VOL. 11, NO. 21, NOVEMBER 2016 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

www.arpnjournals.com

DISCRETE WAVELET BASED DECOMPOSITION OF BRAIN IMAGE FOR DE-NOISING AND RESOLUTION ENHANCEMENT

M. Malathi, K. Sujatha and Sinthia. P
CEAIR Centre for Electronics, Automation and Industrial Research, Dr. MGR Educational and Research Institute, Saveetha Engineering College, Chennai, India
E-Mail: malathi.matlab@gmail.com

ABSTRACT

The main aim of the project is to improve the resolution of brain image via discrete wavelet based decomposition. Magnetic resonance imaging (MRI) scan is better than the X-ray, CT scan and Ultra Scan to detect the location of tumor in human body. Because the resolution is high in MRI scan. Also various features can be recognized from MRI scan. Digital Image Processing (DIP) is performed to avoid the unwanted noise occur in the scanned images. In mathematical scrutiny and functional scrutiny, a discrete wavelet transform (DWT) is a few wavelet transform for which the wavelets are distinctly sampled. Because with additional wavelet transforms, a key benefit it has over Fourier changes is temporal decision: it detains both location information in time and frequency. The discrete wavelet based decomposition is applied in the proposed technique for both normal and abnormal MRI scan brain images. Also seven features such as contrast, correlation, mean, standard deviation, entropy, energy and homogeneity are analyzed for both normal and abnormal images of all types of segmentation process. From the analysis, the computation time is very low and accuracy is high in discrete wavelet based decomposition for de-noising and resolution enhancement.

Keywords: brain image decomposition, MRI Scan, digital image processing, discrete wavelet.

1. INTRODUCTION

Image segmentation refers to the method of partitioning a digital image into multiple districts. The main goal of segmentation is to vary the representation of an image to be more momentous and easier to scrutinize. It is used in order to locate boundaries and objects in pictures. The outcome of image segmentation takes places as a set of regions that collectively covers the whole image. Consequently, medical image segmentation plays a major role in clinical diagnosis. It can think as a tricky problem because medical images generally have poor contrasts, various types of noise, and missing boundaries. The structure of the brain can be scanned by computed tomography (CT) scan or Magnetic Resonance Imaging (MRI) scan. The MRI scan is easier than CT scan for diagnosis. It is not affect on the human body since it does employ any radiation. It is based on the radio waves and magnetic field [1].

Alternatively, brain tumor is one of the leading reasons of death among people. It is proof that the possibility of survival can be increased if the tumor is detected properly at its early period. In most cases, the surgeon gives the treatment for the strokes fairly than the treatment for the tumor. Consequently, detection of the tumor is vital for the treatment. The lifetime of the person who affected by the brain tumor will rise if it is detected premature stage. Hence, there is a need for well-organized medical image segmentation method with few preferred properties such as accurate, minimum user interaction, robust segmentation and fast computation results [3].

Conversely, image segmentation algorithms are based on one of the two basic properties of image intensity values: discontinuity and similarity. In the formal category, the segmentation approach is based on dividing the processed image based on changes in intensity, such as corners and edges. The second one is based on dividing an image into regions that are similar because of a set of predefined criteria. So, there are several segmentation techniques which can be widely used, for example edge-based methods, histogram based methods, artificial neural network based segmentation methods, physical model based approaches, clustering methods (Fuzzy C-means clustering, K-means clustering, Mean Shift, and Expectation Maximization) and region-based methods (region splitting, growing, and merging). There are several challenging issues to image segmentation like development of a unified approach that can be applied to all kinds of images and applications. Constant, the selection of an appropriate method for a meticulous kind of image is a tricky problem. Therefore, there is no universal accepted technique for image segmentation. Hence, it remains a challenging problem in computer vision fields and image processing [2].

One view of image segmentation is a clustering problem that worries how to find which pixels in an image belong together most properly. There is a broad literature on the techniques that carry out image segmentation based on clustering methods. These techniques typically show clustering in one of the two different approaches, either by grouping pixels or by partitioning. In partitioning, the entire image is divided into regions that are ‘‘good’’ along with some criteria. While in the grouping, the pixels are collected together based on a few assumptions that find how to group preferably. There are several clustering algorithms that can be used in image segmentation process, for example Fuzzy clustering and hard clustering or K-means clusters [4]. So, clustering is a challenging field. It can be used as a stand-alone tool to gain insight into the distribution of data in various clusters for additional investigation. Cluster analysis serves as a pre-processing step for additional algorithms, for example classification that would then operate on detected clusters.

