An Automated Approach of CT Scan Image Processing for Brain Tumor Identification and Evaluation

Shabana Urooj* and Amir

Department of Electrical Engineering School of Engineering Gautam Buddha University, Greater Noida, UP India

Abstract: Brain Tumor identification and evaluation requires Computed Tomography (CT) scan and image processing in medical diagnosis. The Manual methods for the detection of abnormal cell growths in brain tissue is both time consuming and non-reliable. This paper initiates with a discussion of a clinical diagnosis case of normal brain tissue and other with tumor affected images. The affected area is identified first with manual approach and further an automated approach is discussed using NI Lab VIEW software for locating the exact position and its evaluation. The described method provides a better way of diagnosing brain tumor in a quick and reliable automated manner. In the view of this, an automatic segmentation of brain MR images is needed to correctly segment White Matter (WM), Cerebrospinal fluid (CSF) and Gray Matter (GM) tissues of brain in a shorter span of time. The manual segmentation of brain tumor is abstruse job and may provide erroneous results.

Keywords: Tumor, CT Scan, Image Processing, Diagonosis.

1. INTRODUCTION

An uncontrolled growth of tissues in brain is known as tumor which can further propagate in life-threatening cancer. Clinical diagnosis requires an efficient medical imaging and processing to detect the exact position and type. Benign tumor is non-cancerous type and malignant tumor is cancerous form of this disease [1]. The benign form grows very slowly, and spreads very rarely, while the malignant form grows rapidly with irregular boundaries, and also attacks to nearby area. Generally, brain tumors are more likely to occur in men than in women. Meningiomas tumor as specific type is more common in women. The ages of 65 to79 and children younger than age 8 are more prone to brain tumor.

Magnetic resonance imaging (MRI) and computed tomography (CT or CAT scan) are the most common types of tests used to diagnose brain tumors. Both MRI and CT scan use computers to create detailed images of the brain. CT scans are a type of X-ray that creates a three-dimensional picture of the head by scanning the head from multiple different angles [2]. A computer combines these images into a detailed, cross-sectional view that shows abnormalities in the brain, or tumors. CT scans can be helpful in diagnosing some types of brain tumors, especially those near or involving bone. They can also show swelling, bleeding, and bone and tissue calcification. A computer then combines these pictures into images of slices of the body. Unlike a regular x-ray, a CT scan creates detailed images of the soft tissues in the body [2]. Quantitative EEG measurement for diagnosis accuracy [9] and EEG signals through beam forming techniques for Seizure Diagnosis are analysed in [10].

The best type of imaging to diagnose most types of brain tumors is MRI. These scans use magnetic fields and radio waves, rather than X-rays, and computers to create detailed pictures of the brain. MR Is show visual “slices” of the brain that can be combined to create a three-dimensional picture of the tumor. MRI scans are very good for looking at the brain and spinal cord and are considered the best way to look for tumors in these areas [3]. The images they provide are usually more detailed than those from CT scans. But they do not image the bones of the skull as well as CT scans and therefore may not show the effects of tumors on the skull. CT scans are not used as often as MRI scans when looking at brain or spinal cord tumors, but they can be useful in some cases. They may be used if MRI is not an option (such as in people who are very overweight or people who have a fear of enclosed spaces). CT scans also show greater detail of the bone structures near the tumor. Here a modified automatic lesion identification (ALI) procedure is described which enables brain tumor identification from single MR images. The automated lesion identification (ALI) method was initially implemented as a toolbox in SPM software package (Wellcome Trust For Neuroimaging, London, UK) to specifically deal with lesion identification on mono-spectral MRI scans. It comprises segmentation, normalization and outlier detection in such a manner [5]. More complex techniques superior to pseudo Zernike moment-based method in terms of kernel generation, numerical stability and easier implementation are reported in [7, 11].

