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AUTOMATIC DETECTION OF EPIDURAL HEMATOMA ON THE BRAIN BY USING IMAGE PROCESSING TECHNIQUES

SAWSAN DHEYAA MAHMOOD

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ADVISOR
ASST. PROF. DR. GÖRKEM SERBES

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A thesis submitted by Sawsan DHEYAA MAHMOOD in partial fulfillment of the requirements for the degree of **MASTER OF COMPUTER ENGINEERING** is approved by the committee on 6.6.2017 in Department of Computer Engineering, Computer Engineering Program.

Thesis Advisor

Asst. Prof. Dr. Görkem SERBES

Yıldız Technical University

Approved By the Examining Committee

Asst. Prof. Dr. Görkem SERBES

Yıldız Technical University ______________________

Prof. Dr. Nizamettin AYDIN

Yıldız Technical University ______________________

Asst. Prof. Dr. Cemal Okan ŞAKAR

Bahçeşehir University ______________________

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May 2017

Sawsan DHEYAA MAHMOOD

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LIST OF SYMBOLS

$\|\| \|\|$	Absolute
$\prod$	A product over a set of terms
$\cap$	Conjunction
Log	Logarithm
pr	Probability
$\sum$	Summation

LIST OF ABBREVIATIONS

AFCM	Alternative Fuzzy C - Mean
ANN	Artificial neural network
ASHA	American Speech Language Hearing Association
BIC	Bayesian Information Criterion
CAD	Computer Aided Diagnosis
CNS	Central Nervous System
CSF	Cerebro- Spinal Fluid
CT	Computed Topography
EDH	Epidural Hematoma
EM	Expectation - Maximization
EMS	Emergency Medical Staff
FCM	Fuzzy C- Mean
FDA	Food and Drug Administration
GLCM	Gray-Level Co-Occurrence Matrix
GM	Gray Matter
ICH	Intracerebral Hematoma
ML	Maximum Likelihood
MM	Mathematical Morphology
MRA	Magnetic Resonance Angiography
MRF	Markov Random Field
MRI	Magnetic Resonance Imaging
NIRS	Near Infraral spectroscopy
PD	Proton Density
Pdf	Probability density function
PET	Positron Emission Tomography
SDH	Subdural Hematoma
SE	Structural Element
TBI	Traumatic brain injury
WM	White Matter
WPT	Wavelet Packet Transform

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ABSTRACT

AUTOMATIC DETECTION OF EPIDURAL HEMATOMA ON THE BRAIN BY USING IMAGE PROCESSING TECHNIQUES

Sawsan DHEYAA MAHMOOD

Department of Computer Engineering

M.Sc. Thesis

Advisor: Asst. Prof. Dr. Görkem SERBES

In modern medicine, detection of a hematoma depends mostly on the utilization of imaging techniques such as Computerized Tomography (CT) and Magnetic Resonance Imaging (MRI). Detection of brain injuries on brain images is a convoluted and challenging task for the radiologist. Challenges mostly occur due to the nearness and nested nature of different types of brain tissues. The diversity of cerebrum structures increase the algorithm complexities required to detect and segment the injury region.

Traffic accidents and falls are the two most frequent causes of traumatic brain injury (TBI), falls being slightly more prevalent. According to American Speech Language Hearing Association, every year, at least 1.7 million (TBIs) occur in the United States and Epidural Hematoma (EDH) cases constitute more than 45 % of the TBI. Studies show that the overall incidence rate for the TBI is approximately 300 per 100,000. Therefore, TBI detection and management is an important health care problem.

In TBI detection and management, the goal of all imaging techniques is to locate the injury site and predict its progression. Each imaging technique has advantages for describing specific types of TBI. However, due to its high detection speed, availability, and high sensitivity, CT is always the primary choice when dealing with TBI. MRI is used less frequently because it requires long image acquisition times, has higher costs, is very sensitive to patient movements ,and is not suitable for patients with claustrophobia.

In this thesis, we aim at detecting, i.e., marking the border and measuring the size of, EDH regions in CT scans of the brain. Proposed system contains many image processing operations, including image segmentation and binary morphology. Gaussian Mixture Modeling (GMM) segmentation is used as the primary method and its results are

compared with the well-known *k*-means segmentation. All the codes in this thesis have been developed in MATLAB software environment and the experimental data consisting of 37 CT images of EDH (or bleeding) cases was obtained from a publicly available dataset named as "https://radiopaedia.org/". Professional help is received from an expert radiologist to select these images and build the ground truth (i.e., the actual boundary information of EDH regions) for them. The doctor has visually inspected all of 37 images and marked the boundaries of bleeding regions by red color using an image editing software. Then, the proposed algorithms were tested on these images, the obtained results were compared with the ground truth provided by the expert, and finally error rates were calculated. Obtained results are very promising and encouraging; on average, proposed GMM based segmentation method yields 85 % detection rate compared to 83 % of *k*-means method.
Keywords: Epidural hematoma on the brain, brain hemorrhage, brain CT scans, Gaussian Mixture Modeling, image segmentation.

ÖZET

GÖRÜNTÜ İŞLEME TEKNİKLERİNİ KULLANARAK BEYİNDEKİ EPİDURAL HEMATOMLARIN OTOMATİK TESPİTİ

Sawsan DHEYAA MAHMOOD

Bilgisayar Mühendisliği Anabilim Dalı
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Tez Danışmanı: Yrd. Doç. Dr. Görkem SERBES

Modern tıpta vücuttaki kanamaların tespiti genellikle Bilgisayarlı Tomografi (BT) ve Manyetik Rezonans Görüntüleme (MRG) gibi tekniklerinin kullanımına bağlıdır. Görüntülerden kraniyal yaralanmaların otomatik tespiti radyologlar için karmaşık ve zorlayıcı bir iştir. Tespit zorlukları genellikle beyin içerisindeki yapıların birbirlerine aşırı yakınlıklarından ve iç içe geçmelerinden dolayı olmaktadır. Beyindeki yapıların çeşitliliği tespit ve ayrıştırma algoritmalarının karmaşıklığını arttırmaktadır.

Trafik kazaları ve düşmeler travmatik beyin hasarlarının (TBH) en çok görülen iki sebebidir, düşme vakaları biraz daha fazla görülmektedir. Amerika Konuşma-Dil-Duyma Derneği'nin verilerine göre, Amerika'da her sene en az 1.7 milyon TBH vakası görülmektedir ve bu vakaların % 45'den fazlasını Epidural Hematom)EH (vakaları oluşturmaktadır .Çalışmalar göstermektedir ki, TBH'lerin görülme sıklığı 100.000 kişide 300'dür .Bu sebeple, TBH'lerin tespiti ve yönetimi önemli bir sağlık hizmeti problemidir.

Araştırma çabalarının çoğunun ana odak noktası Bilgisayar Destekli Tanı (BDT) sistemleri ile ilgilidir. TBH'nin tespiti ve yönetilmesinde, görüntüleme tekniklerinin amacı hasarı tespit ve ilerlemesini tahmin etmektir. Her görüntüleme tekniğinin kendine özgü, TBH çeşitlerini tanımlayabilecek üstünlükleri vardır. Fakat BT hızlı tespit, kolay kullanılabilirlik, yüksek hassasiyet gibi özellikleri sebebiyle TBH'lerin tedavisinde öncelikli seçimdir. MRG ise uzun görüntü alma süresi, yüksek maliyet, hasta hareketlerine aşırı hassasiyet ve kapalı alan korkusu olan hastalarda uygulanamaması gibi eksikliklerinden dolayı daha az kullanılmaktadır.

Bu tezde, beynin BT görüntülerinden EH bölgelerini tespit etmeyi, kanamanın sınırlarını bularak ve boyutunu ölçerek, amaçlamaktayız. Önerilen yöntem, görüntü segmentasyonu ve ikili morfoloji gibi, birçok görüntü işleme operasyonunu içermektedir. Temel yöntem olarak Gauss Karışım Modelleri (GKM) tabanlı bölütleme kullanılmış ve elde edilen sonuçlar *k*-ortalama bölütleme ile karşılaştırılmıştır. Bu tezdeki tüm kodlar MATLAB yazılımında geliştirilmiş ve kanamalı 37 BT beyin görüntüsünden oluşan veri seti halka açık "https://radiopaedia.org/" web sitesinden alınmıştır. Kanamanın gerçek sınırlarını tespit etmek için uzman radyolog hekimden profesyonel yardım alınmıştır. Uzman hekim 37 görüntüyü gözle incelemiş ve kanama alanlarının sınırlarını görüntü işleme yazılımı vasıtasıyla kırmızı ile etiketlemiştir. Daha sonra, önerilen algoritmalar görüntüler üzerinde test edilmiş, elde edilen sonuçlar gerçek sınırlar ile karşılaştırılmış ve en sonunda hata oranları hesaplanmıştır. Elde edilen sonuçlar ümit vericidir ve GKM tabanlı bölütleme ile ortalamada %85 tespit başarısı, *k*-ortalama bölütleme ile de %83 tespit başarısı elde edilmiştir.