ARPN Journal of Engineering and Applied Sciences

'Haar' wavelet is an easiest and oldest wavelet. Daubechies wavelets are most well-liked symbolizing the basics of wavelet sign processing. OW is used for numerous applications and, also named Max tlat wavelets as their frequencies response has supreme frequencies as '0' and 'pi' which are desirable. The properties for few applications like Haar, Oaubechies, Symlets and Coitlets are trimly supported orthogonal wavelets. These wavelets along through Mayer wavelets are able of great modernizations. The Mexican Hat, Moslet and Meyer wavelets are symmetric in appearance; the wavelets are chosen depending upon the capability to examine the signal on meticulous applications.

This article is organized as follows. Introduction about existing scientific research in medical image segmentation for brain tumor detection is presented in Section 2. Section 3 provides the information about discrete wavelet. It describes the multilevel decomposition of image, approximation and de-noising. Section 4 describes the experimental results obtained from the estimation of the proposed methods using 3three types of data sets and converses the central questions derived from them. Conclusion and future work are presented in Section 5.

2. LITERATURE SURVEY

Medical image segmentation is considered as a warm research theme. More than a few researchers have proposed different algorithms and methodologies for image segmentation. Such as, Bandhyopadhyay and Paul [5] suggested K-means clustering technique for brain tumor segmentation. The extortion of the brain tumor section from the processed image needs the segmentation of the brain MRI images to two segments. One segment contains the ordinary brain cells consisting of White Matter (WM), Cerebral Spinal Fluid (CSF) and Grey Matter (GM)). Brain tumor cell presents in the second segmentation. The segmentation technique is constraint by the fact that the images require to be of contiguous imaging layer. The image fusion scheme offered a good result in fusing multiple images. In meticulous cases, it resulted in the loss of intensity. Additionally, it also disregarded the finer anatomic details, for example turns and twists in the boundary of the tumor.

Meena and Raja [6] recommended an approach of Spatial Fuzzy C-means (PET-SFCM) clustering algorithm on Positron Emission Tomography (PET) scan image datasets. The algorithm is nothing but joining the spatial neighborhood information with typical FCM and modernizing the objective function of every cluster. Their algorithm is checked on data collection of patients with Alzheimer’s sickness. They did not estimate objective based quality review that could examine images and did not report their quality devoid of human contribution. Glavan and Holban [7] suggested scheme that using a convolution neural network (CNN) since pixel classifier for the segmentation method of a few X-ray images. The convolution neural network attained the most excellent results in contrast to further configurations. For ensuring a smallest training time of the set of connections, they used simply the curiosity areas from an image. Their scheme identified the major bone areas; however the problems emerged while the bone area presented inequalities and obtain more execution time in training.

Tatiraju and Mehta [8] formed image segmentation by using Normalized Cuts (NC), Expectation Maximization (EM) and K-means clustering. For smaller values of k, the EM algorithms and K-means provide excellent results. For greater values of k, the segmentation is very rough; several clusters materialize in the images at discrete places. The NCuts algorithm offered excellent results for larger value of k, However it takes a long time. Yerpude and Dubey [9] suggested K-Medoids Clustering based color image segmentation. Kmedoids technique uses envoy objects as reference positions fairly than taking the mean value of the objects in each and every cluster. The segmented images are highly reliant on the number of segments. They did not think about discovering best number of segments to offer more precise results.

Islam and Ahmed [10] recommended image segmentation technique derived from K-Mediods, K-means and Hierarchical clustering techniques. After incorporating these algorithms into images, they mentioned that the K-means Clustering method has superior performance and simple to implement than all other clustering techniques. Funmilola *et al*. [11] create the Fuzzy K-C-means system, which brings extra of Fuzzy C-means properties than that of K-means. Fuzzy K-C-means works on grayscale images like Fuzzy C-means. It produces the equal number of iterations like in Fuzzy C-means. The proposed technique shrinks the iterations by testing the distances simply. The drawback is that the result of their suggested system is alike to the result of the Fuzzy C-means algorithm with the exception of few images. The time of Fuzzy C-means is larger than by uppermost 2 s than their recommended technique.

