مجلة جامعة تشرين للبحوث والدراسات العلمية _ سلسلة العلوم الهندسية المجلد (40) العدد (3) 2018
Tishreen University Journal for Research and Scientific Studies - Engineering Sciences Series Vol. (40) No. (3) 2018

A comparison of Image Enhancement Techniques for Recognizing and Classifying Automatically the Medical Images and implement on MRI brain Image

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(Received 11 / 3 / 2018. Accepted 16 / 5 / 2018)

□ ABSTRACT □

The amount of digital images that are produced in hospitals is increasing rapidly. Effective medical images can play an important role in aiding in diagnosis and treatment, they can also be useful in the education domain for healthcare students by explaining with these images will help them in their studies, new trends for image retrieval using automatic image classification has been investigated for the past few years. Medical image Classification can play an important role in diagnostic and teaching purposes in medicine. For these purposes different imaging modalities are used. There are many classifications created for medical images using both grey-scale and color medical images. In this paper, different algorithms in every step involved in medical image processing have been studied. One way is the algorithms of preprocessing step such as Median filter [1], Histogram equalization (HE) [2], Dynamic histogram equalization (DHE), and Contrast Limited Adaptive Histogram Equalization (CLAHE). Second way is the Feature Selection and Extraction step [3,4], such as Gray Level Co-occurrence Matrix(GLCM). Third way is the classification techniques step, which is divided into three ways in this paper, first one is texture classification techniques, second one is neural network classification techniques, and the third one is K-Nearest Neighbor classification techniques.
In this paper, we have use MRI brain image to determine the area of tumor in brain. The steps started by preprocessing operation to the image before inputting it to algorithm. The image was converted to gray scale, later on remove film artifact using special algorithm, and then remove the Skull portions from the image without effect on white and gray matter of the brain using another algorithm, After that the image enhanced using optimized median filter algorithm and remove Impurities that produced from first and second steps.

Keywords: medical image classification, grey-scale and color medical images, Median filter, Histogram equalization (HE), Dynamic histogram equalization (DHE), Contrast Limited Adaptive Histogram Equalization (CLAHE), Feature Selection and Extraction, Gray Level Co-occurrence Matrix (GLCM), texture classification, neural network classification, and K-Nearest Neighbor classification, MRI Brain images, Tracking Algorithm, Modified Tracking Algorithm, Center Weighted Median Filter

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مقارنة بين تقنيات تحسين الصور للتعرف على الصور الطبية تلقائيًا وتصنيفها وتنفيذها على صورة دماغ التصوير بالرنين المغناطيسي

د سمير كرمان*
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(تاريخ الإيداع 11 / 3 / 2018. قُبِل للنشر في 16/ 5 / 2018)

□ ملخّص □

إن الحجم الهائل للصور الرقمية المنتجة من المشافي تزداد بسرعة. الصور الطبية يمكن أن تلعب دوراً مهماً بالمساعدة في التشخيص والمعالجة. و يمكن أن تكون مفيدة أيضاً في مجال التعليم لطلاب الطب بواسطة الشرح لهذه الصور الذي يساعدهم في دراستهم. مجال جديد لاستعادة الصور باستخدام تصنيف الصور الالي تمت مناقشته خلال السنوات الماضية. تصنيف الصور الطبية يمكن أن يلعب دوراً مهماً لأغراض التشخيص و التدريس الطبية. لهذه الاسباب عدة معالجات للصور تم استخدامها.
في هذه الورقة أولاً: تمت دراسة مجموعة من الطرائق المتضمنة خلال خطوات معالجة الصور الطبية، مثل المرشح الوسيط، و معادلة الرسم البياني. ثانياً: تحديد واستخراج الخصائص الهامة للصور، كمصفوفة التدرج الرمادي. ثالثاً: تقنيات التصنيف والتي تقسم الى ثلاث طرق: 1- تصنيف الاكساء، 2- تصنيف الشبكات العصبونية، 3- تصنيف ك- أقرب جار.
رابعاً: تم في هذا البحث استخدام صور الرنين المغناطيسي للدماغ لتحديد منطقة الورم في الدماغ. تبدأ الخطوات بإجراء معالجة أولية للصورة قبل إدخالها الى الخوارزمية بتحويلها إلى صورة ثنائية بتدرج رمادي ليتم بعد ذلك إزالة المعلومات النصية من الصورة (معلومات المريض وبارامترات صورة الدماغ) وذلك باستخدام خوارزمية خاصة، بعد ذلك يتم إزالة أجزاء الجمجمة من صورة الدماغ دون التأثير على المادة البيضاء والمادة الرمادية في الدماغ. ثم بعد ذلك يتم استخدام مرشح معدل (مطور) عن المرشح الوسيط لإزالة الشوائب من الصورة الرقمية الناتجة.

