HMRF MODEL FOR BRAIN TUMOUR SEGMENTATION TO ESTIMATE THE VOLUME OF MRI AND CT SCAN IMAGES

by

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LIST OF ABBREVIATIONS

1D	One-dimensional
2D	Two-dimensional
3D	Three-dimensional
CSF	Cerebral Spinal Fluid
CT	Computerized Tomography
DICE	Dice coefficient
EM	Expectation-Maximization
FN	False Negative
FNR	False Negative Rate
FP	False Positive
FPR	False Positive Rate
GM	Grey Matter
HMM	Hidden Markov Model
HMRF	Hidden Markov Random Field
JAC	Jaccard index
MAP	Maximizing A posteriori probability
ML	Maximum Likelihood
MRI	Magnetic Resonance Image
MRF	Marko Random Field
PET	Positron Emission Tomographic
RF	Radio Frequency
SPECT	Single-Photon Emission Computerized Tomography
TCIA	The Cancer Imaging Archive

TN	True Negative
TNR	True Negative Rate
TPR	True Positive Rate
WM	White Matter

LIST OF SYMBOLS

$V_{c(x)}$	Clique potential
E_{con}	External constraints
E_{image}	Image forces
$\theta^{(0)}$	Initial parameter set
E_{int}	Internal energy
ρ_{iso}	Isosurface
μ	Mean
Z	Normalisation constant factor
$U_{(x)}$	Prior energy function
$P_{(i,j)}$	Probability matrix of the input image
c	Set of all possible cliques
σ	Standard deviation of the Gaussian function
T	Threshold value
σ^2	Variance
V	Volume of the tumour
V_s	Volume of the tumour for one slice

MODEL HMRF UNTUK SEGMENTASI KETUMBUHAN OTAK BAGI PENGIRAAN ISIPADU DARIPADA IMEJ MRI DAN PENGIMBAS CT

ABSTRAK

Pencitraan resonans magnetik (MRI) dan tomografi terkomputer (CT) adalah dua teknologi pengimejan yang paling penting yang membolehkan para doktor memperoleh segmen dan pengiraan tumor otak yang boleh dipercayai. Kajian semasa ini bertujuan untuk membangunkan kaedah diagnostik untuk imej perubatan (MRI dan CT) untuk mencapai segmen dan pengiraan tumor otak yang tepat dan tepat. Kaedah yang dicadangkan dalam kajian ini telah diterapkan pada dataset yang telah dikumpulkan dari Arkib Pengimejan Kanser (TCIA) dan hospital Iraq. Kaedah yang dicadangkan ini berdasarkan kaedah menyesuaikan dan membangunkan model medan Markov random field (HMRF) dan kaedah ambang untuk menjalankan segmentasi tumor otak. Dalam kajian ini, kaedah jejak automatik telah dibangunkan berdasarkan nilai dimensi voksel untuk melaksanakan anggaran tumor otak. Selain itu, kajian ini menawarkan kaedah untuk mempersembahkan ketumbuhan otak dalam bentuk visualisasi 3D dengan menggunakan teknik penyarian isopermukaan. Kajian ini juga telah membangunkan algoritma baru untuk mengenal pasti lokasi ketumbuhan otak menggunakan maklumat statistik. Di samping itu, kajian ini turut mengembangkan bilangan potongan imbasan CT dengan menggunakan min antara dua potongan yang berturutan berdasarkan kaedah yang dicadangkan. Pengesahan dan penilaian bagi kesemua peringkat kajian dijalankan dengan menggunakan kaedah kualitatif dan kuantitatif. Keadaan asas ketumbuhan otak, yang dilakar secara manual oleh ahli radiologi, digunakan untuk menilai keputusan peruasan. Ia mencatatkan keputusan yang memuaskan menggunakan ukuran yang berbeza,

dengan nilai min adalah tinggi bagi Dice = 0.9393, JAC = 0.8908, TPR = 0.9142, TNR = 0.9669, FPR = 0.0313, dan FNR = 0.0834. Anggaran bagi isipadu ketumbuhan otak disahkan secara kualitatif dengan menggunakan piawaian emas yang diperoleh menggunakan kaedah sesaran air (kaedah Archimedes). Selain itu, kaedah manual dengan menggunakan perisian Mango juga dijalankan bagi tujuan perbandingan. Berdasarkan keputusan-keputusan yang diperoleh, kaedah yang dicadangkan menghasilkan kurang hinggar berbanding menggunakan perisian Mango ketika proses mengukur isipadu ketumbuhan. Dengan membandingkan keputusan-keputusan daripada kaedah yang dicadangkan dengan kaedah yang mempunyai piawaian emas, ianya terbukti bahawa kaedah yang dicadangkan menghasilkan visualisasi 3D ketumbuhan otak yang lebih tepat berbanding objek sebenar. Pengesahan imej imbasan CT yang dikembangkan menggunakan dua pendekatan bergantung kepada sampel yang sama (potongan-potongan yang telah disahkan), dan juga pemakaian kaedah statistik menggunakan ciri tekstur. Bagi menguatkan kajian ini dan menjadikannya sedia untuk aplikasi klinikal oleh pengguna akhir, soal selidik telah dijalankan untuk mengesahkan perspektif mereka ke atas sistem yang dicadangkan. Secara umum, berdasarkan hasil yang diperolehi dari keseluruhan proses kaedah yang dicadangkan mencapai segmentasi tumor otak untuk menganggarkan jumlah imej MRI dan CT scan.

