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ADVANTAGES OF USING SIFT FOR BRAIN TUMOR DETECTION

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Abstract

The brain is the anterior most part of the central nervous system. The cranium, a bony box in the skull protects it. Virtually every activity or thought of ours is controlled by our brain. So, it's very dangerous when the proper functioning of the brain is hindered. Brain tumor is one such disease which if not detected early and treated accordingly, can prove fatal.

Structure of the brain is quite complex and hence it is very difficult to detect the abnormalities in early stages. In our paper we will be giving an overview of the various techniques used for brain tumor detection and how SIFT overcomes their limitations.

The techniques discussed include biopsy, manual segmentation, mathematical morphology & wavelet transform, artificial neural network and finally SIFT (Scale Invariant Feature Transform). Biopsy is a surgical method which needs to be performed by highly skilled professionals. The rest other methods use MRI images and thus are non-invasive.

SIFT technique which we are using in our project gives good accuracy, is cost effective and most importantly is invariant to translation, scale, rotation, affine transform, change in illumination, etc.

Keywords— MRI images, SIFT, tumor, k-means, k-NN, DoG

I. INTRODUCTION

Brain tumors are the tumors that grow in the brain. Tumor is an abnormal growth caused by cells reproducing themselves in an uncontrolled manner. It is very important that tumor as fatal as brain tumor be detected as soon as possible.

The structure and function of brain can be studied non-invasively by doctors and researchers using Magnetic Resonance Imaging. It is tedious even for experienced doctors to identify the tumors, especially in its initial stages. In order to both speed up the process and maintain the quality of classification we need a very high quality classification system. By applying the SIFT technique and providing the proper image dataset, it would be easier for doctors to detect the tumors so that the treatment could be started soon enough and precious human lives can be saved.

SIFT has been proved as an effective method to extract keypoints from images which are invariant to translation, scale, rotation, affine transforms, change in illumination, change in 3-D viewpoint, etc[2]. In addition to these properties, they are highly distinctive, relatively easy and straightforward to extract, allow for correct object identification with low probability of mismatch and are easy to match against huge set of local features. It is used extensively in object recognition applications such as face recognition and object based image retrieval. Therefore, we are using SIFT for feature extraction and k-means for classification purpose.

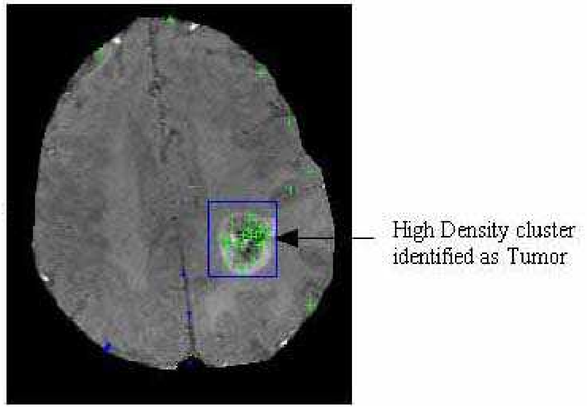

Fig1. Brain Tumor

II. LITERATURE SURVEY

Various methods in use for brain tumor detection include:

A. Biopsy

A biopsy can be performed as part of an operation to remove the brain tumor, or a biopsy can be performed using a needle. A stereotactic needle biopsy may be done for brain tumors in hard to reach areas or very sensitive areas within your brain that might be damaged by a more extensive operation. Your neurosurgeon drills a small hole, called a burr hole, into your skull. A thin needle is then inserted through the hole. Tissue is removed using the needle, which is frequently guided by CT or MRI scanning. The biopsy sample is then viewed under a microscope to determine if it is cancerous or benign. This information is helpful in guiding treatment.

B. Manual Segmentation

For manual segmentation of the brain and tumor, an interactive segmentation tool was used (MRX; GE Medical Systems) on an Ultra 10 workstation (Sun Microsystems, Mountain View, Calif). Human operators outlined the structures section by section by pointing and clicking with a mouse. The program connected consecutive points with lines. An anatomic object was defined by a closed contour, and the program labeled every voxel of the enclosed volume.[10]

