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Changes of Brain Anatomy affects Abnormalities in Brain

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Abstract

The brain carries out cognitive learning and processing different types of information processes. Types of information processes are performed by different anatomical structures. The structure of brain anatomy changes due to the effect of diseases related to brain. Accurate identification of brain abnormalities as tumor, stroke and hemorrhage lesions is the critical task in planning appropriate therapy. CAD systems have been the focus of several research activities, and it is solely based on the idea of analyzing images of different types of brain abnormalities by implementing improved image processing algorithms. In this chapter, a modern and automated approach is used to detect the existence of abnormalities from MRI scan images of the brain. The proposed method includes several stages image segmentation, area and volume calculation, and its location findings.

Keywords: Brain Anatomy; Tumor; Stroke; Hemorrhage lesions

Introduction

The human brain is defined both by its anatomy and the way neurons are shaped, clustered together and connected to each other's and its dynamics. Investigating the relationship between brain structure and function is a central endeavor for neuroscience research for finding brain diseases. In modern times, automated diagnosis involves image segmentation step which is used to extract the abnormal lesions from brain MRI. The different abnormalities types differ in many computerized aspects such as nature, size, its shape, volume, number and its locations of lesions. The term abnormalities used to generalize the tumor, hemorrhage, and stroke because using automated system classification of different types of abnormalities is very difficult. Brain image segmentation attempts to label pixels by tissue type. The detection of abnormalities is essential in the diagnosis and management of a variety of intracranial diseases including hypertensive hemorrhage, hemorrhagic infarction, brain tumor, cerebral aneurysm, vascular malformation, trauma, hemorrhagic changes following radio- or chemotherapy, and hemorrhagic pial metastasis. CAD systems incorporate computers to add a new dimension to physicians for achieving a faster and more accurate diagnosis. The proposed outline of the method helps the physicians to better diagnose human brain abnormalities, for further treatment.

Literature Review

Coherent behavior and cognition determines the relation between neuronal populations in interaction. Even at rest, in the absence of direct environmental stimulations, these interactions drive the synchronization of spontaneous activity across brain systems, shedding light on the large-scale anatomical functional organization of the brain. The study of such patterns of synchronization has known important developments due to recent methodological advances in brain imaging data acquisition and analysis.

CAD systems are usually domain-specific as they are optimized for certain types of diseases, focuses on specific parts of the body and diverse diagnosis methods. Development of such CAD system is challenging since they combine the elements of artificial intelligence and digital images processing. This work proposes a CAD system to assist the radiologist for the detection of hemorrhages, tumors, and stroke lesions in MRI scan images of the human brain to identify their natures. Some of the older works [1] addressed the problem of segmenting the region of intracerebral hemorrhages. Generalized fuzzy c-means algorithm [2] uses both pixel attributes and local spatial information that is weighted in correspondence with neighbor elements based on their distance attributes. The color-converted segmentation with K-means clustering algorithm [3], and regions of the brain related to hemorrhage can be correctly separated from the colored image and it help pathologist to distinguish lesion size and its region exactly. Its application to several datasets with different abnormality sizes, intensities and locations show that it can automatically detect and segment very different types of brain abnormality with good quality. A symmetric based [4] result

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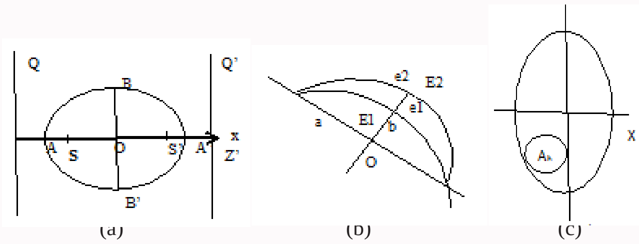

Figure 1: Schematic diagram of hemorrhage classification: a) Elliptic nature; b) Edge of abnormality is considered as two different ellipses; c) Position of abnormality with inter and intra distance.

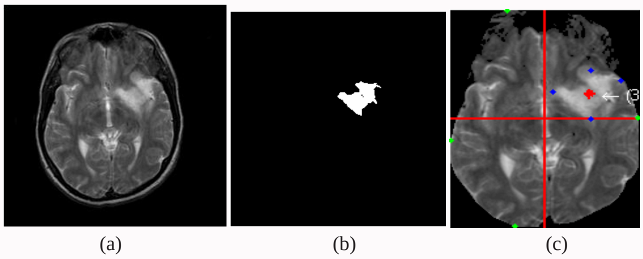

Figure 3: Results on stroke images. (a) Original input image; (b) Segmented region; (c) Position of stroke lesion.