Anahtar kelimeler: beyinde epidural hematom, beyin kanaması, beyin BT taramaları, görüntü bölütlemesi.

CHAPTER 1

INTRODUCTION

1.1 Literature Review

Imaging technology in medicine has been made the doctors see the interior fraction of the body for easy diagnosis. It also has been helped doctors to make keyhole surgeries for arriving the interior parts without really opening too much of the body. A computed tomography (CT) Scanner took over x-ray imaging by making the doctors look at the body's elusive third dimension. With the CT scanner, body's interior can be uncovered with ease and the diseased areas can be identified without causing either annoyance or pain to the patient [1]. Image processing techniques developed for analyzing remote sensing data may be adjusted to analyze the outputs of medical imaging systems to get the preferable advantage to analyze symptoms of the patients with ease [2].

In the past, many types of researches published to build automated systems for detecting hemorrhages in the brain. Some of these researchers follow the same kind of frameworks that proposed in this dissertation. The framework starts with an image preprocessing and segmentation phase followed by a feature extraction phase. Finally, different classifiers are used for the classification and testing phase. Some of the older works [2, 3] concentrate on the problem for segmenting the region of intracerebral hemorrhages. In the former work, they utilized a spatially weighted *k*-means histogram-based clustering algorithm, whereas, in the latter work, they implement a multi-resolution simulated strengthening method. Cheng and Cheng [4] suggested a Fuzzy C-Means (FCM) system built on the multiresolution pyramid for brain hemorrhage examination. The searchers likewise looked at FCM, focused Hopfield neural system [5] and fluffy Hopfield neural arrange [6] in the worldwide thresholding stage. In another work, Liu et al. [7] proposed an Alternative Fuzzy C-Means (AFCM) strategy for the division stage. A later work in view of FCM is the work of Li et al. [8]. The searcher utilized a thresholding technique centered on FCM clustering to sustain just brain regions. The results of his work (clustering) were brain regions that were segmented into slices by using median filtering to reduce the noise in the image, after that he made the maximum entropy threshold and computed for each slice chart to conclude the potential hemorrhage regions. At the last phase, he had determined the hemorrhage regions according to their gray level statistics and location. So, it's extremely encouraging by the results of this work, nevertheless, as the acknowledge of the authors, it is still a precipitate work.

The authors in [9], concentrated how to divide the brain CT images to regions, wherever for each region can be either a hemorrhage region or a normal brain region. It observes that for images having hemorrhages, of course, the regions which have not contain hemorrhage are handled as normal regions which resulting in a highly-imbalanced dataset. For the phase of image processing, the searcher utilized an image segmentation scheme which that uses ellipse fitting, wavelet decomposition, and background removal technique. This approach has accurately high weighted precision/recall rates as 88.5% and 86.3%, nevertheless, as the searcher acknowledge, since this dataset is imbalanced their numbers are too enthusiastic. The weighted precision/recall rate varied between 36.8% to 60%, without considering the type of normal regions. In [10], the approach is built on segmenting the images interested in objects using the extracted the features and watershed method for each object. The extracted features are provided to a neural network for classification. In [11], the searcher concentrated on the problem of locating a hemorrhage at the several slices comprising a single CT scan. Firstly, they implemented a method to separate slices into ones that contain the encephalic region and ones that contain the nasal cavity region. Secondly, the searcher utilizes the wavelet transform to evaluate some features and utilize them for detecting the presence of a hemorrhage on the slices that include the encephalic region. An ordinary approach, that the neurologists had followed it for detecting abnormalities in the brain CT scans, is to separate the brain region into two halves (hemispheres) and notice the difference between them [12]. Many studies have been followed this approach. For example, Datta and Biswas [12] utilize this approach for detecting the location and existence of intracerebral hemorrhages, while Chawla et al. [13] utilize it for determining the classes of brain strokes (hemorrhage, infarct and chronic infarct). They are (both papers) use histograms-based features to evaluate the differences detection. Later, both searcher Chan [14] and Liao et al. [15] focus the problem for diagnosing intracranial hemorrhages.

In 2013, the authors submitted a paper, in this approach they worked to detect if a brain hemorrhage exists or not in a Computed Topography (CT) scans of the brain. Besides, they tried to find the type of the hemorrhage [16]. The authors executed the method which consists a number of stages that contain firstly, image preprocessing, and secondly image segmentation which is used Otsu's method for extracting the hemorrhage region from the image, third feature extraction, and finally classification. The results of the performed experiments, which were much higher than those of previous approaches, were very hopeful [16].

In 2014, the authors submitted a paper, they presented a computer aided diagnosis (CAD) system for classifying brain CT images into normal, hemorrhagic and ischemic. They suggested CAD system to implement Wavelet Packet Transform (WPT) to decompose original (input) image into sub-images and after that extracts texture features from sub-images utilized GLCM. [17]

In 2015, other researchers presented a paper, they suggested a method for detecting whether a brain hemorrhage is existent or not in (CT) scans images of the brain. They implemented a system which consists of a number of stages that contains: first level, image preprocessing, second level, image segmentation, third level, feature extraction, and final level classification. The results of the performed experiments were very promising [18].

In 2016, the authors investigated a survey of applications of knowledgeable performs operations techniques for diagnostic sciences in the biomedical branch of image classification. They utilized watershed algorithm along with artificial neural network (ANN) to a diagnosis of a brain hemorrhage in a more refined manner by feeding CT images. They identified the category of brain hemorrhage that would be very helpful to radiologist in addition to medical students [19].

1.2 Aim of the Thesis

The aim of this thesis is to develop a computer aided diagnosis (CAD) system that enhances the diagnostic performance of Epidural Hematoma (Hemorrhage) (EDH) on CT by clinicians. The mainly objective of this thesis is, first of all, to upgrade a CAD system that accurately addresses small (EDH) to help in the management of patients suffering from head injury or acute neurological disturbance in an emergency setting.

The secondary objective is to concern the type of segmentation based on intensity of the image which is defined by Gaussian mixture model-based segmentation. This method arose as a technique for probability density function (pdf) estimation which is found meaningful applications in numerous biological problems. For augmenting or expanding existing strategies and developing new techniques to achieve correct, quick and reliable computer-based diagnosis of EDH, and for building a diagnostic system helps radiologist in determining and detecting of EDH depending on image processing techniques and new developments in this field. Also, the clinical diagnosis depends on the radiologist opinion which may be suffering from many mistakes. This issue highlights the need for receiving a second opinion so this system helps to increase the accuracy of diagnosis, to decrease the number of false excision of a brain hemorrhage, to speed the discovery of the disease, in addition, to reduce costs imposed on individuals by unnecessary surgeries.

1.3 Hypothesis

There are many methods for detecting the bleeding region of brain injury in CT images. This research study proposed a new method that combines different image processing techniques to extract bleeding regions. These techniques are pre-processing images using histogram image depend on the information that was given in the dataset, image segmentation using Gaussian Mixture Modeling based segmentation, and calculation of the difference between the obtained results and ground truths that are marked by an expert radiologist. Additionally, *k*-means clustering is tested as an alternative clustering method. A comparison between the proposed method's results and *k*-means clustering results are applied by using image subtraction technique to validate our method.

CHAPTER 2

GENERAL INFORMATION

2.1 Anatomy of the Human Brain

The brain is made up of approximately 100 billion neurons. The brain and the spinal cord are the masterpieces of the nervous system. The human brain coordinates the body's function such as vision, memory, learning and other activities. The brain is broadly composed of only two main cell types, the neurons, and the glia cells. The brain consists of three main parts [20], that are called as cerebrum, brain stem, and cerebellum. The cerebrum is the biggest portion of the brain. It is composed of two parts and each part controls the opposite view of the body (right part controls the left side of the body and vice-versa). It is related to emotional function like thinking, memory, and speech. The cerebrum is split into four lobes as displayed in Figure 2.1.

