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A NOVEL APPROACH FOR SEGMENT TUMOR AND EDEMA ALONG WITH HEALTHY TISSUES OF BRAIN

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Abstract--Advanced techniques of medical image processing and analysis find widespread use in medicine. Various imaging modalities like CT scan, MRI, and ultrasound are being used for imaging brain tumors. In recent years, MRI has emerged as the best for clear identification of cancer and other anomalies in breast, prostate, liver, brain etc. The tumor detection becomes more complicated for the huge image database especially when edema is present with the tumor. Robust brain magnetic resonance (MR) segmentation algorithms are critical to analyze tissues and diagnose tumor and edema in a quantitative way. So, the existing system proposed a new tissue segmentation algorithm which segments the brain MR images into tumor, edema, white matter (WM), gray matter (GM), and cerebrospinal fluid (CSF).This system introduced novel algorithm which combines thresholding and morphological operations for Skull Stripping process. Finallysegmentation is performed using self organizing map (SOM) that is trained with unsupervised learning algorithm and fine-tuned with learning vector quantization (LVQ). However it only considers the texture feature for segmentation, it does not consider shape feature for increase accuracy. To solve this problem, the proposed system combines the Texture, shape based features for classifies tumor, edema, white matter (WM), gray matter (GM), and cerebrospinal fluid (CSF). Modified Fourier descriptor is used for extract the shape feature. The segmentation accuracy of the proposed system is high compared to the existing system.

Index Terms—Brain magnetic resonance (MR), image segmentation,learning vector quantization (LVQ), self-organizing featuremap, stationary wavelet transform (SWT).

I. INTRODUCTION

Brain magnetic resonance (MR) image segmentation is a very important and challenging task that is needed for the purpose of diagnosing brain tumors and other neurological diseases. Brain tumors have different characteristics such assize, shape, location, and image intensities. They may deformneighboring structures and if there is edema with the tumor,intensity properties of the nearby region change. In adults, the most common and cancer-causing tumor type is glial tumors that have a high mortality rate. Over 90% of all tumors in persons over 20 years are glial tumors. They occur in the glial cells of the brain and show a rapid growth by extending into the healthy brain tissues.

In this case, we are given some data points for training and also a new unlabelled data for testing. Our aim is to find the class label for the new point. The algorithm has different behavior based on k.

Case 1 : k = 1 or Nearest Neighbor Rule

This is the simplest scenario. Let x be the point to be labeled . Find the point closest to x . Let it be y. Now nearest neighbor rule asks to assign the label of y to x. This seems too simplistic and some times even counter intuitive. If you feel that this procedure will result a huge error , you are right – but there is a catch. This reasoning holds only when the number of data points is not very large.

If the number of data points is very large, then there is a very high chance that label of x and y are same. An example might help – Lets say you have a (potentially) biased coin. You toss it for 1 million time and you have got head 900,000 times. Then most likely your next call will be head. We can use a similar argument here.

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Let me try an informal argument here - Assume all points are in a D dimensional plane . The number of points is reasonably large. This means that the density of the plane at any point is fairly high. In other words , within any subspace there is adequate number of points. Consider a point x in the subspace which also has a lot of neighbors. Now let y be the nearest neighbor. If x and y are sufficiently close, then we can assume that probability that x and y belong to same class is fairly same – Then by decision theory, x and y have the same class.

One of their striking results is to obtain a fairly tight error bound to the Nearest Neighbour rule. The bound is

$$P^* \leq P \leq P^*\left(2 - \frac{c}{c-1}P^*\right) \tag{1}$$

Where P^* is the Bayes error rate, c is the number of classes and P is the error rate of Nearest Neighbour. The result is indeed very striking (atleast to me) because it says that if the number of points is fairly large then the error rate of Nearest Neighbor is less that twice the Bayes error rate. Pretty cool for a simple algorithm like KNN. Do read the book for all the juicy details.

Case 2 : k = K or k-Nearest Neighbor Rule

This is a straightforward extension of 1NN. Basically what we do is that we try to find the k nearest neighbor and do a majority voting. Typically k is odd when the number of classes is 2. Lets say k = 5 and there are 3 instances of C1 and 2 instances of C2. In this case , KNN says that new point has to labeled as C1 as it forms the majority. We follow a similar argument when there are multiple classes.

