Image Enhancement of Medical Images Based on an Efficient Approach of Morphological and Arithmetic Operations

Usha Ramasamy[#1], Perumal K[*2]
*Research Scholar[#1], Associate Professor[*2]*
Department of Computer Applications, School of Information Technology,
Madurai Kamaraj University, Madurai, Tamil Nadu, India

Abstract— *This paper presents a new approach for a medical image pre-processing and enhancing to further segmentation and classification. An idea of this technique is helpful to improve the image contrast and quality as well as to extract if any abnormal part in a brain image. Then the size of structuring element choice, top-hat, bottom-hat morphological operation and some arithmetic operation are used for an image enhancement to increase the image contrast and quality. And image complement operation has incorporated with this process for separate the abnormal tissues from enhanced image when it is needed. The choice of the best size of structuring element in the disk-shaped mask is helpful to increase the image contrast as well as improves the Correct Classification Rate or accuracy for MRI brain-image diagnosis.*

Keywords— *Magnetic Resonance Image, Morphological operations, Top hat transform, Bottom hat transform, Image Enhancement.*

I. INTRODUCTION

Digital image processing works as the vital role in analysis and perception of imaging data which is in the digital form. It consists of different components such as image enhancement, segmentation, feature extraction, and recognition. Among these, image enhancement methods are helpful to improve the image visibility features, to suppress the noise information, to increase the contrast for differentiate the objects from backgrounds and to show image details.

The main goal of enhancement approach is to give better input image more qualified than the original image for other specific application or automated image processing such as segmentation, detection and image recognition. The word 'specific' is most important because the processing methods are many problems oriented.

II. LITERATURE REVIEW

Today enhancement of medical image is a very important issue to diagnose the different medical imaging techniques. The main aim of this concept is upgrade of image data and improves some image quality features for next further medical image diagnosis. The promising outcome in accuracy and convergence rate of suitable image pre-processing and feature extraction methods must be high to ensure the success of next steps [1].

The wavelet transformation technique has applied for medical image enhancement [2]. In this technique, the all high frequency sub-images are decomposed through Haar wavelet transform. Then the noise in the high frequency sub-band field has reduced using the soft-thresholding method. Finally, the qualified output image is secured by inverse wavelet transform and inverse Haar transform.

Another commonly used technique is histogram equalization [3] that enhances the image contrast by improving the gray levels distribution. This technique does not offer better outcomes for whole areas of an image. It may affect the image and border zone. For this reason, there are various generalizations of that method raising its performance [4-5].

To enhance the abdominal ultrasound images, the composition of histogram equalization and wavelet transformation method has proposed [6]. This method helps to refine the edges of abdominal walls. And it has real-time achievement at dynamic applications.

In medical image enhancement, another one of the technique is gamma correction [7]. In this procedure, a gamma value of each window is locally optimized by to minimize the co-occurrence matrix homogeneity of the original image. The gamma correction technique improves dynamic range and image quality.

A new mathematical morphological technique has developed which is helpful to process and analyse the images [8-11]. It gives another alternative possible approach for the shape concept based on image processing.

A morphological filter has proposed [12] to sharpen the medical images. In this approach, first edges are discovered using gradient-based operators, and then a class of morphological filter has manipulated to sharpen the existing edges. In fact, morphology operators, through to increase and decrease the colors in distinct segments of an image have a significant role in to process and detect different existing objects in an image.

Discovering edges of an image using morphological gradient is an instance that has comparable one with that of classic edge-detectors such as Sobel and Canny [13].

In the theory of mathematical morphology, images are tend as sets, and morphological based transformation is obtained from Minkowski addition and subtraction which are used to extract features in images [14]. The proposed work is focused on mathematical morphological transformations of particular image enhancement process.

III. RESEARCH METHOD

Image enhancement is an important process at image based applications for further upcoming segmentation, feature extraction, and classification. In this proposed method, an input image is enhanced by the morphological and some arithmetic operations.