HMRF MODEL FOR BRAIN TUMOUR SEGMENTATION TO ESTIMATE THE VOLUME OF MRI AND CT SCAN IMAGES

ABSTRACT

Magnetic resonance imaging (MRI) and computed tomography (CT) are two of the most important imaging technologies that enable the doctors to gain a reliable segmentation and estimation of brain tumours. The current study aims to develop a diagnostic method for medical images (MRI and CT) to achieve an accurate and precise segmentation and estimation of brain tumours. The proposed method in the study was applied on datasets had been collected from the Cancer Imaging Archive (TCIA) and Iraqi hospitals. The proposed method based on adapting and developing hidden Markov random field (HMRF) model and threshold method to carry out the segmentation of the brain tumours. In this study, an automatic trace method had been developed based on the voxel dimension value to execute the estimation of brain tumour volume. Furthermore, the study provided a method for rendering the brain tumour in 3D visualisation by using isosurface extraction techniques. In this study, a new algorithm has been developed to detect the location of the brain tumour using statistical information. In addition, the present study expands the number of CT scan slices using the mean between two successive slices based on the proposed method. The validation and the evaluation of all the work stages were performed using qualitative and quantitative methods. The ground truth of a brain tumour, which was traced manually by radiologists, is used for the evaluation of the segmentation results. It recorded satisfactory results using different measures where their means are high with Dice = 0.9393, JAC = 0.8908, TPR = 0.9142, TNR = 0.9669, FPR = 0.0313, and FNR = 0.0834. The estimation of the brain tumour volume was validated qualitatively using a real volume, which was obtained using the water displacement

method (Archimedes' method). A comparison was performed using a manual method with Mango software. According to the results, the proposed method produced volume estimation more specific than the Mango software when performing tumour volume measurements. The comparison between the results of the proposed method and those of the real volume revealed that the former produced a more accurate 3D visualisation of the brain tumour compared to real objects. The validation of the expanded CT scan images using two approaches relies on the same sample (validated slices), as well as the utilisation of the statistical method using the texture feature. To strengthen the work, a survey of the work was undertaken to verify the end users perspectives on the proposed method. In general, based on the obtained results of the whole process the proposed method achieved the brain tumour segmentation to estimate the volume of MRI and CT scan images.

CHAPTER 1

INTRODUCTION

1.1 Introduction

In Iraq, the number of cancer patients has increased significantly after the Gulf War events, where 10,000 to 11,000 new cases were recorded each year. The NATO and USA force widespread usage of uranium weapons during the Gulf war in 1991. After the wars in Iraq, uranium has remained as one of the environmentally contaminated radioactivity sources in the uranium weapons exposed areas [1]. Particular, southern Iraq regions recorded an increase between twofold and fivefold in reported cancer cases as well as a recording of an unusual number of congenital disabilities. This increasing rate has raised an international interest, but only a few relevant studies have been published on the cases in these regions [2, 3].

A brain tumour is a mass of abnormal cells in the brain. A tumour may remain in one location, or it may spread out into adjacent tissues [4]. A brain tumour is one of the globally leading reasons for tumour-related deaths, where 10 to 15 of every 100,000 persons diagnosed in USA and Europe alone per year [5]. The brain tumour is considered the second leading reason for cancer-based deaths among children in ages between 1 and 19 years. Moreover, it is the second major reason for cancer-based deaths among young persons up to age 39 years in men and the fifth reason in women between 20 and 39 years [5-8]. In medicine, due to the brain structure, which differs from other organs of the human body, the doctors need an accurate imaging technology to examine the internal portions of the brain for a clear diagnosis and treatment of a brain tumour. Volume measurements of brain tumours have been performed in clinics and hospitals using manual segmentation, which is time-consuming, labour intensive, and subject to significant variations in inter-operator performance. The main purpose of the current study is to develop a new diagnostic method for medical images.

There are several types of imaging techniques utilised in the diagnosis and therapy of brain tumours such as computed tomography (CT), magnetic resonance imaging (MRI), single-photon emission computed tomography (SPECT), and positron emission tomography (PET), among which the first two types are used in this study. In this chapter, CT and MRI will be discussed and compared. The widely used medical imaging modalities, CT scan, and MRI have been typically applied according to the valuable information they provide for various medical and clinical diagnosis [8-10].

In this study, the collected datasets are categorised into two groups based on the source. The first dataset 26 cases is obtained from The Cancer Imaging Archive (TCIA) [11] and the second dataset 26 cases from Iraqi hospitals. The total number of dataset is 52 cases, 26 of them are CT cases and 26 of them MRI cases; the cases contain regular volume data, which are of different thickness and different measurements.

Volume measurement of brain tumours using manual segmentation has been performed in clinical practice. However, it is time-consuming, labour intensive, and subject to considerable variation in intra- and inter-operator performance [12, 13]. Medical image segmentation is normally the first step in the majority of analysis procedures. It is also a critical step that influences the final result of the entire application as the rest of the analysis completely depends on the obtained data from this step. The segmentation of two-dimensional (2D) slices, which are obtained from

CT or MRI, leads to some applications such as three-dimensional (3D) reconstruction, tumour volume estimation, and visualisation for diagnostic purposes for planning of treatment, surgery, etc. [14-16].

