ISSN No. 0976-5697
Volume 3, No. 7, Nov-Dec 2012
International Journal of Advanced Research in Computer Science
RESEARCH PAPER
Available Online at www.ijarcs.info

An efficient segmentation of MRI images using different methods of wavelet transform

Ram Krishna Deshmukh*
Department of ET&T
CSVT University
Bhilai, India.
ramkrishnadeshmukh@gmail.com

Yogesh S. Bahendwar
Department of ET&T
CSVT University
Bhilai, India.
y_bahendwar@rediffmail.com

Abstract: Segmentation is the process of separate an observed image into its homogeneous or constituent regions. The goal of segmentation is to simplify or change the representation of an image into something that is more meaningful and easier to analyze. It is important in many computer vision, medical field and image processing application. In computer vision, segmentation refers to the process of partitioning a digital image into multiple regions. Spinal cut MR Images have a number of features, especially the following: Firstly, they are statistically simple; MR Images are theoretically piecewise constant with a small number of classes. Secondly, they have relatively high contrast between different tissues. Additionally, image segmentation has applications separate from computer vision; it is frequently used to aid in isolating or removing specific portions of an image. Image segmentation is typically used to locate objects and boundaries in images. The problem becomes more compound while segmenting noisy images. Segmentation of medical imagery is a challenging task due to the complexity of the images, as well as to the absence of models of the anatomy that fully capture the possible deformations in each structure. Spinal cut tissue is a particularly complex structure, and its segmentation is an important step for derivation of computerized anatomical atlases, as well as pre- and intra-operative guidance for therapeutic intervention. Watershed based image segmentation using wavelet model. Image segmentation, feature extraction and image components classification form a fundamental problem in many application of multi-dimensional signal processing. The paper is devoted to the use of wavelet transform for feature extraction associated with image pixels and their classification in comparison with the watershed transform. A specific attention is paid to the use of Haar, db wavelet or other transform as a tool for image compression and image pixels feature extraction. Proposed algorithm 'bio' & different wavelet is verified for simulated images and applied for a selected MR image, using image processing in the MATLAB platform.

Key words: *MRIS, IFE & SDF feature extraction, WST, WT & PSNR, MSE.*

*For future corresponding.

I. INTRODUCTION

The contrast in an MR image depends upon the way the image is acquired. MRI is an advanced medical imaging technique providing rich information about the human soft tissue anatomy. It has several advantages over other imaging techniques enabling it to provide 2-dimensional data with high contrast between soft tissues. However, the amount of data is far too much for manual analysis/interpretation, and this has been one of the biggest obstacles in the effective use of MRI. For this reason, automatic or semi-automatic techniques of computer-aided image analysis are necessary. Segmentation of MR images into different tissue classes, especially gray matter, white matter and cerebrospinal fluid, is an important task. Brain MR Images have a number of features, especially the following: Firstly, they are statistically simple; MR Images are theoretically piecewise constant with a small number of classes. Secondly, they have relatively high contrast between different tissues. By altering radio frequency and gradient pulses and by carefully choosing relaxation timing, it is possible to highlight different component in the object being imaged and produce high contrast images.[5]

II. WEIGHTING AND DENSITY

MR images can be acquired using different techniques. The resulting images highlight different properties of the depicted materials. The most common weightings are T1 and T2, which highlight the properties T1-relaxation and T2-relaxation respectively. Selection of the most appropriate weighting is important for a successful segmentation [1].

T1-images show high contrast between tissues having different T1-relaxation times. Tissues with long T1-relaxation time emit little signal and thus they will be dark in the resulting image. In T1-images air, bone and CSF have low intensity, gray matter is dark gray, white matter is light gray, and adipose tissue has high intensity. T1-images have high contrast between white matter and gray matter.[1]

In T2-images, white matter and gray matter are gray and have similar intensities. CSF is bright, while bone, air, and fat appear dark. As opposed to T1-images, T2-images have high contrast between CSF and bone. The contrast between white matter and gray matter is not as good as in T1-images.

Spin density or Photon Density (PD) is the most like Computed Tomography (CT) of all the MR contrast parameters. The spin density is simply the number of spins in the sample that can be detected. The observed spin density in medical imaging is always less than the actual spin density due to the fact that many spins are bound and lose signal before they can be observed.