الكلمات المفتاحية: تصنيف الصور الطبية، صور التدرج الرمادي والصور الملونة، المرشح الوسيط، معادلة الرسم البياني، معادلة الرسم البياني الديناميكي، تحديد واستخراج الخصائص، مصفوفة توارد التدرج الرمادي، تصنيف الاكساء، تصنيف الشبكات العصبونية، تصنيف ك-أقرب جار.صور الرنين المغناطيسي للدماغ، خوارزمية الأثر، خوارزمية الأثر المعدلة، خوارزمية المرشح الوسيط المركزي الموزون.

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Introduction

Due to the immense need of effective and accurate medical image retrieval application, new trends for image retrieval using automatic image classification has been investigated for the past few years. It is believed that the quality of such medical system can be improved by a successful classification of images so that the irrelevant images can be filtered out. here are numerous online collections of medical images[5]. On-line atlases of images can be found for many medical domains including dermatology, radiology, ophthalmology, cytopathology and gastroenterology.

The field of image processing has seen much research and progress since 1964, when a computer to correct various types of image distortions [6] processed the pictures of the moon transmitted by Ranger 7. Generally, for modification and analysis of an image, image processing refers to a broad class of algorithms. During acquisition, post-processing, or rendering/visualization, Image Processing refers to the initial image manipulation [7]. For converting the captured RGB image found from the real source, preprocessing steps are essential so that they can be capable for performing any binary operations onto it [8]. Image processing modifies pictures to develop them (enhancement, restoration), extract information (analysis, recognition), and change their structure (composition, image editing) [9]. Image processing is exploited for improving the visual appearance of images to a human viewer and preparing images for measurement of the features and structures present [10]. In image pre-processing Denoising, Restoration, Pre-Segmentation, Enhancement, Sharpening and Brightness Correction are some of the steps comprised [11]. Noise reduction is an important step for any complicated algorithms, in computer vision and image processing [12], Denoising is necessary and the initial step to be taken prior to the image data is analyzed, the effort of image denoising is to improve an image that is cleaner than its noisy observation. Therefore, a substantial technology in image analysis is noise reduction and the initial step to be taken prior to images is analyzed [13]. Shapes and textures are the Features must be extracted in preprocessing step. Shape is an important property in the medical image processing domain. X-ray images with similar shapes may belong to the same category. Zernike moments have been reported to be a good descriptor for shape description. Co-occurrence matrix is one of the most traditional techniques for encoding texture information. Texture is one of the most important defining characteristic of an image. It describes spatial relationships among grey-levels in an image. A cell defined by the position (i, j) in this matrix registers the probability at which two pixels of grey levels i and j occur in two relative positions. A set of co-occurrence probabilities (such as, energy, entropy, contrast) has been proposed to characterize textured regions [14]. Classification is a technique to detect the dissimilar texture regions of the image based on its features. It can be used to classify the feature sets of the image that characterized as different regions [15, 16]. In this paper the classification techniques step is divided into three ways, first one is texture classification techniques, second one is neural network classification techniques, and the third one is data mining classification techniques.

Objective

this paper, presents a review on different groups of classification methods, such as texture classification, neural network classification, and K-nearest neighbor classification, after that we compare between these methods.

Block Diagram of the Classification System

The medical images are pre-processed so as to avoid noises by using median filter. The shape and texture features are extracted. Then, the extracted features are classified. The process flow is depicted in Figure (1).