Wilson and Dhas [12] used Fuzzy C-means and K-means in that order to determine the iron in brain SWI. In this work, they checked the recital of the mainly four well-known clustering methods: Maximization Expectation, Fuzzy C-means, Mean Shift, and K-means. They prepared a comparison between their proposed method and these algorithms in features of accuracy and processing time. The checked algorithms were applied on three dissimilar data sets contains 255 MRI images of the brain have tumor cells. In their integration, they removed the saved time; of course, avoided over-segmentation and under-segmentation, retained image information and attained the precision.

3. PROPOSED DISCRETE WAVELET BASED SEGMENTATION

Wavelet techniques are very useful tool for digital signal processing like de-noising, approximation and decomposition. Wavelets demonstrate an efficient depiction of images. An image is decomposed into horizontal, vertical, diagonal, approximation and sub bands. In this work, the discrete wavelet based image approximation, de-noising and decomposition is proposed for automatic brain tumor detection. Multilevel

VOL. 11, NO. 21, NOVEMBER 2016 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

decomposition puts a signal through combination of low-pass and high-pass filters. The approximation coefficients are given by the output of low pass filter (LPF) and the detail coefficients are provided by the output of the high pass filter (HPF). In this scheme, the discrete functions are work like a wavelet input. These are the easiest wavelets; these structures are used in several techniques of discrete image processing and transforms. The significant research defy of this work is to develop the visual quality of brain image via image processing to detect brain tumor at premature stage.

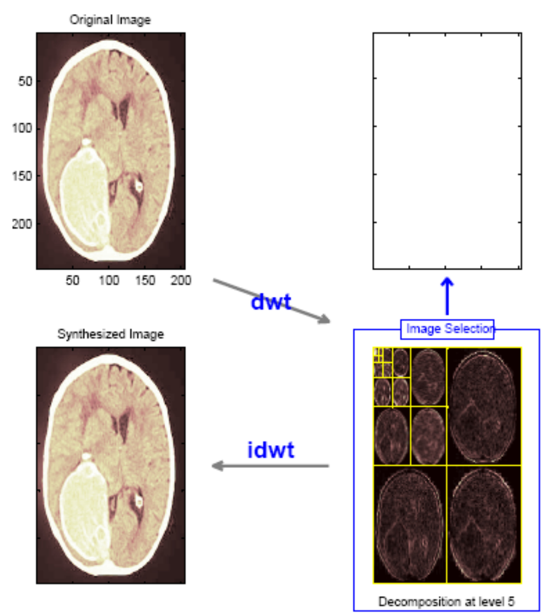

Figure-1. Block diagram of decomposition of discrete 2d-DWT.

Discrete wavelet transform are mainly used for digital image processing such as segmentation, decomposition and de-nosing. Original image are split into equal quarter size. Whole Images are split into 4 pixels in the first level decomposition. From the four pixels, only one pixel is selected for further de-composition into again four pixels. Similarly, decomposition process is followed up to five levels. These kind of decomposition process is called as multi level 2d-DWT as in Figure-1.

