

DETECTION AND FEATURE EXTRACTION OF MRI AND CT IMAGES USING MEDICAL IMAGES

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ABSTRACT

An efficient procedure for specifically defining the tumor boundary present in an input MRI picture is proposed in this article. Various mammogram photographs were taken and examined for the comparative analysis. CA segmentation and other existing algorithms such as Otsu's thresholding and canny edge detection were used to model brain MRI images. CA segmentation is the best choice out of any of these segmentation processes. Its simplicity over a single slice and lower susceptibility to initialization, reliability in terms of computation time, robustness against diverse and heterogeneous tumor forms, computational efficiency, and ease of use are all factors. In oncologic imaging, segmentation of brain tumors on diagnostic photographs is important for cancer management and surveillance. With the advent of image driven surgical methods, it is becoming more common. Outlining the brain tumor contour, which is normally performed manually on contrast enhanced T1-weighted MRI in current clinical practice, is a critical phase in preparing spatially localized radiotherapy. Cellular Automaton-based seeded tumor segmentation is used to segment solid brain tumors in this article. It aids physicians and researchers in the preparation of radio surgery and the evaluation of treatment reaction. The findings show that the collected pictures may be used to make an accurate diagnosis.

Keywords: Medical Image, MRI, CT, Canny Edge and Image Segmentation

INTRODUCTION

The physical properties of the aquatic world render underwater photography a difficult task. Since light is exponentially attenuated when it passes through water, underwater photographs are marked by low clarity. As a consequence, scenes are badly contrasted and cloudy. In plain water, light attenuation restricts the perceptibility gap to around twenty meters, and in obscure water to five meters or less. Absorption, which eliminates light energy, and scattering, which shifts the trajectory of the light stream, induce light

attenuation. The ultimate efficiency of underwater imaging devices is influenced by the absorption and scattering mechanisms of light in water. Underwater picture improvement is one way to increase object recognition in an underwater setting. While there is a lot of research being done to improve camera quality, there isn't much research being done to improve the quality of underwater images. Image improvement strategies such as Histogram equalization, Contrast extending, contrast constrained adaptive histogram equalization, Bi-Histogram Equalization, and Bin underflow will be discussed here. Equalization of bin overflow histograms for underwater photos. As a result, CLAHE will minimize noise enhancement. The gradient of the mapping function is dominated in bin underflow (BU) and bin overflow (BO) by constraining the probability density function. With a single parameter, the BUBO process will have the rate of enhancement from non to complete HE. The HE can execute image processing tasks such as black/white level stretch, automated brightness monitoring, and variable rate contrast enhancement thanks to the enhancement rate control mechanism [1]-[6].

The tumor boundary in the input brain MRI is precisely defined using this segmentation process. Tumor cut algorithm with Cellular Automata segmentation is used. A sensitivity parameter is used in this algorithm to conform to the issue of tumor segmentation in heterogeneous tumors. An implied level set surface is evolved on a tumor likelihood map built from CA in order to enforce spatial smoothness. A line drawn on the tumor's maximum diameter offers enough knowledge to start the algorithm. In the intensity-hue-saturation transform domain, a multi-modal medical image fusion method is created. Both spatial attribute details and functional information contents can be effectively collected by the IHST. In terms of entropy and reciprocal knowledge, edge information, standard deviation, peak signal to noise, and structural similarity, visual and statistical studies indicate that the fusion efficiency can be substantially improved over that of five traditional approaches [7]-[11].