A. *Morphological Image Transformations*

Generally, this image transformation technique is classified into three steps as follows,

- Top-hat transform
- Bottom-hat transform
- Arithmetic operations

Top-hat transform applies morphological top-hat filtering method on input MRI brain image to extract small elements and details of an image. And it gives the distinction between the input image and its opening by some structuring element [15]. Generally, the top-hat transformation can be defined by the below equation,

$$T_w(f) = f - f \circ b \qquad (1)$$

Bottom hat transform is a mathematical morphological operation which is helpful to get the difference between closing and input image [15]. And it can be defined by the following equation,

$$T_b(f) = f \bullet b - f \qquad (2)$$

Here $\bullet$ indicates the closing operation and symbol $\circ$ represents the opening operation.

Image arithmetic morphological operation is very simple and therefore fast. The standard

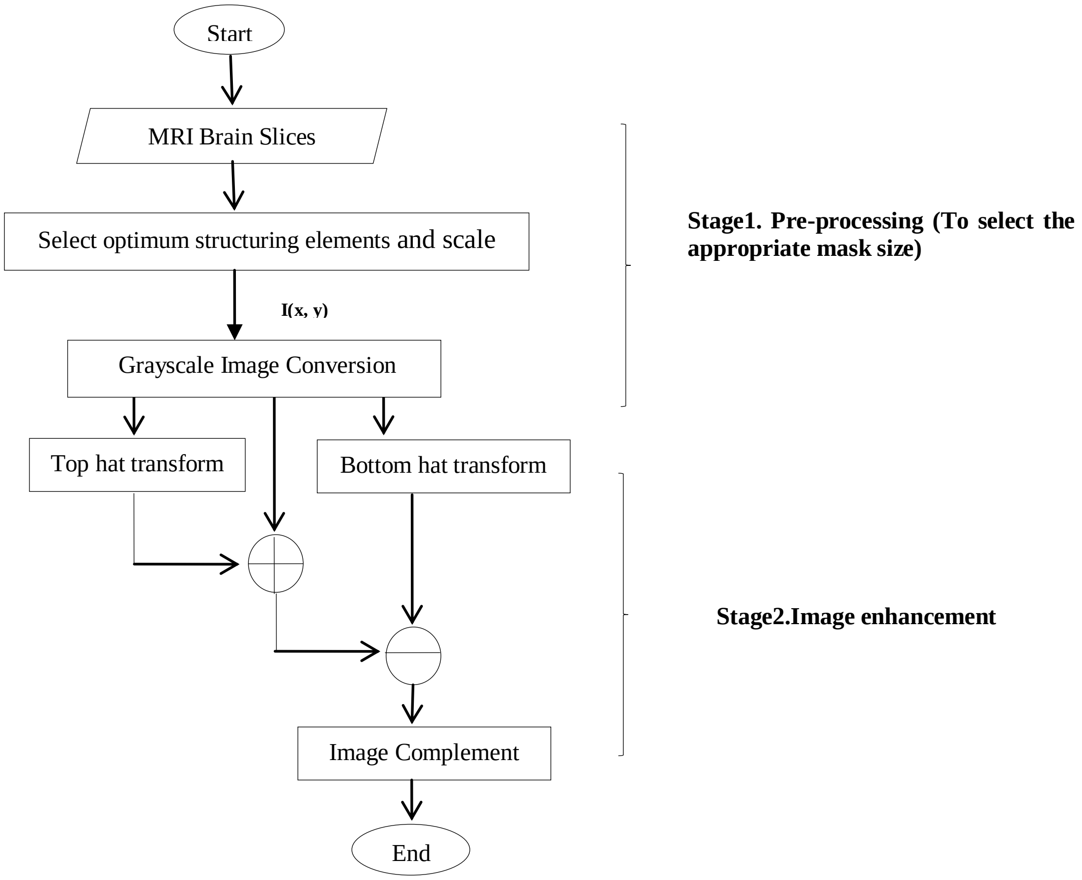

Fig 1: Hierarchical Transformation Technique (HTT-image pre-processing and enhancement using morphological operations and arithmetic operations)

arithmetic operations applied on two or more images in pixel by pixel way. Here the value of a pixel in the output image depends only on the values of corresponding pixels in the input image, i.e. the size of input and output image should be same.

Finally, the enhanced image is generated by the sum of the original image I(x, y) with the top-hat transform of original image $T_w(f)$ and it is subtracted from the bottom-hat transform of original image $T_b(f)$. The proposed image enhancement procedure is represented in Fig 1.

