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A Review On Skull Stripping Techniques Of Brain MRI Images

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Abstract. Skull stripping is the segmentation of the brain tissues from other tissues, such as the skin, fat, muscles, neck, eyeballs etc. The existence of non brain tissues considered as kull stripping in MRI is a critical step in pre-processing of brain images. For the investigation and treatment of brain injury and disease, segmentation of the newborn MRI brain is significant. Therefore, MRI brain frames require mathematical morphology analyses called skull stripping to isolate the brain from extracranial or non-brain structures. This article summarises the methods available for skull stripping and the recent literature on existing skull stripping procedures. There are still highly challenging fields through the research and analysis of brain images in areas generated with a new, robust and automated technique for stripping MRI skulls.

Keywords: Skull stripping, Segmentation, Brain, MRI, Clinical Image, Machine Learning, Deep Learning.

I. Introduction

The whole-brain segmentation is an effective technique for analysing neuroimaging data, called skull stripping [1]. In the context of the spatiotemporal maps for brain activity, the approaches also provide precise head modelling that may be utilised to merge MRI information with EEG and MEG sensor information [2].

Skull stripping entails the removal of non-brain tissue, which is a key step in neuroimaging investigation. Most skull strips treat the brain as a continuous area isolated from non-brain material with cerebrospinal fluid [3]. Today, even with high-quality T1 weighted MR images, there is little relationship between the brain and other cranial structures in the form of a duct and the tissue line connection of the venous sinuses. Brain imaging is an important element in removing non- cerebral tissues such as the skull, scalp, vein or meninges [4].

In numerous medical applications, brain imagery has been commonly used to detect brain illnesses such as brain tu- mours, stroke, paralysis, and breathing problems. The major steps for brain imaging were over decades of skull stripping, pre-processing, and subsequent analysis of MRI images [1], [4]–[7]. Earlier clinical applications involving MRI brain image with skull stripping included brain mapping, brain cancer analysis, categorisation of tissues, epilepsy analysis and segmentation of brain tumours. MRI brain scans are employed in this investigation since the soft tissue is easily modified with clearer images of brain disorders [8].

Skull stripping means the segmentation of the brain from tissues other than the brain, such as the skin, fat, muscles, neck, eyeballs etc. In neuro-image analysis, it is an important pre-processing step [9]. Before using further image processing procedures such as registration, tissue grading, or compression, the brain regions are removed from the skulls. There are many algorithms in the literature for automated and semi-automatic skull stripping. All approaches are most prominent: brain surface extraction tool (BET), brain surface removal, Watershed algorithms (WAT), HWA and skull stripping graphical cuts [7], [10]–[13].

Brain extraction is generally dubbed skull stripping from a volumetric dataset, magnetic resonance imaging (MRI) of T1 (T1W). It is important pre-processing and is typically the first step in most brain MRI studies, for example, the recon- struction of the cortical surface (CSR), volumetric brain (MR) identification of the tissue, analysis of multiple sclerosis, assessment of schizophrenia, Alzheimer's disease [1], [6], [14], [15]. Brain MRIs are superior, non-imaging soft tissue contrast, like computed tomography (CT) and X-rays. Brain MRIs are superior. Due to the dark brain borders, low con- trast MRIs, and lack of intensity normalisation. Furthermore, utilising MRI datasets with clinical disorders will make whole-brain extraction more difficult [15].

In addition, manual brain delineation from MRI is also known to affect both intra- and inter-rater variables, even among trained people [1]. Manual brain segmentation is typically considered the "ground truth" or "gold standard" for skull stripping in brain MRIs and is commonly used to evaluate alternative semi-automatic and automated procedures. But physical skull stripping is a long time-consuming task, but it is done [10]. It also requires an intimate understanding of anatomy in the brain and works to a considerable extent. It is therefore not sufficient or efficient. Several ways are of- fered to tackle skull stripping in brain MRIs in the last two decades to address these challenges and constantly evolved. However, due to the huge variety of MRI data sets and standards, each technique restricts. The most commonly utilised imagery technique in the medical industry is MRI (Magnetic Resonance Imaging) [11]. It is non-invasive and requires no ionising radiation, such as x-rays. The MRI of head scans exposes the intricacies and anatomical characteristics of the human brain [11]. Hence, the study intends to examine skull stripping in brain MRIs and various methods used in the ex- traction.

II. Related Work

For the investigation and treatment of brain injury and disease because of prematureness, segmentation of the newborn MRI brain is significant. Immediately following the birth of a child, neurodevelopment includes crucial maturation pro- cesses that are objectively assessed through brain imaging. The volume of brain tissue has changed as a result of age. Tissue categories other than WM, GM, and CSF are discovered in newborn brain segmentation to characterise the devel- opment of the brain. Accurate skull stripping is of greater importance in this case [16].