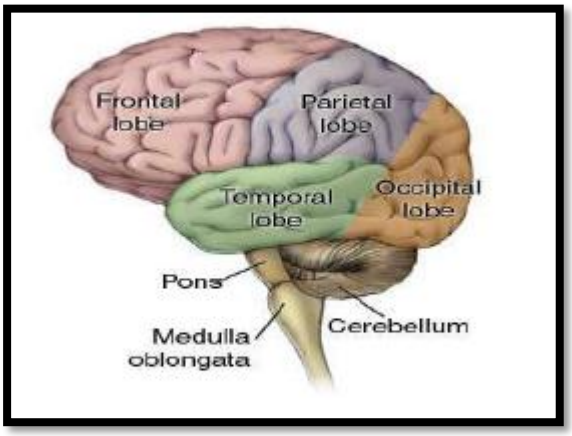


Figure 2. 1 The four lobes of the brain [21].

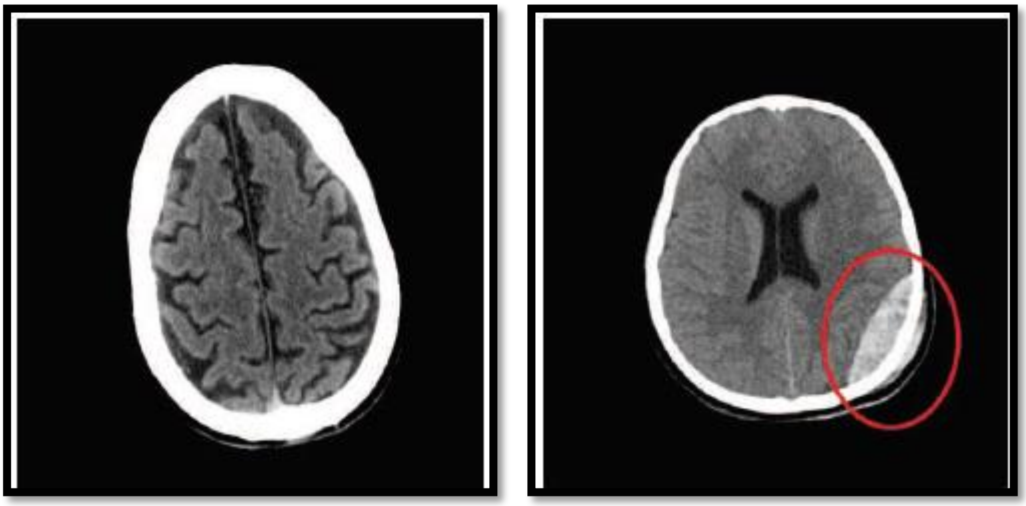
- The frontal lobe is involved with organizing, problem-solving, planning, selective attention and emotions.
- The partial lobe is related to the movement, orientation, recognition and perception of stimuli which control sensation.
- The occipital lobe involves processing of visual information.
- The temporal lobe is related to perception and recognition of auditory stimuli, olfactory stimuli, visual and verbal memory [20].

The cerebellum concerns balance and coordination responsibilities for psychomotor function. The brain stem controls the essential living function such as breathing, regulating the heart rate and the blood pressure. It is at the base of the brain and links the cerebral cortex, white matter, and the spinal cord [22].

2.2 Different Kinds of Traumatic Brain Injuries

2.2.1 Epidural Hematoma

Epidural or extradural hematoma, what is more, it is identified as an epidural hemorrhage, is a kind of traumatic brain injury (TBI) in which an accumulation of blood occurs between the skull and dura mater (the tough outer membrane of the central nervous system) and the skull. The layer of dura mater is also surrounded the spinal cord. Often due to trauma, because of the accumulation of blood may increase pressure in the intracranial space, the condition can be highly fatal, can compress sensitive brain tissue, and can happen brain shift [20]. The trauma condition is seen in one to three percent of head injuries. Around 15% - 20% of epidural hematomas are fatal Epidural Hematoma (EDH) and they are observed in 1%-4% of TBI patients. Fatal EH is usually formed when there is a bleeding between the space of dura mater and skull (Figure 2.2, bottom for right of the first image). It occurs due to direct impact, which is also the reason that it is easy for doctors to predict the progression of EDH as compared to Subdural Hematoma (SDH) [22].

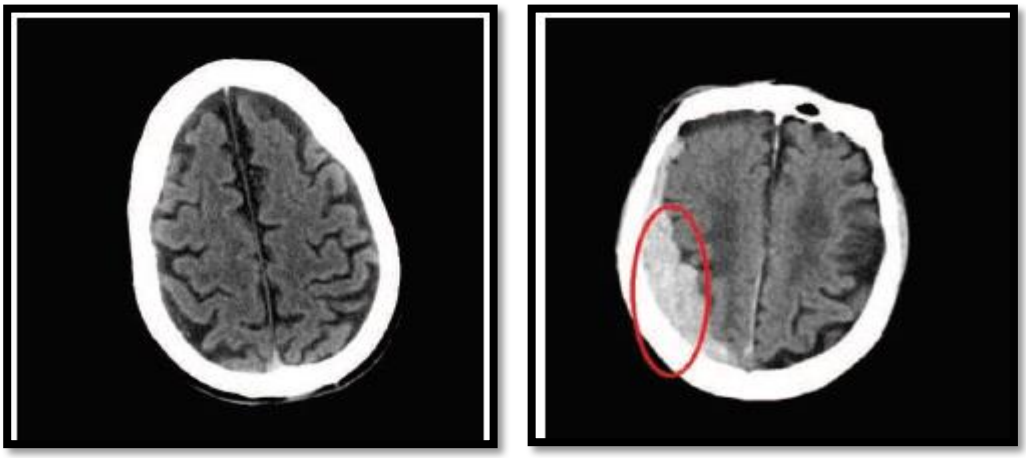


(a) Normal Brain (b) Epidural Hemorrhage

Figure 2. 2 Normal brain image with Epidural hematoma [16].

2.2.2 Subdural Hematoma

When bleedings occur in subdural space, the subdural hematoma (SDH) is formed. It is observed in about 10 to 20% of TBI patients, often due to traffic accidents, offensive aggression and in accidental sport falls. SDHs are generally not directly caused by fracture of the skull, as often is the case for EDH. It has a higher mortality rate than EDH, and is an important cause of death in severely injured patients [22]. SDHs most commonly occur when the cortical veins in the subdural space are broken; the resulting bleeding expands the subdural space between dura and arachnoid (Figure 2.3, at the bottom for left of the first image). It is often caused by a violent movement to the head resulting in torn veins passing between these layers. Because there is no visible head injury and veins bleed slower than arteries, symptoms may not appear for a day or a week or more. The seriousness of the injury depends on the amount of bleeding.

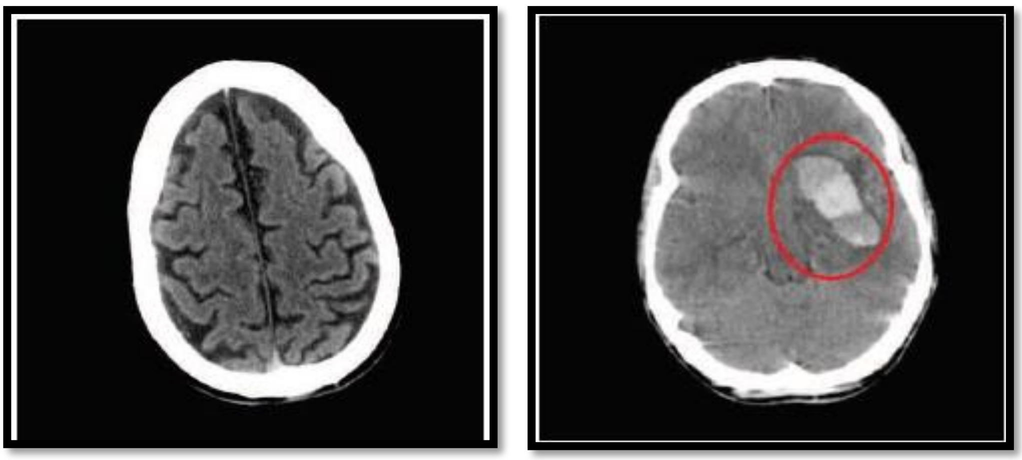


(a) Normal Brain (b) Subdural Hemorrhage

Figure 2. 3 Normal brain image with subdural hematoma [16].