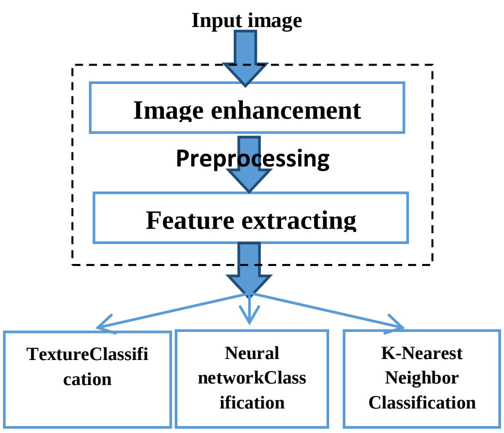
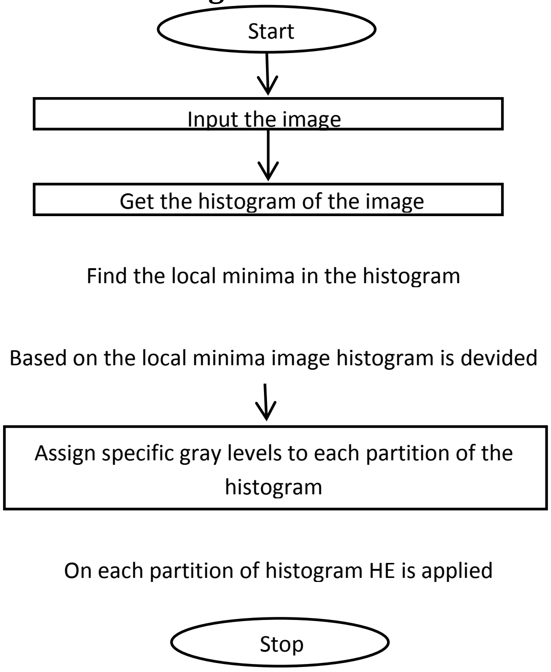


Fig. (1) Block Diagram of classification system

Preprocessing

Image enhancement technique is applied to improve the image quality it provides better grey intensities distribution. Median filter is used to enhance the image, wherein segmentation process is done to find the region of interest (ROI). The ROI is found by segmenting the biggest region in the image. Connected Component Labeling (CCL) is applied for this purpose. CCL scans an image and groups its pixels into components based on pixel connectivity.

III.1. Image Enhancement



Generally for improving contrast in digital images, Histogram equalization (HE) is the method that commonly used but in result it gives unnatural artifacts like intensity saturation, over-enhancement and noise amplification. To overcome these problems [17] there was a need to partition the image histogram, at first image histogram was partitioned into two parts and then different transformation functions were applied on each partition. After that image histogram was partitioned into many partitions and same process was applied with some additional features. Dynamic histogram equalization (DHE) is the multi histogram method and Contrast limited adaptive histogram equalization (CLAHE) is the extension of Adaptive histogram equalization (AHE). These methods are compared to HE and found that both methods give better result than HE but DHE method also gives better result than CLAHE. The flowchart for the DHE algorithm is shown in Figure (2).

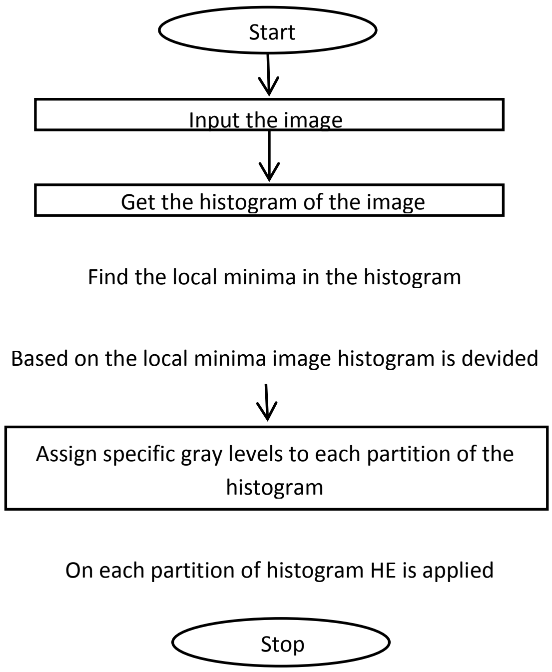
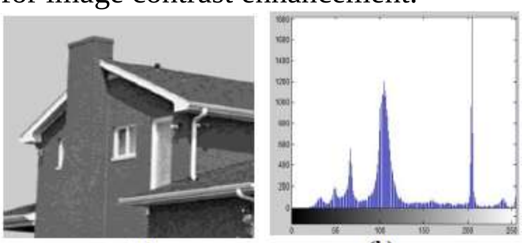
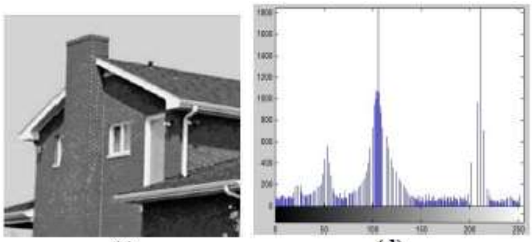