One of the straight forward extension is not to give 1 vote to all the neighbors. A very common thing to do is *weighted kNN* where each point has a weight which is typically calculated using its distance. For eg under inverse distance weighting, each point has a weight equal to the inverse of its distance to the point to be classified. This means that neighboring points have a higher vote than the farther points.

It is quite obvious that the accuracy *might* increase when you increase k but the computation cost also increases. The aforementioned conventional studies have several problems: 1) only limited types of skin lesions are acceptable for the classification; 2) the systems do not explain the reasons for the classification results; and 3) the systems were developed and evaluated with only ideal condition images and did not consider the condition of test images.

The wavelet transform is similar to the Fourier transform (or much more to the windowed Fourier transform) with a completely different merit function. The main difference is this: Fourier transform decomposes the signal into sines and cosines, i.e. the functions localized in Fourier space; in contrary the wavelet transform uses functions that are localized in both the real and Fourier space. Generally, the wavelet transform can be expressed by the following equation:

$$F(a,b) = \int_{-\infty}^{\infty} f(x)\, \psi^*_{(a,b)}(x)\, \mathrm{d}x \tag{2}$$

where the * is the complex conjugate symbol and function ψ is some function. This function can be chosen arbitrarily provided that it obeys certain rules.

As it is seen, the Wavelet transform is in fact an infinite set of various transforms, depending on the merit function used for its computation. This is the main reason, why we can hear the term"wavelet transform" in very different situations and applications. There are also many ways how to sort the types of the wavelet transforms. Here we show only the division based on the wavelet orthogonality. We can use *orthogonal wavelets* for discrete wavelet transform development and *non-orthogonal wavelets* for continuous wavelet transform development. These two transforms have the following properties:

- The discrete wavelet transform returns a data vector of the same length as the input is. Usually, even in this vector many data are almost zero. This corresponds to the fact that it decomposes into a set of wavelets (functions) that are orthogonal to its translations and scaling. Therefore we decompose such a signal to a same or lower number of the wavelet coefficient spectrum as is the number of signal data points. Such a wavelet spectrum is very good for signal processing and compression, for example, as we get no redundant information here.
- The continuous wavelet transform in contrary returns an array one dimension

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larger than the input data. For a 1D data we obtain an image of the time-frequency plane. We can easily see the signal frequencies evolution during the duration of the signal and compare the spectrum with other signals spectra. As here is used the non-orthogonal set of wavelets, data are highly correlated, so big redundancy is seen here. This helps to see the results in a more humane form.

DWT uses a kernel (the wavelet), LPC models the signal using its own past samples without a pre-selected kernel. I quite like LPC ou autoregressive modelling, as I prefer to call it.

II. LITERATURE SURVEY

A. Existing System

- Manual Segmentation: An automated brain tumor segmentation method was developed and validated against manual segmentation with three-dimensional magnetic resonance images in 20 patients with meningiomas and low-grade gliomas. The automated method (operator time, 5-10 minutes) allowed rapid identification of brain and tumor tissue with an accuracy and reproducibility comparable to those of manual segmentation (operator time, 3-5 hours), making automated segmentation practical for low-grade gliomas and meningioma.
- Bayesian network: A Bayesian network is a graphical structure that allows us to represent and reason about an uncertain domain. The nodes in a Bayesian network represent a set of random variables, X = X1,..Xi ,...Xn, from the domain. A set of directed arcs (or links) connects pairs of nodes, Xi → Xj , representing the direct dependencies between variables. Assuming discrete variables, the strength of the relationship between variables is quantified by conditional probability distributions associated with each node. The only constraint on the arcs allowed in a BN is that there must not be any directed cycles: you cannot return to a node simply by following directed arcs.

Bayesian networks (BNs), also known as belief networks (or Bayes nets for short), belong to the family of probabilistic graphical models (GMs). These graphical structures are used to represent knowledge about an uncertain domain. In particular, each node in the graph represents a random variable, while the edges between the nodes represent probabilistic dependencies among the corresponding random variables. These conditional dependencies in the graph are often estimated by using known statistical and computational methods. Hence, BNs combine principles from graph theory, probability theory, computer science, and statistics.