III. MR IMAGE SEGMENTATION

Segmentation of medical imagery is a challenging task due to the complexity of the images, as well as to the absence of models of the anatomy that fully capture the possible deformations in each structure. Brain tissue is a particularly complex structure, and its segmentation is an important step for derivation of computerized anatomical atlases, as well as pre- and intra-operative guidance for therapeutic intervention.

MRI segmentation has been proposed for a number of clinical investigations of varying complexity. Measurements of tumor volume and its response to therapy have used image gray scale methods as applied to X-ray, Computerized Tomography (CT) or simple MRI datasets. However, the differentiation of tissues within tumors that have similar MRI characteristics, such as edema, necrotic, or scar tissue, has proven to be important in the evaluation of response to therapy. Other applications of MRI segmentation include the diagnosis of brain trauma where white matter lesions, a signature of traumatic brain injury, may potentially be identified in moderate and possibly mild cases. These methods, in turn, may require correlation of anatomical images with functional metrics to provide sensitive measurements of brain trauma. MRI segmentation methods have also been useful in the diagnostic imaging of multiple sclerosis.

IV. SEGMENTATION PROCESS

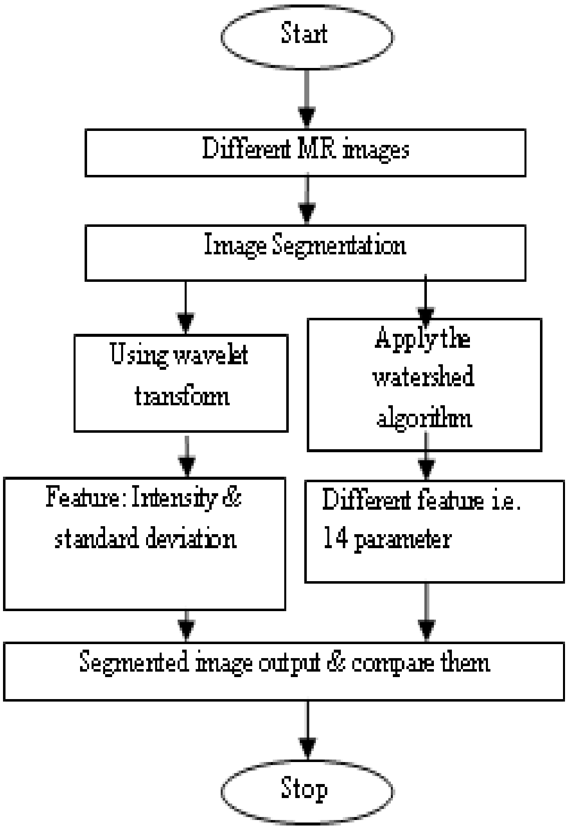


Figure. 1 Preprocessing of segmentation

V. WAVELET TRANSFORM

Wavelet transforms have been successfully used in many fusion schemes. A common wavelet analysis technique used for fusion is the discrete wavelet transform (DWT) [2, 3]. It has been found to have some advantages over pyramid schemes such as: increased directional information[2]; no blocking artifacts that often occur in pyramid-fused images [2]; better signal-to-noise ratios than pyramid-based fusion [3]; improved perception over pyramid-based fused images, compared using human analysis [2, 3].

A major problem with the DWT is its shift variant nature caused by sub-sampling which occurs at each level. A small shift in the input signal results in a completely different distribution of energy between DWT coefficients at different scales. A shift invariant DWT (SIDWT), yields a very over-complete signal representation as there is no sub-sampling.

VI. WATERSHED ALGORITHM

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 [4].

In order to reduce the deficiencies of watershed, many pre-processing techniques are proposed by the different researcher's presents a robust watershed segmentation using wavelets where wavelets technique is used to de-noise the image and an efficient watershed algorithm based on connected components.

A proposed method of watershed segmentation using prior shape and appearance knowledge to improve the segmentation results etc. But most of the techniques previously proposed consider the over segmentation problems and focus on the denoising of the image [5]. The image low contrast and under segmentation problem is not yet addressed by most of the researchers.