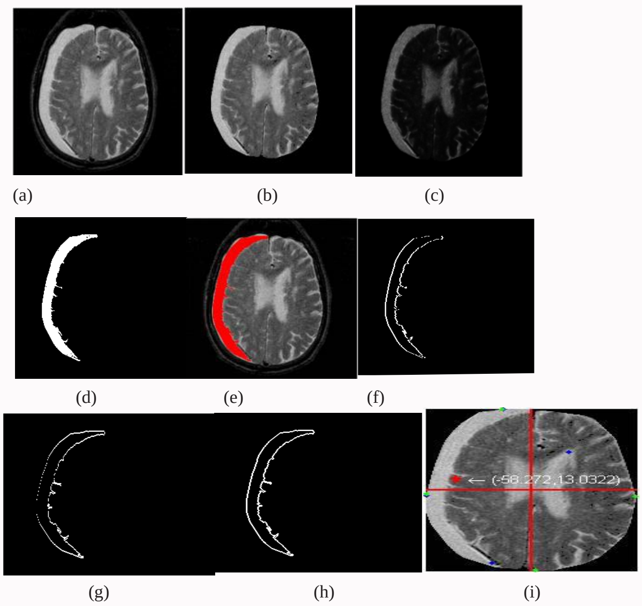

Figure 2: Hemorrhage segmentation results. a) Input MRI of the brain; b) Applying artifacts and skull removal; c) After gamma transformation; d) Segmented abnormal portion; e) Abnormal portion indicated by red marks; f) Horizontal contour; g) Vertical contour; h) Contour of abnormal region; i) Localization of abnormal region.

constitutes the initialization of a segmentation method based on a combination of a deformable model and spatial relations, leading to a precise segmentation of the abnormalities.

Proposed Method

The data set of image database [5,7] of T1, T2, and PD MRI containing multiple image slices has been used here. The RGB image has been converted to a grayscale image using a weighted sum of the R, G and B components multiplied by a constant. Intensity value obtained using standard deviation is used as threshold intensity for binarization of MRI of brain.It is very much helpful for extracting brain portion and differentiating it from to the non-brain portion. Since there is a significant intensity difference between the background and the foreground of brain MRI, so the use of standard deviation based binarization has been successfully implemented for brain stroke detection purpose. After applying wavelet decomposition up to level, two non-brain regions are totally separated from the brain in a discrete form which is not useful for the approach as there is a possibility that abnormality may get lost and to rectify this problem a quick hull algorithms as proposed in [6] is implemented. The convex hull of a set of points in the plane is the shape taken by a rubber band that is placed "on the points" and allowed to shrink to a state of equilibrium. A polygon is convex if it is simple and all its internal angles are less than p. Quick-hull described in [6] is a divide-and-conquer algorithm, similar to quicksort, which divides the problem into two sub-problems and discards some of the points in the given set as interior points, concentrating on remaining points. The obtained image is now a binary image in which only brain portion is denoted with one, and all non-brain portions contains zero. This convex image is multiplied with the original image, and the resultant image is free of any previously existing artifacts, noise, and skull as such removals are critical for brain abnormality detection. T2 and PD types of images need some alteration from binarized results. The alteration has been performed on connected component located within $1/6^{th}$ of total height from the center along a vertical line (separation line between two lobes), and centroid position of connected components must be within $1/4^{th}$ from the center horizontal distance. The specification of selecting the range signifies the probable appearance of the corpus callosum. If any region is found within the region, compare both left and right along the horizontal straight line. If any region is found along the horizontal line within range and object size is within 1.5 times range then vanish both region. If any region found symmetry line (horizontally) on centroid but not 1.5 scales, then remove smaller one (this is because if any abnormality connected with CC) if it belongs to within 1/3 from the center along x, 1/3 from the center along y directions.