Fig. (2) Flow Diagram for DHE Method

DHE separates the histogram depends on local minima. Formally, it implements a one-dimensional smoothing filter on the histogram to dispose meaningless minima. Then it makes sub-histograms taking the portion of histogram that falls between two local minima. Figure (3) shows an illustrating example of using Dynamic Histogram Equalization (DHE) for image contrast enhancement.



(a) (b)



(c) (d)

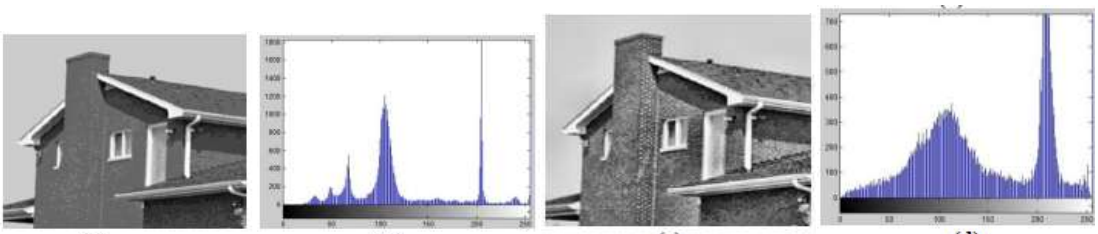
Fig. (3) Illustration of DHE: (a) Input image, (b) Histogram of the output image, (c) Output image by the DHE method, (d) Histogram of the output image.

The algorithm for CLAHE is shown in Figure (4).

1. Input the image and calculate the grid size based on maximum image dimension.
2. Starting from top left corner Find grid points on the image.
3. for each grid point
   -Calculate histogram with area equal to window size and grid point as centre.
   -Clip the histogram above the clip limit and use it to find CDF.
4. for each pixel
   - find 4 neighbor grid point for pixel and based on their CDF find the mapping of that pixel at 4 grid points.
5. Apply Interpolation among these values to get mapping at the current pixel location.
6. Now map this intensity into the output image with range [min max].

Fig (4). Algorithm for CLAHE Method

Figure (5) shows an illustrating example of using Contrast Limited Adaptive Histogram Equalization (CLAHE) for image contrast enhancement.



(a) (b) (c) (d)

Fig.(5) Illustration of CLAHE: (a) Input image, (b) Histogram of the output image, (c) Output image by the CLAHE method, (d) Histogram of the output image.

III.2. Feature extracting

Feature extraction is an important step in image classification. It allows representing the content of images as perfectly as possible [18].

III.2.1. Color Features

In image classification and image retrieval, the color is the most important feature [19, 20]. The color histogram represents the most common method to extract color feature. It is regarded as the distribution of the color in the image. The efficacy of the color feature resides in the fact that is independent and insensitive to size, rotation and the zoom of the image [21, 22].

III.2.2. Texture Features

Texture feature extraction is very robust technique for a large image which contains a repetitive region. The texture is a group of pixel that has certain characterize. The texture feature methods are classified into two categories: spatial texture feature extraction and spectral texture feature extraction [22, 23, 24].

III.2.3. Shape Features

Shape features are very used in the literature (in object recognition and shape description). The shape features extraction techniques are classified as region based and contour based [22, 24]. The contour methods calculate the feature from the boundary and ignore its interior, while the region methods calculate the feature from the entire region.