The majority of algorithms for the art of skull stripping for adult MR images were established. The newborn images don't allow a highly precise segmentation of adult brain sizes with these procedures. Adult MRI brains have a distinct brain and skull boundary. However, the skull and brain are not easily separate in neonatal brain MRIs. In adult MRIs, distinct tissues, which give more information for proper skull removal, are identified rather clearly than newborn volumes [5].

Neonatal brain extraction is distinct compared to adult brain volumes. The poor image quality characterises newborn data because of its fundamentally decreased spatial resolution, low contrast between fabrics and confused tissue intensity dis- tribution [17]. The brain surface extractor and the brain extraction device are two especially popular skull removals (BET). BSE can be discerned between the brain and non-brain tissues by combining anisotropic diffusion filters and Marr-Hildreth rim sensors. The BET begins with a spherical mesh around the brain centre of gravity with a shifting pat- tern. The first volume of the inner and outer force is moved to the brain border. BET changes parameters quickly and is generally responsive. However, it can lead to misleading brain areas [7].

Other skull strip reduction approaches to disrupt the relationship between brains and non-brains after morphological op- erations with intensity thresholds and morphs [13]. The approach removes closely linked distances and an algorithm (DWAT). The brain utilised the active contours when the curve was integrated into a higher dimension function, mini- mising bias sensitivity. The hierarchy of masks from several models is used by Rehman et al. [18] to generate a consen- sus mask for the brain segmentation. The discriminatory model is the random classification of forests that is taught in brain border monitoring. The generative model is a point model that ensures an appropriate outcome. For final segmenta- tion, the contour is changed graphically. It provides a segmentation mechanism for the developing tumour of the brain. The graph cuts combine probability increases with lesser segmentation in trees [12].

Digital image processing has increased medical diagnostic coverage and quantitative analysis. Medical imaging has be- come more common in computer-based medical imaging technology over recent decades due to the development of the digital age. The rapid development of computerised medical images and a computer-aided diagnostic allowed several techniques to image to find uses in medical image treatment [6]. MRI is the most widely used medical imaging technolo- gy. It's a flexible, non-invasive imaging tool with no ionising radiation like rays. It gives information on the architecture of soft tissue, not externally evident. MRI is spatially robust and provides anatomical structure extra information for quantitative pathological or clinical trials [19].

For brain research, MRI is extremely useful. It can envision both internal and external structures of anatomical character- istics utilised to detect even minute changes that happen over time in these structures. MRI scans can reveal cross-sector ages from top to bottom, side or back in any direction. Thus, the 3D brain images of MR are more prevalent in medical applications and are utilised for diagnosis, therapy, surgery and imagery research [20].

MR brain scans have several advantages over conventional methods of imaging. MR pictures of the brain and other cra- nial features are crisper than other imaging methods. Early diagnosis and the assessment of much brain-related mortality is important to MRI. MRI can portray the brain in any plane without the physical movements of a patient. CT scans on one plane, the axial, are limited [21].

The study employs computerised methods to analyse brain data from different brain photographs such as volumetric analysis, anatomical structure study, traceable pathology, diagnosis, treatment and computer planning. In 3D volumetric data, the MRI equipment delivers the brain image [21].

Before brain pictures are assessed, several image processing procedures are necessary. The processing of images encom- passes a variety of applications, including segments that are vital for medical photos. In the segmentation of medical pic- tures, various approaches are described. These techniques are generally split into grids, texture-based, model-based seg- mentation and atlas-based segmentation [22].

Brain MRI pictures are often quantitatively processed to remove the brain from skull removal. Because brain regions are better segmented, pre-treated brain images with automatic scratching help to identify several diseases in the brain pre- cisely [2], [16], [18], [23].

In addition, the first procedure important of the removal in brain image images of MR images in a broad range of clinical applications is skull stripping, accuracy and speed of non-brain tissue. The accurate methods for removing skulls help boost the speed and accuracy of the predictive and diagnostic procedures in medical applications. The skull stripping lit- erature includes various automated algorithms. Each skull stripping procedure has advantages and limitations [15].

Swiebocki-Wiek [24] explain MR brain photographs' stripping through anisotropic diffusion and morphological process. Automatic scaling using image con-tour and a brain segmenting approach is developed from MRI human head scans which use morphological operation and associated component analysis to identify the brain in brain T1-weighted MR pictures.