B. Proper Mask Size Selection

In morphology-based methods, achieving the suitable result and computation reduction time are different depends on the shape and size of a mask. So that selection of mask in appropriate size and shape is an important one to perform the desired results.

The disk-shaped mask is an independent of changes in rotation, and generally, a disk-shaped mask is more used at medical based images other than the line, square, octagon, pair shaped masks. Since big or small masks are strengthened or weaken the different parts of an image, it is impossible to gather detailed information on the contrast of different images using only one structuring element. This is a reason, one mask in a particular shape and size may not appropriate for other applications [14].

The size of the mask is also dependent on an input image and it can differ from one image to another. This is why the selection of the size of the structuring element is a most important one to eliminate the noisy information but not to damage objects of interest. In this proposed method, the size of a disk-shaped mask has changed until the optimum results are obtained. The best enhanced image is chosen among the 'N' transformed images using Absolute Mean Brightness Error.

```
Require: Input image I, maskSize m, StructuralElementsRange n
Begin
  n[ ]← 0
  pos ← 1
  size ←m
  for i=1 to n
    se ← strel ('disk', size)
    ImTrans←subIm(addIm(I,topHatIm(I,se)), botHatIm (I, se))
    StatMea←PSNR&AbsoluteMeanBrightnessError(I,ImTrans)
    pos ←pos+1
    size ← size+m
  end
  MinAMBE ← min (n)
  FindPos ← find (n=minAMBE)
  OptSize ← findPos*m
  Flag ←OptSize
End
```

Fig 2: Pseudo code for optimum size of disk-shaped structural element selection

In this stage, MRI brain DICOM image (I), structural elements range (n) and size of the mask (m) has given as an input to this system. An input brain image is transformed into 'N' number of times until the appropriate optimum size of a mask as desired. The total number of input image transformation depends upon the division of structural element range (n) and size of the mask (m).

To do the image analysis, two basic qualitative measurements Peak Signal to Noise Ratio, Absolute Mean Brightness Error are computed for each N number of transformations of input MRI brain image. The degree of brightness preservation in an image has measured by using Absolute Mean Brightness Error (AMBE) [16]. AMBE gives the difference between original and enhanced image. And this can be represented by below formula as,

$$AMBE = |(E(x) - E(y)| \qquad (3)$$

Where E(x) is an average value of input image, E(y) is an average value of enhanced output image.

The degree of contrast in the grayscale image is calculated by Peak Signal to Noise Ratio (PSNR) [17]. The highest value of PSNR represents the high-quality image. It can be defined by the below equation,

$$PSNR = 10\log\frac{(2^n - 1)^2}{MSE} \qquad (4)$$

The mean squared difference between the input and output image is called as Mean Square Error (MSE). It can be represented by,

$$MSE = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I(i,j) - K(i,j)]^2 \qquad (5)$$

Where I and K are input image and enhanced image respectively. An image size is M×N.

From this image qualitative measurement, the lowest AMBE value of transformed image has been considered to be an as optimum image. Finally, image complement operation applied on this optimum image to separate the abnormal tissues from enhanced image if it is required.

IV. Results and Discussion

The Collected MRI brain DICOM image has pre-processed and enhanced by using this new hierarchical transformation technique. The selection of size and shape of structuring element of an image I(x, y) depends upon the qualitative measurement of high PSNR (Peak Signal to Noise Ratio) and lower AMBE (Absolute Mean Brightness Error).

Selection of structural element size for one image is varied from another image depends on the value of high PSNR as well as low AMBE values are shown in below Table1 and 2 for sample image1 and 2 respectively.

