A Review on Detection of Traumatic brain Injury using Visual-Contextual model in MRI Images

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Abstract— Recently, there are various computational methods to analyze the traumatic brain injury (TBI) from magnetic resonance imaging (MRI).The detection of brain injury is very difficult task in the medical science. There are various soft techniques for the detection of the patch of brain injury on the basis of MRI image contents. This paper gives brief analysis about the different methods to determine the normal and abnormal tissues of the brain.

Keywords- *MRI images; visual-contextual model; Traumatic brain injury (TBI).*

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I. INTRODUCTION

Traumatic brain injury, often referred to as TBI, is most often an acute event similar to other injuries. That is where the similarity between traumatic brain injury and other injuries ends. One moment the person is normal and the next moment life has abruptly changed. In most other aspects, a traumatic brain injury is very different. Since our brain defines who we are, the consequences of a brain injury can affect all aspects of our lives, including our personality. A brain injury is different from a broken limb or punctured lung. An injury in these areas limit the use of a specific part of your body, but your personality and mental abilities remain unchanged. Most often, these body structures heal and regain their previous function. Brain injuries do not heal like other injuries. Recovery is a functional recovery, based on mechanisms that remain uncertain. No two brain injuries are alike and the consequence of two similar injuries may be very different. Symptoms may appear right away or may not be present for days or weeks after the injury. One of the consequences of brain injury is that the person often does not realize that a brain injury has occurred.

Most people are unaware of the scope of TBI or its overwhelming nature. TBI is a common injury and may be missed initially when the medical team is focused on saving the individual’s life. Before medical knowledge and technology advanced to control breathing with respirators and decrease intracranial pressure, which is the pressure in the fluid surrounding the brain, the death rate from traumatic brain injuries was very high. Although the medical technology has advanced significantly, the effects of TBI are significant.

TBI is classified into two categories: mild and severe.

A brain injury can be classified as mild if loss of consciousness and/or confusion and disorientation is shorter than 30 minutes. While MRI and CAT scans are often normal, the individual has cognitive problems such as headache, difficulty thinking, memory problems, attention deficits, mood swings and frustration. These injuries are commonly overlooked. Even though this type of TBI is called “mild”, the effect on the family and the injured person can be devastating. Severe brain injury is associated with loss of consciousness for more than 30 minutes and memory loss after the injury or penetrating skull injury longer than 24 hours. The deficits range from impairment of higher level cognitive functions to comatose states. Survivors may have limited function of arms or legs, abnormal speech or language, loss of thinking ability or emotional problems. The range of injuries and degree of recovery is very variable and varies on an individual basis.

The effects of TBI can be profound. Individuals with severe injuries can be left in long-term unresponsive states. For many people with severe TBI, long-term rehabilitation is often necessary to maximize function and independence. Even with mild TBI, the consequences to a person’s life can be dramatic. Change in brain function can have a dramatic impact on family, job, social and community interaction.

TBI is the leading cause of mortality and morbidity in the world for individuals under the age of 45. Traumatic brain injuries are classified in penetrating or closed, and the pathophysiological processes differ for each. Primary injury is the mechanical damage occurring at the moment of impact, and secondary injuries are the non-mechanical aspects that result, including altered cerebral blood flow and metabolism, excitotoxicity, edema (swelling), and inflammatory processes. The extensive tearing of nerve tissue throughout the brain obtains these additional injuries since neurotransmitters are released, resulting in disturbance of the brain's normal communication and chemical processes. Permanent brain damage, coma, or death is possible. As per the clinical studies and those using experimental models of TBI, manual quantitative analysis has been used to evaluate TBI in MRI. These manual studies are used to identify the location and size of a lesion from MRI with correlative histology and assessment of long term neurological effects. However, manual detection of lesions in TBI is very difficult and often requiring 1) hours per scan is required for manual region-of-interest analysis, 2) a trained operator to improve the analysis, 3) large data sets for statistically sound analysis but, and 4) multi-modal it becomes resource intensive and multi-modal inputs as mild or subtle alterations on MR images are often difficult to identify (low contrast). In the present study, the ability of computer vision and learning techniques to assess subtle alterations on quantitative T2 maps after induction of TBI. Currently, neurological injuries are evaluated using the Glasgow Coma Scale (GCS) ,it evaluates a patient consciousness level through his/her ability to respond to motor, verbal and visual stimuli.

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II. RELATED WORK

Anthony Bianchi [1] proposed advance approach to detect mTBI lesion from MRI and improve the performance of visual and contextual modeling. The contextual model estimates the progression of the disease using subject information, such as the time since injury and the knowledge about the location of mTBI. The visual model utilizes texture features in MRI along with a probabilistic support vector machine to maximize the discrimination in unimodal MR images. These two models are fused to obtain a final estimate of the locations of the mTBI lesion.

N.Zhange [2] proposed SVM classification followed by region growing. It gives prior segmentation knowledge and features. It requires registration and it is highly depend on the prior segmentation.

