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Research Article

A ROBUST AUTOMATED BRAIN CANCER CELL SEGMENTATION USING COLOR SCHEME MAPPING AT DIFFERENT HYPER SPECTRAL DENSITY

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ABSTRACT

The novel concept of preprocessing and color segmentation is defined for brain cancer cell detection. The color scheme makes the human persistence of vision better with good analysis and better justification. Different banding of frequencies at different level decided the level of quantization level is defined. In this proposed paper 8 different quantization levels for the frequency band estimation are used and there by detect color segmentation of cancerous cells. The precision of the color segmentation is decided by the sharp edges or immediate transaction of the pixel information values. The proposed work identifies even the smallest segment of the cell with automated technique.Each slice of images extracts information at different frequencywhich provides the high frequency information about the presence of tumour.

INTRODUCTION

Analyzing the edge of the tumor at the early stage is prominent which makes medical imaging an emerging research area. MRI is a prominent and effective approach providing the information about the soft tissues of various interests. Different modalities of MRI are used for the proper clinical diagnosis of the brain tumour. High frequency components from the images are provided by Magnetic resonance imaging (MRI). MRI incorporates different contrasts among tissue types is obtained. As of today medical diagnostic technology for detection of brain cancer the ultimate decision is by doctor. The exposure knowledge of doctor decides the presence of tumour. In today's technology there is no automated system for cancer teller. A small ambiguity decision of an unskilled, inexperience doctor may results with huge loss of life, keeping this as challenge and present research work of robust algorithm to find even the smallest segment of cell in brain can be identified automatically. Each slice of images extracts information at different frequency which is of large scale and provides exact information based on the level of content incorporated with cell energy information. To extract high frequency components of MR image is difficult task. The quantization levels are incorporated with 8 different levels i.e., 2^8. This novel approach leads to a new cutting edge technology and to make the MRI machines smarter.

METHODOLOGY

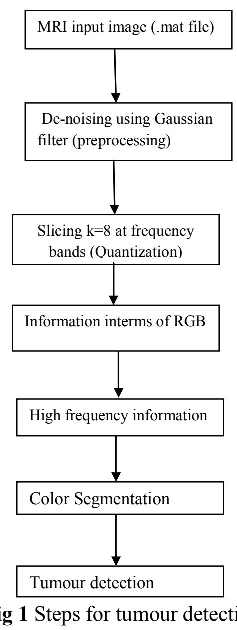

Fig 1 Steps for tumour detection

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Data Set

Different sequences namely T1 weighted, T2 weighted and FLAIR images are collected from JSS Hospital Mysore.

Pre-processing

The preprocessing of biomedical image like MRI scanned images is a bigtask, since the type of the noise is unknown at high frequency characteristic .With the unknown type of noise entity it's better to use any 2D filters of Gaussian type. Smoothing of the image is done with returns a rotationally symmetric Gaussian low pass filter of size HSIZE with standard deviation SIGMA (positive) as shown by the mathematical equation.

A Gaussian function often simply referred to as a Gaussian is of the form,

$$f(x) = ae^{-(x-b)^2/2c^2}$$

Where a, b and c are arbitrary real constants. Gaussian functions are often used to represent the probability density function of a normally distributed random variable with expected value μ=b and variance σ^2=c^2. In this case, the Gaussian is of the form,

$$g(x) = 1.e^{\wedge} - 0.5\left(\frac{x-\mu}{\sigma}\right)^2 /\sigma\sqrt{2\Pi}$$

HSIZE can be a vector specifying the number of rows and columns in H or a scalar, in which case H is a square matrix. Image filter is designed symmetric such a way that filter N-D filtering of multidimensional images. It filters the multidimensional array with the multidimensional filter H. Logical or it can be a no sparse numeric array of any class and dimension. The result, has the same size and class .Each element of the output, is computed using double-precision floating point. This function may take advantage of hardware optimization for data type's uint8, uint16, int16, single, and double to run faster. IN the course of preprocessing pixel size of 3*3 a smallest size is considered for better result and computing Gradient concept will be added advantages for estimating the normal gradient technique.

Color segmentation

The high frequency coefficient image contains information's at different levels which has to be extracted, so here different quantization level is defined, sort it based on the mapping technique of the pixel cell with different quantization levels. Construction of tree tank helps me to scale at different levels and there by extracting information at different frequencies. Doing color segmentation at different levels of frequency and there by building pairs of related cells within the brain imaging , enhances the better distinguishing factors of normal and abnormal cells. With the gradient techniques I get two different values which will be applied for pairing Termed as C1 and C2.The main challenge is to find the predicated values or cells within the region based on merging test and find union of matricwith mathematical model. The mapping of C1 and C2 continuously yield the best result. The color component is extracted at different levels with the following mathematical model as

$$dR = \left(imageseg(c1) - imagedeg(c2)\right)^2;$$
$$dG = \left(imageseg(c1 + npixels) - imageseg(c2 + npixels)\right)^2;$$
$$dB = \left(imageseg(c1 + 2 * npixels) - imageseg(c2 + 2 * npixels)\right)^2$$

The components of red, green and blue is estimated with derivative function, such that even the smallest derivative element of RGB is identified, so all the cells are distinguished based on color segmentation.