VII. METHODOLOGY

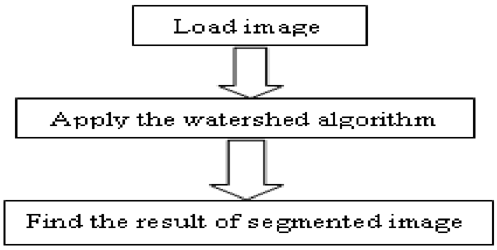


Figure.2 Process of image segmentation based on watershed

&

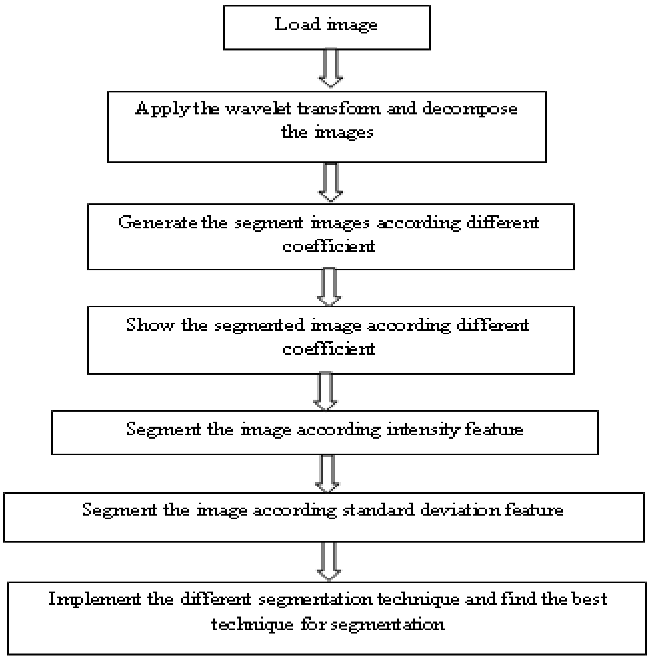


Figure. 3 Process of image segmentation based on wavelet.

VIII. RESULT

We segment the different MRI images by wavelet & watershed methods. The result is shown in fig.4 to fig.7 & fig.8 to fig.9. In this paper we apply the two segmentation technique. For these two techniques we segment the different images like our image and MRI images. This is shown in fig.4 to fig.9. The wavelet segmentation is mainly for gray images and its segment, in only for area of interest. In the watershed technique we segment the images on different texture based, the segmentation images are shown in result.

A. Segmented output of Brain MR Image using WAVELET:

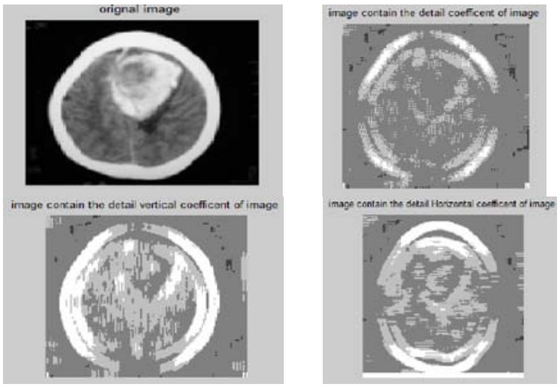


Figure.5 (a) original image, (b) detail coefficient, (c & d) Vertical & Horizontal coefficient of image segmentation using wavelet transform.

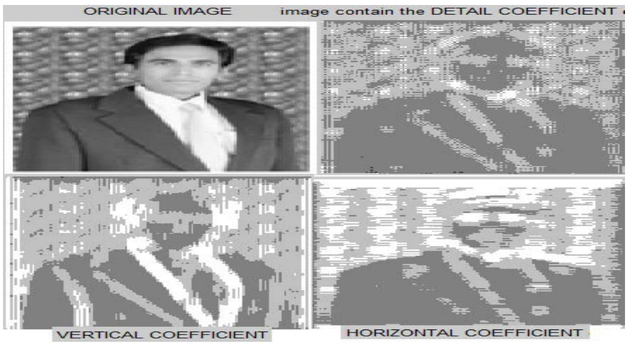


Figure.5Example image of author (for fig.4)