III.2.4. Gray Level Co-occurrence Matrix (GLCM)

The Gray Level Co-occurrence Matrix (GLCM) is a statistical method of examining texture that considers the spatial relationship of pixels [25].
GLCM contains information about the position of the pixels that have the same value of gray levels. A GLCM is a 2-dimensional array, P, in which both rows and columns representing a set of possible values of the image[4],[6].It is a matrix showing how often a pixel with intensity (gray-level) value i occurs in a specific spatial relationship to a pixel with the value j. It is defined by (i,jld,Ө), which expresses the probability of the couple of pixels at Ө direction and interval. Once the GLCM is created various features can be computed from it [25] .In order to estimate the similarity between different gray level co-occurrence matrices, Haralick had proposed 14 different statistical features extracted from GLCM [26,27].To reduce the computational complexity, only some of these features are selected in this paper, specifically: Energy, Contrast, Homogeneity and Correlation. The four statistics applied to co-occurrence probabilities are discussed before:

1- **Energy**: Energy reaches a maximum value that equal to one. High energy values occur when the gray level distribution has a constant or periodic form. Energy has a normal range. The GLCM of less homogeneous image will have large number of small entries

$$Energy = \sum_i \sum_j g_{ij}\, 2$$

2- **Contrast**: it measures the amount of local variations present in the image. A low contrast image presents GLCM concentration term around the main diagonal and low spatial frequency features

$$Contrast = \sum_i \sum_j (i-j)^2 g_{ij}$$

3- **Homogeneity**: This statistic measures image homogeneity as it assumes larger values for maller gray tone differences in pair elements. It is more sensitive to the presence of near diagonal elements in the GLCM. It has maximum value when all elements in the image are equal.

$$Homogenity = \sum_i \sum_j \frac{1}{1+(i-j)^2} g_{ij}$$

4- **Correlation**: The feature correlation is a measure of linear dependency of gray tones in the image.

$$Correlation = \frac{\sum_i \sum_j (ij) g_{ij} - \mu_x \mu_y}{a_x a_y}$$

Classification

Medical image classification provides a challenge on the identification of similar medical images: this is an interesting problem due to the subtle changes between different image sources. For instance, inside the range of microscopy images there exist different acquisition devices (light, electron, fluorescence or transmission) which are able to capture different tissue details. Despite of that, the resemblance between image cues is high and poses a challenging problem from a classification perspective [28].

IV.1. Texture classification

Textures are one of the vital features in image processing and especially biomedical image analysis. Although, textures look intuitive, so far a single unifying of them have not been suggested, which could present a comprehensive definition for textures.

Therefore, researchers proposed different methods for extraction of texture features, which each group of features have their positive and negative properties as well. Textures as an important property in medical images have attracted much attention in CAD systems [29]. Texture analysis methods can be divided in different sub-categories. In this paper we present some of the most important branches of texture analysis methods which find a proper application in medical image analysis [30].

IV.1.1. Statistical Methods

Statistical features consist of different categories such as first-order, second-order statistical methods, Local Binary Pattern (LBP) methods and so forth. These features especially LBP have been the center of attention because of obtaining promising results which they recently have achieved in different applications with changing in level of noises, illumination, sizes of textures. As medical images are affected by many artifacts during imaging providing an invariant group of features is crucial in these applications. In the following subsections we describe some of the important methods of the statistical approaches for texture analysis.

IV.1.1.1. LBP Methods

The other important category of statistical methods is Local Binary Pattern (LBP) based approaches [8]. In [9] a new LBP method has been proposed which tries to incorporate spectral features into LBP method. Therefore, LBP will be more robust and powerful to invariant texture analysis in this case. Different types of this method have been proposed for texture analysis of biomedical applications and find a great attention in CAD systems [31,32].

IV.1.1.2. First order and second order methods

The first order statistical features include the features which are extracted from the statistical property of image histogram including mean, variance, standard deviation and etc. Although these features are very straightforward and simple, they provide a good description of texture in the image. Moreover, there are three main sub-categories which have been proposed for second-order statistical features including Spatial Grey-level Difference Method based on the analysis of co-occurrence matrix [33], the Grey-Level

Difference and the Grey-Level Run Method. Statistical features have widely been used for extraction of relevant features in CAD systems [34].