Results and Discussion

The methodology has been applied to the hemorrhage, stroke, and different tumor lesions and the results on that abnormalities has been describing in this section. The method has been tested on hemorrhage, tumor, and stroke data set [5,7]. In the case of hemorrhage classification from MRI of the brain, it is possible to conceptually treat hemorrhage lesion as two ellipses and calculate semi-major, semi-minor axis with eccentricity and with respect to these values, categorization of chronic subdural hematoma is possible. If ellipse formation is possible, then the distance from a different position to the skull and area of the lesion is calculated. With such calculation, it can be classified as cerebral hemorrhage, vascular dementia, intra-parenchymal hemorrhage and acute stroke. Figure 1 shows Schematic diagram of hemorrhage classification.

The area obtained after segmentation is then verified using area difference between two ellipses. The algorithm concentrates on the position of the lesion, skull distance, and center distance. The epidural hemorrhage is characterized by its convex shape and its close fitting with the skull. Finally, the intra-parenchymal hemorrhage is characterized by its distance from the skull. In Figure 2 shown below, hemorrhage has been found on the left lobe of the brain. There is no relation with the skull portion, and it is classified as cerebral and intracranial hemorrhage. In the experiments conducted, the algorithm is implemented on T2, T1 and PD type of MRI images for cerebral hemorrhage detection and the methods successfully detected an abnormality, but when applying to other kinds of hemorrhage detection, the skull elimination steps are excluded (in preprocessing skull removal is optional). The images shown in Figure 2 belong to a 49-year-old African-American woman [5] with a history of hypertension and diabetes mellitus. The scan was performed when the patient experienced numbness and tingling of the left leg for about one day. Systemic arterial blood pressure was 240/130.

There was no weakness, facial droop, visual change; no upper extremity or right lower extremity sensory abnormality; no bowel or bladder dysfunction; no headache, fever, shortness of breath, chest pain, nausea, vomiting, diaphoresis, vertigo or light-headedness, no back pain, and no history of seizures. An epidural hematoma is located into the potential space between the dura, which is inseparable from cranial periosteum, and the adjacent bone. A Subdural hematoma is diagnosed by mass effect, which is depicted as the displacement of the blood vessels onangiograms on the skull. Subarachnoid hemorrhage appears when bleeding happens into the subarachnoid space around the brain and spinal cord. The testing dataset [5] consists of 460 MRI images of the human brain with a different type of hemorrhage including some normal brain image. Among the images, 40 are of the normal brain while the remaining images represent brains with at least one of the three types of the brain hemorrhage.An image of a normal brain shows a distribution of gray matter that appears clear in the texture-like fissures, while an abnormal brain has a shape which appears brighter than the normal gray matter. Abnormal regions of the brain differ in characteristics than the normal brain, but the diversity of characteristics is notable when compared to any other organ for T1, T2 and PD type of MRI images. Thus accurate segmentation is very important and considerable attention has been given to achieve the same. For brain hemorrhage segmentation several steps have been proposed, and details are shown in Figure 2 below. Figure 2(a) is the input MRI of the brain and Figure 2(b) is after applying artifacts and skull removal method. Figure 2(c) is the output image after power law transformation has been applied on the convexed image which is helpful to segment the brain hemorrhages. Figure 2(d) shows binary segmented hemorrhage portion. In Figure 2(e) depicts the hemorrhage portion within the brain image marked by red region for visualization. Figure 2(f) shows the contour detection by horizontal contour detection, and Figure 2(g) show the vertical contour detection. Contour lines are not continuous for the horizontal and vertical contour that is why both are combined to obtain the final contour image which is continuous and is shown in Figure 2(h). Figure 2(i) shows the localization of hemorrhage and accordingly classified based on their localization information into different types of the brain hemorrhage.

Conventional T2-weighted images and PD images have converted to a high signal in the lesion and showed a large area of abnormal signal in the region clinically suspected: the portion of left hemisphere supplied by the middle cerebral artery. The stroke lesion bright signal is seen here because of the presence of excess water which has a prolonged relaxation time. The method segments the stroke lesion and localizes the centroid of lesion that helps in diagnosis of stroke. Figure 3(b) is the segmented part for an input Figure 3(a) after using power law transformation in skull removal image. Finally, in Figure 3(c) shows the position of the abnormal part into the brain hemisphere.

Conclusions

Accurate measurements of abnormalities thickness, area, volume, and localization of lesion from MRI scan have been successfully implemented by the proposed system. This is critical for early, reliable and accurate detection of tumor, stroke, and hematoma for providing early diagnosis and treatment, prompt transfer of the patient to a medical facility capable of MRI scanning and neurological intervention if necessary.

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