Table1. PSNR and AMBE values for after MRI brain abnormal sample image1 transformation at different sized structural elements.

image 1	Se=5	Se=10	Se=20	Se=30	Se=35	Se=40	Se=50	Se=60	Se=75	Se=100
PSNR	24.0823	24.3714	25.3921	24.9280	**24.6339**	24.5800	23.9313	23.0904	21.6924	20.2348
AMBE	4.6105	3.9687	2.5902	1.1685	**0.0131**	1.5049	3.2698	5.0606	7.2511	10.6493

Table2. PSNR and AMBE values for after MRI brain normal sample image2 transformation at different sized structural elements.

image 2	Se=55	Se=10	Se=20	Se=30	Se=40	Se=55	Se=70	Se=85	Se=95	Se=100
PSNR	21.1770	21.3088	21.7658	21.9913	22.0460	21.7487	21.8303	**21.8518**	21.8945	21.9452
AMBE	4.2851	7.7934	7.0096	6.5441	6.0425	4.2851	2.5140	**0.4012**	1.6505	2.3845

Optimum enhanced transformed imageFigure3.(c) and Figure5.(d) are much clearer and better when comparing with these original images.

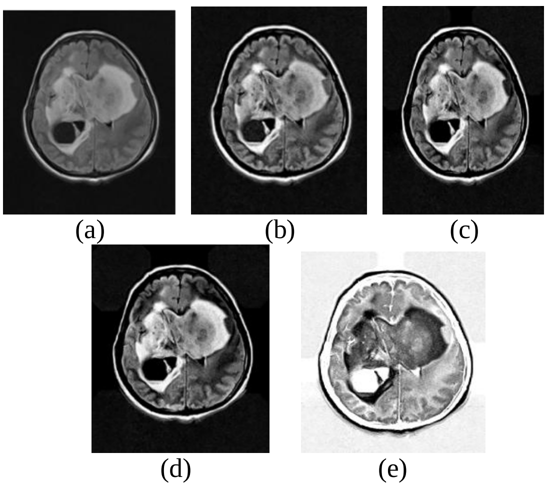

Fig 3: (a) Original MRI abnormal brain image at the size of 1100 pixel by 656 pixels(b) Transformed image-1 with structural element size=25 (c) Optimum enhanced transformed image-2 with structural element size=35 (d) Transformed image-3 with structural element size=55(e) Image Complement of optimum enhanced transformed image-2 for a sample image 1.

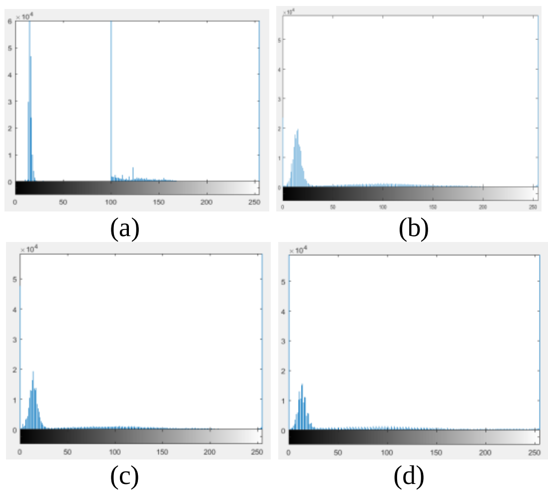

Fig 4: (a) Original MRI abnormal brain image histogram (b) Histogram of transformed image-1 (c) Histogram of optimum enhanced transformed image-2 (d) Histogram of transformed image-3 for a sample image1.

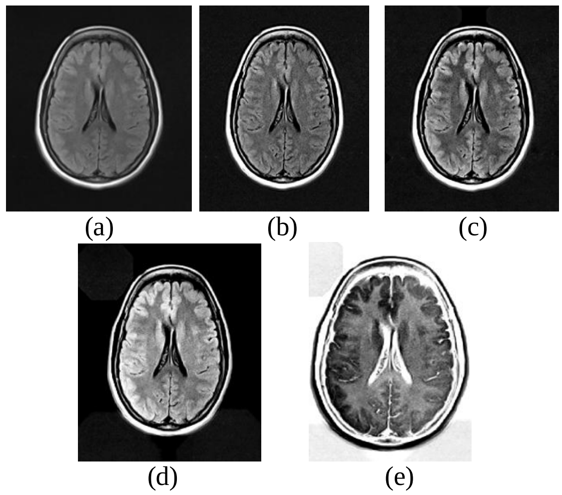

Fig 5: (a) Original MRI normal brain image at the size of 1100 pixel by 656 pixels (b) Transformed image-1 with structural element size=10 (c)Transformed image-2 with structural element size=40 (d) Optimum enhanced transformed image-3 with a structural element size=85 (e) Image complement of optimum enhanced transformed image-3 for a sample image 2.