IV.2. Neural network classification

Neural networks are well known for their good performance in classification and function approximation, and have been used with success in medical image processing over the past years, particularly in the case of preprocessing (e.g. construction and restoration), segmentation, registration and recognition. Table 1 gives an overview of the main types of neural network used in these fields; detailed description of most important applications is included in the remainder of this section [35]. Multilayer Perceptron (MLP) neural network is a tool frequently used in differentiating between benign and malignant lesions. Its topology consists of sensory units which include the input layer, one or more hidden layers (also known as intermediary), and an output layer [36]. The learning process is supervised; that is, the desired outputs are required. A supervised learning algorithm analyzes, through comparative actions between inputs and the desired output, the training data and produces an inferred function, which can be used for mapping new examples. An optimal scenario will allow for the algorithm to correctly determine the class labels for unknown instances. After performing comparisons in the learning method (the backpropagation), the synaptic weights are adjusted continuously reaching for convergence. In this step, the discrepancy between the responses produced by the network and the desired signal is evaluated. The network adjusts the values of the synaptic weights and this process is finished only when the error assumes an acceptable value [36]. The cross-validation method is used to evaluate data generalization. This procedure was performed through random partitioning of the dataset into two subsets: training and test [36]. The training was accomplished only in phantom images due to the low number of malignant cases in actual clinical exams. Thus, 144 ROIs from phantoms images were used for classification, 72 corresponding to benign and 72 to malignant images. From these 144 images, 70% were designated for training and 30% for validation.

Table (1): Main neural networks used in medical image processing

	Preprocessing	Segmentation	Registration	Recognition
Feed forward NN	√	√	-	√
Radial basis function NN	-	-	√	√
Hopfield NN	√	√	-	√
Self-organizing feature NN	√	√	√	
Adaptive resonance theory	-	-	-	√

	Preprocessing	Segmentation	Registration	Recognition
NN				
Cellular NN	√	-	-	-
Convolution NN	-	-	-	√
Probabilistic NN	-	√	-	√
Fuzzy NN	√	√	-	√
Neural ensemble		√	√	√
Massive training NN	√	-	-	√

IV.2. k-Nearest Neighbor Pattern classification

The k-Nearest Neighbor (k-NN) is a non-parametric algorithm. The algorithm first stores the feature vectors for training set and afterwards for classification of a new instance, it finds set of k nearest training examples in the feature space, afterwards assigns the instance to the class having more examples in the given set [37]. In the work of Suguna & Thanushkodi [39], an improved k-NN using genetic algorithm was utilized to reduce high calculation complexity with low dependency on the training set and no weight difference between each class. Latifoglu et al. [42] proposed a medical system based on principal component analysis (PCA), k-NN weight pre-processing and artificial immune recognition system (AIRS) for diagnosis of atherosclerosis disease. However, there are certain limitations of this algorithm: it can only store the local information with high calculation complexity and it takes longer time for computation of new query. It can handle binary and continuous attributes but not directly discrete ones [38]. However, few recent studies try to overcome limitation of traditional k-NN, for example in the work of [40, 41, 42] are able to produce better results.

MRI Brain Image Enhancement UsingFiltering Techniques

In this paper, we have use MRI brain image to determine the area of tumor in brain. The steps started by preprocessing operation to the image before inputting it to algorithm. The image was converted to gray scale, later on remove film artifact using special algorithm, and then remove the Skull portions from the image without effect on white and gray matter of the brain using another algorithm, After that the image enhanced using optimized median filter algorithm and remove Impurities that produced from first and second steps, then we used the Gaussian Pyramid algorithm with Laplacian pyramid algorithm for detecting edges in the image, Finally we use Hough transform to determine the area of tumor using Theta and Voting graph. That is a new way was applied for benefit from the properties of Hough Transformation to detect circle regions and then make a decision for normal or abnormal regions.

VII. PREPROCESSING TECHNIQUES
VII.1 Removal of film artifacts

This paper presents an integrated method of the adaptive enhancement of brain tissues in two-dimensional (2-D) MRI images. The MRI brain image consists of film artifacts or label on the MRI such as patient name, age and marks. film artifacts that are removed using tracking algorithm .Here, starting from the first row and first column, the intensity value of the pixels are analyzed and the threshold value of the film artifacts are found.
The threshold value, greater than that of the threshold value is removed from MRI. The high intensity values of film artifacts are removed from MRI brain image. The following figures explain the process of preprocessing stage.