C. Mathematical Morphology and wavelet transform

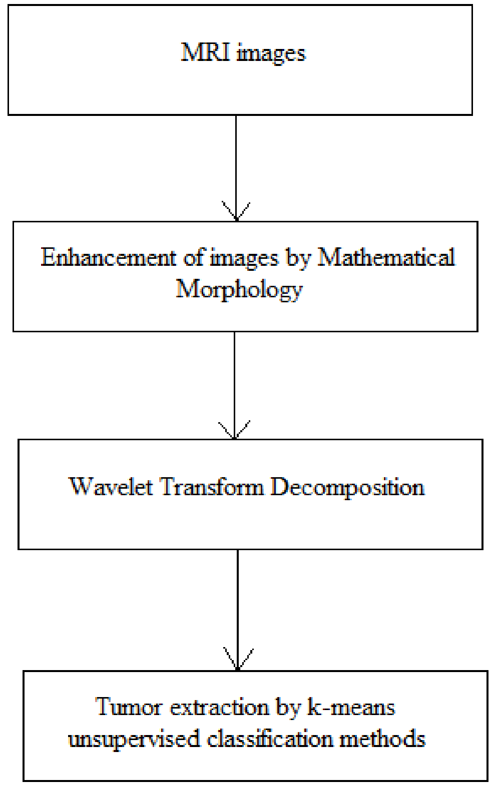

Fig2. Steps for the system implementation

Enhancement

Image enhancement has been applied successfully to different fields such as medical, industry and military fields. Enhancement in medical imaging is the use algorithms to make image clearer and to ensure optimum presentation of all digital computer processing. It proves to be useful and important to the medicine diagnosis. This may aid interpretation by humans or computers. Enhancement aims at improving the quality of a given image. It can be accomplished by removing noise, enhancing contrast, emphasizing edges and modifying shapes.

For contrast enhancement based on mathematical morphology theory there are two methods: the first is Top-Hat which deals with images after the segmentation process. This algorithm enhances the edges of the segmented region of interest. The second algorithm deals with the contrast of the original image to enhance the segmentation process. Here, we consider the second morphological contrast enhancement algorithm. A detailed theory of mathematical morphology is provided in [12].

i) Segmentation

After pre-processing phase, a segmentation algorithm was adopted.

In literature there exist two major classes of segmentation techniques: edge based segmentation approach and region based segmentation approach.

Daubechies wavelet is used for detection and segmentation of tumors.

ii) Classification

The K-means unsupervised classification algorithm for tumor extraction is used. Being the most widely used technique, the K-means partitions the data set D containing n items into a user specified number of clusters K.

D. Artificial Neural Network

i)Tumor segmentation

The first step in the system presented here is to isolate the tumor region from the rest of the image. Various image processing techniques are used to separate the tumor region. Image preprocessing consists mainly of Histogram Equalization. The main problem in the process of detection of edge of tumor is that the tumor appears very dark on the image which is very confusing. To overcome this problem, Histogram Equalization was performed. Segmentation subdivides an image into its constituent parts or objects.

Thresholding has been used for segmentation as it is most suitable for the present application in order to obtain a binarized image with gray level 1 representing the tumor and gray level 0 representing the background.

The fundamental enhancement needed is to increase the contrast between the whole brain and the tumor. Contrast between the brain and the tumor region may be present but below the threshold of human perception. Thus, to enhance the contrast between the normal brain and tumor region, a sharpening filter is applied to the digitized MRI resulting in noticeable enhancement in image contrast.

i) Feature extraction

The work involves extraction of the important features for image recognition. The features extracted give the property of the texture, and are stored in knowledge base. The extracted features are compared with the features of unknown sample Image for classification.

ii) Knowledge base

Knowledge is any chunk of information that effectively discriminates one class type from another. In this case, tumor will have certain properties that other brain tissues will not and vice-versa. Knowledge contained in feature space is extracted and utilized.