Diabetes is rapidly spreading throughout the world, especially in Indian society. Diabetes-related diseases such as Diabetic Retinopathy are becoming increasingly prevalent as a consequence of this (DR). When the retina's tiny blood vessels have a large amount of glucose, vision is blurred, and will ultimately lead to blindness. If these problems are not treated quickly, they will cause a great deal of disability in the patient as well as a great deal of expense and work for clinicians and the government. As a consequence, an electronic diagnostic device is needed to speed up the practitioner's job and reduce patient morbidity. Micro aneurysms are tiny secular pouches that occur as small red spots that are triggered by local distension of capillary walls. Hemorrhages are massive blood clots and may arise as a consequence of this. The optic disk, which is a yellow lipid circular area from which blood vessels arise, is where hard exudates are formed. The fovea is an area of the retina that determines the retina's nucleus and has the best visual acuity. The dysfunctional blood vessels are segmented utilizing marker-controlled watershed segmentation. Then there's function extraction, which entails extracting feature values from a variety of funds photographs. A genetic algorithm must be used to remove valid attributes (GA). As a consequence, the study may be improved by classifying them based on anomalies, showing an integrated device that can differentiate between usual and pathological vasculature on the optic disc. It may be part of a mechanism that reduces manual grading and workload, or it could be a method that prioritizes patient grading queues [12]-[17].

PROPOSED SYSTEM

Picture fusion strategies are sometimes divided into three stages, namely pixel level, feature level, and decision level of representation, based on the stage at which fusion takes place; it is often divided into three groups depending on the stage at which fusion takes place; it is often divided into three classes, namely pixel category, feature level, and decision level of representation. Based on the equipment or processing processes used in the image fusion operation, pixel image fusion approaches may be classified into many groups. Color-related procedures, mathematical strategies, arithmetic/numerical approaches, and combined approaches are the three categories. Thanks to the growing need in clinical applications, multi-modal medical image fusion, which allows clinicians to quickly understand a lesion by combining photographs from various modalities, has emerged as a recent and exciting research field. The sum of information captured from the source images defines the accuracy of the fused result. In terms of entropy and reciprocal knowledge, edge information, standard deviation, peak signal to noise, and structural similarity, visual and statistical studies indicate that the fusion efficiency can be substantially improved over that of five

traditional approaches. Furthermore, color saturation may be minimized to a significant degree, resulting in a more pleasing visual experience. MRI and CT images were first subjected to the intensity-hue-saturation transform. The strength portion alone was taken for further processing from this result. Finally, the fuzzy logic principle was used to construct the fused image. The merged picture would provide more detail than the two input pictures together.

The usage of the Multi-Wavelet Transform (Haar wavelet) in the integration of various medical imaging modalities such as Computed Tomography (CT) and Magnetic Resonance (MR) results in a new picture with significantly enhanced knowledge quality for diagnosis. Figure 1 show an image fusion based on the MWT that was applied, evaluated, and compared to an existing Wavelet-based fusion algorithm in our proposed process. Furthermore, the Entropy (H), Root Mean Square Error (MSME), Peak Signal to Noise Ratio (PSNR), and Correlation Coefficient were analyzed and provided with more effective output steps (CC). The MWT-based image fusion algorithm produces a marginally stronger fused image than the Wavelet algorithm, according to the quantitative output measure parameters.