2.2.3 Intracerebral Hematoma

Intracerebral Hematoma (ICH) normally occurs when a blood vessel in the brain breaks and causes bleeding in different parts of the brain like basal ganglia, cerebellum and brain stem. ICH is observed in about 20% of patients with acute SDH, but it is not usually accompanied by EDH [20]. ICH is made in 0.4-9% of patients having intracranial hematomas and can be present in about 40% of patients in an autopsy. ICH has a relatively high mortality rate (Figure 2.4). Different studies have shown total mortality rates of 30-40% after 1 month, around 50% after 1 year and 75% after 11 years [22]. We can see the three types of hematoma as in (figure 2.5)



(a) Normal Brain (b) Intracerebral Hemorrhage

Figure 2. 4 Normal brain image with intracerebral hematoma [16].

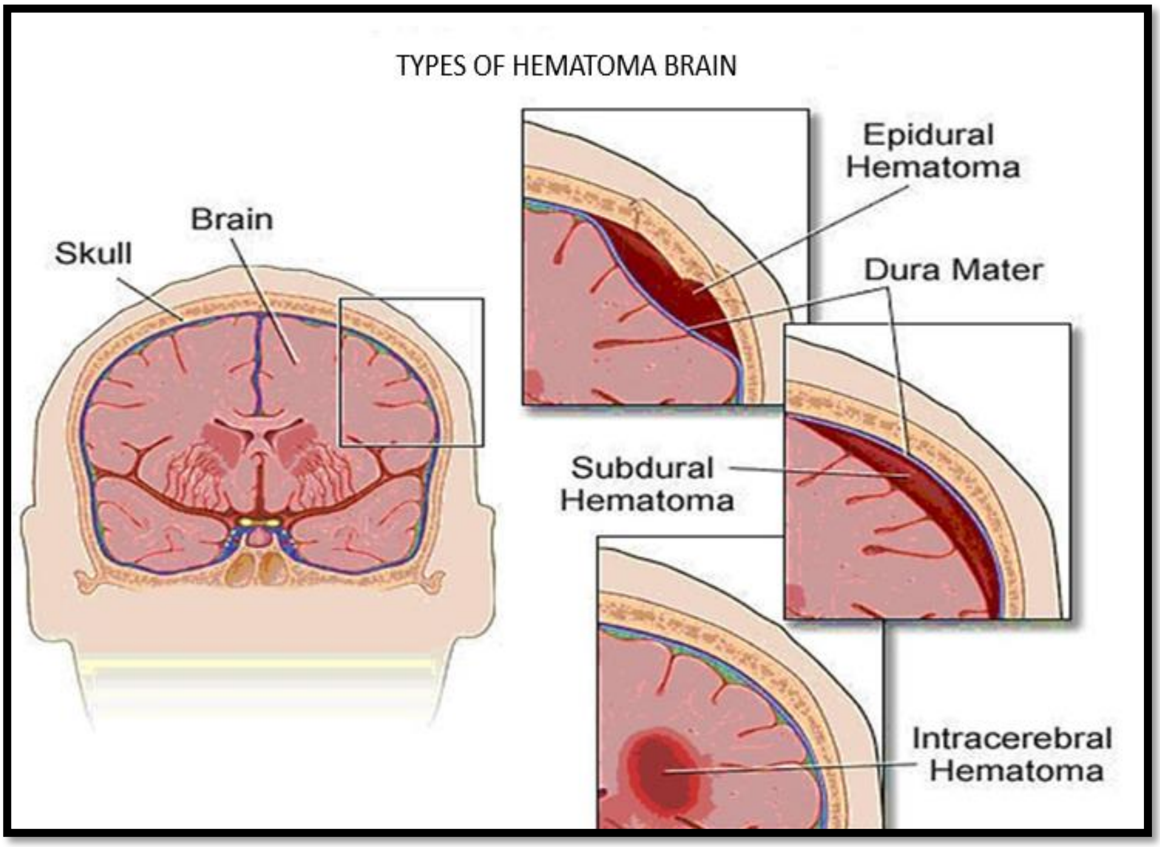


Figure 2. 5 Normal brain images along with the three types of hemorrhage [23].

2.3 Treatment of Epidural Hematomas

Emergency Medical Staff (EMS) personnel are most of the time first to treat the patients with head injury and transport them to a hospital. EMS staff treat TBI patients according to predefined guidelines [11]. As TBI occurs, the EMS first make an immediate assessment and stabilize the patient's airways [12]. Following that, an immediate CT scan is arranged to investigate the extent of secondary injuries. Monitoring of epidural pressure is also done and if necessary treatment is given to reduce the epidural pressure [11].

According to (ASHA) Every year, at least 1.7 million (TBIs) occur in the United States, Epidural Hematoma (EDH) cases constitute more than 45% of the TBI. Therefore, detection and follow up of EDH cases in an important issue. However, upon closer examination of TBI rates, it appears that TBI-related ED visits increased by 70% from 2001 to 2010, while hospitalization rates increased by only 11%. Additionally, deaths related to TBI decreased by 7% over the same 10-year span (CDC, 2014).

Depending upon the size of the hemorrhage and on which part of the brain it has occurred there are different complications. Patients can have a headache, lose consciousness, loss of vision, and many other complications. Surgical management of posttraumatic epidural hematomas are generally based on certain guidelines [5].

2.4 Techniques for Diagnosing Traumatic Brain Injuries

The goal of all techniques for detection and imaging is to predict the progression of TBI. Each technique such as CT and MRI has advantages for describing specific types of TBI, but CT is always the primary choice when dealing with TBI [24]. The reason for this is its high detection speed, availability, and high sensitivity. There are variants of CT like CT angiography, CT perfusion and Dual CT, each employed for different types of TBI. (MRI) is used in cases when results are not clear with CT and its recommended use also depend upon the patient's symptoms. MRI is far better than CT in explaining certain types of TBI that cannot be detected by CT at all [24]. However, due to patient claustrophobia, high costs, long measurement times, and its sensitivity to patient movements MRI is used less frequently [25].

2.4.1 History of CT

In 1970, Sir Jeffrey Hounsfield collected mathematical reconstruction formula with a rotating device that could both generate and detect X-rays, producing a prototype for the modern-day CT scanner. For this work, he had to get both a Nobel Prize and a knighthood. [26]

2.4.2 The Essential Principle of CT Scan

- Utilizes X beams connected in succession of cuts over the organ.
- Images remade from X ray retention data.
- X beam shaft moves around the patient in a roundabout way.
- CT scan provides a 3D show of the intracranial life structures developed from a vertical arrangement of transverse hub tomograms.
- Each tomogram could represent a horizontal slice out of the patient’s head [28].

2.4.3 X-Ray Physics

The most essential principle as addition radiography of any type is the following statement: different tissues are absorbed of different degrees of X-rays. Intensive tissues, such as bone, absorb the most x-rays, and hence permit the fewest through the body part being studied to the film or detector reverse. Conversely, tissues with low intensity (air/fat), absorb almost none of the x-rays, allowing at most to pass through to a film or detector opposite. [26]

2.4.4 Computed Tomography

Contrary to conventional x-rays, with the CT detector x-ray source and scanning, situated 180o across each other, move 360o around the patient, constantly sending and detecting information through x-rays as they pass through the body. Very concentrated X-ray beams are used, which reduces the degree of dispersing or blurring [27]. Lastly, a computer manipulates and integrates the obtained data and assigns numerical values based on the superfine differences in x-ray attenuation. Based on this rate, a gray-scale axial image is created that can identify objects with even little differences in density [26].