1.2 Brain tumour

The brain has a very complex structure, the portion of the vertebrate central nervous system enclosed in the skull. The brain is the best protected organ in the body. It has multiple layers of protection starting with the first layer of protection being the watery fluid (cerebrospinal fluid) which flows within spaces between the meninges and into spaces (ventricles) within the brain. The second is the layers of tissues (meninges), and the third is the skull bones. A brain tumour is an evolution of abnormal cells in the brain that may constitute and remain in one location or may spread out into adjacent tissues. The brain tumour exists in types as malignant (cancerous) or benign (non-cancerous) malignant tumours have a faster growth rate than benign tumours [17]. Brain tumour is characterised by a large variety of tumour types, and a distinction is made between primary tumours arising directly from brain tissue and secondary tumours, which are brain metastases from other malignant diseases [8, 18].

Brain oedema, defined as an increase in brain water content occurs around aggressive brain tumours and contributes to morbidity and death. Oedema forms as a result of a leaky blood tumour barrier and persists when the brain fails to clear the excess fluid [19, 20].

1.2.1 Glioma

Glioma a brain tumour that begins in a glial, or supportive, cell, in the brain or spinal cord. Malignant gliomas are the most common primary tumours of the central nervous system and 80 percent of all malignant brain tumours. They are often resistant to treatment and carry a poor prognosis. These tumour tend to grow and infiltrate into the healthy brain tissue, which makes surgical removal very difficult and complicates treatment [18, 21].

1.3 Medical imaging techniques

The introduction of advanced imaging techniques has improved the quality of medical care available to patients significantly. Medical imaging is the technique and process of creating visual descriptions of the interior of a body for clinical analysis and medical intervention, as well as visual representation of the function of some organs or tissues. Medical imaging seeks to reveal internal structures hidden by the skin and bones, to diagnose and treat disease. It also enables them to perform keyhole surgeries for reaching the internal parts without making large openings on the body [22]. There are many imaging modalities that are used by the clinicians for diagnosing and treating the abnormalities in the human body: these are X-ray, CT scan, ultrasonography, MRI, SPECT, PET, mammography, and optical imaging [23].

1.3.1 Computed tomography

CT is the mathematical rebuilding of a cross-sectional image of the body by measuring the intensity of X-rays transmitted as a thin slice through the patient's body tissue. CT is often the first imaging technique utilised in brain tumour evaluation because of its wide availability and low cost. It is further considered as a beneficial screening tool for the detection of abnormal tissues in the brain. The use of ionising radiation is the major disadvantage of both CT scan and X-ray imaging. A radiographer can be exposed to only a limited dose, which is 20 mSv per year with a maximum of 100 mSv in a consecutive five-year period (where the sievert (Sv) is the unit of absorbed radiation dose) [24-26] because ionising radiation can be harmful to body tissues. Differential attenuation of X-rays in the body gives rise to image contrast between tissues. For example, the soft tissues cause less attenuation of X-rays, whereas the attenuation is specifically efficient in bones throughout the course of the X-ray beam crossing. A simple 2D projection of tissues placed between a film and X-ray source is produced in planar X-ray radiography. A tight collimation of X-ray source to interrogate a thin slice through the patient is performed in CT scan images (see Figure 1.1). The important advantages of CT compared to MRI are rapid image acquisition, display of calcifications in soft tissues, and better bone details. A series of one-dimensional (1D) projections are produced at various angles by the rotation of detectors and source together around the patient. A reasonable contrast between soft tissues and 2D image are then obtained by reconstructing the above data. Acquisition of complete 3D images in a single breath-hold of the patient is now possible by recent developments in multi-slice and spiral CT scans [8, 23].