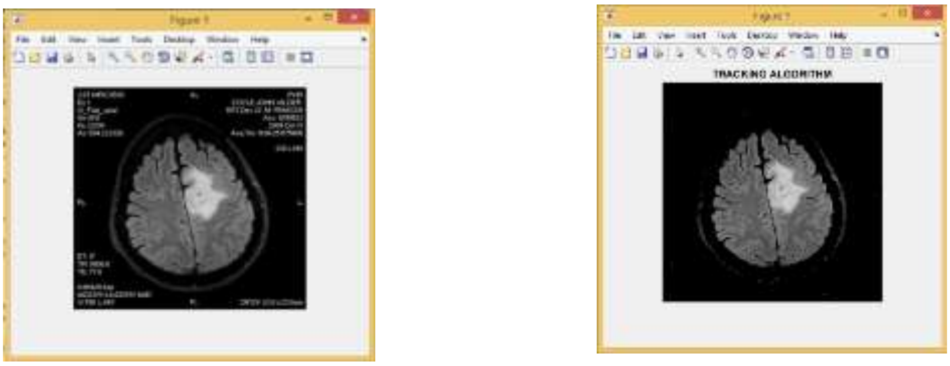


Figure (6) Removal of film artifacts

VII.2 Removal of Skull using Modified Tracking Algorithm

After removing the film artifacts, another part of the MRI which is not required for our further processing is the skull The modified Tracking Algorithm is used to remove unwanted portion of MRI that means left, right and top skull portions .The MRI image obtained after removing the film artifacts and labels is taken. Start from left side first row, first column of the given matrix and select the peak threshold value from left side of the matrix and assign flag value to 200. If the current pixel intensity value ranges from 200-255 then, the set the flag value to zero and thus the left skull Portion of the MRI is removed. Repeat these steps to remove the right and top skull portion of the MRI.

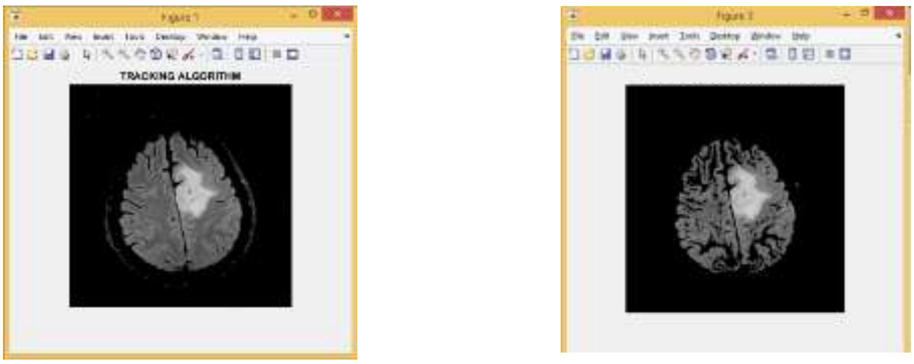


Figure (7) Removal of Removal of Skull

VIII. HISTOGRAM MODELING

Intensity transformation functions based on information extracted from image intensity histograms vital role in image processing, in areas such as enhancement, compression, segmentation, and description. This section is on obtaining, plotting, and using histograms for image enhancement.

VIII.1. Image Histograms

The histogram of a digital image with L total possible intensity levels in the range [0, G] is defined as thediscrete function h(rk) = nk where rk is the kth intensity level in the interval [0, G] and nk is the number ofpixels in the image whose intensity level is rk. Often, it is useful to work with normalized histograms, obtained simply by dividing all elements of h(rk) by the total number of pixels in the image, which denote by n: p(rk)= h(rk) / n = nk / n for k = 1,2, …., L from basic probability, recognize p(rk) as an element of the probability of occurrence of intensity level rk.

VIII.2. Histogram Equalization

Let us consider for a moment that intensity levels are continuous quantities normalized to the range [0, 1],and let Pr(r) denote the probability density function (PDF) of the intensity levels in a given image, where the subscript is used for differentiating between the PDFs of the input and output images. Suppose perform the following transformation on the input levels to obtain output (processed) intensity levels.

VIII.3. CENTER WEIGHTEDMEDIAN FILTER

In medical image processing, necessary to perform a high degree of noise reduction in an image beforeperforming high-level processing steps. Median Filter can remove the noise, high frequency components from MRI without disturbing the edges and it is used to reduce' salt and pepper' noise. This technique calculates the median of the surrounding pixels to determine the new (denoised) value of the pixel. A median is calculated by sorting all pixel values by their size, then selecting the median value as the new value for the pixel. The amount of pixels which should be used to calculate the median.