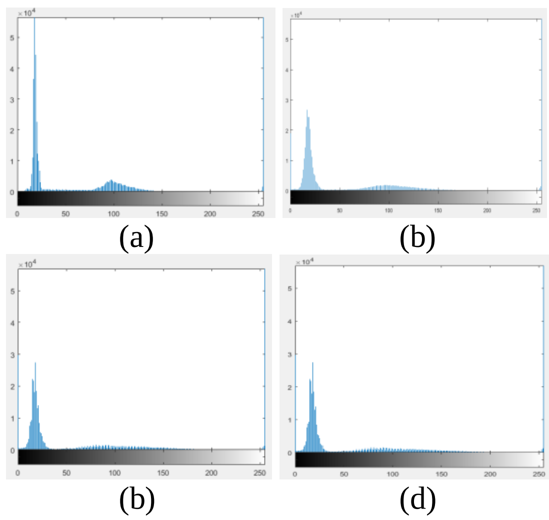

Fig 6: (a) Original MRI normal brain image histogram (b) Histogram of transformed image-1 (c) Histogram of transformed image-2 (d) Histogram of optimum enhanced transformed image-3 for a sample image 2.

Image complement operation has applied on obtained optimum enhanced transformed image for further segmentation process which is also helpful to locate if any abnormal portion at the brain or any other medical images.

The collected sample MRI image dataset contains with 30 normal and 30 abnormal images in the size of 1100 pixel by 656 pixels. Here 20 images and 10 images have taken from each normal and abnormal class for the training set and testing set respectively.

By setting the constant size of SE selection to all images gives less accuracy when compared with an optimum size of SE selection for each image in training and testing set those are represented in Table3 and 4.

Table3. Average performance of SFTA Texture Feature-based Naïve Bayes Classifier with optimum size of structural element selection in percentage

Performance Analysis	Optimum SE(Structural Element) Selection
Sensitivity	90%
Specificity	90%
Accuracy	**90%**

Table4. Average performance of SFTA Texture Feature-based Naïve Bayes Classifier with constant size of structural element selection in percentage

	Structural Element (SE) size									
Performance Analysis	**Se=5**	**Se=10**	**Se=15**	**Se=20**	**Se=25**	**Se=30**	**Se=35**	**Se=40**	**Se=45**	**Se=50**
Sensitivity	90%	80%	80%	50%	50%	60%	80%	60%	40%	50%
Specificity	50%	40%	40%	70%	70%	80%	70%	70%	50%	50%
Accuracy	70%	60%	60%	60%	60%	70%	**75%**	65%	45%	50%

Then the graphical representation of experimental work in the constant size of SE selection and optimum size of SE selection are represented in below Fig 7.

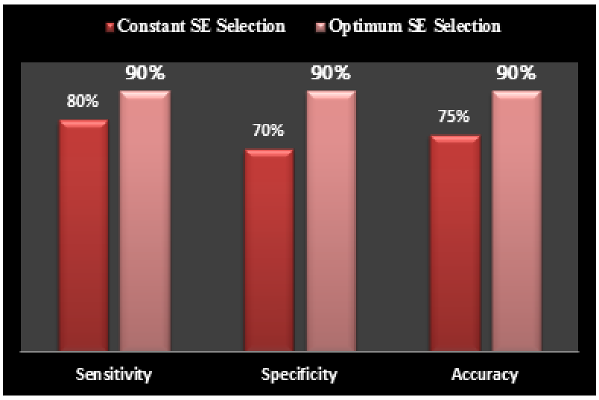

Fig 7: Classification outcomes of different methods of disk-shaped Structural Element selection.

Thus the proposed optimum size of disk-shaped SE selection in hierarchical transformation technique achieves highest percentage results in terms of classification analysis such as sensitivity, specificity, and accuracy.