Classification /Scaling of image at different values of Frequency

The scaling involves different modules like Log derivatives, Predication, Mapping based on the factors of building the segmentation map with the average color in each segment. The process of log derivate gives the smallest change that is done in the segmentation of cells i.e., scaling up to 1 cell per segment. Post log derivative we generate two bins for processing of different Q levels with log delta and log reg variables to find the total energy confined with the cell or the information. Sequentially we follow with predicative algorithm by comparing c1(nontumour) and c2 (tumour part) values and logically AND with predicate values to find the new root to link both regions. If the tree tank is greater than c1 it maps to c1 else it maps to c2 and in the worst condition both are not equal it maps to the values itself generated by tree tank, mean to say no information in the image. The merge regions are defined both c1 and c2 values are not equal .there by different segments are generated with RGB color scheme. The validation of all the three colors and sorted RGB, defines the cluster formation with iterative mapping sparing the boundary conditions with gradient values. Function outputs the x-derivative and y-derivative of the input I. If I is 3D, then derivatives of each channel are available in xd and yd. IMSEG Color an image based on the segmentation ISEG = IMSEG (I, LABELS) Labels ISEG with the average color from I of each cluster indicated by LABELS.

RESULTS

The results at different level of K (from 1 to 8) are shown below. Input image at gray level showing all the components of the image before color segmentation is shown in Fig1.

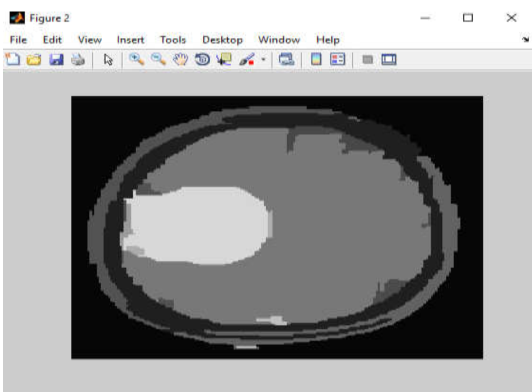

Fig 1 Input image at gray level before segmentation.

From the statistical values shown in Fig2 it's very clear that different mapped values maps different region for validation of quantization of different frequency bands with color space segmentations.

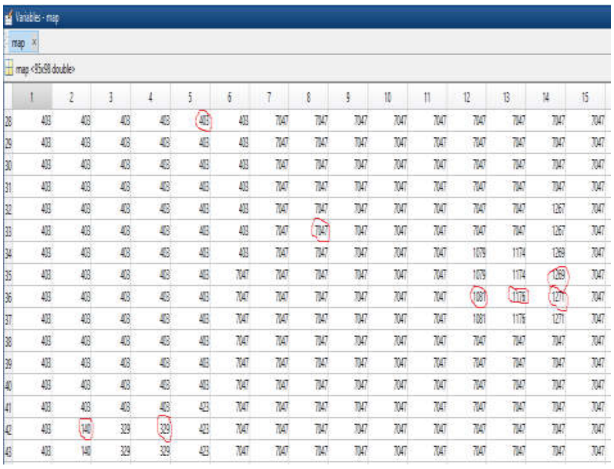

Fig 2 Different frequency bands with color space segmentations.

quick_I1{4, 1} <95x98x3 double>

0.3418	0.3418	0.3418	0.3418	0.3418	0.3418	0.3418	0.3418	0.3418
0.3418	0.3418	0.3418	0.3418	0.3418	0.3418	0.3418	0.3418	0.3418
0.3418	0.3418	0.3418	0.3418	0.3418	0.3418	0.3418	0.0836	0.1387
0.3418	0.3418	0.3418	0.3418	0.3418	0.3418	0.3418	0.0836	0.1387
0.3418	0.3418	0.3418	0.3418	0.3418	0.3418	0.3418	0.3418	0.1387
0.3418	0.3418	0.3418	0.3418	0.3418	0.3418	0.3418	0.3418	0.1387
0.3418	0.3418	0.3418	0.3418	0.3418	0.3418	0.3418	0.3418	0.1387
0.3418	0.3418	0.3418	0.3418	0.3418	0.3418	0.3418	0.3418	0.1387
0.3418	0.3418	0.3418	0.3418	0.3418	0.3418	0.3418	0.3418	0.1387
0.3418	0.3418	0.3418	0.3418	0.3418	0.3418	0.3418	0.3418	0.1387
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0.3418	0.3418	0.3418	0.3418	0.3418	0.3418	0.3418	0.3418	0.3418
0.3418	0.3418	0.3418	0.3418	0.3418	0.3418	0.3418	0.3418	0.3418
0.3418	0.3418	0.3418	0.3418	0.3418	0.3418	0.3418	0.3418	0.3418
0.3418	0.3418	0.3418	0.3418	0.3418	0.3418	0.3418	0.3418	0.3418
0.3418	0.3418	0.3418	0.3418	0.3418	0.3418	0.3418	0.3418	0.3418
0.3418	0.3418	0.3418	0.3418	0.3418	0.3418	0.3418	0.3418	0.3418
0.3418	0.3418	0.3418	0.3418	0.3418	0.3418	0.3418	0.3418	0.3418
0.3418	0.3418	0.3418	0.3418	0.3418	0.3418	0.3418	0.3418	0.3418

Fig 3 Result obtained after segmentation for a scale of color scheme.