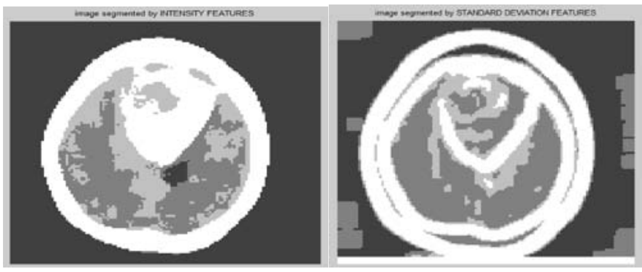


Figure.6 wavelet result (a) Intensity feature (b) SD feature of image segmentation.

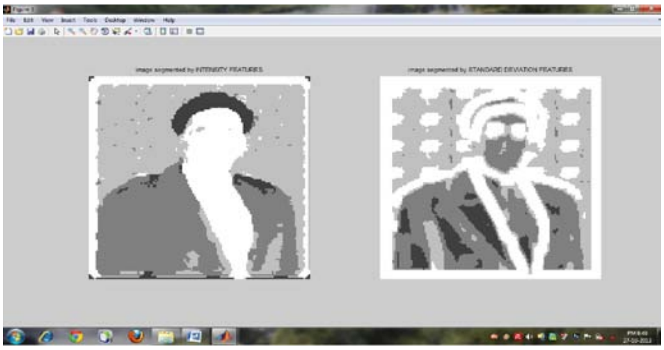


Figure.7 Example image of author (for fig.6)

B. Segmented output of Brain MR image using WATERSHED:

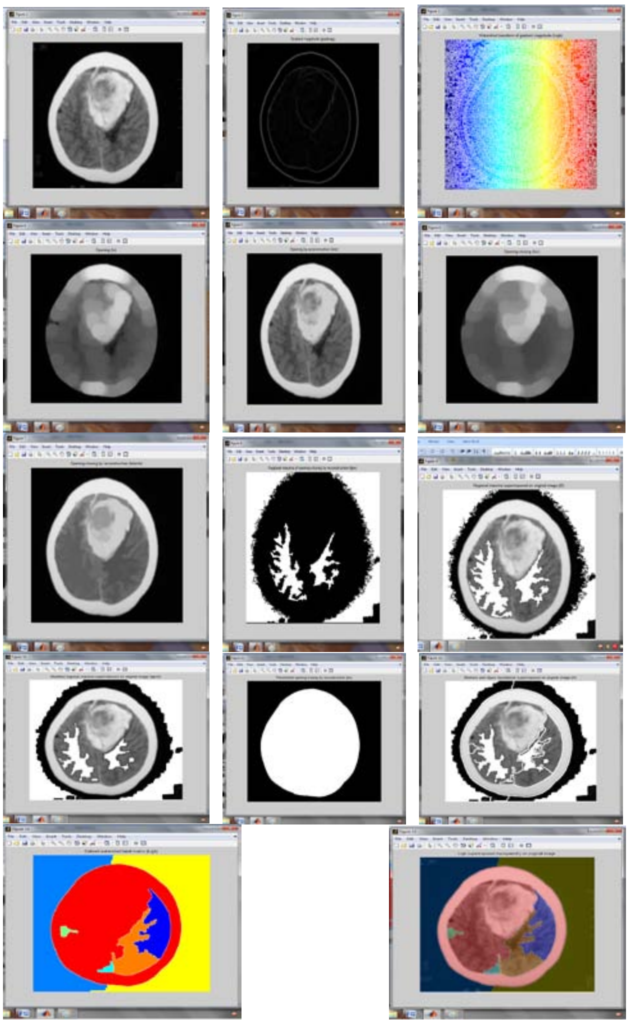


Figure. 8 Segmented watershed result (1) to (15) dif. feature.

IX. CONCLUSION

In this paper we segment images using wavelet and watershed transform. In wavelet we use ‘bio 3.3’. Which is only one wavelet which choose randomly but wavelet is very big family, there are many wavelets are available. It is very difficult to decide which wavelet is best for feature, we have to segment the MRI images by different wavelet and find which the best wavelet for MRI image segmentation.