A weighted median filter controlled by evidence fusion is proposed for removing noise from MRI brainimages with contrast. It has a great potential for being used in rank order filtering and image processing. Theweights of the filter are set based on intensity value of the pixels in the MRI image. Here we used four weights such as 0, 0.1, 0.2 and 0.3. if the intensity value of the pixel is 0 then consider the weight of the pixel is 0. Else if the range of pixel intensity between 1-100 then the weight is 0.1,else if the range of pixel intensity between 101-200 then the weight is 0.2, otherwise the weight of the pixel is 0.3. the above weights are multiplied with pixel intensity .after that the median filter is applied for calculate weighted median filter.

The center weighted median (CWM) filter, which is a weighted median filter giving more weight only to thecentral value of each window, is used. This filter can preserve image details while suppressing additive white and/or impulsive-type noise. The statistical properties of the CWM filter are analyzed. It is shown that the CWM filter can outperform the median filter. It is shown that the CWM filter is an excellent detail preserving smoother that can suppress signal-dependent noise as well as signal-independent noise [9].

In a CWM filter, the center sample is assigned a larger weight, i.e. w(0, 0) = 2K + 1where K >= 0, and all other non-zero weights are equal to one, i.e. w(i,j) = 1 for i not equal to 0 and j not equal to 0. K is a nonnegative integer.A CWM filter is completely specified by two parameters, the window size and the center weight. The filtering behavior of a CWM filter will thus be controlled by these two parameters. Denote a CWM filter with center weight 2K + 1 by CWM(M; 2K + 1), where M is the number of the samples in the window, e.g., M = (2N + 1) x (2N + 1) for a connected square window.

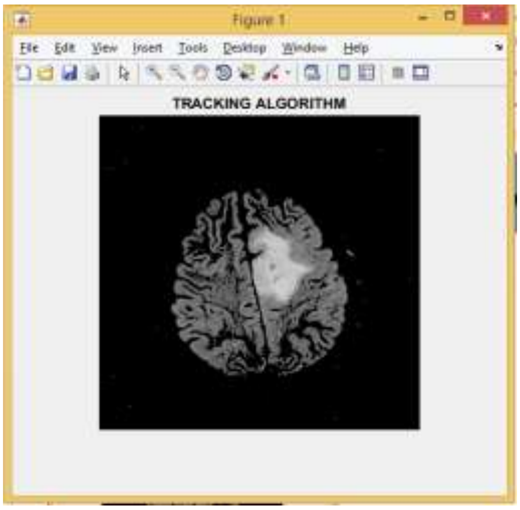


Figure (8). Enhanced MRI Brain image

IX. EXPERIMENTS AND RESULTS

This algorithm has been tested with various types of textured images acquired in the database. This proposed approach has been implemented by using mat lab. The experimental results are tested in Intel Core i3 2.5 GHz processor with 4 GB RAM. It is very difficult measure to the improvement of the enhancement objectively. If the enhanced image can make observer perceive the region of interest better, then we can say that the original image has been improved. In order to compare different enhancement algorithms, it is better to design some methods for the evaluation of enhancement objectively. The statistical measurements such as variance or entropy can always measure the local contrast enhancement; however that show no consistency for the MRI. Performance of the Median filter, Weighted Median filter, and center weighted median filters are analysed and evaluated. Table1 shows the performance of listed filters.

TABLE (1) PERFORMANCE ANALYSIS FILTERS

Sn	Filters	PSNR	ASNR
1	Median	0.91543	0.9267
2	Weighted Median	0.92667	0.9278
3	Center Weighted Median	0.92726	0.9280

X. SUMMARY AND CONCLUSIONS

Our proposed method is based on a combination of different approaches to preprocess and enhance the brain MRI images. The gray level transformation, logarithmic transformation, histogram equalization and median filtering are presented. Initially the MRI brain image is acquired from MRI brain data set to MATLAB 7.1.
After acquisition the MRI is given to the preprocessing stage, here the film artifacts (labels) are removed. Next, the high frequency components and noise are removed from MRI using the following filters. Such as Median filter, Weighted Median filter and Center Weighted Median filter. The performance of above filters are measured and evaluated. Finally the best filter of center weighted median filter is identified and used for MRI brain image enhancement. It is used for removing noise from MRI brain images with high contrast.

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