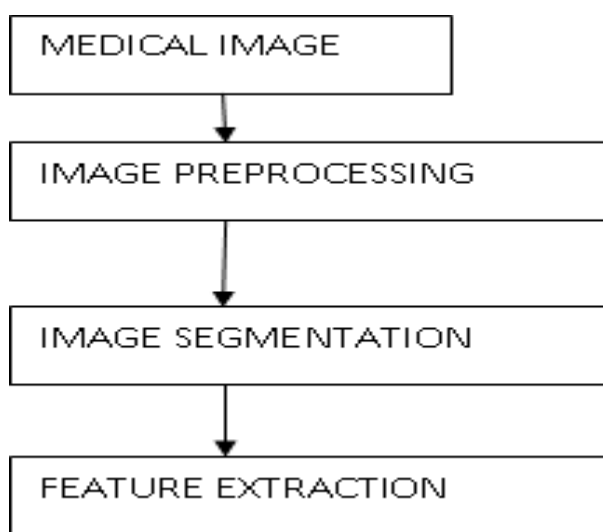


Figure.1. Flow Chart of Proposed Method

Marker-controlled watershed segmentation uses a simple method to calculate a segmentation feature from foreground and context markers. Segmentation features have been changed to only have minima at the foreground and context marker points. As a result, it is the updated segmentation function's watershed transform. If you can define, or "mark," foreground items and background positions, segmentation utilizing the watershed transforms works best. External markers, often known as pixels, usually belong to the context, while internal markers identify the target position. Patient movement, improper concentration, poor alignment, shadows, and insufficient lighting may cause a large percentage of photographs to be of such poor quality that research is hampered. In this article, blood vessels are removed to classify diabetic retinopathy. Since the fundus image's contrast appears to be bright in the middle and fade out to the sides, preprocessing is needed to reduce this impact. These photographs may be preprocessed to ensure a high degree of effectiveness in automatic abnormality detection.

The method of integrating meaningful visual knowledge from two or more photographs into a single high-information picture is known as image fusion. Satellite imagery, remote sensing, and medical imaging are only a few of the areas where image fusion is used. Image fusion was first used in satellite imagery, but its applications have since expanded to include robots, medical imaging, remote sensing, and other fields. Several algorithms for improving picture fusion have been suggested. Satellite image fusion was effectively completed using algorithms such as the Intensity-Hue-Saturation (IHS) and the Wavelet Transform. Color picture fusion algorithms include IHS. In both satellite and medical image fusion applications, image fusion based on the wavelet transform was efficient. Medical imaging entails collecting high-resolution photographs in order to increase diagnostic precision. There are many medical imaging methods that are well-known. The two most popular imaging techniques for rigid bone structures are magnetic resonance

imaging (MRI) and computed tomography (CT). As a result of the fusion of CT and MR images, an integrated image with more detail content is generated. Researchers in the area of fusion of multiple modality medical photographs have already made many attempts.

The Wavelet Transform is being used in the rest of the attempts. The Discrete Wavelet Transform (DWT) with Haar Wavelets is a type of fusion process that has become increasingly popular in recent years. Using the discrete wavelet transform, each source picture is first decomposed into a multi-scale representation. The root representations and a fusion law are then used to construct a composite wavelet pyramid. Finally, an inverse discrete wavelet transform of the composite multi-scale representation yields the fused picture. The DWT also does a multi-resolution image processing. Although pyramid representation does not add any spatial details in the decomposition process, DWT offers directional information and provides a non-redundant pyramid representation of the original images. Furthermore, images produced by wavelet-based fusion method have a better signal-to-noise ratio than images generated by pyramid picture fusion method while using the same fusion law. It is not possible to produce a single picture that includes all pertinent detail regarding the objects in view due to the optical lens's restricted focus depth. There are several image fusion approaches to choose from, however we've selected the ones that provide a contribution to image processing. An image's Entropy (H) is an indicator of its knowledge quality. It's the average number of bits used to quantify the image's intensities. Entropy is a measure of how much information is contained in a given picture. If the entropy of the fused image is higher than that of the parent images, it means the fused image has more detail.

The correlation coefficient compares the source and fused images in small scale configurations to see how identical they are. The CC value ranges from -1 to +1. More detail is stored while the association significance is larger. When the comparison and fused images are identical, the optimal meaning is one; as the dissimilarity grows, it becomes less than one. Closer values to +1 mean that the initial and fused pictures are very similar, whereas closer values to -1 indicate that they are very different. The four meaningful output metrics entropy, Peak Signal to Noise Ratio, Root Mean Square Error, and Correlation Coefficient were used to determine the efficacy of the two image fusion algorithms utilizing our proposed Multiwavelet Transform (Haar Wavelet) with the Image fusion algorithm. The findings showed that the efficiency of the Life fusion algorithms varies slightly. It has also been shown that the best success criteria can be related to the application in question. Using all fusion methods, the fused picture greatly enhanced the material details in the Slides, according to visual interpretation. The brain is a highly complex organ with a broad variety of functions. It acts as a monitoring center for body processes and helps us to deal with our surroundings.