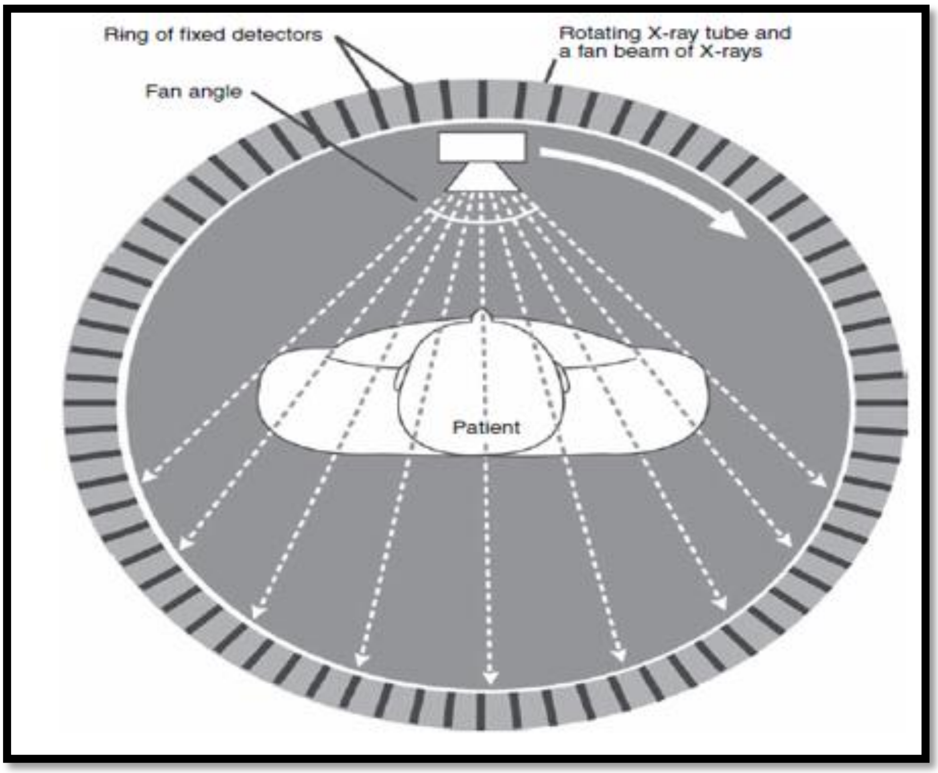


Figure 2. 6 Principle of CT scan image (Helical system. Ring of detectors surrounding a patient) [28].

Pixels: (Picture element): Each scan slice is collected of many pixels which perform the scanned volume of tissue. The pixel has been the scanned area on the x- and y-axis of a given thickness. [26]

Attenuation coefficient: In CT scanning, the attenuation coefficients are mapped to an arbitrary scale between –1000 (air) and +1000 (bone). (See Figure 2.7 below) The tissue includes within each pixel engrosses a certain amount of the x-rays which pass through it (example: bone absorbs a lot, air almost none). This ability to prevent x-rays as they pass through a substance is known as "attenuation". For a, given body tissue, the amount of attenuation is comparatively constant, and is known as that tissue's "attenuation coefficient".)

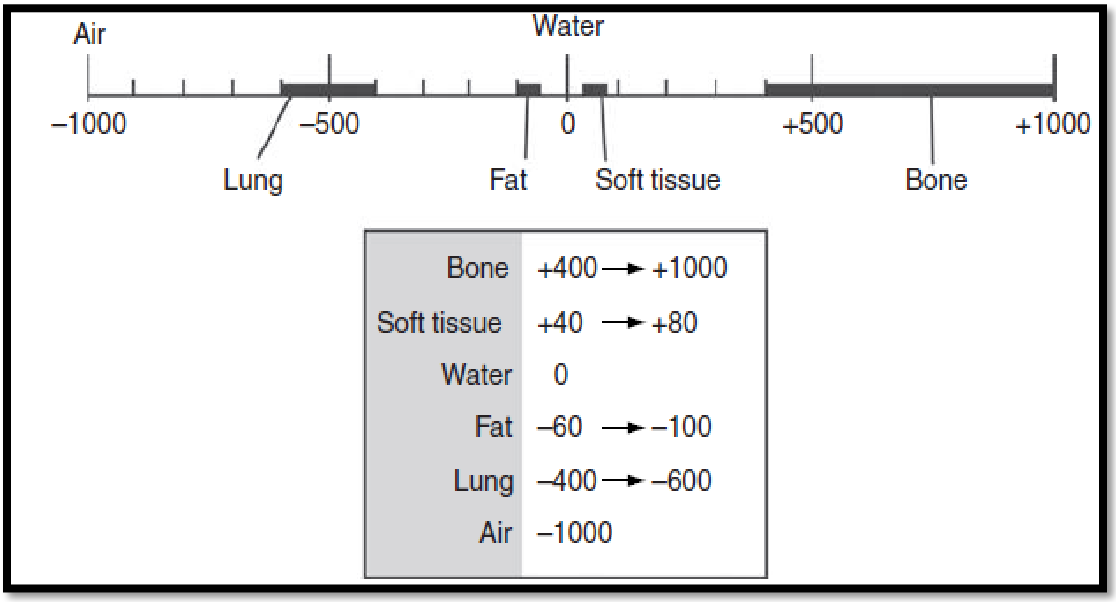


Figure 2. 7 Hounsfield Scale of the CT numbers. [28].

2.5 Brain Tissues in Computed Tomography and The Magnetic Resonance Imaging

(CT) and (MRI) are the two modalities that are regularly used for brain imaging. Modern medical imaging technology such as MRI, X-ray, CT, Positron Emission Tomography (PET) and ultrasound has given physicians a non-invasive means to visualize internal anatomical structures and diagnose a wide variety of diseases [27]. MRI is a strong and versatile modality. Compared to other such techniques, MRI has perfect soft tissue differentiation, high spatial resolution, contrast and does not use ionizing radiation which may be harmful to patients. Such characteristics have shown MRI to be an appreciated tool in the clinical and surgical environment [28].

With an MRI scan, it is possible to take images from different sections at most every angle, whereas a CT scan only shows cross-sectional images. Therefore, it gives us more detailed information [27]. The distinction amongst ordinary and anomalous tissue is frequently clearer on the MRI examine than on the CT scan. CT images are widely used in the diagnosis of ischemic stroke, hemorrhage and hematoma because of being more accessible in clinical setting, cheaper to operate, quicker in scanning time and more reliable, it is faster acquisition and compatibility with most life support devices [28].

Some patients cannot undergo MRI because of claustrophobia. MRI is also not feasible, on the off chance that patients have a metallic embed, similar to metallic heart valves, aneurysm cuts or other ferromagnetic material which will be influenced by a sturdy magnetic field. Additionally, patients with severe bleeding are not reasonable for MRI scanning, on the grounds that the blood clots will turn into a tissue which is difficult to distinguish from the normal tissue. However, CT provides more excellent geometrical accuracy of the image [27]. CT remains the method of option for unconscious patients with suspected intracranial hemorrhage and hematoma at the emergency room. With CT images, the most differentiation happens among bone, cerebrum tissue and Cerebro-spinal liquid (CSF). Bone appears splendid, CSF seems dim and cerebrum tissue shows up fairly in the middle of [29]. CT now and again called as CAT scan, utilizes exceptional X-beam gear to acquire image data from distinctive edges around the body and after that utilize computer processing of the information to demonstrate across area of the body tissues and organs [27]. Two safe and natural forces like the magnetic field and radio waves are used to produce vivid images of internal body parts in MRI technique. These images commonly capture the fine details of the anatomical brain structures, such as three major brain tissue types: gray matter, white matter and Cerebrospinal fluid as displayed in Figure 2.8. Gray Matter (GM) is one of the prime components of the Central Nervous System (CNS) and is the region where the functional stimuli are processed. White Matter (WM) is another major component of the CNS and its connective fibers are responsible for passing messages between functional areas, while CSF, surrounding the surface of GM, protects the brain from mechanical pressure [29].

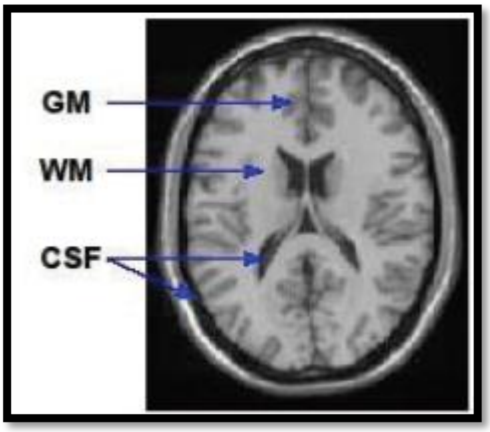


Figure 2. 8 Three major tissue classes of the brain [GM-Gray Matter; WM White Matter; CSF-Cerebro-Spinal Fluid], [28].