X. ACKNOWLEDGMENT

The authors would like to thank the reviewers for their comments that helped to improve the quality of this paper.

XI. REFERENCE

[1]. D.L. Pham, J. L. Prince, "Adaptive fuzzy segmentation of magnetic resonance images, IEEE Trans. Medical Imaging, vol. 18, 1999.
[2]. H. Li, S. Manjunath, and S. Mitra. Multisensor image fusion using the wavelet transform. Graphical Models and Image Processing, 57(3):235–245, 1995.
[3]. T.Wilson, S. Rogers, and M. Kabrisky. Perceptual based hyperspectral image fusion using multi-spectral analysis. OpticalEngineering, 34(11):3154–3164, 1995.
[4]. P. Scheunders and J. Sijbers. Multiscale watershed segmentation of multivalued images. In International Conference on Pattern Recognition, Quebec, 2002.
[5]. Ram Krishna Deshmukh &Yogesh Bahendwar, International Journal of Advanced Research in Computer Science, 3 (1), Jan –Feb, 2012, 65-69.
[6]. Ram Krishna Deshmukh &Yogesh Bahendwar, "A competent MRI images segmentation using wavelet transform", International Journal of Computer Science and Management Research,Vol. 1 Issue 5, Dec. 2012.
[7]. Ram Krishna Deshmukh &Yogesh Bahendwar, "MR image segmentation using wavelet and watershed transforms", International Journal of Societal Application of Computer Science,Vol. 1 Issue 2 Dec. 2012.
[8]. Ram Krishna Deshmukh &Yogesh Bahendwar,"image segmentation with standard deviation feature using wavelet transforms", International Research Journal of Computer Science Engineering and Applications, Vol. 1 Issue 3 Dec. 2012.
[9]. Ram Krishna Deshmukh, Y. Bahendwar, "Content-Based Image Retrieval Systems -Using 3D Shape Retrieval Methods with Medical Application", International Journal of Advanced Research in Computer Science, Vol. 3, No. 1, Jan-Feb 2012.
[10]. Ram Krishna, Yogesh Bahendwar, "Content-Based Image Retrieval Systems in Medical Applications – Clinical Benefits and Future Directions", International Journal of Computer Science and Network Security, Vol. 12, No. 9, Sep. 2011, pp. 113-120.

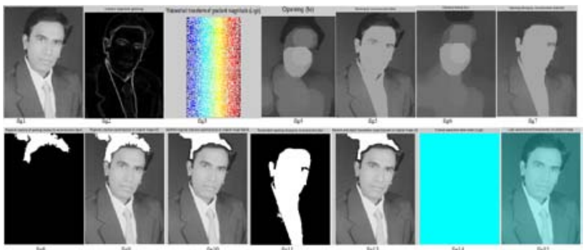
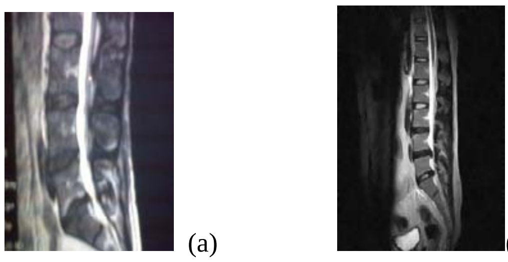