*Address correspondence to this author at the Department of Electrical Engineering School of Engineering Gautam Buddha University, Greater Noida, UP India; Tel: 91 120-2346015; Fax: 91 120 2344000;
E-mail: shabanabilal@gmail.com

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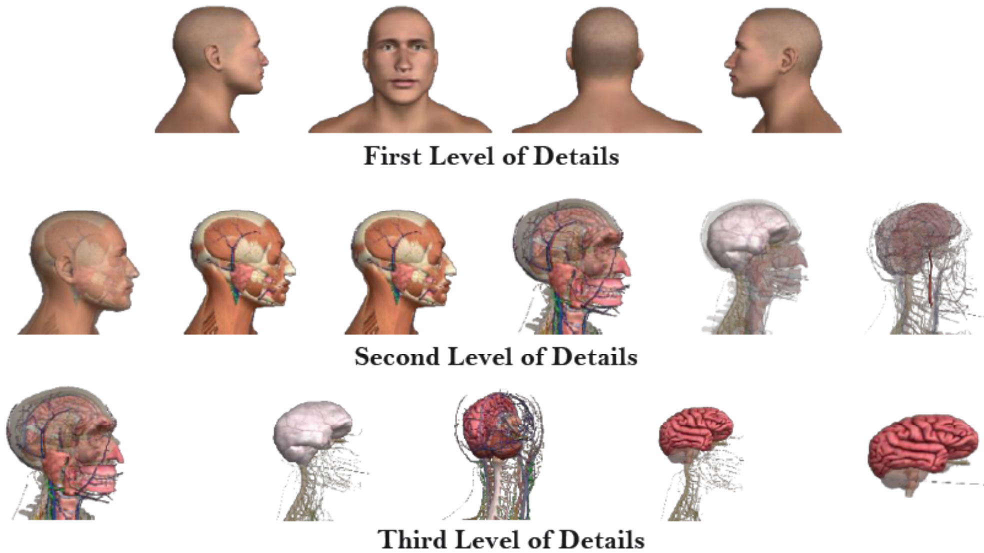

Figure 1: Level of Details in 3D Navigated Anatomy view for an adult male [6].

Neurosurgery processes is incorporating computer helped surgical planning and advent imagery guiding techniques. The viability of accuracy of anatomic three-dimensional (3D) modeling remarkably improves spatial information of the connections of critical structures (*e.g.*, functionally significant cortical areas, vascular structures) and disease. Image-processing tools and equipment provide interactively represented 3D visual information that is nearly similar to the view of the surgeon during the time of surgery [4].

2. CLINICAL DIAGNOSIS

The present research considers two clinical case, the first one of a 45 year old male with normal CT scan result and the second case of a 41 year old male patient suffering from benign tumor from Delhi State Cancer Institute located in New Delhi, India. The scan results were clinically analyzed and reported.

The first case with normal CT scan is analyzed first with 3D Navigated Anatomy of brain to understand the structural normality and functionality of tissues. The serial sequence imaging of brain is analyzed as shown in Figure **1** in 3D view for an adult male using Zygote Body, formerly Google Body. The first level of details describes the various views of adult male head. This view presents an outline sketch of brain and skull. This helps in understanding the CT scan outline view for evaluation of tumor position and dimensions. The second level of details analyses the sequential refinement of internal details of brain anatomy. This helps in identifying the depth and location of tumor affected area. The enveloping meanings are shown, followed by the internal details including dura-mater and cerebrum. The clinically important internal parts of cerebrum and different lobes are presented in third level of details. This overview helped us in understanding the effectiveness of CT scan data and further helped in analyzing the sliced images. Further, the white matter and grey matter of cerebrum were easily evaluated for tumor using these 3D navigated anatomies.