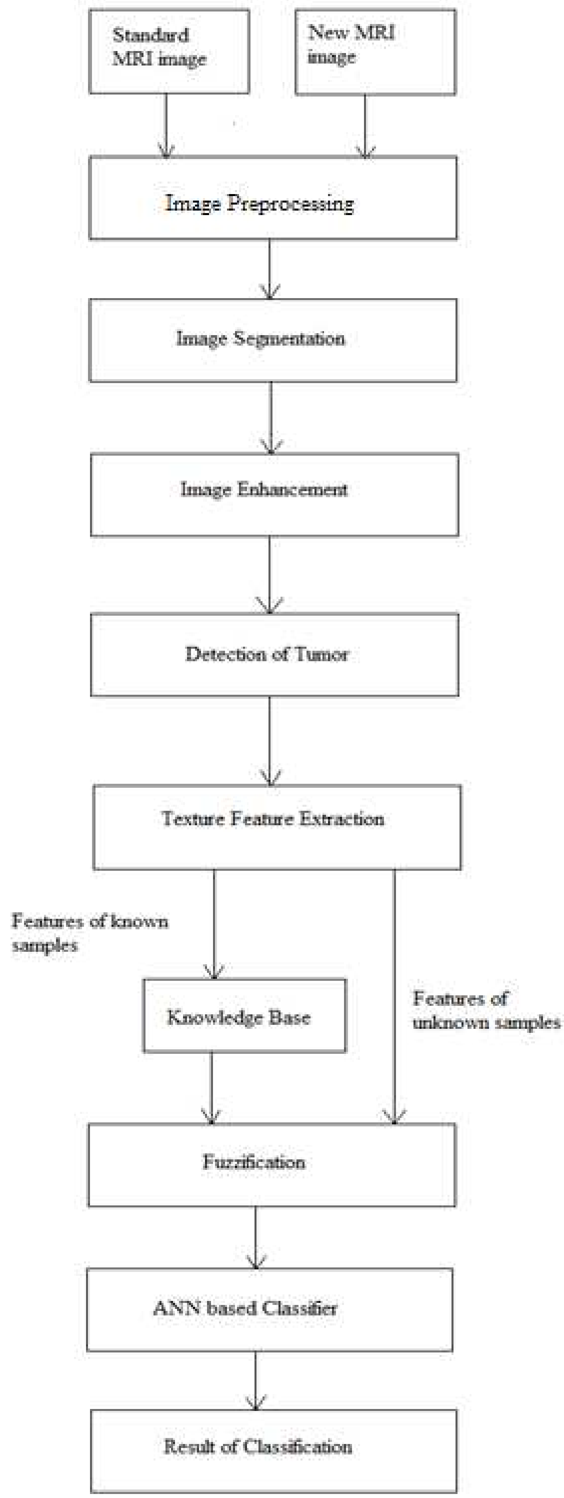

Fig3. Steps for brain tumor detection using artificial neural network

iii) Neuro fuzzy classifier

A Neuro-Fuzzy Classifier is used to detect candidate circumscribed tumor. Artificial Neural Network (ANN) is used for classification purpose.

III. PROPOSED METHOD

The principal of proposed method to detect the tumor automatically from the cerebral images is as follows.

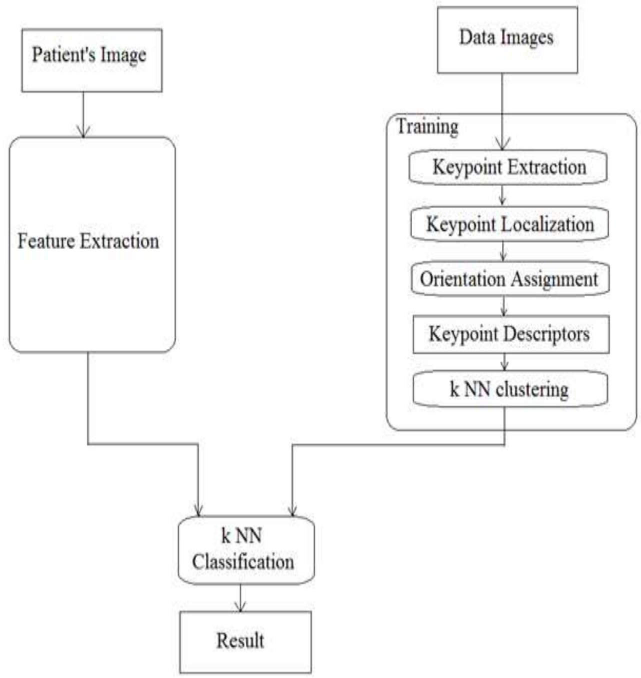

Fig4. Stages for detecting tumor using SIFT

Lowe's SIFT method for image feature generation transforms an image into a large collection feature vectors, each of which is invariant to image translation, scaling and rotation, partially invariant illumination changes and robust to local geometric distortion. Key locations are defined as maxima and minima of the result of difference of Guassian function applied in scale space to a series of smoothed and resampled images.