A brain tumor is an irregular mass of tissue in which certain cells expand and propagate uncontrollably, seemingly untouched by natural cell regulation mechanisms. A tumor's expansion takes up space within the head, interacting with natural brain function. Increased strain in the head, moving the brain or pressing towards the skull, and invading and destroying nerves and healthy brain tissue are both forms that a tumor can inflict harm. The nature of signs that arise is determined by the location of a brain tumor. Because of its invasive and infiltrative nature in the confined room of the intracranial cavity, every brain tumor is potentially serious and life-threatening. The threat level is determined by a number of variables, including the form of tumor, its position, scale, and stage of growth. The quality of therapy available and the probability of a favorable result are dictated by the tumor's type, grade, and location. Unlike certain other tissues, removing portions of the brain without creating major disruptions of body processes is very complicated.

Some tumors deform other materials and occur in combination with edema, which alters the intensity properties of the surrounding environment. An edge is a boundary or contour where any of the physical features of the picture shift significantly. These adjustments may take a number of forms, such as changes in strength, color, or texture. The importance of a single physical alteration in a picture is defined by the image's existence in general. In the case of brain tumors, manual segmentation is a challenging and time-consuming process for many human experts. This makes the use of an artificial brain tumor segmentation tool much more appealing. Medical specialists must segment brain tumors from magnetic resonance images (MRI). This is an essential yet time-consuming process.

RESULTS AND DISCUSSION

The difficulties involved with automated brain tumor segmentation have spawned a plethora of solutions. Several segmentation approaches have been established by the digital image processing group. On the basis of (a) Pixel (b) Area or Texture (c) Density, these segmentation strategies work on brain pictures. For detecting a boundary or border in an image, several edge detection methodologies in the form of numerous algorithms are used. The rest of them are focused on the detection of places where pixel strength differs. It's important that the boundary detection algorithm is unaffected by image characteristics. These edge detection algorithms are usually focused on directional derivative equations, which result in computationally expensive tasks or prior awareness of the image's existence. It inhibits the process's applicability. In image segmentation, region-based active contour models are commonly used.

The edge function, which is based on the image gradient, is used in active contour models. These models can only detect artifacts with gradient-defined edges. This transform is good for representing linear edges since it focuses on representing the picture in many sizes. Wavelets decompose images into just three directional high pass sub bands: longitudinal, horizontal, and diagonal, capturing just a small amount of directional detail. The help of one wavelet is a rectangle, according to wavelet theory. When a wavelet is used to reflect multi-dimensional features including contours, non-zero coefficients develop exponentially and can't be ignored because of their high amplitude, indicating that directional sensitivity is lost. As a consequence, wavelet cannot be treated as a real sparse representation. Other signal analysis approaches ignore facets of data that wavelet analysis may show, such as patterns, breakdown points, discontinuities in higher derivatives, and self-similarity. In certain instances, wavelet analysis may compact or de-noise a signal without triggering severe degradation.

Since the VOI is absolutely bounded by the context seeds, each direction linking within and outside the VOI is blocked by a seed. The effect of labeling just the data inside the area is therefore the same as labeling the whole amount. As a result, the computation period is drastically decreased. The fact that the consumer just traces the line on a single slice of the tumor volume is an apparent disadvantage. As a consequence, there's no assurance that the tumor's depth would equal the VOI. In extreme instances with slightly concave-shaped tumors, the full width line would not be fully surrounded by the tumor. Even in such situations, if an input 1-D line is correctly drawn to fall within the tumor area, this algorithm will successfully perform segmentation. Because of three major factors, smoothing is an essential phase in segmenting brain tumors from post-contrast T1 images:

The first explanation is that a tumor region is characterized as an area surrounded by tumor tissue, even though the strength characteristics are likely to be natural. Second, misclassified necrotic regions can be included in tumor regions that are normally covered by enhanced tissue. Finally, nearby vascular systems that are stimulated by contrast agent administration may be excluded. The CA algorithm has the benefit of simultaneously calculating the distance between each cell and the nearest seed. However, the resulting intensity map only contains one-sided detail, i.e., the gap between label groups. The algorithm is run separately for each class with corresponding class seeds (tumor and healthy) in order to construct a probabilistic map that can be used in an active surface (a level set surface) evolution.