Some sequential images for the first case of a 45 year old male with normal CT scan results are shown in Figure **2** with intravenous contrast medium, from base

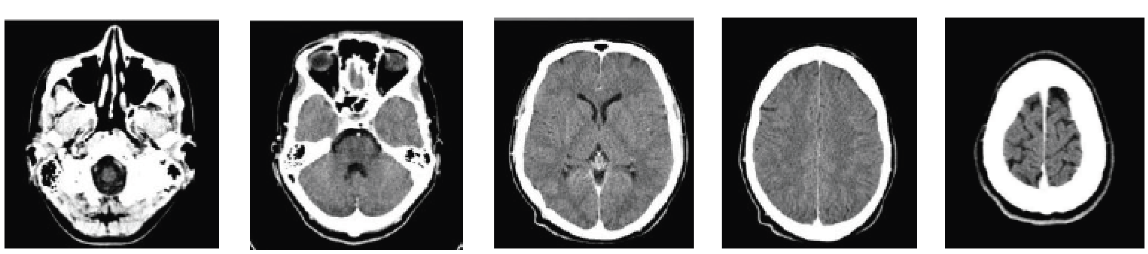

Figure 2: CT Scan Image slices of a normal 45 Year Old Man (Case 1) [6].

of skull to top. The 5 slices of grey scale images from each row of a 34 slice report is taken for this case. No abnormal cell growth is observed across the slices as reported by the clinical diagnosis.

The second case of a 41 year old male patient suffering from low-grade astrocytoma tumor is presented. The location is in right frontal lobe and it is localized with slow growth. The 5 slices of scanned images shows non enhancing insular mass as shown in Figure **3** below.

By comparing the above two cases, the visual correlation can predict in second case for an insular mass with black color in right frontal lobe. The second and third slice of first case needs to be observed for comparison.

3. IMAGE PROCESSING AND TUMOR EVALUATION

The images of normal brain scan in Case 1 and images of tumor affected brain in Case 2 are analyzed using NI LabVIEW using a script creation in Vision Assistant. Several other medical applications implemented by NI LabVIEW are proven in [8, 12]. The basic approach of evaluation is shown in Figure **4**, shown below. First, images are acquired from CT scan of the above two cases.

The red plane in image is first excluded by color plane extraction and further each value of pixel is detected by Histogram. The local Threshold background corrections applied for clarifying tumor boundaries. Low pass Fast Fourier Transformation is applied for further clarity. Finally, the length, area and location of the tumor is evaluated and correlated with 3D Navigated model.

The image in Figure **5**(**a**) below shows the normal CT scan without tumor and the second with tumor. One image is selected to analyze and evaluate tumor from each case. The original acquired images are scripted for solarized color plane extraction in this step and red

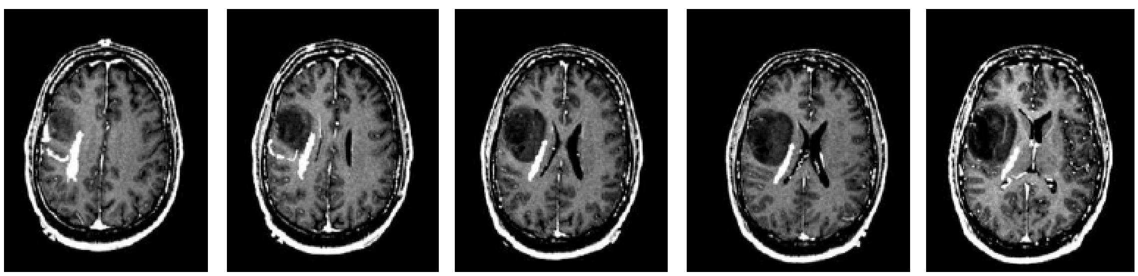

Figure 3: CT Scan Images Slice of an astrocytoma Tumor affected 41 Year Old Man (Case 2) [6].