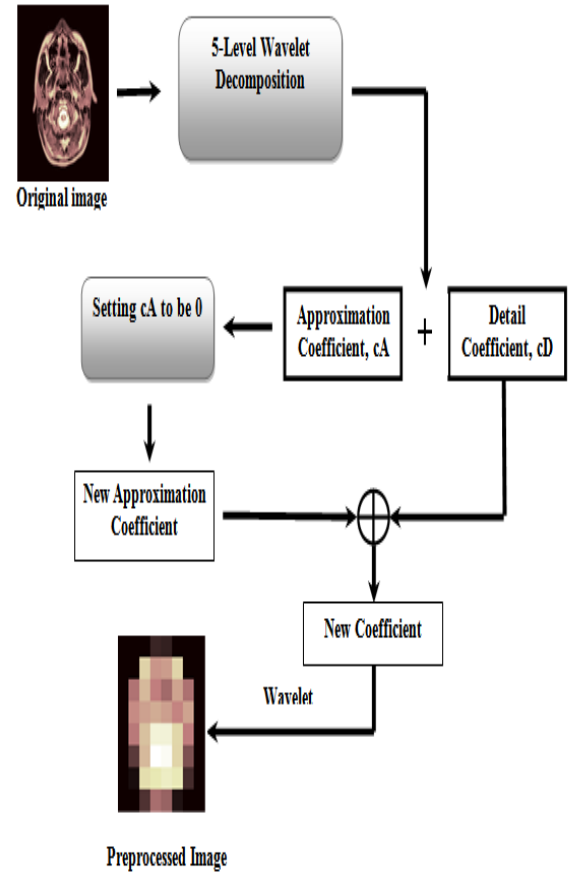

Figure-2. Brain architecture by using discrete wavelet decomposition.

The structure of discrete wavelet based decomposition is shown in Figure-2. Brain image is taken as input image and it is translated into detailed coefficient and approximation coefficient by using high pass and low pass filters. The approximation coefficient value set as zero to eliminate the low frequency, which contains in the input image. Residual coefficients are used for image reconstruction. Incorporate the new approximation coefficients into detail coefficients to create a novel coefficient. Wavelet reconstruction technique is used in the novel coefficient to translate into preprocessed image.

4. RESULTS AND DISCUSSIONS

The discrete wavelet based brain tumor detection on the MRI scan brain image is implemented and tested. Multi- level decomposition is performed by using a discrete wavelet to represent MRI scan picture. In each and every approximation stage, the largest 50 coefficients of diagonal, vertical, horizontal and approximation is used to exist the trait vector of the equivalent mammogram is shown in Figure-3.

ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

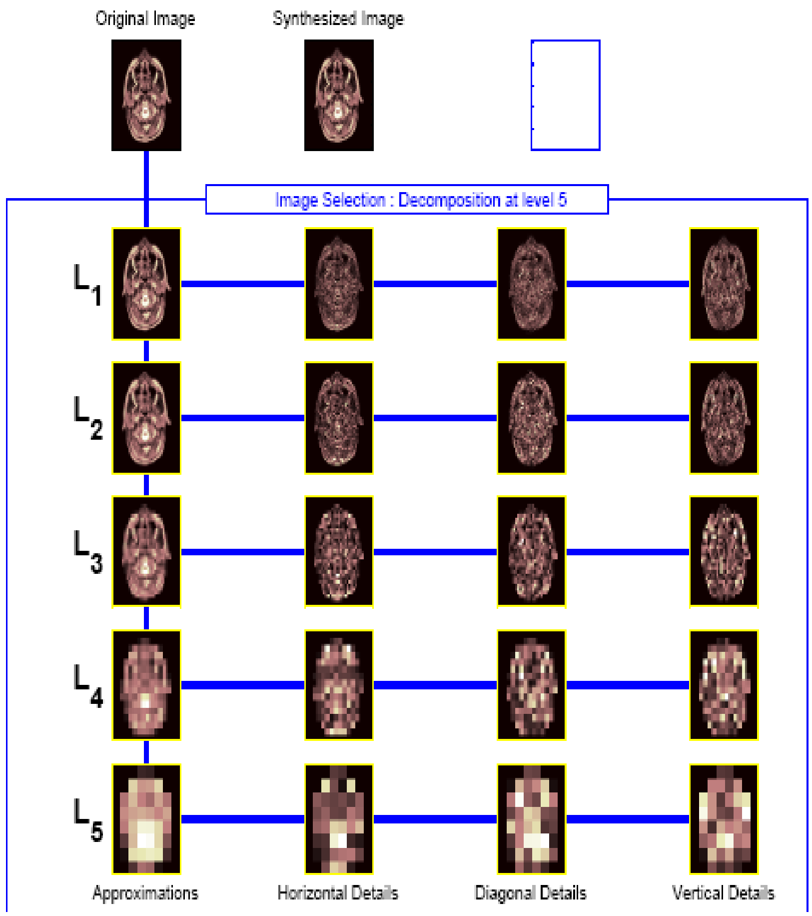

Figure-3. Diagonal, vertical, horizontal and approximation details of the input brain image.