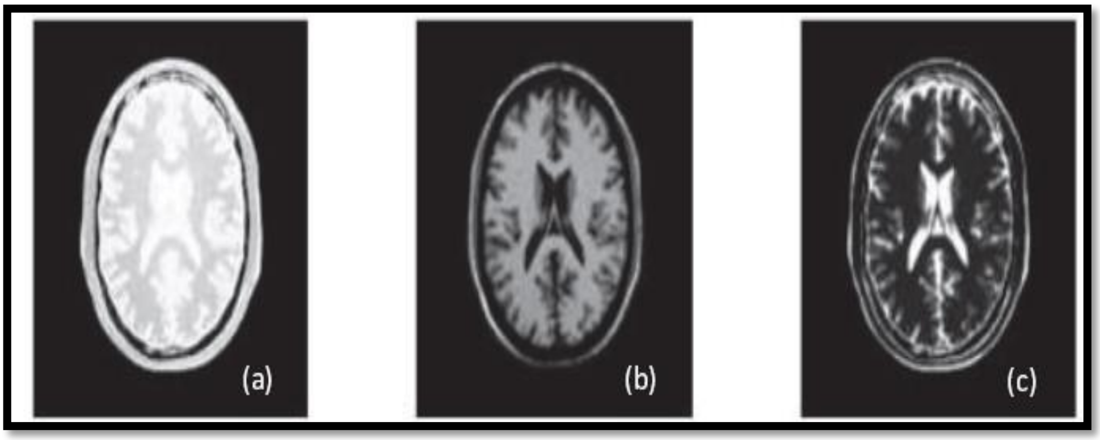


Figure 2. 9 PD contrast (a); T1 (b) and T2 (c), [28].

The contrast presented in this image at most due to the different proton density between tissues. accordingly shown in Figure 2.9, the T1-weighted image has very clear contrasts among all tissues (typically, CSF, GM and WM), however, the T2-weighted and the Proton Density (PD) weighted image show less clear contrast among the tissues.

2.6 CT or MRI: Which One is Better for Hemorrhage Detection?

After consulting many medical experts and reading through the literature, CT images are chosen in this work. CT images are famed to have many preferences over MRI, for example, more extensive accessibility, lower cost, and higher speed. Additionally, CT scanner may be supported over MRI scanner due to quiet related issues, for example, the patient being too vast to fit in the MRI scanner, claustrophobic, has metallic or electrical implants or is unable to remain motionless for the duration of examination due to age, pain or medical conditions. Finally, the nature of CT images is sufficiently high to precisely analyze brain hemorrhage [30].

So, we can summarize that CT imaging modulating has the following advantages over MRI such as:

- wider availability.
- low cost and higher speed. Fast scanning and superior contrast with the helping of computer.
- patient-related issues.
- the nature of CT pictures is sufficiently high to precisely analyze brain hemorrhage.
- multi-slice CT scans could have up to 64 slices for each per scan.
- retrieve and display CT images easier.
- save huge amounts of time and effort, CT takes fewer than 5 minutes. An MRI, on the other hand, can take up to 30 minutes. [29].
- One advantage of an MRI is that it does not use radiation while CT scans do. This radiation is harmful if there is repeated exposure.

2.7 Computer Aided Methods of Diagnosing Epidural Hematoma

Computer-Aided Diagnosis (CAD) frameworks utilize PCs to help physicians achieve a quick and exact conclusion. Computer aided design frameworks are normally area particular as they are upgraded for specific sorts of ailments, parts of the body, diagnosis methods, etc. They analyze different type of in-put like as symptoms, laboratory tests results, medical images, etc. depending on their domain [16]. One of the most common kinds of diagnosis is the one that depends on medical images. Such frameworks are extremely helpful since they can be coordinated with the software of the medical imaging machine to provide quick and accurate diagnosis [17]. On the other hand, they can challenge since they join the components of artificial intelligence and computerized images handling. This work shows a CAD framework to help detect hemorrhages in CT scans of human brains and distinguish their sorts on the off chance that they exist [17].

Computer-aided diagnosis (CAD) in medical imaging has made a fast progress in the last decade [31]. can upgrade the abilities of physicians and diminish the time required for precise diagnosis. The fundamental thought of CAD is to help radiologists in translating medicinal images by utilizing the computer system to give second sentiment or clinical validation. Examines on CAD frameworks and innovation demonstrate that CAD can help to improve the analytic precision of radiologists, help the weight of expanding workload, reduce tumor misdetection and enhance intra-per use fluctuation [31]. Computer aided design research in mind MRI are incorporated recognition of variations from the norm of aneurysms in attractive resonance angiography (MRA) images, Alzheimer's disease, multiple sclerosis [31], and multimodal MRI for tumor detection. Many techniques which have been proposed for various medical imaging modalities [17].

2.8 Segmentation of Images

Introduction

The segmentation is very important part in the image processing. For further procedure conversion, a whole image into many parts which is approximately easier and having an important effect. The entire image will be covered by these several parts that are rejoined. The segmentation has been depending on numerous features that are included in the image. Therefore, features may be either texture or color [32]. Before denoising an image, it is segmented to recoup the original image. The principle aim of segmentation is to debase the data for simple examination. Segmentation is also helpful in Image Analysis and Image Compression [33].

Segmentation is the way toward portraying objects in 2-or 3-D images. In this process, each pixel-voxel is assigned to a label so that pixels-voxels with same label share certain characteristics and correspond to different objects in the image [32].

A raw 3-D image, whether it is MRI, CT or microscopy image typically has a vast number of pixels-voxels and it is very computationally demanding to work with such data directly. In contrast, when we segment an image, we obtain a much easier description of the image, where different objects are identified and labeled. We can then conveniently and powerfully apply plentiful measurement, analysis, and recognition tasks on the segmented image objects [34].

In additional, using 3-D segmentation information, one can also create 3-D rendering of different objects of interest. This could be extremely practical, for instance, in medical imaging applications, where various objects would be various organs or types of tissues, so as to the doctors can easily find, concentrate, and work on the areas/volumes of interest [33].

Segmentation is used frequently in numerous branches of medical image processing applications, like the treatment planning, the tissue's quantification of volumes, computer-aided surgery and localization of pathology. In order to define or find object boundaries, typically gradient based techniques are applied onto the pixel-voxel values in the image [35].

Consequently "edge detection" and "segmentation" are closely related topics in the context of image processing [32].

2.9 Algorithms of Segmentation

As a result of its key role, i.e., identifying objects in images, in image processing, segmentation has been the subject of extensive research in the past 3-4 decades [32]. Once can found hundreds of segmentation processes in the literature, however, due to the nature of the segmentation problem, most of these algorithms are problem- or case-specific, as such, they have limited applicability to other problems [32].

Therefore, we believe that reviewing basic segmentation algorithms, which have a generalized scope and form the starting point of other more specialized techniques, will be more far-reaching and beneficial. As we will be mainly working with 3-D volumes/images, we will briefly discuss each algorithm with respect to its application on 3-D images [35].

As mentioned, many different segmentation algorithms have been investigated and proposed, however we can generally classify them into two categories, namely, structural and statistical techniques. Structural techniques try to find structural properties like edges and then segment the volume of interest. Statistical techniques aim at implementing segmentation built on the mathematical/statistical analysis of data (voxel values) and do not give any attention to the structural information [34].

2.9.1 Structural Techniques

We will briefly cover/discuss five methods under this category, i) edge detection, ii) morphological techniques, iii) graph-searching algorithms, iv) deformable models, and v) iso-surfaces and level sets [35].

2.9.1.1 Edge Detection

The aims of this technique at finding/detecting edges or surfaces in the volume to perform segmentation and works in two stages.

First, local edges are detected by utilizing some form of gradient operation, and then local edges are gathered together to form boundary contours that separate the voxels of the desired area from the rest [33]. A number of 3-D edge (surface) detecting operators have been proposed to this purpose, which are all essentially extensions of the classical 2-D edge-detection operators such as Robert's and Sobel's [33]. One favorable position of edge detection methods is that they work extremely well on datasets with great contrast between different regions, where edges can be detected with high accuracy and confirmed visually. On the hand, as these algorithms detect all the edges, even the non-significant ones or the ones due to noise, things may clear out of hand simply [35].

In other words, it becomes not easy to associate the detected edges and the different regions/objects within the image. Further than, as one may expect, these algorithms do not implement well on images with moderately low contrast between regions and high noise. As a result, these algorithms are not predictably used on their own, but combined with other algorithms, like thresholding on edge strength, to address the segmentation problems [34].

2.9.1.2 Morphological Techniques

Mathematical morphology (MM) uses set transformations for image analysis [35].

It checks the interaction between the objects in the image and predefined objects of particular shape and size called the structuring element (SE) in that image. As the SE is normally symmetric, it represents the basic shape information as a set of vectors referenced to its center. During morphological operations, the center of the SE scans the whole image and the correlation/overlap between the portions of the image that lies under

SE is used to define the transformation and SE. Hence, the transformed image or resultant corresponds to SE distribution in the whole image [34].

The two most fundamental operations in MM are “erosion and dilation” and all of the other composite MM operations are just not the same combinations of these two. There are several subtypes MM edge detectors such as, erosion residue (image (eroded image), dilation residue (dilated image (image), MM gradient (dilated image (eroded image), and reduced noise MM gradient [35].

