by the proposed and base algorithms is shown in Table 2.
The algorithm runs exceedingly fast and can produce results in seconds. This speed is more than comparable with the techniques proposed by Comaniciu and Meer (2002) and Christoudias *et al*. (2002). From the table, it is evident that the proposed method for segmentation outperforms the base system. While computing the percentage difference efficiency, the proposed method is 44.26% efficient in terms of speed of segmentation.



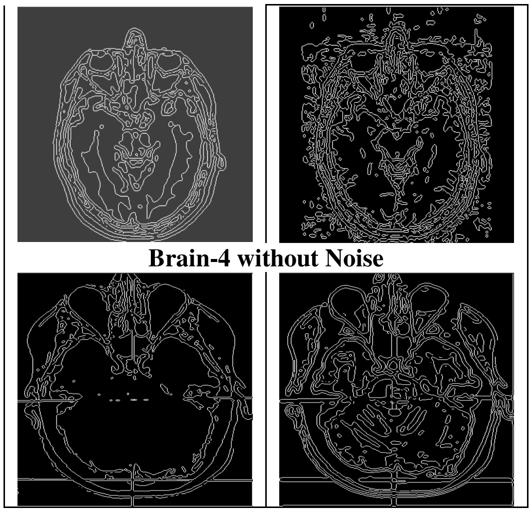


Figure 8 : Edge Preserving Capacity

TABLE 2 : SEGMENTION TIME TAKEN

Image	Proposed (Time in Seconds)	Base (Time in Seconds)
Brain 1	0.88	1.43
Brain 2	1.12	2.34
Brain 3	1.41	2.31
Brain 4	1.59	2.89

All these results stress the fact that the multi-scale morphological based watershed segmentation algorithm has been improved by the introduction of noise removal and optimal threshold value selection algorithm.

CONCLUSION

This paper presented an enhanced version of the multiscale morphological based watershed segmentation algorithm for segmenting MR images. The enhancement was provided in terms of noise removal and automatically selecting the optimal threshold value for segmentation to avoid over segmentation. This novel framework has been applied to brain segmentation and was able to consider both, noisy and noiseless images. The segmentation task was tested on various images and the experimental results obtained by the segmentation process are more efficient and reliable when compared to the current techniques. The present model assumes Gaussian noise in the medical images. As it is known, different noise have varying effects on the medical images. In future, several other noises are planned to be considered. The computation efficiency of the algorithm is also not tested, which will be done in future. Other types of medical images like ultrasonic images, x-ray images will also be tested in future.

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