The purpose of this work was to optimize and increase the accuracy of tissue segmentation of the brain magnetic resonance (MR) images based on multispectral 3D feature maps. We used three sets of MR images as input to the in-house developed semi-automated 3D tissue segmentation algorithm: proton density (PD) and T2-weighted fast spin echo and, T1-weighted spin echo. First, to eliminate the random noise, non-linear anisotropic diffusion type filtering was applied to all the images. Second, to reduce the nonuniformity of the images, we devised and applied a correction algorithm based on uniform phantoms. Following these steps, the qualified observer "seeded" (identified training points) the tissue of interest. To reduce the operator dependent errors, cluster optimization was also used; this clustering algorithm identifies the densest clusters pertaining to the tissues. Finally, the images were segmented using k-NN (k-Nearest Neighborhood) algorithm and a stack of color-coded segmented images were created along with the connectivity algorithm to generate the entire surface of the brain. The application of pre-processing optimization steps substantially improved the 3D tissue segmentation methodology.

- Space-invariant low-pass filtering: Low pass filtering, otherwise known as "smoothing", is employed to remove high spatial frequency noise from a digital image. Noise is often introduced during the analog-to-digital conversion process as a side-effect of the physical conversion of patterns of light energy into electrical patterns.

There are several common approaches to removing this noise:

- If several copies of an image have been obtained from the source, some static image, then it may be possible to sum the values for each pixel from each image and compute an average. This is not possible, however, if the

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image is from a moving source or there are other time or size restrictions.

- If such averaging is not possible, or if it is insufficient, some form of low pass spatial filtering may be required. There are two main types:
    - reconstruction filtering, where an image is restored based on some knowledge of the type of degradation it has undergone. Filters that do this are often called "optimal filters".
    - enhancement filtering, which attempts to improve the (subjectively measured) quality of an image for human or machine interpretability
- Segmentation :Region based segmentation

Region growing

Region growing is simplest in region-base image segmentationmethods . The concept of region growing algorithm is check the neighboring pixels of the initial seed points, then determine whether those neighboring pixels are added to the seed points or not. Therefore, it is an iterative process.

Region growing algorithm**:**

- Choose the seed points.
- If the neighboring pixels of the initial seed points are satisfy the criteria such as threshold, they will be grown. The threshold can be intensity, gray level texture, and color…etc.

Region merging and splitting

Region merging and splitting is a developing algorithm in segmenting the images. It is used to differentiate the homogeneity of the image.

Region merging and splittingalgorithm:

- Splitting step:
  We choose the criteria to split the image based on quad tree. At the same time, we can determine the numbers of splitting levels gradually.

- Merging step:
  If the adjacent regions satisfy the similarity properties, we will merge them.

3. Repeat step 2 until it is not changed.

- Level set algorithm: Level Sets are an important category of modern image segmentation techniques are based on partial differential equations (PDE), i.e. progressive evaluation of the differences among neighboring pixels to find object boundaries. Ideally, the algorithm will converge at the boundary of the object where the differences are the highest.

The Fiji plugin provides two PDE based methods, the more basic fast marching and the advanced active contour algorithm.

Fast marching works similar to a standard flood fill but is more sensitive in the boundary detection. While growing the region it constantly calculates the difference of the current selection to the newly added pixels and either stops if it exceeds a pre selected gray value difference or if it would exceed a certain pre-selected rate of growth. This algorithm is sensitive to leaking - if the object has a gap in the boundary, the selection may leak to the outside of the object.

Level sets advance a contour like a rubber band until the contour hits an object boundary. The rubber band like nature (= curvature) prevents the contour from leaking if there are gaps in the boundary. The strength of the rubber band and a gray level difference can be pre-selected.

The speedy fast marching can be used as input for the slower active contours. If the image is very large, starting with Fast Marching and using the contour from the fast marching to refine the object with Level Sets can significantly speed up the object detection.

- K-NN Classifier:In this case, we are given some data points for training and also a new unlabelled data for testing. Our aim is to find the class label for the new point. The algorithm has different behavior based on k.