Renske de Boer [3] proposed the k-nearest neighbor for initial tissue segmentation. Gray matter is reclassified to lesion or non-lesion using the FLAIR channel, an automatic lesion segmentation method that uses only three-dimensional fluid-attenuation inversion recovery (FLAIR) images. It uses a modified context-sensitive Gaussian mixture model to determine voxel class probabilities, followed by correction of FLAIR artifacts. It evaluates the method against the manual segmentation performed by an experienced neuroradiologist and compares the results with other unimodal segmentation approaches.

F.Kruggel [4] proposed texture based segmentation for lesion .It utilizes high dimensional texture features. The co-occurrence features with PCA and the distance to cluster centers is used to make a probability map of injury.

M.L.Seghier [5] proposed tissue classification with an iteratively learned abnormal class. Tissue segmentation with an extra class is followed by outlier detection in the gray/white matter classes. In this smoothing causes problems with small lesions.

Carolina [6] proposed various context based object categorization model which contains semantic, spatial and scale context. In this work it addresses the problem of incorporating different types of contextual information for robust object categorization in computer vision and also examines common machine learning models.

Yu Sun [7] proposed symmetry integrated injury detection for brain MRI and asymmetric detection by kurtosis and skewness of symmetry affinity matrix. In this paper it can be detect injuries from variety of brain images since it make use of symmetry as dominant features and does not rely on prior models and training phases.

O.Marques [8] proposed the roadmap to enhance current image analysis technologies by incorporating information from outside the target object, including scene analysis as well as metadata. This review is intended to introduce researchers in computer vision and image analysis incorporate with context modeling.

M. Kafai [9] proposed a stochastic multi-class vehicle classification system which classifies a vehicle (given its direct rear-side view) into one of four classes Sedan, Pickup truck, SUV/Minivan, and unknown. A feature set of tail light and vehicle dimensions is extracted which feeds a feature selection algorithm to define a low-dimensional feature vector. The feature vector is then processed by a Hybrid Dynamic Bayesian Network (HDBN) to classify each vehicle.

J. C. Platt [10] proposed Platt's probabilistic outputs for Support Vector Machines has been popular for applications that require posterior class probabilities. In this note, it gives an improved algorithm that theoretically converges and avoids numerical difficulties.

R.Perko [11] proposed a framework for visual context-aware object detection. Methods for extracting visual contextual information from still images are proposed, which are then used to calculate a prior for object detection. An in-depth analysis is given discussing the contributions of the individual contextual cues and the limitations of visual context for object detection.

K. A. Tong [12] proposed CT remains the first-line imaging procedure in the acute evaluation of head injury; magnetic resonance (MR) imaging is becoming increasingly important for more detailed analysis of the degree and type of traumatic brain injury (TBI), as well as for predicting clinical outcome. This addresses the MR techniques of diffusion-weighted imaging (DWI), MR spectroscopy (MRS), and Susceptibility-weighted imaging (SWI), which provides valuable information that could significantly change the management of TBI.

L.F.Costa [13] gives an integrated and conceptual introduction to this dynamic field and its myriad applications. Beginning with the basic mathematical concepts, it deals with shape analysis, from image capture to pattern classification, and presents many of the most advanced and powerful techniques used in practice.

I. Kharatishvili [14] compared MRI markers measured at acute post-injury phase to indicators of injury severity in the ability to predict the extent of histologically determined post-traumatic tissue damage. It used lateral fluid-percussion injury model in rat that is a clinically relevant model of closed head injury in humans, and results in PTE in severe cases.

A. Obenaus [15] evaluated temporal and regional changes after mild fluid percussion (FPI) and controlled cortical impact (CCI) injury using T2-weighted-imaging (T2WI) and diffusion-weighted imaging (DWI) MRI over 7 days. Region of interest analysis of brain areas distant to the injury site (such as the hippocampalpus, retrosplenial and piriform cortices, and the thalamus) was undertaken.

Seung-Hyun Lee [16] proposed a modular Bayesian network system to extract context information by cooperative inference of multiple modules, which guarantees reliable inference compared to a monolithic Bayesian network without losing its strength like the easy management of knowledge and scalability.

T.Morris [17] gives the causes of traumatic brain injury and effects such as short term and long term symptoms and detailed information of traumatic brain injury .This paper also surveyed the people affected by traumatic brain injury in all over the world.

N. C. Colgan [18] proposed in vivo sequelae of traumatic brain injury (TBI) following lower and higher levels of impact to the frontal lobe using quantitative MRI analysis and a mechanical model of penetrating impact injury levels, with greater significance for higher impacts.

R.C.Cantu [19] gives the information about second impact syndrome, it also gives the causes and its effects on the brain which are in extreme cases may cause death.

S. K. Divvala [20] proposed an empirical evaluation of the role of context in a contemporary, challenging object detection task .In this work, it presents our analysis on a standard dataset, using top- performing local appearance detectors as baseline. It evaluates several different sources of context and ways to utilize it.

CONCLUSION

This paper gives the various methods for the detection of brain injury from MR brain images. The early detection is very important for saving the previous life. So, to get the correct and efficient detection of TBI and to reduce load on the human observer which is also time consuming, these automated soft techniques are highly desirable.

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