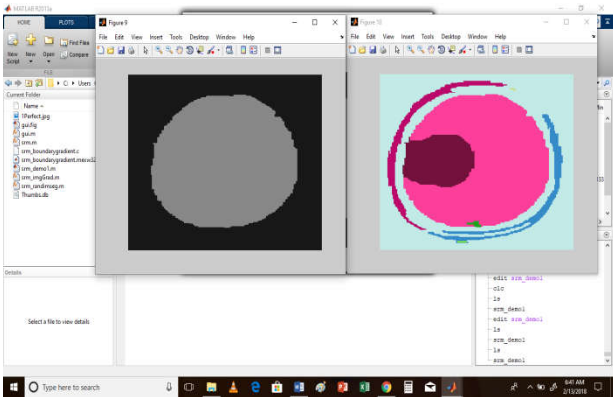


Fig 4 Segmented Tumour

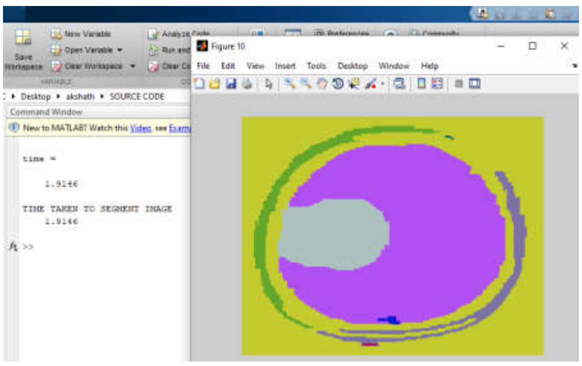
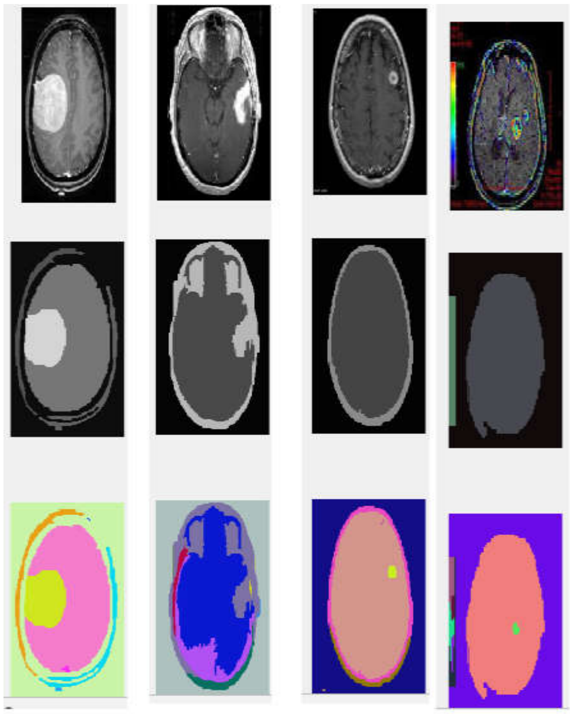


Fig 5 Time taken to segment tumour

Values obtained after segmentation for a scale of color scheme for one of the slice shown in Fig3. Fig4 indicates two images, the left hand is the output obtained after removing skull, fluid totally said as noise removal .The right hand side image is color segmented of different components where in the brain cell is distinguished very clearly. Fig5 measures time taken to segment the brain tumour and computed to be fast and efficient of 1.9146 Seconds.



a b c d

Fig.6 Vertical shown figure represents original image, sliced imaged and color segmentation image.Figure a represents a large size of tumor ,Figure (b) represents without tumor ,Figure (c) represents a small sized tumor (even smallest occurrence is detected) and Figure (d) represents a 3D original image of MRI standard that is process by our algorithm to detect smallest early stage of tumor.

CONCLUSION

The primary advantage of high frequency banding with quantization imaging is that, because an entire spectrum is acquired at each point, the operator needs no prior knowledge of the sample, and post processing allows all available information from the dataset to be mined. High frequency banding with quantization imaging can also take advantage of the spatial relationships among the different spectra in a neighborhood, allowing more elaborate spectral-spatial models for a more accurate segmentation and classification of the image. Fast computers, sensitive detectors, and large data storage capacities are needed for analyzing. Significant data storage capacity is necessary since high frequency banding with quantization imaging cubes are large, multidimensional datasets, potentially exceeding hundreds of megabytes. All of these factors greatly increase the cost of acquiring and processing data. As a relatively new analytical technique, the full potential of high frequency banding with quantization imaging has not yet been realized and still it's a research work in biomedical application.

Future Work

The proposed technique can be further modified for the automatic detection of brain tumour which is interfaced to the MRI machine to make smarter to distinguish normal and abnormal images in slices which can be a cutting edge technology.

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