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B. Proposed System

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III. ARCHITECTURE

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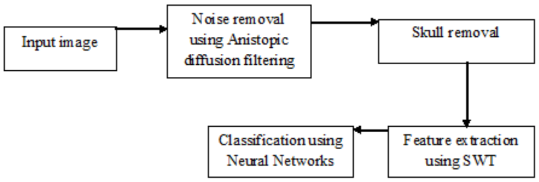

- Anisotropic Diffusion Filtering

Nonlinear anisotropic diffusion filters are iterative, ``tunable" filters introduced by Perona and Malik. Gerig et al. used such filters to enhance MR images. Sapiro and Tannenbaum used a similar technique to perform edge preserving smoothing of MR images. In the extreme case, such smoothing might produce a profile of RF inhomogeneity in the images. Others have shown that diffusion filters can be used to enhance and detect object edges within images.Since these filters smooth or enhance MR images and detect edges, they might also be used for RF correction and/or intracranial boundary detection in MR images.

The original formulation, presented by Perona and Malik in 1987,[1] the space-variant filter is in fact isotropic but depends on the image content such that it approximates an impulse function close to edges and other structures that should be preserved in the image over the different levels of the resulting scale space. This formulation was referred to as anisotropic diffusion by Perona and Malik even though the locally adapted filter is isotropic, but it has also been referred to asinhomogeneous and nonlinear diffusionor Perona-Malik diffusion[5] by other authors. A more general formulation allows the locally adapted filter to be truly anisotropic close to linear structures such as edges or lines: it has an orientation given by the structure such that it is elongated along the structure and narrow across. Such methods are referred to as shape-adapted smoothing or coherence enhancing diffusion. As a consequence, the resulting images preserve linear structures while at the same time smoothing is made along these structures. Both these cases can be described by a generalization of the usual diffusion equationwhere the diffusion coefficient, instead of being a constant scalar, is a function of image position and assumes a matrix (or tensor) value (see structure tensor).

Perona and Malik formulate the anisotropic diffusion filter as a diffusion process that encourages intraregion smoothing while inhibiting interregion smoothing. Mathematically, the process is defined as follows:

$$\frac{\partial}{\partial t} I(\bar{x},t) = \nabla \bullet \left(c(\bar{x},t) \nabla I(\bar{x},t) \right) \quad (4)$$

In our case, $I(\bar{x},t)$ is the MR image. $\bar{x}$ refers to the image axes (i.e. x, y, z) and t refers to the iteration step. $c(\bar{x},t)$ is called the *diffusion function* and is a monotonically decreasing function of the image gradient magnitude:

$$c(\bar{x},t) = f(|\nabla I(\bar{x},t)|) \quad (5)$$

Noise Removal Using Anisotropic Diffusion

This process is used to remove the noise in the image.

Step1:Set number of iteration, Diffusion co-efficient and filter co-efficient. The filter co-efficient should be in the range of -1, 0,1

Step 2:Apply convolution filter for input image and filter co-efficient.

Step 3:Perform the filter in real and imaginary part for the input image and diffusion co-efficient for all 8 filter co-efficient.

Step 4:Add original image and all filter co-efficient filtered image.

- Skull Removal

Skull removing, also known as whole brain segmentation is an important step to remove the non cerebral tissue such as skin, skull, fat, muscle, and connective tissues, which are not regions of interest in this study.

Gaussian Filter

The Gaussian smoothing operator is a 2-D convolution operator that is used to `blur' images and remove detail and noise. In this sense it is similar to the mean filter, but it uses a different kernelthat represents the shape of a Gaussian (`bell-shaped') hump.

Gaussian distribution in 1-D has the form:

$$G(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{x^2}{2\sigma^2}} \quad (6)$$

where = standard deviation of the distribution.

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Otsu's Thresholding

Converting a greyscale image to monochrome is a common image processing task. Otsu's method, named after its inventor Nobuyuki Otsu, is one of many binarization algorithms.

Otsu's thresholding method involves iterating through all the possible threshold values and calculating a measure of spread for the pixel levels each side of the threshold, i.e. the pixels that either fall in foreground or background. The aim is to find the threshold value where the sum of foreground and background spreads is at its minimum.

In Otsu's method we exhaustively search for the threshold that minimizes the intra-class variance (the variance within the class), defined as a weighted sum of variances of the two classes:

$$\sigma_w^2(t) = \omega_1(t)\sigma_1^2(t) + \omega_2(t)\sigma_2^2(t) \quad (7)$$

Weights ω_i are the probabilities of the two classes separated by a threshold t and σ_i^2 are variances of these classes.