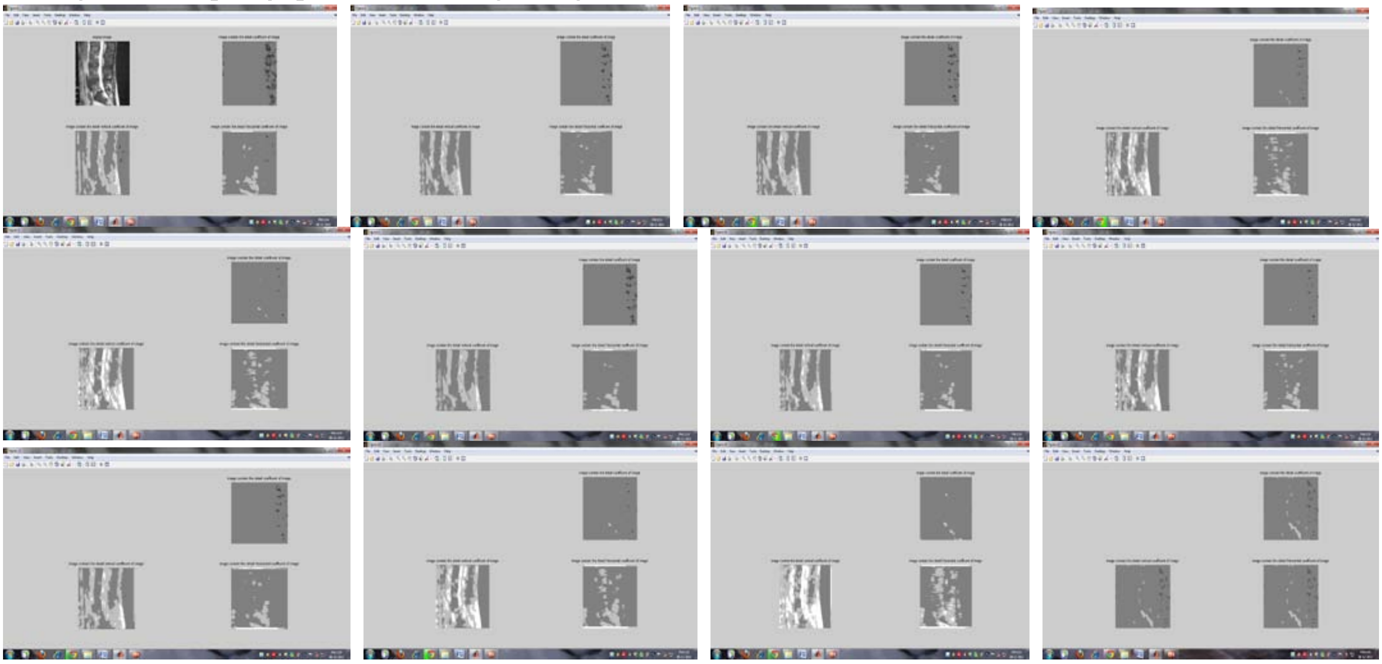
Fig.9 Segmented Image(auther) for Watershed Technique.