V. CONCLUSIONS

This work provides an efficient proposed HTT method for image enhancement to improve the contrast as well as the increase the image quality. Image enhancement is a most important one at the image processing methodologies which is helpful to enhance the visual appearance for further automated image diagnosis methods segmentation, detection and pattern recognition. In the disk-shaped mask, constant size of structural element selection and optimum structural element selection methods had compared in terms of qualitative measurement of PSNR and AMBE. From this experimental work, optimum disk-shaped structural element selection achieves the better contrast, highest PSNR as with lowest AMBE, and highest correct classification rate than the constant size of structural element selection.

REFERENCES

[1] D. Jude Hemanth and J. Anitha, "Image Pre-processing and Feature Extraction Techniques for Magnetic Resonance Brain Image Analysis", Computer Applications for Communications, Networking, and Digital Contents, Communications in Computer and Information Science, Vol.350, pp.349-356, © Springer-Verlag Berlin, Heidelberg, Jan 2012.

[2] Y. Yang, Z. Su, and L. Sun, "Medical Image Enhancement Algorithm Based on Wavelet Transform", IEEE Electronics Letters, Vol.46, pp.120-121, Jan 2010.

[3] C.J. Moore, "Medical Image Processing: The Characterization of Display Changes Using Histogram Entropy", Image and Vision and Computing, Vol.4, pp.197-202, 1986.

[4] Qian Wang, Liya Chen, and Dinggang Shen, "Fast Histogram Equalization for Medical Image Enhancement", Proceedings of the 30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Vancouver, British Columbia, Canada, pp.2217-2220, 20-24 Aug 2008.

[5] N. Sengee, B. Bazarragchaa, K. Tae Yun, and C. Heung Kook, "Weight Clustering Histogram Equalization for Medical Image Enhancement", Proceedings of the IEEE International Conference on Communications Workshops, Honolulu, Hawaii, USA, 1-5, pp.14-18 June 2009.

[6] J.C. Fu, H.C. Lien, and S.T.C. Wong, "Wavelet-based Histogram Equalization Enhancement of Gastric Sonogram Images", Computerized Medical Imaging and Graphics, 24.pp.59-68, Jan 2000.

[7] S. Asadi Amiri, and H. Hassanpour, "A Preprocessing Approach for Image Analysis Using Gamma Correction", International Journal of Computer Applications, vol.38-No.12, pp.38-46, Jan 2012.

[8] Petros Maragos, "Differential Morphology and Image Processing", IEEE Transactions on Image Processing, Vol.5, No.6, pp.922-937, June 1996.

[9] F. Oritz, and F. Torres, "Vectorial Morphological Reconstruction for Brightness Elimination in Colour Images", ELSEVIER, Real-Time Imaging, Vol.10, pp.379-387, Dec 2004.

[10] X.-J. Jing, N. Yu, and Y. Shang, "Image Filtering Based on Mathematical Morphology and Visual Perception

Principle", Chinese Journal of Electronics, Vol.13, pp.612-616, 2004.

[11] Richard Alan Peters, "A New Algorithm for Image Noise Reduction using Mathematical Morphology", IEEE Transaction on Image Processing, Vol.4, pp.554-568, May 1995.

[12] A. Mahmoud Tarek, and Marshall Stephen., "Medical Image Enhancement Using Threshold Decomposition Driven Adaptive Morphological Filter", Proceedings of the 16th European Signal Processing Conference, Lausanne, Switzerland, pp. 25-29 Aug 2008.

[13] T. Chen, Q.H. Wu, R. Rahmani-Torkaman, and J. Hughes, "A Pseudo Top-Hat Mathematical Morphological Approach to Edge Detection in Dark Regions", PERGAMON, Pattern Recognition, 35, pp.199-210, 2002.

[14] J. Serra, "Image Analysis and Mathematical Morphology", Academic Press, New York, 1982.

[15] Suman Thapar, and Shevani Garg, "Study and Implementation of Various Morphology Based Image Contrast Enhancement Techniques", International Journal of Computing and Business Research, Proceedings of 'I-Society 2012', 2229-6166, 2012.

[16] R. Gonzalez and R. Woods, "Digital Image Processing", 2nd edition. Prentice Hall, Jan 2002.

[17] Jean-Luc Starck, Emmanue J. Candes, and David L. Donoho, "The Curvlet Transform for Image Denoising", IEEE Transactions on Image Processing, Vol.11, No.6, June 2002.