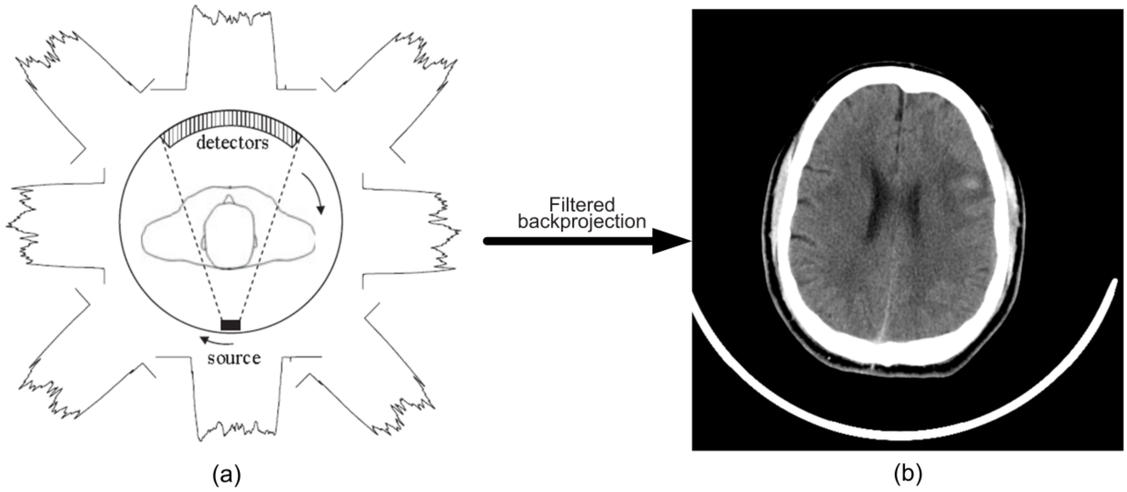


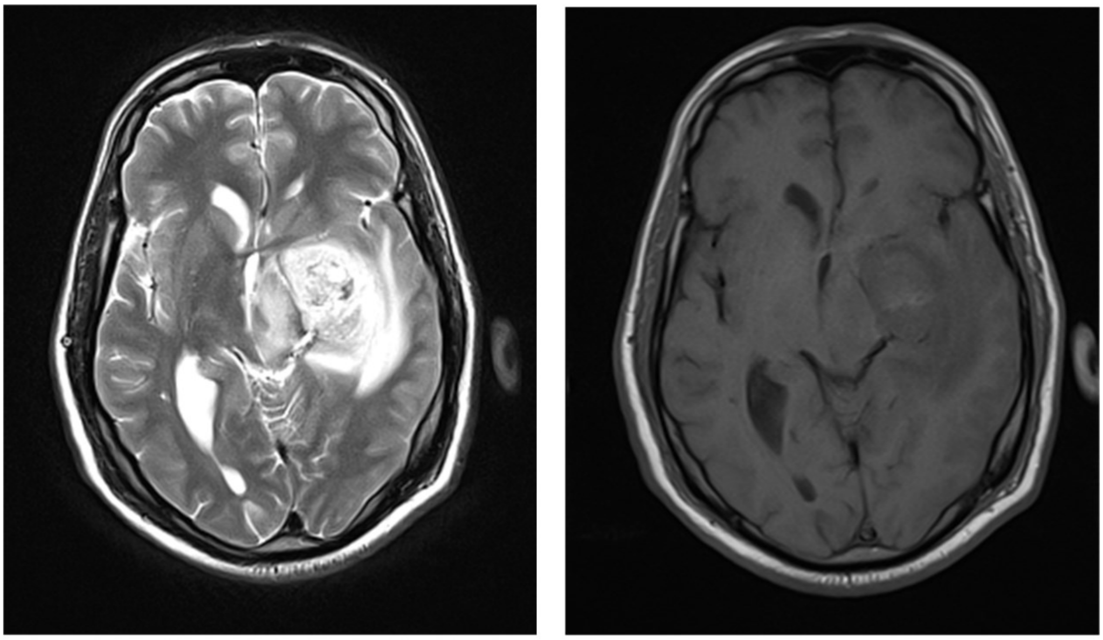
Figure 1.1. (a) Physical principle of computed tomography (CT) involves synchronous rotation of the X-ray tube and multiple detectors to record a series of one-dimensional projections. The CT scan image (b) is produced by the process of filtered back projection [23].

1.3.2 Magnetic Resonance Imaging

MRI is a technique that doctors use to obtain a visual representation of a soft tissue inside the body. MRI scanners use strong magnetic fields, radio waves, and field gradients, which are very necessary to produce images of any part of the body. The human body mostly contains water molecules, each containing two hydrogen nuclei (a single proton). When the patient is inside the strong magnetic field of the scanner, the magnetic moments of protons line up with the direction of the field, and afterwards, the radio wave frequency (RF) are applied for a short time in a different direction. This sudden shift causes certain atoms in the patient’s body to produce individual signals (also a radio wave). The MRI scanner detects those individual signals and then sends the signal information to a computer. The intensity of the received signal is then plotted on a grey scale and cross-sectional images are built up [9, 23].

Multiple transmitted RF pulses are used in sequence to assert particular tissues or oddity. When the transmitted RF pulse is switched off, a different assertion occurs because different tissues relax at different rates. The time of full relaxation for the protons is measured in two ways. The first is called T1 relaxation, which is the time taken for the magnetic vector to return to its resting state. The second is called T2 relaxation, which is the time required for the axial spin to return to its resting state. The images that are created by the difference in relaxation rates in different tissues is called T2- or T1-weighted images [9, 23, 27].

T2-weighted sequences are considered the most sensitive for the detection of tumours and oedema extents [21], whereas T1-weighted sequences following contrast enhancement can improve diagnostic information relating to tumour grade and provide better localisation of the tumour area [21]. Figure 1.2 shows an example of T1-weighted and T2- weighted images of a high-grade glioma.



(a) (b)

Figure 1.2. MRI of brain: (a) T2-weighted image; (b) T1-weighted image

In the current study, CT scan and T2-weighted MRI images will be used due to three reasons: they are the most commonly used, they are readily available from hospitals and medical centres, and finally, there is high possibility of obtaining a database. Table 1.1 shows the most important advantages and disadvantages of using CT and MRI. CT scan and MRI images usually present the best spatial and contrast images resolution and are excellently suited for anatomic visualisation of deep structures of the brain.

Table 1.1. Most important advantages and disadvantages of using MRI and CT

Modality	Advantages	Disadvantages
Computed Tomography	1. Shorter imaging time. 2. Better spatial resolution. 3. Low cost of the scanner. 4. Improving cancer diagnosis and treatment. 5. Good for extra-axial brain tumour assessment. 6. S02patial resolution and a better contrast ratio of the body.	1. Exposure to radiation. 2. Only one plane acquisition and most of the time anisotropic. 3. Imaging of posterior fossa (is a small space in the skull, found near the brainstem and cerebellum) is limited due to bone artefacts.
Magnetic Resonance Imaging	1. The enhanced soft tissue detail it provides in addition to its potential promise in predicting not only the presence but also severity of an adverse local tissue reaction. 2. Better detection of mass and atrophy(decrease in size or wasting away of a body part or tissue). 3. Can image at any angle without the use of potentially ionizing radiation. 4. High neuroanatomical definition (tissue differentiation). 5. Accurate detection of vascularity of tumour (in various planes acquisition).	1. High cost. 2. Long study time. 3. Loud noises and confined space. 4. Not possible in intraoperative assessment. 5. Lower spatial fidelity. 6. The sometimes sequence is very time-consuming. 7. MRI cannot be performed in the presence of certain metallic biomedical devices or foreign bodies.