Thresholding with morphology-based mathematical methods uses histogram analysis and edge detection thresholds to segregate both the brain and non-brain regions, together with a range of morphological operations — erotic dilations, opening, closure etc. It distinguishes the brain skull by utilising histogram thresholds and mathematical morphology fil- ters. Shankar and Karuppanagrounder [23] have devised a multi-stage strategy using anisotropic filters, histograms thresholds, morphology filters and brain snakes. A similar histogram (HBRS) approach is based on histograms and mor- phological procedures. An automated stimulation method called the SMHASS based on the deformable and So- masundaram and Kalavanthi [14] suggested the histogram analyses. At first, a basic segmentation of thresholds and mor- phological processes was the best beginning point for deformation. The local grey image-level controls distortion of the simple mesh, and the grey segmentation information is collected [21].

The brain removal algorithm for T1W and T2W (BCA) was created by Roslan et al. [25] through diffusion, morpholo- gies, and the examination of connectivity (CCA). BCM (Fuzzy c-means and morphological operations) were proposed for the two-dimensional (2-D) brain extraction by Li et al.

[11]. A well-known publicly available skull stripping instru- ment, the Brain Surface Extractor (BSE) is created by Wang et al. [15]. It uses a mixture of anisotropic diffusion filtering and a detector of the Marr-Hildreth edge of the brain and non-brain region and several morphology procedures. BSE is exceedingly quick and causes highly explicit segmentation of the full brain. The fundamental defect of this technique is that parameter adjustment is frequently used to operate on a specific brain MRI dataset. The grayscale processing and morphological processes were the basis for the approach.

Grey level thresholds are applied using the method proposed by Bauer et al. [26], which eliminates remote connections to build a fine brain mask. Other methods are similar. A graphics-cut technique was employed instead of morphological fil- ters to smooth the brain contour. Priya and Chacko [19] proposed HEAD as the automatic technique for scaling, incorpo- rating an efficient histogram analysis process and binary morphology procedures to segment the brain accurately. Bhadauria et al. [27] have suggested the intelligent and resilient mathematical approach. It is mainly adverse since mor- phologic work depends on fixed parameters, such as structured parts' shapes and sizes (for erosion, dilation, opening, etc.) [22]. The human person (user) usually selects the threshold value from several starting thresholds for initial segmen- tation. Another concern is that a general method for various brain MRI data sets is very difficult to design. Several brain MRI resolutions and sequences have been found difficult to deal with automatically [5]. The main groupings are mathe- matical morphological methods, intensity, deformable surface methods, atlas, hybrid approaches.

III. Skull Stripping Technique

The traditional skull stripping methods can be categorized into morphology based, intensity based, deformable based, template based and hybrid methods.

a. Techniques based on morphology

Morphological erosion and dilation are used to separate the skull and brain. As a final step, these methods perform over- lap tests on candidates' brain regions of interest in adjacent slice images. Existing methods that use mathematical model- ling make it difficult to determine the optimal morphology size for separating brain tissues from non-brain tissues [4,17].

b. Intensity-based methods

Using intensity-based methods, brain and non-brain regions are separated. Histogram-based methods, edge-based meth- ods, and region-growing methods are all intensity-based methods. These methods use a model of the intensity distribu- tion function to classify brain and non-brain tissues in brain images (IDF). Low resolution, noise, low contrast, and other imaging artefacts [27] are to blame for the low quality of the image.

Bauer et al. [26] proposed WAT, a T1-weighted intensity-based algorithm. An intensity-inverted image is flooded with a 3D algorithm. This causes the image to be over-segmented and highly sensitive to noise. The dura, skull, and other non- brain structures may not be removed [26].

c. Deformable surface method

Deformation models are used to develop skull stripping methods that deform an active contour to fit the brain surface, identified using selected image characteristics during the procedure. The energy-driven dynamic curve moves towards the object's boundaries [11]. Shrinkage and expansion are described by the term "curve evolution." They depend on two factors: the curve's initial location and its gradient. In addition to detecting both the interior and exterior boundaries of an object simultaneously, these methods are sensitive to noise and must be used with extreme caution. The level set theory is used to implement the active contour model. A skull stripping method based on edge detection and threshold classifi- cation techniques, on the other hand, tends to produce less robust and accurate results [24].

d. Atlas- or template-driven methods

In the atlas/template method, a brain MRI image is fitted with an atlas/template to separate the brain from the skull. There is no clear relationship between regions and pixel intensities in brain images. The number of templates used to dis- tinguish brain regions and atlases is among the variables among these methods [28].

Rehman et al. [18] described skull stripping to prepare for the cortical surface reconstruction process. Using a tessellated ellipsoidal template, an intensity-normalised image is deformed into the skull's inner surface shape. The template is de- formed using an MRI-based forc9e and a curvature-reducing force. Due to this second force, a priori knowledge of the smoothness of the inner surface of the skull is encoded [21]

e. Hybrid Methods

Results from multiple skull stripping approaches are combined to account for their limitations. Using more than one method makes it possible to produce a more accurate result by combining approaches that fall into the categories above. Brain tissue was segmented from magnetic resonance images by Bhadauria et al. [27], who combined three existing computer vision techniques.