Low contrast candidate points and edge response points along an edge are discarded. Dominant orientations are assigned to localized key points. These steps ensure that the key points are more stable for matching and recognition. SIFT descriptors robust to local affine distortions are then obtained by considering pixels around the radius of the key location, blurring and resampling of local image orientation planes.

i) Scale-space extrema detection

This is the stage where the interest points, which are called keypoints in the SIFT framework are detected. For this, the image is convolved with Guassian filters at different scales and then difference of successive Guassian blurred images are taken.

$$L(x,y,k\sigma) = G(x,y,k\sigma) * I(x,y)$$

Keypoints are then taken as maxima/minima of the Difference of Guassian (DoG) that occur at multiple scales. Specifically, a DoG image is given by

$$D(x,y,\sigma) = L(x,y,k_i\sigma) - L(x,y,k_j\sigma),$$

Where $L(x,y,k_i\sigma)$ is the convolution of the original image $I(x,y)$ with the Gaussian blur $G(x,y,k\sigma)$ at scale k.

Hence a DoG image between scales $k_i\sigma$ and $k_j\sigma$ is just the difference of the Gaussian-blurred images at scales $k_i\sigma$ and $k_j\sigma$. For scale space extrema detection in the SIFT algorithm, the image is first convolved with Gaussian-blurs at different scales. The convolved images are grouped by octave (an octave corresponds to doubling the value of σ), and the value of k_i is selected so that we obtain a fixed number of convolved images per octave. Then the Difference-of-Gaussian images are taken from adjacent Gaussian-blurred images per octave.

Once DoG images have been obtained, keypoints are identified as local minima/maxima of the DoG images across scales. This is done by comparing each pixel in the DoG images to its eight neighbors at the same scale and nine corresponding neighboring pixels in each of the neighboring scales. If the pixel value is the maximum or minimum among all compared pixels, it is selected as a candidate keypoint.

ii) Keypoint localization

After scale space extrema are detected (their location being shown in the uppermost image) the SIFT algorithm discards low contrast keypoints and then filters out those located on edges. Resulting set of keypoints.

Scale-space extrema detection produces too many keypoint candidates, some of which are unstable. The next step in the algorithm is to perform a detailed fit to the nearby data for accurate location, scale, and ratio of principal curvatures. This information allows points to be rejected that have low contrast (and are therefore sensitive to noise) or are poorly localized along an edge.

iii) Orientation assignment

In this step, each keypoint is assigned one or more orientations based on local image gradient directions. This is the key step in achieving invariance to rotation as the keypoint descriptor can be represented relative to this orientation and therefore achieve invariance to image rotation.

The magnitude and direction calculations for the gradient are done for every pixel in a neighboring region around the keypoint in the Gaussian-blurred image L. An orientation histogram with 36 bins is formed, with each bin covering 10 degrees. Each sample in the neighboring window added to a histogram bin is weighted by its gradient magnitude and by a Gaussian-weighted circular window with a σ that is 1.5 times that of the scale of the keypoint. The peaks in this histogram correspond to dominant orientations. Once the histogram is filled, the orientations corresponding to the highest peak and local peaks that are within 80% of the highest peaks are assigned to the keypoint. In the case of multiple orientations being assigned, an additional keypoint is created having the same location and scale as the original keypoint for each additional orientation.

iv) Keypoint descriptor

Previous steps found keypoint locations at particular scales and assigned orientations to them. This ensured invariance to image location, scale and rotation. Now we want to compute a descriptor vector for each keypoint such that the descriptor is highly distinctive and partially invariant to the remaining variations such as illumination, 3D viewpoint, etc. This step is performed on the image closest in scale to the keypoint's scale.

First a set of orientation histograms are created on 4x4 pixel neighborhoods with 8 bins each. These histograms are computed from magnitude and orientation values of samples in a 16 x 16 region around the keypoint such that each histogram contains samples from a 4 x 4 subregion of the original neighborhood region. The magnitudes are further weighted by a Gaussian function with σ equal to one half the width of the descriptor window. The descriptor then becomes a vector of all the values of these histograms. Since there are 4 x 4 = 16 histograms each with 8 bins the vector has 128 elements. This vector is then normalized to unit length in order to enhance invariance to affine changes in illumination. To reduce the effects of non-linear illumination a threshold of 0.2 is applied and the vector is again normalized.