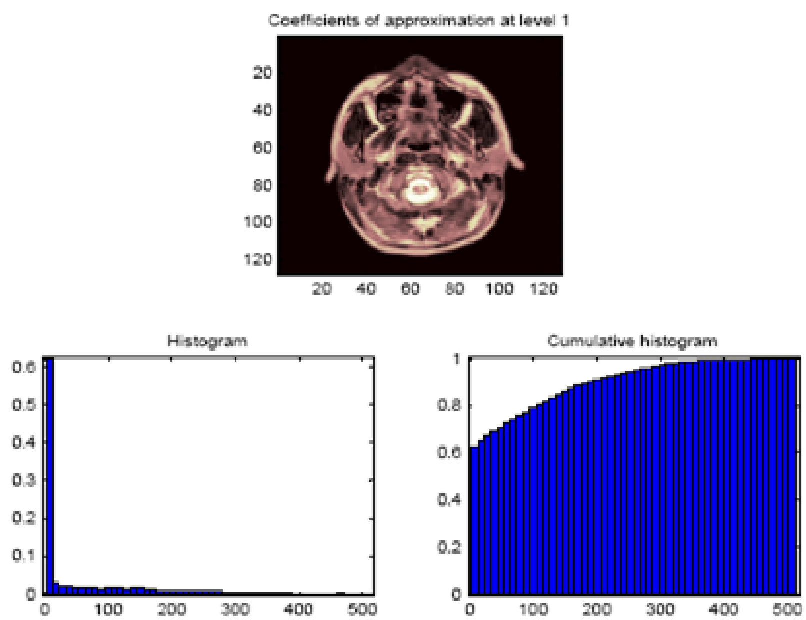

Figure-4. Cumulative histogram and approximation coefficient at level 1.

ARPN Journal of Engineering and Applied Sciences

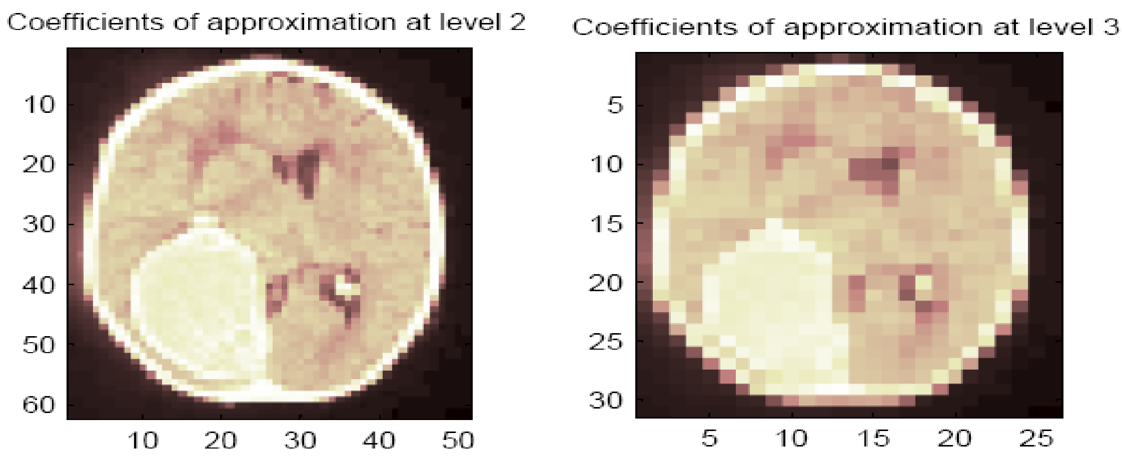

Figure-5. Approximation coefficient of brain image at level 2 & level 3.

