Abstract: Image segmentation is typically used to locate objects and boundaries in images. 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. There are basically three different approaches to image segmentation. First is region based, which relies on the homogeneity of spatially localized features and other pixel statistics, the second one is based on the methods of boundary finding relying on the gradient features at a subset of the spatial positions of an image or near an object boundary, whereas the third one is pixel classification approach. Additionally, image segmentation has applications separate from computer vision; it is frequently used to aid in isolating or removing specific portions of an image. The problem becomes more compound while segmenting noisy images. The segmentation problem can be categorized as (i) Supervised and (ii) Unsupervised approach. 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. 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 is verified for simulated images and applied for a selected MR image processing in the MATLAB environment.

Key words: MR image segmentation, intensity feature extraction, watershed transform, standard deviation feature & wavelet transform. *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 3-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 (GM), white matter (WM) and cerebrospinal fluid (CSF), 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.

II. WEIGHTING

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].

A. T1-weighted images

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, while white matter is light gray, and adipose tissue has high intensity. T1-images have high contrast between white matter and gray matter.

B. T2-weighted images

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.

C. Spin density

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

Start

Different MR images

Image Segmentation

Using wavelet transform

Apply the watershed

Feature: Intensity & standard deviation

Different feature i.e. 14 parameter

Segmented image output & compare them

Stop

Fig. 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.

The Dual Tree Complex Wavelet Transform (DT-CWT) [4] is an over complete wavelet that provides both good shift invariance and directional selectivity over the DWT, although there is an increased memory and computational cost. Two fully decimated trees are produced, one for the odd samples and one for the even samples generated at the first level. The DT-CWT has reduced over completeness compared with the SIDWT, an increased directional sensitivity over the DWT and is able to distinguish between positive and negative orientations giving six distinct sub-bands at each level, the orientations of which are ±15; ±45; ±75. The DT-CWT gives perfect reconstruction as the filters are chosen from a perfect reconstruction bi-orthogonal set [4].

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 [5].

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

Load image

Apply the watershed algorithm

Find the result of segmented image

Fig.2 Process of image segmentation based on watershed
VIII. RESULT

We segment the different MRI images by wavelets & watershed methods. The result is shown in fig.4 to fig.7 & fig.8 and fig.9. In this paper we apply two segmentation techniques. For these two techniques we segment the different images like author image and MRI images. This is shown in fig.4 to fig.9. The wavelet segmentation is mainly for grayscale images and its segments, in specified area. In the watershed technique we segment the images on different texture base and the segmented images are shown in result.

A. Segmented output of Brain MR Image using WAVELET

B. Segmented output of Brain MR image using WATERSHED
IX. CONCLUSION

In this paper we segment images using wavelet and watershed transform. In wavelet we use ‘rbio 3.3’, which is the wavelet chosen randomly but wavelet is having very big family, therefore choosing one of them is very difficult. To decide which wavelet is best according to feature, we have to segment the MRI images by the wavelet and find which one is best wavelet for MRI image segmentation.

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XI. REFERENCE

Fig. 9 Example image of author (for fig.8).