Otsu shows that minimizing the intra-class variance is the same as maximizing inter-class variance:

$$\sigma_b^2(t) = \sigma^2 - \sigma_w^2(t) = \omega_1(t)\omega_2(t)\left[\mu_1(t) - \mu_2(t)\right]^2 \quad (8)$$

which is expressed in terms of class probabilities ω_i and class means μ_i.

The class probability $\omega_1(t)$ is computed from the histogram as t:

$$\omega_1(t) = \Sigma_0^t p(i)$$

while the class mean $\mu_1(t)$ is:

$$\mu_1(t) = \left[\Sigma_0^t p(i)\,x(i)\right] / \omega_1 \quad (9)$$

where $x(i)$ is the value at the center of the ith histogram bin. Similarly, you can compute $\omega_2(t)$ and μ_2 on the right-hand side of the histogram for bins greater than t.

The class probabilities and class means can be computed iteratively. This idea yields an effective algorithm.

Skull RemovalAlgorithm

- Compute histogram and probabilities of each intensity level
- Set up initial $\omega_i(0)$ and $\mu_i(0)$
- Step through all possible thresholds $t = 1 \ldots$ maximum intensity
  - Update ω_i and μ_i
  - Compute $\sigma_b^2(t)$
- Desired threshold corresponds to the maximum $\sigma_b^2(t)$
- You can compute two maxima (and two corresponding thresholds). $\sigma_{b1}^2(t)$ is the greater max and $\sigma_{b2}^2(t)$ is the greater or equal maximum
- Desired threshold $= \dfrac{\text{threshold}_1 + \text{threshold}_2}{2}$

Skull Removal Process

- Apply Gaussian filter with [5 5] size and 0.7 mean
- Find global threshold for image.
- Assign 0 to the pixels whose intensity is greater than the threshold.
- Obtain a threshold value using Otsu's thresholding.
- Convert image to black and white using Otsu's threshold.
- 6. Apply twice morphological dilation following twice erosion using an octagon structuring element with a radius of 3 to remove the connections between brain and other tissues.
- 7. Trace region boundaries to find objects within the image.
- Recognize the object that has the maximum perimeter as the brain region
- Assign 1 to inside and 0 to outside of this object to obtain a mask that shows brain region.

- Artificial Neural Networks

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In machine learning and cognitive science, artificial neural networks (ANNs) are a family of statistical learning models inspired by biological neural networks (the central nervous systems of animals, in particular the brain) and are used to estimate or approximate functions that can depend on a large number of inputs and are generally unknown. Artificial neural networks are generally presented as systems of interconnected "neurons" which exchange messages between each other. The connections have numeric weights that can be tuned based on experience, making neural nets adaptive to inputs and capable of learning. For example, a neural network for handwriting recognition is defined by a set of input neurons which may be activated by the pixels of an input image. After being weighted and transformed by a function (determined by the network's designer), the activations of these neurons are then passed on to other neurons. This process is repeated until finally, an output neuron is activated. This determines which character was read.

Like other machine learning methods - systems that learn from data - neural networks have been used to solve a wide variety of tasks that are hard to solve using ordinary rule-based programming, including computer vision and speech recognition.

Types Of Artificial Neural Networks

Artificial neural network types vary from those with only one or two layers of single direction logic, to complicated multi–input many directional feedback loops and layers. On the whole, these systems use algorithms in their programming to determine control and organization of their functions. Most systems use "weights" to change the parameters of the throughput and the varying connections to the neurons. Artificial neural networks can be autonomous and learn by input from outside "teachers" or even self-teaching from written-in rules.

Computational Power

The multi-layer perceptron (MLP) is a universal function approximator, as proven by the universal approximation theorem. However, the proof is not constructive regarding the number of neurons required or the settings of the weights.

Work by HavaSiegelmann and Eduardo D. Sontag has provided a proof that a specific recurrent architecture with rational valued weights (as opposed to full precision real number-valued weights) has the full power of a Universal Turing Machineusing a finite number of neurons and standard linear connections. Further, it has been shown that the use of irrational values for weights results in a machine with super-Turing power.