Table 1: Comparison of different techniques used in skull stripping

S/N	re f	Techniqu es	Input MR brain image type	Limitati on
1.	[3]	Thresholding and morphological operationsbased on histograms.	Coronal and sag-ittal T1-weightedbrain images.	It is difficult to find the optimal morphology size for separating brain tissues from non-brain tis-

				sues because it is sensitive to small data variations.
2.	[1]	Morphological operations are performed onhistograms.	Images with aT1 weighting	When the image contains a varie-ty of image artefacts, a good skull stripping result is not ob-tained.
3.	[9]	2D Marr-Hildreth operator for anisotropicdiffusion filtering and edge detection.	Images with T1-and T2 - weighting	Due to the presence of dura mat- ter, Marr–Hildreth edge detectorsmay not distinguish clearly be-tween the brain and dura matter in some cases.
4.	[5]	Morphological processing, anisotropic diffu-sion filtering.	Images with aT1 weighting	This occurs when the image hasa high level of noise.
5.	[7]	Algorithms using anatomical information orconnectivity to determine thresholds.	Images with a sagittal orienta-tion in 3D	Images are scanned, and arte- facts, such as noise and inhomo- geneity of intensity, are analyzed to determine the best method.
6.	[19]	Combination of a global similarity transfor-mation and local deformations of free form.	Images with aT1 weighting	Pathological brain images such as tumours are not compatible with this method because it re-quires gross anatomical structure whereas tumours can drastically alter the brain's morphology.
7.	[11]	Transformation of 2D contour geometries us-ing dynamic	Image with a T1weighting	Pathological images were notimproved.
8.	[8]	The GM and WM compartments are summedafter tissue segmentation using classification.	Images with aT1 weighting	On abnormal images, the seg-mentation failed to be accurate.
9.	[15]	Operations such as morphological threshold-ing in the foreground and background	Images with aT1 weighting	Due to morphological operations,the brain may be over-or under-segmented.

10.	[20]	There are also level sets and dense three-dimensional registration.	Three-dimensional T1-weighted images	It uses a complex level set andregistration process, which re-quires more computation time.

IV. Challenges and Issues in Skull Stripping

Drains the skull, since brain images are intrinsically insufficient, is an advanced and challenging task. Automatic meth- ods for removing skulls should give robust, effective, confident and accurate results of vast volumes of data sets [28]. Noise and various imaging artefacts in MRI might result in unforeseen distortions of the brain's pictures that can consid- erably impair its quality. Automatic removal of skulls is a frequent and complicated theme in literature. Some of the dif- ficulties with skull removal techniques are:

- Brain images on different machines are produced with varied image settings, and they create images with differ-ent contrasts and scanning quality for a given tissue type.
- The signal strength of different brain areas is often overshadowed; certain non-brain tissues, such as the neck and scalp, are equivalent to brain tissue intensity.
- Echos within the air/tissue barrier can be seen in the brain's picture.
- A partial volume effect blurs the distinction of intensity between the tissue classes on both the tissues' bounda- ries, causing the brain image to be noisy or ring around with the motion artefacts (blood vessels, muscles etc.). Brain structures are not uniform and are different from people.
- The limits of intensity are not completely anatomical, and many of the boundaries do not sharpen the image of the brain.
- The presence of imagery and other sounds owing to sensors and related electrical systems can compromise brainimage quality and make skull removal challenging.

V. Conclusion

The skull stripping is a preparatory step for eliminating innate non-brain tissue from MR brain pictures, which is crucial for clinical and neuroimaging research. Several techniques are suggested; manual or half-automatic procedures are la- bour-intensive, time-consuming, operating reliant and unwanted in large-scale investigations. Robotic skull removal technologies enable predictive and diagnostic procedures to segment and analyse the brain picture quickly and accurate- ly. But the bulk of the scraping methods have been employed primarily in pictures of T1 weighted brain. Many of the available ways are not applied in other types of brain pictures and recommendations. Because the appearance of brain pictures can significantly alter between scans, an effective skull removal approach that works in sequences and scanners is also problematic. The present skull clearing methods are adapted to certain sorts of inquiry or work on the best possi- ble situation for a particular population. The manual intervention and exclusion of people from neuroimaging research would be considerably decreased by a reliable and resilient approach for various brain morphologies and acquisition se- quences without necessitating parameter adjustments. There are still highly challenging fields through the research and analysis of brain images in areas generated with a new, robust and automated technique for stripping MRI skulls.

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