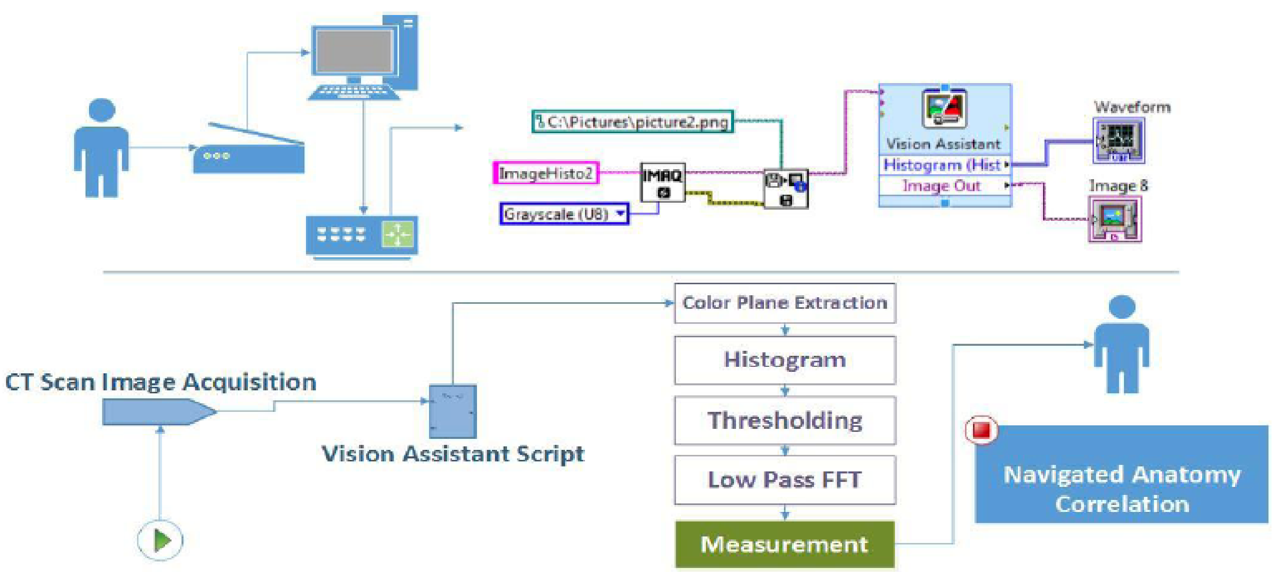

Figure 4: CT Scan data processing Approach for Brain Tumor detection.

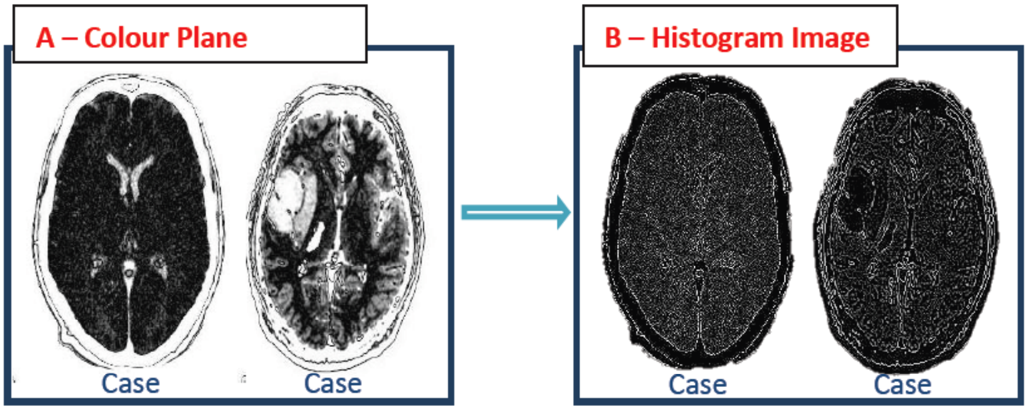

Figure 5: Image Processing for Case 1 and Case 2.

Table 1: Histogram Measurement Values for Case 1 and Case 2

	Minimum Value	Maximum Value	Mean Value	Standard Deviation	Number of Pixels
Case 1	0	225	32.60	45.51	151456
Case 2	0	225	94.44	72.16	149234

plane extraction is removed. Further in the next image Figure **5**(**b**), Histogram is evaluated and applied to detect each pixel value in the image. Number of pixels is observed with maximum and minimum values as shown in Table **1**.

Figure **6** above shows sequential processing of tumor affected case. Edge detection is done in image a, and then inverse saturation is again done for focusing on the tumor area. Further, the image, as shown in c is applied for thresholding for edge separation. The foreground and background is thresholded for different values and pixels to get a clear view. Fourier transform (FFT) is used to compute the Discrete Fourier transform (DFT) and it's inverse. Here we have used it as a filter for our image. Low pass FFT with thresholding helped to segregate tumor edges and finally a clear image is observed as shown in Figure **6**(**d**).