1.4 Brain tumour segmentation

Image segmentation is dividing an image into different regions depending on a homogeneity criterion for image analysis [22, 28]. Medical image segmentation is the procedure of labelling all voxels in the image to indicate the tissues types and anatomical structures. The aim of segmentation is to facilitate and change the exemplification of an image into a more significant image that can be analysed and interpreted easily [23, 29]. In other words, segmentation aims to present the image in a new region to provide richer information than that which exists in the original medical image. The collection of labels that are produced throughout segmentation is called a ‘label map’, which describes its function as a voxel-by-voxel guide to the original image. Segmentation is commonly utilised to improve visualisation of CT scan and MRI images and enable quantitative measurements of image structures [30].

Brain tumour segmentation is particularly challenging because tumours have widely varying shapes in size and location, and have intensities that overlap with healthy brain tissues. Brain tumour segmentation can be performed either manually by persons (usually, a radiologist or a trained medical professional) or in an automated method. During a manual segmentation method, the radiologists perform the diagnosis depending on their anatomical knowledge as well as on information derived from the medical image. In the automated method, the segmentation is performed automatically, using some methods and algorithms that usually depend on either the image intensity or the grey-scale image gradient. Automated methods are usually semi-automatic since an operator needs to set initial boundaries and conditions or provide feedback between iterations [22, 31].

1.5 Segmentation methods

Segmentation is an important step in medical image analysis for computer-aided diagnosis and classification of radiological evaluation. The image partitioning process using a predefined criterion into characteristic regions by grouping together with neighbourhood pixels is described as image segmentation. The features of pixels that represent the objects in the image can be used to determine the similarity criterion. Alternatively, a technique of pixel classification is a segmentation in which the similarity regions are permitted to be formed in the image. The methods of image segmentation can be broadly categorised into four classes see Figure 1.3 [22, 32-34]:

i. Threshold-based methods: are simple and effective region segmentation methods, in which the objects of the image are classified by comparing their intensities to one or more intensity thresholds.
ii. Pixel-based methods: in these methods, the closed regions that belong to the objects in the image are formed by using estimation or heuristic methods, which are derived from histogram statistics of the image.
iii. Region-based methods: in these methods, the closed regions that belong to the objects in the image are formed by direct analysis of the pixels in a region expansion process using a predefined similarity criterion.
iv. Model-based methods: in these methods, a connected and continuous model is built for a specific anatomic structure by incorporating a prior knowledge of the object such as shape, location, and orientation. Some models include prior statistical information drawn from a population of training datasets.

In the current study, the proposed method focuses on the hidden Markov random field expectation-maximization (HMRF–EM) algorithm and threshold method.

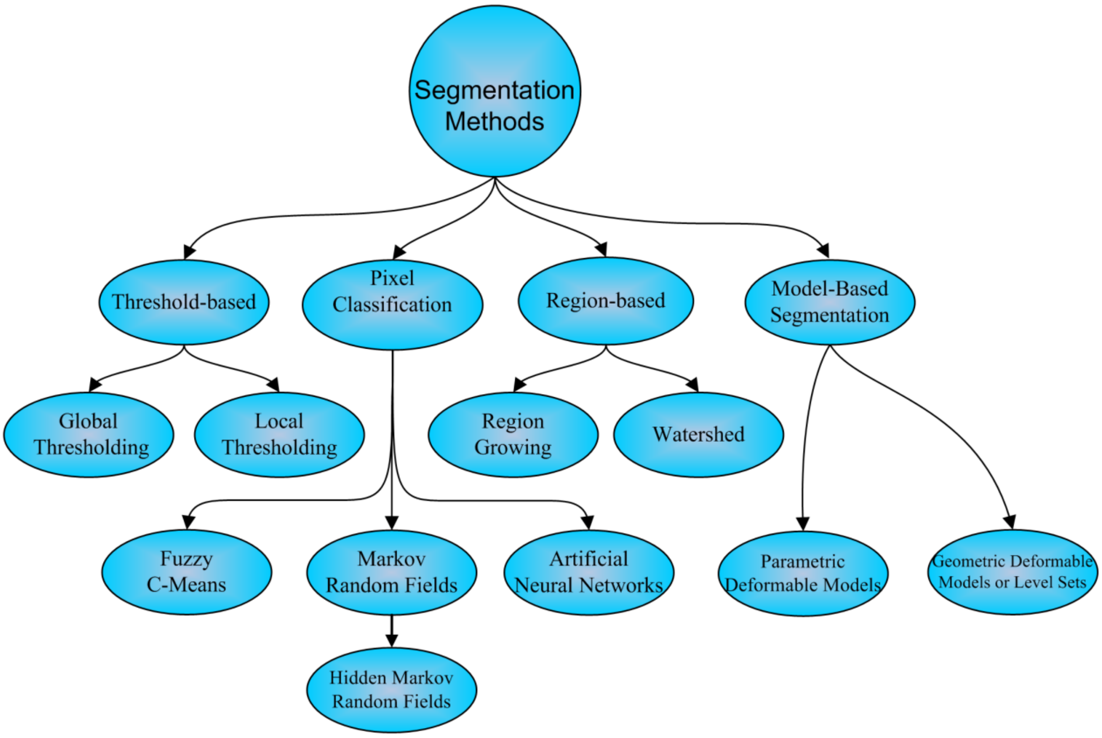


Figure 1.3. Methods of image segmentation

1.5.1 Threshold-based methods

Thresholding is the most straightforward and most commonly used technique to segment an image. It may be utilised directly to an image, and can also be combined with pre- and post-processing techniques [35, 36]. Intensity is a simple property that the pixels can share in a region. Therefore, thresholding is a simple method of segmenting such regions by the separation of dark and light regions. By turning all pixels above the threshold to one and all pixels below the threshold to zero, the binary images are developed by thresholding from grey-level to two values [28, 37].