One of the most advanced multi scale measurement methods is the contour let transform (CT). Aside from the true two-dimensional (2D) image expansion filtering, the flexible directional filtering allows the image's intrinsic geometrical form to be captured. The shift-invariance, which means less sensitivity to image shift, can be achieved in the NSCT by allowing redundancy. The non-sub-sampled pyramid (NSP) achieves the NSCT's multi-scale property by using non-sub sampled filters (NSFs) to divide the frequency plane into a low-frequency sub band and many annular high-frequency sub bands. Meanwhile, non-sub sampled directional filters (NSDFs) achieve the multi-directional property by further integrating high-frequency coefficients into wedge-shaped directional sub bands. Figure 2 illustrates how quantifying necrotic regions inside a whole tumor is a major challenge in determining tumor progression. The main concern associated with stereotactic radio surgery is delayed radiation necrosis, which usually happens three months or more following operation. Tumor necrosis may occur as a consequence of radiotherapy or as a result of the tumor's growth, as in high-grade gliomas. The aim is to use only contrast enhanced T1 weighted MRI volumes to measure the necrotic and enhanced portions of the tumor. This is achieved using a two-step sequential algorithm. The procedure first segments the tumor length, which includes both improved and

necrotic tissues. The necrotic and improved groups are divided in the second phase throughout the entire tumor volume.

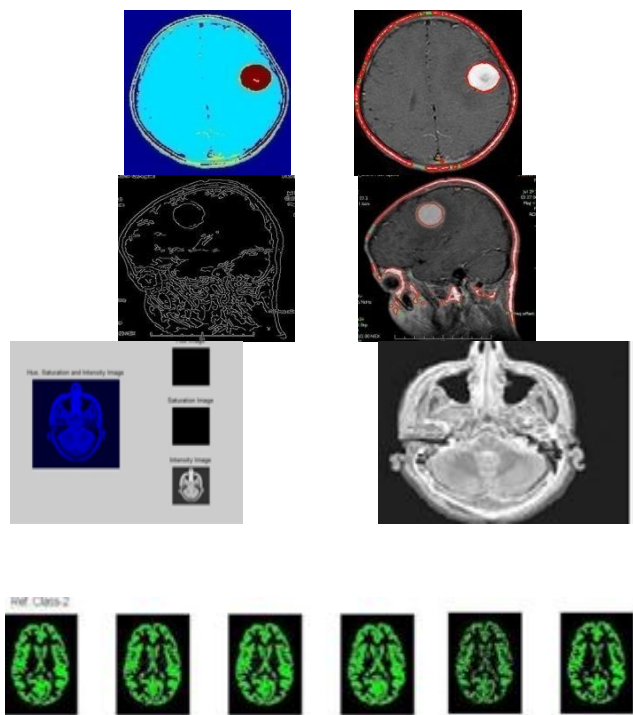


Figure.2. Segmentation of the Medical Image Using Various Techniques

MATLAB was used to model the development of input brain MRI pictures, and it was evaluated on a number of brain MRI images. The MATLAB edition used was 7.12. For modeling, the image processing toolbox is included. Axial, coronal, and sagittal brain photographs are used in the image archive used to verify the proposed procedure. The MRI used for the input is in digital format. Table 1 provides a comparison of the proposed scheme's findings with those of other segmentation algorithms in order to say that the proposed scheme's results are superior. Automatic brain tumor segmentation from MR photos is a difficult process that requires knowledge of anatomy, MRI mechanics, radiologist vision, and picture recognition dependent on strength and form from a variety of disciplines. Since brain tumors come in a range of sizes, forms, and locations, as well as various picture intensities, there are many problems and difficulties involved with brain tumor segmentation. From various directions in the picture, the IHS can efficiently capture both spatial feature information and functional information contents. Despite the fact that the proposed algorithm performed admirably in our tests, there is still more analysis to be done.