As we notice, all of these subtypes are based on eroded and dilated images, for this reason, they are simple to achieve satisfactory edge detection performance and they are simple to implement/use. Even so, these detectors should be followed by other fine-tuning operations in the processing pipeline [33].

2.9.1.3 Graph-Searching Algorithms

In these algorithms, the properties of edges are embedded in an objective function and the edge which minimizes this function is required.

By representing the minimization problem as a shortest path problem on a graph, search algorithms such as dynamic programming (F* algorithm) or heuristic search (A* algorithm) can be used to find surfaces and edges in a volume [32]. These algorithms are mainly effective at what time the apportion between regions in the anticipated segmented volume are not well defined [32].

Even if the partitions between regions is broken, these algorithms may still perform well but they require the surfaces to be represented as graphs, which could be a problematic issue. From volume visualization point of view, another disadvantage is that these algorithms deal with surfaces, therefore, in order to get the voxel description of the surfaces, a conversion must be done [35].

2.9.1.4 Deformable Models

Due to variability of object shapes and sizes, and the variation in image quality (i.e. The issue of noise), image segmentation remains to be a problematic mission. Therefore, classical segmentation techniques such as edge detection and thresholding may not perform effectively or require some post-processing steps to remove invalid object boundaries [34]. With the purpose of address these problems, Deformable models are surfaces, curves, or solids defined within an image or volume domain and they deform or move under the effected of internal and external forces. In this physics-based modeling example, the data apply internal forces keeping the model smooth/intact during, while deformations “external” forces to the deformable model which moves the model towards the object boundaries [33].

Deformable models obtained acceptance after they were proposed in computer graphics and computer vision in late 1980’s [10-11]. Mathematically, a deformable model moves as indicated by its dynamic equation and search for the minimum of a given energy function. The most as often as possible used external forces are obtained from the gradient image [35].

Physically centered deformable models can be split into three groupings: probabilistic deformable models, dynamic deformable models, and energy minimizing snakes’ models.

Typically, a deformable model initialized near the region-of-interest and it is allowed to deform into the boundary. One then manually adjusts or fine-tunes the fitting by using interactive capabilities of the model [32].

For segmentation of 3-D images/volumes, each 2-D slice of the volume is segmented separately, the result can be used as a reference for neighboring slices, and the process is repeated. The resulting sequence of 2-D contours are then connected to form a continuous 3-D surface model [35]. However, this 3-D segmentation approach is together laborious and requires a post-processing step to link the sequence of 2-D contours into a continuous surface [33].

Additionally, the reconstructed surface can have various discontinuities. A true 3-D segmentation technique could overcome all these shortcomings giving rise to smooth 3-D surfaces directly. Research is underway to develop direct 3-D deformable model based segmentation, where 3-D balloons (approximating spheres using polygons) are used as the initial shapes [32].

In this methodology, the model fitting process is expressed as the minimization of a cost function involving a weighted sum of three terms: a deformation potential that expands the model vertices to the object boundary, an image term which identifies features like edges and opposes the balloon expansion, and a term that maintains the topology of the model by constraining each vertex to remain close to the centroid of its neighbors.

Some studies proposed deformable super-quadrics and deformable generalized cylinders, incorporating global shape parameters of a super-ellipsoid and generalized cylinder, respectively [14-15]. Local degree of freedom was based on elastic properties and action of external forces. These models can be manipulated to extract unrefined shape features from visual data, which can be used for indexing onto a database of stored models to provide shape recognition [33].

Local deformations help in reconstructing the details of complex shapes to provide shape reconstruction. By constraining boundaries to be smoother and incorporating other preceding information about an object shape, deformable models offer strength to both boundary gaps and noise. Hence one can express object boundaries in a consistent mathematical format and coherent [34].

This boundary explanation can then be readily used in subsequent steps. For instance, since deformable models are applied on the continuum, the resultant boundary representation can accomplish sub-voxel accuracy, a highly desirable property for many imaging applications. A disadvantage of deformable models is that they require user intervention to place an initial model in the image [35].

2.9.1.5 Iso-surfaces and Level-Sets

Iso-surfaces are defined by connecting voxels with intensities equal to the iso-value in a 3-D volume/image [35]. Level-sets are basically moving fronts (curves) in 3-D obtained in a non-parametric fashion. The underlying philosophy of this technique is to use iso-surfaces as a modeling approach that could be serve as an alternative to parameterized models [35].

Level-sets are numerical techniques conceived to track the evolution of interfaces, i.e. iso-surfaces. Other numerical techniques attempt to follow moving boundaries by putting a collection of marker points on the evolving surface and then changing their position to follow the moving surface. In contrast, level-set methods exploit a strong link between moving surfaces and equations from computational fluid dynamics [32].

The level-set method has been shown to be effective for segmentation in medical datasets. Literature shows that level sets could be used to simulate conventional deformable surface models [33]. The level-set representation takes a number of practical and theoretical advantages over conventional surface models, particularly in the context of deformation and segmentation.

First, level-set models are topologically flexible, they can simply represent complicated surface shapes that can, in turn, form holes, divided to form several objects, or combine with the other objects to form a unique structure. These models can include several of degrees of freedom, and therefore could be accommodate complex shapes. Thus, there is no need to re-parameterize the model as the shape undergoes significant changes [34].

2.9.2 Statistical Techniques

These algorithms do not take into account any structural information and perform segmentation by statistical analysis of pixel/voxel values only.

2.9.2.1 Histogram Based Thresholding Approaches:

Thresholding may be probably the simplest of the segmentation methods for scalar volumes. In this method, a single "threshold" value is used to generate a binary partition of the voxel intensities [36].

All voxels with intensities bigger than the threshold could be grouped into one class (e.g., object) and those with intensities below the threshold could be grouped into another class (e.g., background). Hence, use of a single threshold thus results in a binary segmented volume [35].

As for the calculation of the threshold value to be used in segmentation, intensity level histograms are used. These methods first generate the histogram of voxel values in the image using some suitable number of bins (e.g. 256 bins used for an 8-bit gray level image) and then employ optimization of a criterion function [34].

For instance, Otsu introduced "between-class variance" as a criterion function to determine the optimal threshold to segment an image into two nearly uniform regions. Thresholding methods are called global if a single threshold is calculated for the entire image. In local thresholding, the image is divided into sub-blocks and a threshold is calculated for each sub-block [37].

Although simple, this method is very profound-effective in segmenting volumes with good contrast between regions. Thresholding technique are also frequently utilizing for the primary segmentation of images previous to the application of more sophisticated segmentation method for the purpose of speeding the convergence [33]. A comprehensive review of the thresholding methods can be found in [35].

A disadvantage of histogram-based thresholding methods is their disregard of the spatial context (pixel/voxel neighborhood), i.e., they do not make use of the intensity values of the surrounding pixels in deciding for the class of the current pixel. Another drawback is that thresholding is very sensitive towards noise and intensity inhomogeneities that may be present within objects [38].

2.9.2.2 Clustering Based Thresholding Approaches

Clustering, looks for the natural groupings in a multidimensional data set via employing a similarity metric. We can view image segmentation as the assignment of the observed intensities (pixel/voxel values) into similar groups. Then, a clustering technique can be employed to segment images into regions or clusters [35].

Clustering can be split into two main categories namely, {hierarchical and partitional clustering}. Hierarchical methods construct the clusters via recursively partitioning the samples in either a top-down (divisive hierarchical clustering) or bottom-up (agglomerative hierarchical clustering) fashion [38].

Partitioning methods start from an initial partitioning and moves the samples from one cluster to another at each iteration, until the Sum of Squared Error (SSE, the total squared Euclidian distance of samples to their respective cluster centers) is minimized. Both methods typically require that the number of clusters could be pre-set by the user [37].

In *k*-means clustering, is also known as minimum variance partition, the SSE is used as a criterion. *k*-means clustering is computationally very efficient and gives satisfactory results if the clusters are compact and well separated, but the number of clusters has to be specified a priori. The *k*-means algorithm may or may not converge to the global minimum depending on the initially selected cluster centers [38].

Image segmentation can also be done using Fuzzy C-Means (FCM) clustering [22-23]. Unlike *k*-means, which every observation has a clear-cut the binary membership, the FCM method proposes a fuzzy membership that assigns “a degree of membership” for each class. The thought of degree of the membership in fuzzy clustering is like the posterior probability in a mixture modeling setting [36].

By monitoring data points that have the close membership values to existing classes, making new clusters is possible; this is the chief advantage of FCM clustering over *k*-means [36].