1.5.2 Hidden Markov random field

The notion of an HMRF model is derived from hidden Markov models (HMMs). HMMs are defined as stochastic processes generated by a Markov chain, whose state sequence cannot be observed directly, but only through a series of observations. Most clustering methods do not study the dependency between the pixels in the image surface or spatial information. The unsupervised clustering method of the Markov random field (MRF) provides a way to integrate spatial information into the clustering process. In several cases, this decreases both the effect of noise on the clustering result and the possible problem of cluster overlapping [38].

An HMRF model is a graphical probability model in which the true states are not observed but are estimated indirectly through an observation field. Each observation is assumed to be a stochastic function of the state sequence [38, 39]. By HMRF, the segmentation algorithm captures three features that are of particular importance for CT scan and MRI images; these features are nonparametric distributions of tissue intensities, neighbourhood correlation, and signal inhomogeneity. The advantage of the HMRF model comes from the way in which the spatial information is encoded through the mutual influences of neighbouring pixels [40-42].

1.6 Applications of segmentation

Segmentation is a primary step prior to the description, recognition, or classification of an image and its constituents [15]. The classic method of medical image analysis that relies on the investigation of 2D grey-scale images on a pixel is not sufficient for many applications. When the desired quantitative information is about the contour, size, or shape of patient anatomy, image segmentation is often the critical first step

[16, 37]. The applications of interest that depend on image segmentation include volumetric measurement, 3D visualisation research into shape representation of anatomy, image-guided surgery, the location of tumours, and detection of anatomical changes over time.

1.6.1 Volumetric measurement (tumour volume estimation)

One of the most important applications of segmentation is volumetric measurement. This involves calculating the volume of areas accurately, either automatically or semi-automatically. Measurement of the volumes of anatomical structures is necessary for medical studies on both normal and abnormal tissues, among which is tumour volume estimation. This method is weighted to segmentation because manual segmentation is not possible to accurately measure anatomical volumes visually [43]. It requires a time-intensive process to obtain accurate measurements of such areas, as the current method employs manual segmentation.

1.6.2 3D visualisation

The segmentation of medical images allows for the visualisation of patient anatomy through the creation of 3D surface models. The benefit of the surface model representation of anatomy is that it provides a 3D view from any angle, which is an improvement over 3D cross-sections through the original grey-scale data. Surface models can be created from segmented data using an algorithm such as HMRF–EM, fuzzy, thresholding, etc. [43].

1.6.3 Location of tumours

Determining the location of brain tumours accurately is very important in the diagnostic process. The segmentation of an MRI or CT scan image can help in determining the accurate location of the brain tumour and how far it has spread.

1.6.4 Image-guided surgery

One of the medical applications is the image-guided surgery where the segmentation is advantageous. In order to extract brain tumours and to execute complicated biopsies, surgeons must follow complex trajectories to avoid anatomical hazards such as blood vessels or functional brain areas. The pre-surgical procedure, path planning and visualisation is performed using preoperative CT scans and MRI along with 3D surface models of the patient's anatomy [44, 45].

During the procedure, the segmentation is used to obtain preoperative results; the surgeon has access to the preoperative planning information, as 3D models and grey-scale data are displayed in the operating room. Moreover, the segmentation of real-time image that is generated during the surgery has been used for quantitative monitoring of the progression of surgery in tumour resection and cryotherapy [43].

1.7 Problem statement

Image segmentation is a key step in image processing for image analysis. It is possible to make high-level image analysis and full understanding of the medical image through image segmentation [46]. Segmenting the brain CT scan and MRI images into grey matter (GM), white matter (WM), cerebrospinal fluid (CSF), and the brain tumour plays a vital role in a comprehensive spectrum of clinical and research applications. Since the manual segmentation performed by medical professionals is time-consuming, expensive and subject to operator variability, automated and semi-automated segmentation algorithms have become the challenging topic that requires new or developed algorithm [47, 48]. Among these algorithms are the statistical model-based approaches (HMRF, MFR) that have attracted many research attention [13, 40, 49, 50]. However, the statistical model still needs to be refined by identifying the optimal form of models [51, 52].

Tumour volumes estimated on CT and MRI images have been utilised in the evaluation of brain tumours and have impacts on the diagnosis and treatment. Currently, radiologists perform the traced manual method for volume measurement by the largest distance between in-tumour points and the maximum perpendicular diameter and only a rough approximation from a single 2D projection image. Measuring volume manually is time-consuming (done on each slice separately), requires expert knowledge, and radiologists dependent on intra- and inter- observer variability [12, 47, 53, 54].

The 2D images cannot precisely convey the complexities of human anatomy, hence interpretation of such complex anatomy in 2D images requires a trained person. Radiologists are trained to interpret the complex anatomy in 2D images. The radiologist sometimes finds it is difficult to communicate the interpretations to a physician who may have difficulty in imaging the 2D anatomy. This leads to the need for reconstructing the 2D cross sectional image data of a tumour into 3D data. The 3D visualisation of the tumour data helps in better understanding of the topology and the shape of a tumour. Therefore, how to reconstruct a reliable surface from the sequential parallel 2D cross-sections becomes a crucial issue in biomedical 3D visualisation. The original Marching Cubes algorithm [55] for isosurface extraction examined all pixels in the data set. A massive amount of research has directed on reducing the number of used pixels while constructing an isosurface in 3D [56-60]. These methods utilise data structures to examine only those pixels that contain a portion of the isosurface. While the search structures introduced by many of these methods increase the storage requirements, the acceleration gained by the isosurfacing technique offsets this overhead. Marching Cubes can generate an extraordinary number of polygons, which take time to construct and to 3D render. For very large surfaces, the isosurface extraction and rendering times limit the interactivity.