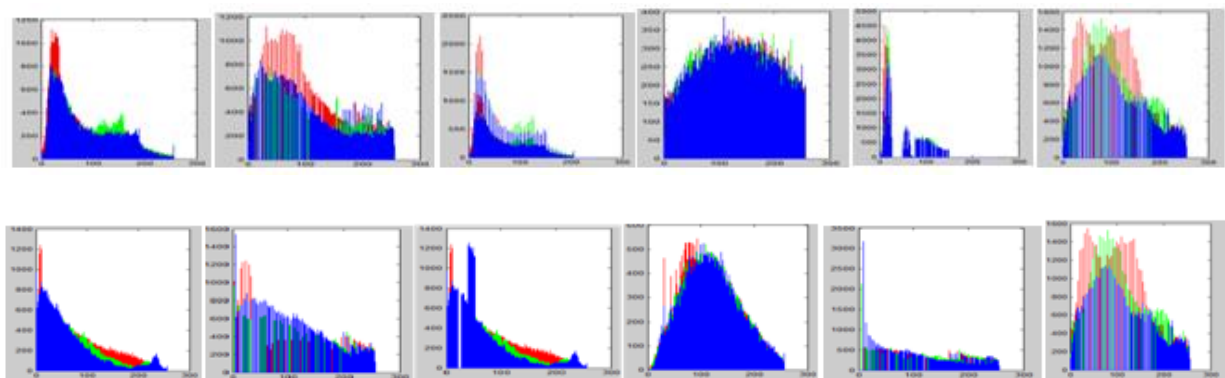


Figure.3. Histogram Equalization of the Medical Image

When the available data of an image is represented by near contrast values, the Histogram Equalization process typically improves the global contrast of several pictures. The intensities on the histogram may be better spread with this modification. This encourages places with poor local contrast to achieve an increase of contrast. This is accomplished by histogram equalization, which essentially spreads out the most repeated strength levels. Contrast stretching (also known as normalization) is a basic image enhancing technique that helps to increase image contrast by stretching the spectrum of intensity values found in the image to cover a desired range of values. Until stretching may begin, the upper and lower pixel value limits over which the picture would be normalized must be defined. Sometimes, these constraints are merely the minimum and maximum pixel values that the picture form in question permits. Histogram equalization is extended to sub-images utilizing the CLAHE process. Each pixel of the original image is in the sub-middle images.

Table 1. Analysis of Medical Image Using Fusion Method

Fusion method	Metrics			
	Entropy	RMSE	PSNR	CC
MRI	7.5897	1.05568	48.5268	0.8116
CT	2.5898	14.0528	25.5898	0.1396

CONCLUSION

The border of a heterogeneous tumor with irregular boundaries, the proposed method is more accurate. Different segmentation algorithms are used to produce the output segmented image for evaluating the tumor's boundary. Otsu's thresholding, canny edge detection, and other segmentation algorithms were used for simulation. The performance of the CA algorithm's segmentation is compared to Otsu's thresholding simulation results and canny edge detection results. To conform to the heterogeneous tumor segmentation issue, a sensitivity parameter is added. The suggested algorithm detects the tumor area boundary very well. It took 8.9 seconds to measure. The user contact period is just a few seconds, and the calculation time is calculated by the tumor volume. Computation time is shortened substantially due to the underlying parallelism of the suggested various algorithms. User contact time rises with the amount of tumors in the case of metastases. It is time effective, resilient to diverse and heterogeneous tumor forms, computationally efficient, and easy to use. Various characteristics of the tumor area can be extracted in future research. The brain tissue deficiency is defined after the chosen characteristics are identified using a neural network.

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