Further, the final image of Figure **6**(**d**) is used to measure the dimension and location of tumor. The located tumor is simulated in 3D Navigated model to have a clear outlook of affected space. The approach is presented in Figure **7** below and measured values are indicated in Table **2**.

CONCLUSION

The present research provided an enhanced approach of locating and evaluating brain tumor

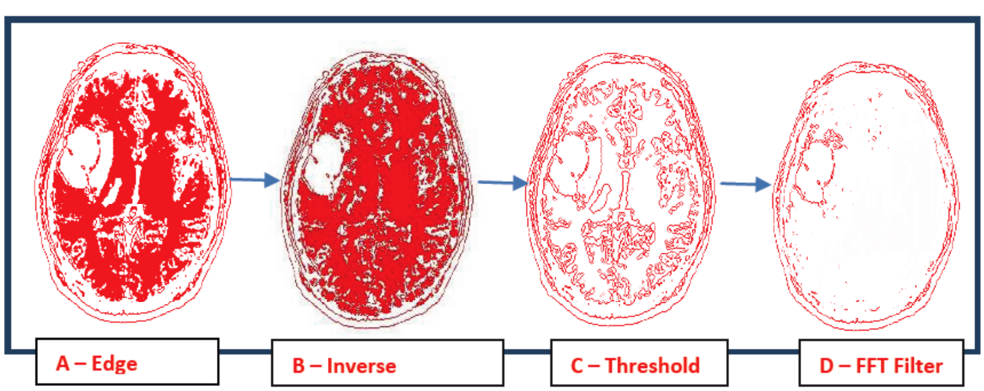

Figure 6: Sequential processing of Tumor Image for Case 2.

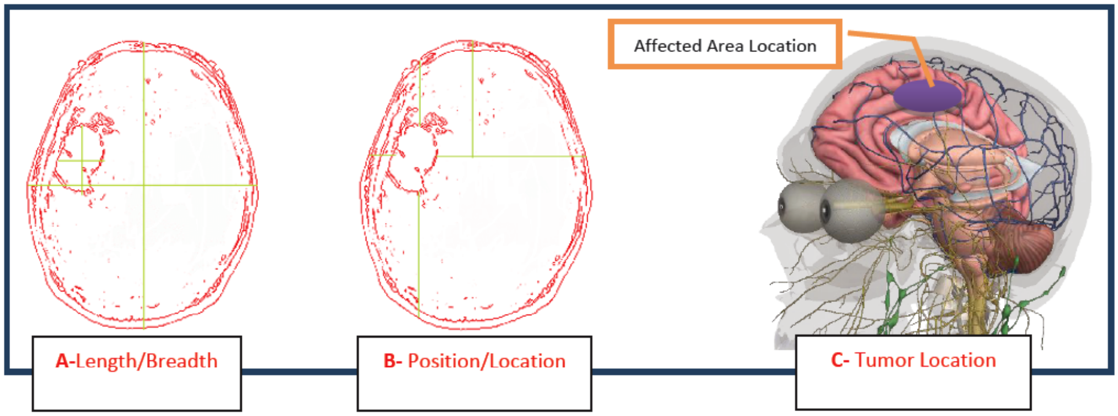

Figure 7: Dimension and Location Measurement for brain tumor in Case 2.

Table 2: Tumor Measurement Values for Case 2

	Brain Length	Brain Width	Tumor Length	Tumor Width	Brain Area	Tumor Area	Tumor Pixel ratio %
Values	186 mm	156 mm	41.23 mm	28.87 mm	25763 mm^2	1973 mm^2	4.97

through CT scan image processing. The correlated method of analyzing the disease through 3D Navigated model and processed image in LabVIEW provided a clear clinical diagnosis report for further treatment and understanding. The sequential image processing script provided an improvised and automated method for brain tumor detection and can also further help in analyzing the intensity of this disease. The method proved itself as a reliable, efficient and low cost method for tumor detection and evaluation (efficient and reliable on the basis of accuracy and time taken by Image processing and evaluation). In the Table **2**, the measures are from the LabVIEW software model.