Although the CT scan is one of the most important devices used for detection, diagnosis, and volume estimation of brain tumours, this device involves a most common disadvantage that is the high radiation dose to patients [10]. The biological effects of ionising radiation vary with the type and energy. A measure of the risk of biological harm is the dose of radiation that the tissues receive. The average effective radiation dose of CT- Head is 4 mSv [26]. Therefore, reducing the number of the slice is required to reduce time, effort and cost.

1.8 Objectives of the study

The main objective of this study is to develop the diagnosis method for medical images (CT and MRI). To achieve this objective, the following specific objectives summarise the importance of this study:

1. To modify the HMRF model to segmente brain tumours in CT scan and MRI images.
2. To develop an automatic trace method based on the voxel dimension value to estimate the volume of brain tumours.
3. To present a visualisation of brain tumours in 3D from CT scan and MRI images using isosurface extraction techniques and create a new algorithm to specify the location of the brain tumour.

4. To expand the number of CT scan slices using the mean between two successive slices based on the proposed method (e.g. expand the number of CT scan slices from 54 to 106).

1.9 Main contributions

1. This study has modified the HMRF model and threshold method to segment the brain tumours and to obtain more accurate results from CT scan and MRI images.
2. The study shows that the brain tumour volume has been estimated by developing the automatic trace method based on the voxel dimension value.
3. The study has enabled the rendering of brain tumours in 3D for the end-user to visualise a tumour.
4. This study has also developed a new algorithm that allows detecting the location of a brain tumour using statistical information.
5. The study is the first to expand the number of CT scan slices using the mean of two successive slices based on the proposed method.

1.10 Scope of the study

This study primarily focuses on modifying the HMRF model for brain tumour segmentation to estimate the volume of CT scan and MRI images. The HMRF model with threshold method is used in the segmentation stage. In this study, the obtained datasets were classified into two datasets. The first dataset was obtained from TCIA and the second dataset from Iraqi hospitals.

The HMRF model and threshold method were utilised to segment brain tumours. In addition, this study also estimated the volume of brain tumours by developing automatic trust method that can view the brain tumour in 3D visualisation for the end-user to visualise the tumour as well as the extension area of the tumour in the brain. Another new algorithm was built for detecting the tumour location in the brain using statistical information.

The validation and the evaluation of all the proposed method stages are implemented using qualitative and quantitative methods. The performance of the HMRF and threshold is evaluated quantitatively and qualitatively. In the estimation of the brain tumour volume using the proposed method, the qualitative validation is carried out using a survey conducted on 19 end users, while the quantitative evaluation is carried out using the Archimedes' method as well as by comparison with the Mango software. To encourage the work and make it ready for application to CT scan and MRI by the end users, a survey of the work was undertaken to ascertain their perspectives on the proposed method.

1.11 Thesis outline

This thesis consists of six chapters, which are briefly described as follows. **Chapter 1** provides an overview of the scientific background relevant to the topic of this study. Additionally, this chapter presents the problem statement, objectives of the study, main contributions, scope of the study, and thesis outline. **Chapter 2** comprises a literature review about methods (HMRF–EM and threshold, volume estimation, and 3D visualisation) that are related to the study. **Chapter 3** describes the theoretical concepts of the segmentation algorithms used in this study, technique for volume estimation of the brain tumour, and 3D visualisation technique. **Chapter 4** presents the data collection, workstation computer, software, tools, and methodology used in this study, validation and evaluation, and procedures of the workflow. **Chapter 5** focuses on the findings of this study and provides a discussion of the processing analyses. In addition, it presents the validation and evaluation of the proposed method. Finally, the conclusions and recommendation for future studies are presented in **Chapter 6**.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

Currently, in the medical diagnostic field, the medical images perform a crucial role. The performance of human observers in diagnosing the medical images is influenced by their personal subjectivity. One major task of this study is to develop a diagnostic method for brain tumour images, which includes segmentation, volume estimation, 3D visualisation, and location determination. To explain the new method, various principles on these methods based on previous works are first discussed. This chapter presents various techniques for brain tumour diagnosis concerning the related literature including their results and how the previous studies relate to the current study.

2.2 Pre-processing

Image pre-processing is one of the preliminary steps, which are highly required to ensure the high accuracy of the subsequent steps. Skull stripping of CT scan and MRI images is an important pre-processing step for segmentation of brain tumour step. The skull-stripping problem is a difficult task, which aims to extract the brain matter from the skull, eliminating all non-brain tissues, or it is the removal of non-cerebral tissues such as bones, scalp, fat, veins, eyes, skin, or meninges. This procedure requires a semi-global understanding of the image, as the brain is constituted of different structures with various geometric and intensity properties (cerebellum, cortex etc.), as well as a local understanding of it. In addition, the presence of imaging artefacts, anatomical variability and varies contrast properties [61, 62]. The extra cortical voxels in CT scan and MR brain images are often removed in order to facilitate accurate analysis of cortical structures. Brain extraction is necessary to avoid the misclassifications of surrounding tissues, skin, and scalp as WM or GM [63, 64]. Skull stripping methods are classified into three types: intensity based, morphology-based and deformable model based. Region-based methods view brain regions as a group of connected pixel data sets. These regions have muscles, cavities, skin, optic nerves, etc. The extraction of the brain region from the non-brain region is done by methods like region growing, active contour, watershed and mathematical morphological methods. Some previous works that performed skull stripping are: Roy et al. [62], Benson et al. [65], Kleesiek et al. [66], Villafruela et al. [67], Moldovanu et al. [68], Benson & Lajish [69], Galdames et al. [70], and Bauer et al. [71]. The active contour was implemented in this study to achieve this task.