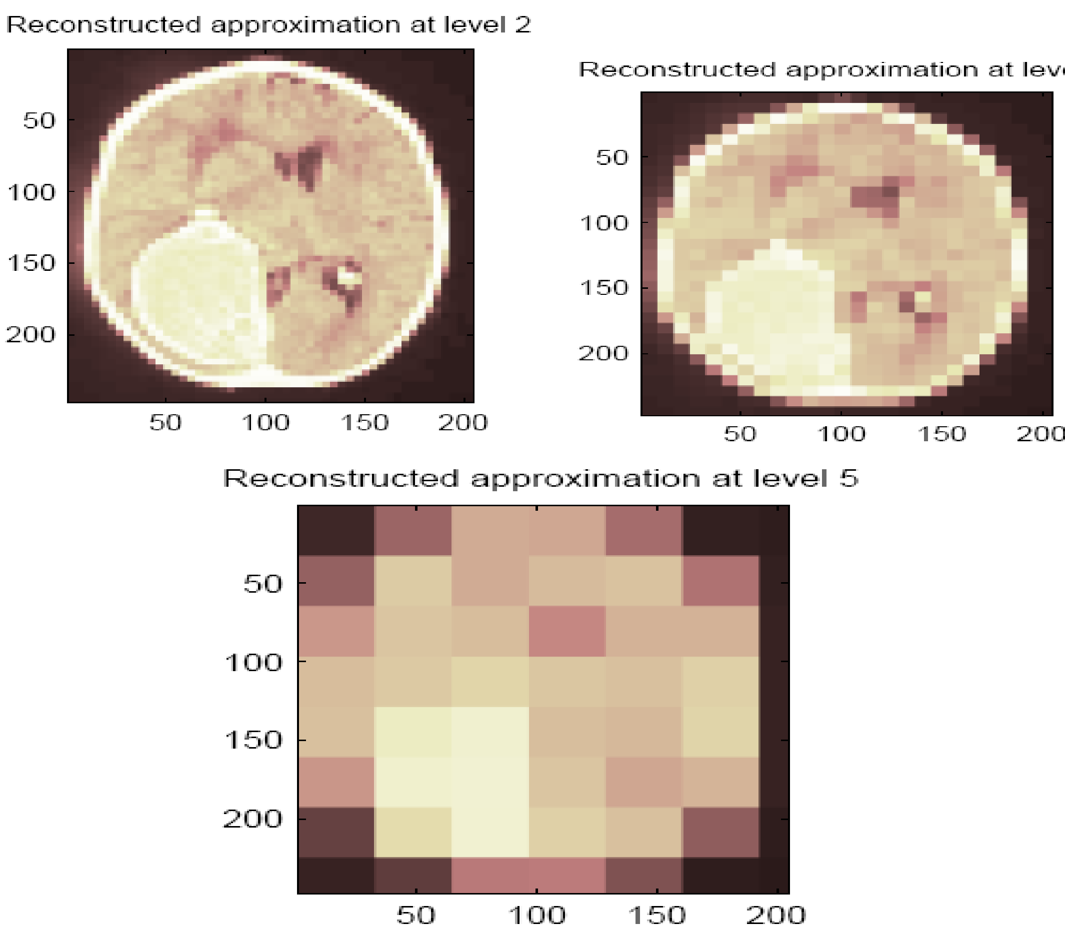

Figure-6. Reconstructed approximation of brain image at level 2, 3, 5.

From the Figure-4 and Figure-5, coefficient of approximation is analyzed from level1 to level5. Also cumulative histogram of brain image is examined by using the discrete wavelet. The brain images are re-constructed at different level as shown in figure6. Also unwanted noise occur in the image is removed by de-noising process as shown in Figure-7.

VOL. 11, NO. 21, NOVEMBER 2016 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