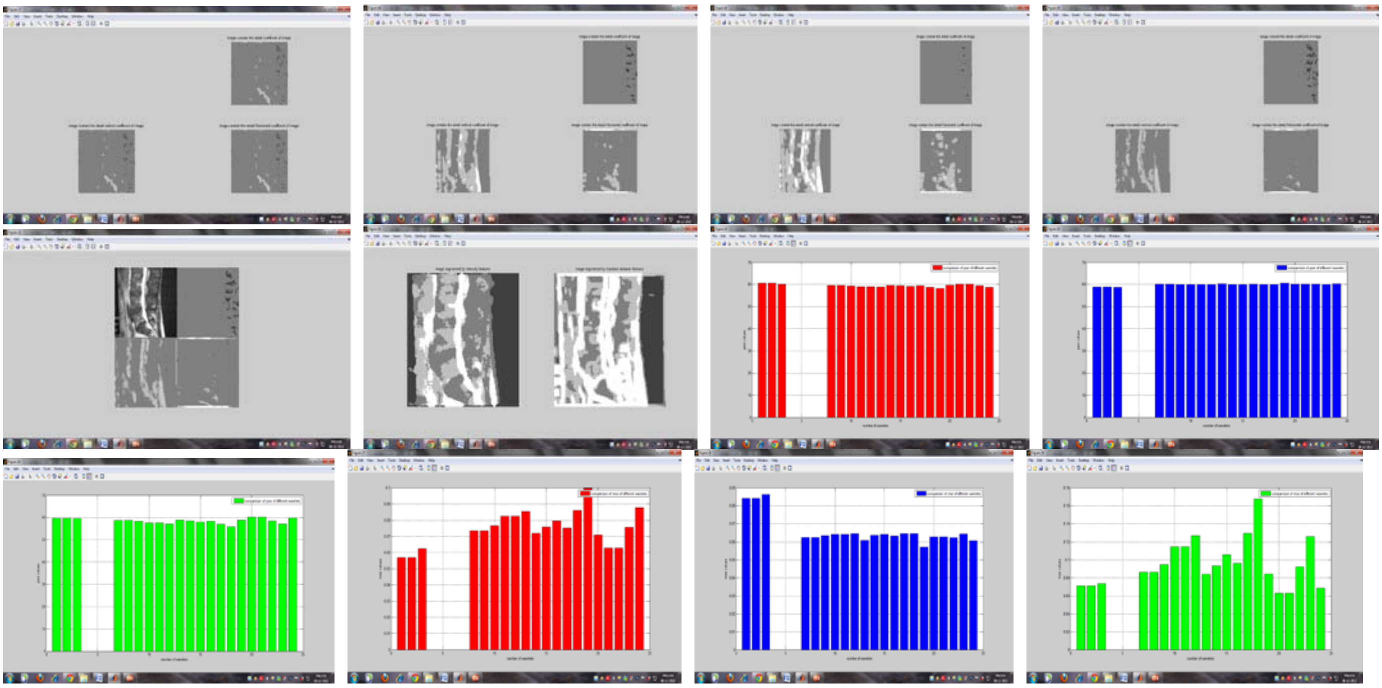


(a) (b)

Fig.10 (a & b) Input spinal cut image for wavelet segmentation.

A1. ***Segmented output of Spinal cut MR Image using WAVELET TRANSFORM***





A2. Best PSNR AND MSE Value For spine MRI image:

1. The max. PSNR is **56.596963** the wavelet filter is Haar.
2. The max. PSNR is **56.291178** the wavelet filter is Bior (3.3)
3. The max. PSNR is **56.291178** the wavelet filter is Bior (3.3).
4. The min. MSE is **0.1423590** the wavelet filter is Haar.
5. The min. MSE is **0.1527430** the wavelet filter is Bior.(3.3).
6. The min. MSE is **0.1527430** the wavelet filter is Bior.(3.3)

A3. PSNR AND MSE Value For spine MRI image:-

S. No.	wavelets	PSNR1	PSNR2	PSNR3	MSE1	MSE2	MSE3
1	Haar	56.5970	55.5810	56.2382	0.1424	0.1799	0.1546
2	Db1	56.5970	55.5810	56.2382	0.1424	0.1799	0.1546
3	Db3	56.5499	55.2346	56.0259	0.1439	0.1948	0.1624
4	Db5	56.5070	54.9377	55.8285	0.1453	0.2086	0.1699
5	Db7	56.3160	54.5307	55.5374	0.1519	0.2291	0.1817
6	Db9	56.2394	54.1944	55.2757	0.1546	0.2475	0.1930
7	Sym2	56.5788	55.4136	56.1517	0.1430	0.1869	0.1577
8	Sym4	56.5041	55.0421	55.9251	0.1454	0.2036	0.1662
9	Sym6	56.3987	54.7020	55.6616	0.1490	0.2202	0.1766
10	Coifc1	56.5279	55.0867	55.9744	0.1446	0.2016	0.1643
11	Coifc3	56.2200	54.1600	55.2693	0.1553	0.2495	0.1933
12	Coifc5	55.9219	53.6018	54.7502	0.1663	0.2837	0.2178
13	Bior1.1	56.5970	55.5810	56.2382	0.1424	0.1799	0.1546
14	Bior1.5	56.2912	56.2912	56.2912	0.1527	0.1527	0.1527
15	Bior2.4	56.5744	55.0300	55.8678	0.1431	0.2042	0.1684
16	Bior2.8	56.4608	54.2755	55.3156	0.1469	0.2430	0.1912
17	Bior3.3	56.5930	55.5978	56.1379	0.1425	0.1792	0.1582
18	Rbior1.1	56.5970	55.5810	56.2382	0.1424	0.1799	0.1546
19	Rbior2.4	56.1245	54.3875	55.4551	0.1587	0.2368	0.1852
20	Rbior3.3	55.5806	54.1930	55.2871	0.1799	0.2476	0.1925
21	Rbior4.4	56.3616	54.6596	55.6385	0.1503	0.2224	0.1775
22	Rbior6.8	56.1665	54.0694	55.1711	0.1572	0.2548	0.1977

Table1. PSNR and NRMSE Values for Detail, Vertical & Horizontal coefficient.