REFERENCES

[1] Zacharaki EI, Wang S, Chawla S, Soo Yoo D, Wolf R, Melhem ER, et al. Classification of brain tumor type and grade using MRI texture and shape in a machine learning scheme. Magnetic Resonance in Medicine 2009; 62(6): 1609-1618. http://dx.doi.org/10.1002/mrm.22147

[2] Pelizzari CA, Chen GT, Spelbring DR, Weichselbaum RR, Chen CT. Accurate three-dimensional registration of CT, PET, and/or MR images of the brain. Journal of computer-assisted tomography 1989; 13(1): 20-26. http://dx.doi.org/10.1097/00004728-198901000-00004

[3] Posada-Gómez R, Sandoval-González OO, Sibaja AM, Portillo-Rodríguez O, Alor-Hernández G. Digital Image Processing Using Lab VIEW), Practical Applications and Solutions Using LabVIEW™ Software 2011; 297-316.

[4] Posada-Gómez R, Sandoval-González OO, Sibaja AM, Portillo-Rodríguez O, Alor-Hernández G. Digital Image Processing Using Lab VIEW.), Practical Applications and Solutions Using LabVIEW™ Software 2011; 297-316.

[5] Cathy Price J, Ana Sanjuan, Laura Mancini, Goulven Josse, Geva. Automated identification of brain tumors from single MR images based on segmentation with refined patient-specific priors 2013; 1-5.

[6] Grover RK, The Director "data is taken from DELHI STATE CANCER INSTITUTE, NEW DELHI" under their allowance. (2015)

[7] Singh SP, Shabana Urooj, "Combined Rotation- and Scale-Invariant Texture Analysis Using Radon-Based Polar Complex Exponential Transform", Arabian Journal for Science & Engineering, 9th April 2015, DOI 10.1007/s13369-015-1645-6. http://dx.doi.org/10.1007/s13369-015-1645-6

[8] Shabana Urooj, Khan M, Ansari AQ, Aime L Ekuakille, Salhan AK, "Prediction of Quantitative Intrathoracic Fluid Volume to Diagnose Pulmonary Oedema Using LabVIEW", Computer Methods in Biomechanics and Biomedical Engineering - A Taylor & Francis title. DOI 10.1080/10255842.2011.565054 May 2011.

[9] Lay-Ekuakille A, Vergallo P, Griffo G, Conversano F, Casciaro S, Shabana Urooj, *et al.* "Entropy Index in Quantitative EEG Measurement for Diagnosis Accuracy" IEEE Transactions on Instrumentation and Measurement, June 2014; 63(6): 1440-1450. http://dx.doi.org/10.1109/TIM.2013.2287803

[10] Vergallo P, Lay-Ekuakille A, Giannoccaro NI, Massaro A, Shabana Urooj, Caratelli D, *et al.* "Processing EEG Signals through Beamforming Techniques for Seizure Diagnosis", 6th IEEE International Conference on Sensing Technologies (ICST 2012) held on 18th to 21st Dec 2012 at Kolkata India 978-1-4673-2248-5/12, pp497-501.

[11] Satya P. Singh, Shabana Urooj, "Rotational-Invariant Texture Analysis Using Radon and Polar Complex Exponential Transform", Advances in Intelligent Systems & Computing, Volume 327, 2015, pp 325-333. http://dx.doi.org/10.1007/978-3-319-11933-5_35

[12] Shabana Urooj, Lay-Ekuakille A, Ansari AQ, Khan M, Vergallo P, Trotta A. "Volumetric Estimation of Thorax with Cylindrical Model and Anthropometric Measurements", IEEE International Symposium on Medical Measurements and Application, MEMEA 2011, Bari, 30-31 May 2011, 213-315, ISBN 978-4244-9337-1/11.

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http://dx.doi.org/10.15379/2409-3394.2015.02.02.2