The Gaussian blur filter has been widely used for de-noising and provides a more extensive area surrounding the tumour in medical image processing [72-79]. It is necessary to pre-process CT scan and MRI images to reduce noise and to enhance the contrast between regions [80]. By implementing Gaussian blur filtering; the new value of pixel (x, y) is the weighted average of the pixels around itself Gaussian blur filtering gives the image smoother, which means the deviation of the pixels in a coding block, will become minimal, and thus will reduce the process of segmentation, estimation, and quantisation [16, 81-83].

2.3 Segmentation brain tumour

The segmentation of an image involves the separation or division of the image into regions of similar attributes [37]. The identification of particular regions in an image is usually referred to as segmentation [84, 85]. Medical image segmentation is the process of partitioning a CT scan or MRI image into multiple segment sets of pixels.

The aim of the image segmentation is to change and simplify the representation of an image into a more meaningful one that is easily analysed and interpreted [22, 28]. More precisely, image segmentation is the procedure for allocating a label to every pixel in a CT scan or MRI image so that, the pixels with the same label share certain characteristics. The result of image segmentation is a set of segments that collectively cover the entire image or a set of contours extracted from that image. All of the pixels in a region are similarly based on some characteristic or computed properties, such as colour, texture, or intensity. The final aim in a significant number of the image processing applications is to extract important features from the image data, which are used to interpret, describe, or understand the scene that can be produced by the device. Segmentation is an important tool in medical image processing. It has been useful in many applications and measurements of areas and volumes in medical image datasets, surgery simulations, surgical planning, measuring tumour volume and its response to therapy, and studying brain development [16, 31, 34, 86].

The goal of the segmentation algorithms applied to the brain CT scan, and MRI images is to detect all types of brain abnormalities by separating them from the regular tissues. This process is not natural because of the variations in the structures of the brain's tissues themselves. The intensity distribution of normal tissues is very complicated because of the similarity between these different tissues [80]. Since the CT scan and MR images are formed from a large number of pixels, the segmentation process became computationally complex and needed efficient computer memory. To overcome segmentation ambiguity, multi segmentation methods should be adopted [87-89]. The successful analysis of multi-dimensional images may be accomplished by utilising several supervised or unsupervised segmentation methods.

Based on the degree of required human interaction as illustrated by [90-92], segmentation of brain tumour methods can be categorised into three types: fully automatic segmentation, semi-automatic segmentation, and manual segmentation. The inconveniences, some principal advantages, and description of each category have been given in next sections.

2.3.1 Manual segmentation

Painting of the anatomical structures or manual drawing of structures of interest or the boundaries of the tumour with labels is involved in manual segmentation [93]. The additional knowledge, such as anatomy is also used along with the information presented in the image by human experts (trained technologists /anatomists /radiologists) in manual segmentation. To facilitate image display and drawing regions of interest, software tools having sophisticated graphical user interfaces are required in manual delineation. Practically, the selection of a region of interest (ROI), which is the tumour region, is a time-consuming and a tedious task. The relevant regions are carefully delineated from the most representative slices which are selected by human experts after going through the dataset slice by slice, produced by CT and MRI scanners in the form of multiple two-dimensional cross-sections (slices). An injected contrast provides the intensity enhancement with a single image which forms the typical base of manual segmentation of brain tumours [14, 90]. Poor segmentation results will most likely be obtained if the person drawing the ROI is not well versed in that particular brain anatomy or is not a trained technologist/anatomist/radiologist. Sometimes unclear images are produced, and human ratter's view is limited due to the task of the slice by slice marking of the tumour regions [94]. This results in the appearance of a stripping effect in less optimal segmented images. Considerable inter as well as intra-ratter variability exists for selected regions, and it is needless to mention that an operator is also required for manual ROI delineation [14]. Considerable differences are presented in the resultant segmentation of each expert. Comparison with manual segmentation is used for quantitative and qualitative assessment of segmentation results in fully and semi-automatic segmentation methods, for which the manual segmentation is habitually used as validation ground truth in spite of the expected inter and intra-ratter variability. The apparent advantages of ideally fully automated or semi-automated segmentation over manual segmentation will be presented by the methodologies of these techniques. Although in clinical trials, the manual segmentation is still widely used, mainly where the differentiation and characterisation of tissues require human expertise and knowledge [90].

2.3.2 Semi-automatic segmentation

To manually correct the segmentation results, to check the precision of results, or to initialise the method, the intervention of a human operator is often required in semi-automated brain tumour segmentation. With the intention of having the least possible human interaction, semi-automated segmentation of brain tumour is being focused in most of the recent research. The user interface, the interactive part, and computational portion are the major components of an interactive brain tumour segmentation method, as described by [90, 95], One or more pieces of a programme capable of producing a delineation of a tumour provided some parameters are presented in computational part. The information between the computational part and user is mediated by interactive part. The translation of data input by the user into program parameters and the outcome generated by the computational part into visual feedback to the user is done by interactive part. The input and output devices controlled by the user interface develop the actual communication between the user