www.arpnjournals.com

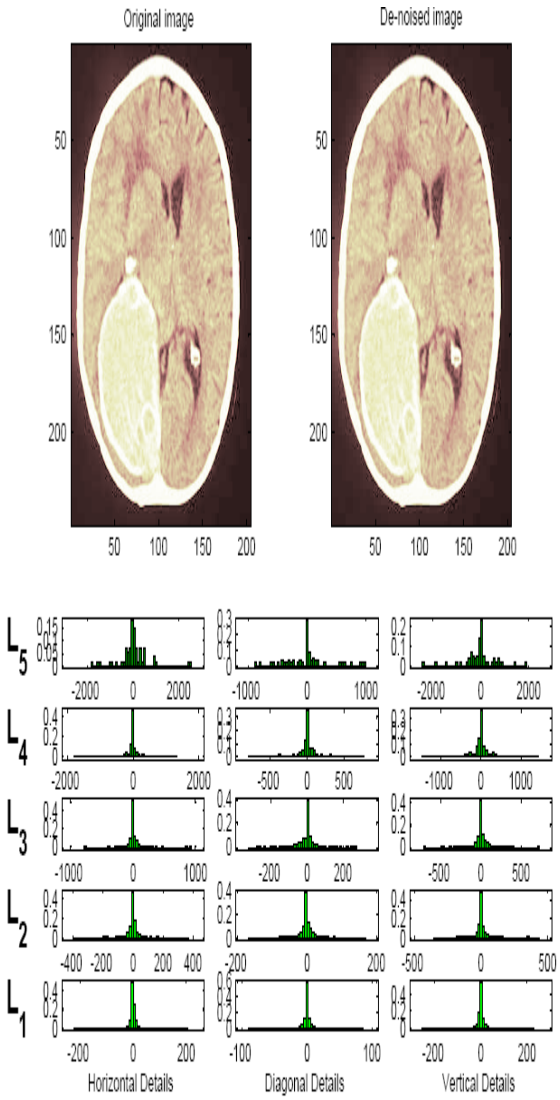

Figure-7. De-noised brain image using discrete wavelet.

5. CONCLUSIONS

Discrete wavelets offer efficient and stable representation of pictures. In this work, a MRI scan brain picture is used. Initially, brain image is decomposed using discrete wavelet functions, and then a set of coefficients is removed from each and every decomposition stage. The result shows that, the extracted features based on approximation (low frequency) provide a better concert when compared to the details (high frequency) coefficient. In this work, the variations between wavelet sub bands (details and approximation) are studied and practically implemented. Also de-noised process is studied and practically implemented.

REFERENCES

Patel J, Doshi K. 2014. A study of segmentation methods for detection of tumour in brain MRI. Adv Electron Electr Eng. 4(3): 279-284.

Seerha GK, Kaur R. 2013. Review on recent image segmentation techniques. Int J Comput Sci Eng (IJCSE). 5(2): 109-112.

Kaur J, Agrawal S, Vig R. 2012. Integration of clustering, optimization and partial differential equation method for improved image segmentation. Int J Image Graph Signal Process. 4(11): 26-33.

Panda M, Patra MR. 2008. Some clustering algorithms to enhance the performance of the network intrusion detection system. J Theor Appl Inform Technol. pp. 795-801.

Bandhyopadhyay SK, Paul TU. 2013. Automatic segmentation of brain tumour from multiple images of brain MRI. Int. J Appl Innovat Eng Manage (IJAIEM). pp. 240-248.

Meena A, Raja K. 2013. Spatial Fuzzy C-means PET image segmentation of neurodegenerative disorder spatial Fuzzy C-means PET image segmentation of neurodegenerative disorder. Indian J Comput Sci. Eng (IJCSE). pp. 50-55.

Tatiraju S, Mehta A. Image Segmentation using k means clustering, EM and normalized Cuts, University Of California Irvine, technical report.

Yerpude A, Dubey S. 2012. Colour image segmentation using K-medoids clustering. Int. J Comput Technol Appl, pp. 152-4.

Islam S, Ahmed M. 2013. Implementation of image segmentation for natural images using clustering methods. Int J Emerg Technol Adv Eng. pp. 175-180.

Christe SA, Malathy K, Kandaswamy A. 2010. Improved hybrid segmentation of brain MRI tissue and tumour using statistical features. J Image Video Process. pp. 43-49.

Funmilola A, Oke OA, Adedeji TO, Alade OM, Adewusi EA. 2012. Fuzzy K-C-means clustering algorithm for medical image segmentation. J Informat Eng Appl. 2(6): 21-32.

Wilson B, Dhas JPM. 2014. An experimental analysis of Fuzzy C-means and K-means segmentation algorithm for iron detection in brain SWI using Matlab. Int J Comput Appl. 104(15): 36-8.

Robi Pollikar. 2001. A Wavelet Tutorial Part I. Fundamental Concepts and an Overview of Wavelet Theory. Second Edition.