Employing Artificial Neural Networks

Perhaps the greatest advantage of ANNs is their ability to be used as an arbitrary function approximation mechanism that 'learns' from observed data. However, using them is not so straightforward, and a relatively good understanding of the underlying theory is essential.

- Choice of model: This will depend on the data representation and the application. Overly complex models tend to lead to problems with learning.
- Learning algorithm: There are numerous trade-offs between learning algorithms. Almost any algorithm will work well with the correct hyperparameters for training on a particular fixed data set. However, selecting and tuning an algorithm for training on unseen data requires a significant amount of experimentation.
- Robustness: If the model, cost function and learning algorithm are selected appropriately the resulting ANN can be extremely robust.

With the correct implementation, ANNs can be used naturally in online learning and large data set applications. Their simple implementation and the existence of mostly local dependencies exhibited in the structure allows for fast, parallel implementations in hardware.

Types Of Models

Many models are used in the field, defined at different levels of abstraction and modeling different aspects of neural systems. They range from models of the short-term behavior of individual neurons , models of how the dynamics of neural circuitry arise from interactions between individual neurons and finally to models of how behavior can arise from abstract neural modules that represent complete subsystems. These include models of the long-term, and short-term plasticity, of neural systems and their relations to learning and memory from the individual neuron to the system level.

In flat model we are using Bayesian network The Bayesian network will classify the tumor according

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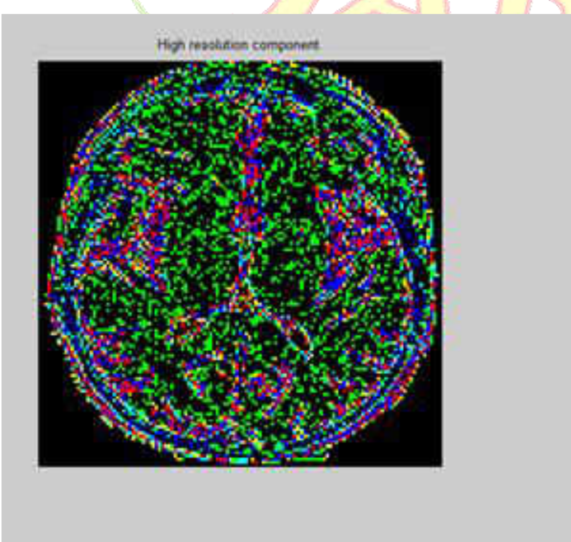
to the feature value. The test image feature value is compare with the trained image feature.

- Stationary Wavelet Transform

The Stationary wavelet transform (SWT) is a wavelet transform algorithm designed to overcome the lack of translation-invariance of the discrete wavelet transform (DWT). Translation-invariance is achieved by removing the downsamplers and upsamplers in the DWT and upsampling the filter coefficients by a factor of $2^{(j-1)}$ in the jth level of the algorithm. The SWT is an inherently redundant scheme as the output of each level of SWT contains the same number of samples as the input – so for a decomposition of N levels there is a redundancy of N in the wavelet coefficients. This algorithm is more famously known as "*algorithme à trous*" in French (word *trous* means holes in English) which refers to inserting zeros in the filters. It was introduced by Holschneider et al.

IV. IMPLEMENTATION

Theproposed system combines the Texture, shape based features for classifies tumor, edema, white matter (WM), gray matter (GM), and cerebrospinal fluid (CSF). Modified Fourier descriptor is used for extract the shape feature. The segmentation accuracy of the proposed system is high compared to the existing system.



The above figure shows the high resolution component. Stationary wavelet will be applied here.

V. CONCLUSION

In this study, the segmented brain MR images into healthy tissues such as GM, WM, and CSF along with the diseased tissues, tumor, and edema. The removal Noise Anisotropic diffusion filtering are used. And then skull removal process is done by using Gaussian filtering and Otsu's thresholding. And then features extraction is done using stationary wavelet transform (SWT) to decompose images into subbands. And performed spatial filtering methods on these subbands to obtain feature vector. Finally, tissues are classified using neural networks.

In future work fuse all scanning type of images using wavelet based fusion method and also segment the brain region separately using Fuzzy C means algorithm and find area of the brain tumor based on area that classifies the type of tumor.

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