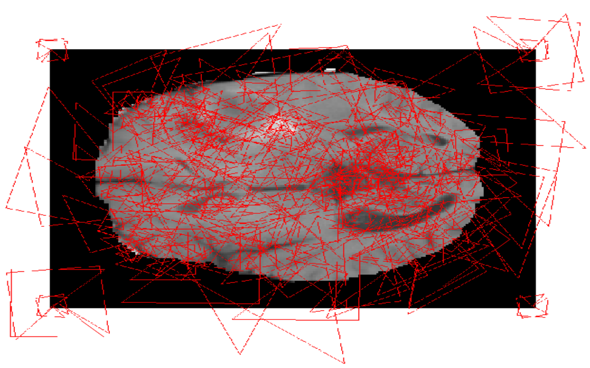

Fig5.Processed image

v) K Nearest Neighbour (kNN) classification

Here we implement the K-NN algorithm for classification purpose. The k-nearest neighbour algorithm is amongst the simplest of all machine learning algorithms: an object is classified by a majority vote of its neighbours, with the object being assigned to the class most common amongst its k nearest neighbours (k is a positive integer, typically small). If k = 1, then the object is simply assigned to the class of its nearest neighbour.

IV. ADVANTAGES OF SIFT OVER OTHER METHODS

In biopsy a hole has to be drilled into the skull, it's like a mini operation. Biopsy is expensive & time consuming as compared to other methods. It needs lots of equipments, planning and experts to do a biopsy. But after the examination the severity and type of the tumor can be confirmed. Drawbacks include high cost, need of highly skilled personnel, time and fatigue induced errors.

Use of imaging techniques makes the procedure non invasive. Manual method as discussed in the paper, is one such technique where MRI images are used. it is less time consuming compared to biopsy but more time consuming than the remaining methods. Like biopsy the professionals need to be trained and efficient in this job as the detections are made on the basis of minor changes which are difficult to be visible through human eyes. It is cheap as compared to other methods. But again, it could be error prone due to fatigue induced by the entire process.

In case of wavelet morphology, the detection is carried out in 3 steps – enhancement, segmentation and classification and k-means is used for classification. In this the software enhances the images and then divides it to locate the tumor. It is less expensive than biopsy. It is less time consuming than biopsy and manual method.

In Artificial Neural Network method, the image go through many stages. Just like wavelet transform it has enhancement, segmentation and classification. It uses neuro-fuzzy logic and ANN based classifier which is not their in wavelet transform. It is less expensive than biopsy. Also, it is less time consuming than biopsy and manual method. But, the implementation is tedious.

SIFT has been proved to give accurate results and that too quickly which are invariant to scale, orientation and minor affine changes. In the above techniques the age difference between the patients whose image is to be compared with the database images should not be more than couple of years, but since SIFT is scale invariant the age difference could be upto 10 years or so.

The following table summarizes the observations made by us. It gives the comparison among the techniques studied in this paper.

Table I Comparison of Various Techniques

Biopsy	Manual method	Wavelet transform	Artificial neural network	SIFT

Expensive.	Cheapest method.	Less expensive than biopsy and ANN.	Less expensive than biopsy and more expensive than all the other methods.	Less expensive.
Time consuming compared to others.	Less time consuming compared to biopsy.	Less time consuming than biopsy and manual method.	Less time consuming than biopsy and manual method and more than wavelet and SIFT.	Less time consuming.
Needs lots of equipments, planning and experts.	Lots of equipments are not needed like biopsy.	Experts are required for coding but it is not essential to have an expert to run the program.	Programming is difficult as compared to other techniques. Again to run the program, experts are not needed.	Less complicated code as compared to ANN and experts are not needed once installation is done.
Drilling hole into a skull, this procedure is complicated and has some risks.	Such risk is not involved.	Such risk is not involved.	Such risk is not involved.	Such risk is not involved.
Most accuracy is achieved, but error could be induced due to fatigue. Also, imaging techniques could be further used to aid the doctors for treatment and surgery.	Accuracy is good but again fatigue induced error could creep in.	Accuracy is good but when the ages of the patient whose images are to be matched should be close. No fatigue induced errors.	Accuracy is better than wavelet transform but when the ages of the patient whose images are to be matched should be close. No fatigue induced errors.	Accuracy is good even when the ages of the patient whose images are to be matched are not close. The age difference could be about 10 years. No

				fatigue induced errors.
Not scale invariant	Not scale invariant	Not scale invariant	Not scale invariant	Scale invariant

V. CONCLUSION

In this paper various techniques for brain tumor detection are discussed. First of all, biopsy is discussed. Though it gives accurate results, being a surgical process, it is time consuming, costly and needs highly skilled professionals to do the job. Other techniques include manual segmentation, mathematical morphology and wavelet transform, artificial neural network and SIFT. These are based on processing of MRI images and thus are non invasive. Among them SIFT proves to be most efficient as it is invariant to translation, scale, rotation, etc. Also, its implementation is relatively easy and cost effective.

After comparing them based on various parameters, it is found out that SIFT technique is the most suitable for the purpose.

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