In Mixture-Model-Based Thresholding approach, we assume that the pixel/voxel values of the image come from a multi-modal density. In the image histogram, each of the bumps correspond to a mode or class, i.e. a weighted normal density with some suitable mean and standard deviation [38].

These bumps simply indicate that there are values for which the numbers of pixels attaining those values are relatively high, hence, they may correspond to certain object/region (e.g., a certain type of tissue) in the image. Therefore, if we can estimate the probability density function (pdf) of the pixel/voxel values, we can then use the pdf to find probabilities of any pixel/voxel value belonging to different classes/modes/regions/objects [38]. Consequently, the first step in the application of this approach to an image segmentation problem is obtaining the image histogram, so that a rough idea about the pdf of pixel/voxel values can be obtained. We should notice that, even though the histogram remains a useful/practical tool of great value, the pdf estimation is a tricky problem in itself [38].

For instance, depending on the bin selection, the appearance of the histogram may change considerably. That is, if the histogram estimate of the pdf is not obtained carefully, some modes may disappear or some may appear falsely. Luckily, in the case of image data, we mostly know what the pixel values can be [38].

For instance, while dealing with a grayscale image of 256 intensity values/levels, it is obvious that we should set the histogram bin centers at 0, 1,.., and 255 [38].

In spite of clustering algorithms do not need training data, they do need an initial segmentation (or equivalently, initial parameters). The expectation-maximization (EM) algorithm has confirmed greater sensitivity to initialization than the *k*-means, or fuzzy C-means algorithms [35].

These clustering algorithms do not immediately incorporate spatial modeling and can therefore be more sensitive to noise and intensity inhomogeneities. This lack of spatial modeling, nevertheless, can provide significant advantages for fast computation. Robustness to noise can be incorporated utilize Markov random field modeling [35].

2.9.2.3 Markov Random Field (MRF) Modeling Based Segmentation

The MRF modeling itself is not a segmentation method per se, but it is a statistical model which can be utilized within segmentation methods [39]. MRFs model spatial interaction among neighboring or nearby voxels. These local correlations offer a mechanism for incorporating the fact that most pixels belong to the same class as their neighboring pixels [38].

MRFs are often integrated into clustering segmentation algorithms like the k-means, under a Bayesian previous model. The segmentation could be done by maximizing a posteriori probability of the segmentation given the volume data utilizing iterative methods like iterated conditional modes or simulated annealing [38].

A difficulty related with MRF models is the proper choice of the parameters supervisory the strength of spatial interactions [39]. besides high a setting could be result in an excessively smooth segmentation and a loss of important structure details. In addition, obtaining MRF models are usually computationally very intensive [39].

Despite these disadvantages, MRFs are widely used to model not only segmentation classes, but also intensity inhomogeneities.

2.10 Image Segmentation: Cluster Analysis

One of the goals of image analysis is to identify groups of similar pixels in an image that correspond to similar composition and chemical or biological properties. This operation is referred to as image segmentation. It is used to separate zones in biomedical samples or to obtain an insight into the variation of chemical composition along the surface scanned. Clustering multispectral images is dealt with in [32]. In general, clustering is the partitioning of a dataset into subsets (the clusters) so that the differences between the data within each cluster are minimized and the differences between clusters are maximized according to some defined distance measure. The Euclidean distance can be used to assess the proximity of data:

$$d(xi, xj) = \sqrt{\sum_{l=1}^{d}(Xil - Xjl)^2} \tag{2.1}$$

Where xi and xj are two pixels and d is the total number of variables. Distances can also be defined differently from a mathematical point of view [32].

Clustering, it is also known as unsupervised classification, looks for the natural groupings in a multidimensional data set via employing a similarity or dissimilarity measure. In clustering, classes which are unknown and explored from the data itself. Whereas clustering divides the data into similar groups, classification assigns an observation to one of the already-known groups. Clustering can be split into two main categories namely: {partitional and hierarchical clustering}. Given n samples, each of which may be represented by a d-dimensional feature vector, the aim of the partitional clustering method is to partition the samples into K clusters so that the features in a sample group are more similar to one another than to those features in different sample groups. Every clustering method will normally produce clusters, but they may not guarantee that the discovered clusters are always meaningful. However, clustering, in general, can be very useful as an exploratory tool.

There are two popular partitional clustering strategies: square-error and mixture modeling. The summation of the squared Euclidian distances among the samples in a cluster and the cluster center which is called within cluster variation. The sum of the within-cluster variations in a clustering scheme is used as a criterion in *k*-means clustering [19]. This clustering is also known as minimum variance partition.

CHAPTER 3

MATERIALS AND METHODS

3.1 Material

Epidural hematoma is a widespread disease at the last two centuries, possibly affect any age without exception. So, radiologists made valuable efforts to diagnose this disease in the early stage, the interests on this disease have encouraged a number of researchers in the field of the computer vision and the image processing to build systems which are helping radiologist of the diagnosis of disease. The radiologist is dealing with a patient in a medical clinic, while the researchers in the field of image processing are dealing with images in order to diagnose disease (data set), which were identified by the brain hemorrhage experts to serve as a reference for researchers to make sure of the results accuracy. The results got from diagnostic systems provide a dependable second opinion for the radiologists and this is the main aim of such systems. Through mathematical and statistical analysis for digital images, these systems can realize the features and characteristics that cannot be identified with the naked eye. CAD system is used to diminish the mistakes that could be found in radiologist examinations and reduce the amount of repetitive and boring tasks that be done by clinicians. Several groups around the world are trying to assist the radiologist in evaluating of brain bleeding by developing effective systems and devices.

We built the dataset and collected it from the medical location web "https://radiopaedia.org/" The dataset consists of 37 CT images of human brain. These images include epidural hematoma CT images (EDH). In this study, CT images are used for diagnosis of brain hemorrhage. CT scan is able to image bone, soft tissues and blood vessels all at the same time. CT images are read first. Then brain CT image is converted into jpeg. This image is given to the system for pre-processing.

We got a help from “Prof Dr. Ismail Oran, Ege University, School of Medicine, Department of Radiology, Bornova, Izmir Turkey” to build the ground truth of these images by detecting the bleeding of the brain image and surrounding it by a red color, Figure.3.1.in this work all the images were taken which contain epidural hematoma and made a comparison between our segmentation results and the ground truth, for two methods (GMM, *k*-means). All results were obtained by using MATLAB (V. R2014a).

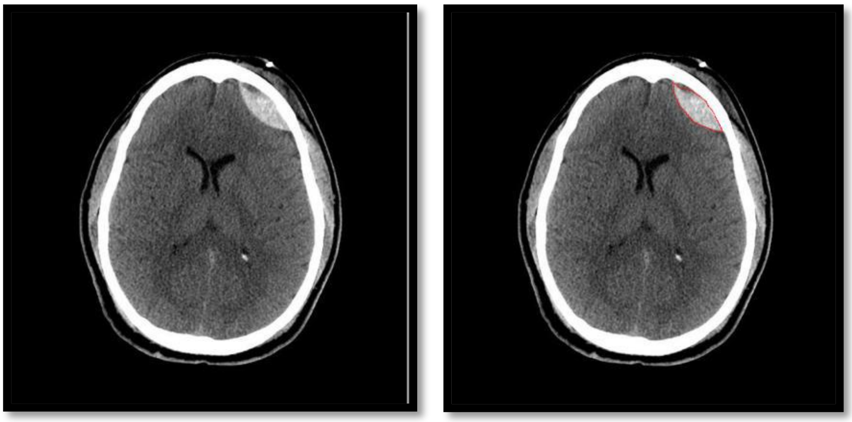


Figure 3. 1 Original image and marked image

3.2 Proposed Method

At this section, we will talk about the details of the proposed method. Firstly, a general diagram is explained main steps of proposed method after we will discussion in the following subsections. The approach consists mainly of two parts: the steps of execution programming part and the segmentation parts (which consists of several subparts such as image preprocessing and enhancement, image segmentation). Several methodologies that can be valuable for the image processing part exist . The focus here is on segmentation, which has been shown to be very useful in problems similar to the one at hand. In the segmentation stage, we used two methods to extract the hemorrhage region from the image our proposed method is Gaussian Mixture Model based segmentation (thresholding) versus *k*-means segmentation after getting the results of the segmentation, calculated the difference error between segmented image and ground truth. the accompanying stride, discriminative features of the region of interest (ROI) are extracted.

Finally, we used MATLAB [2014] to write the code to carry out the image processing and segmentation parts.

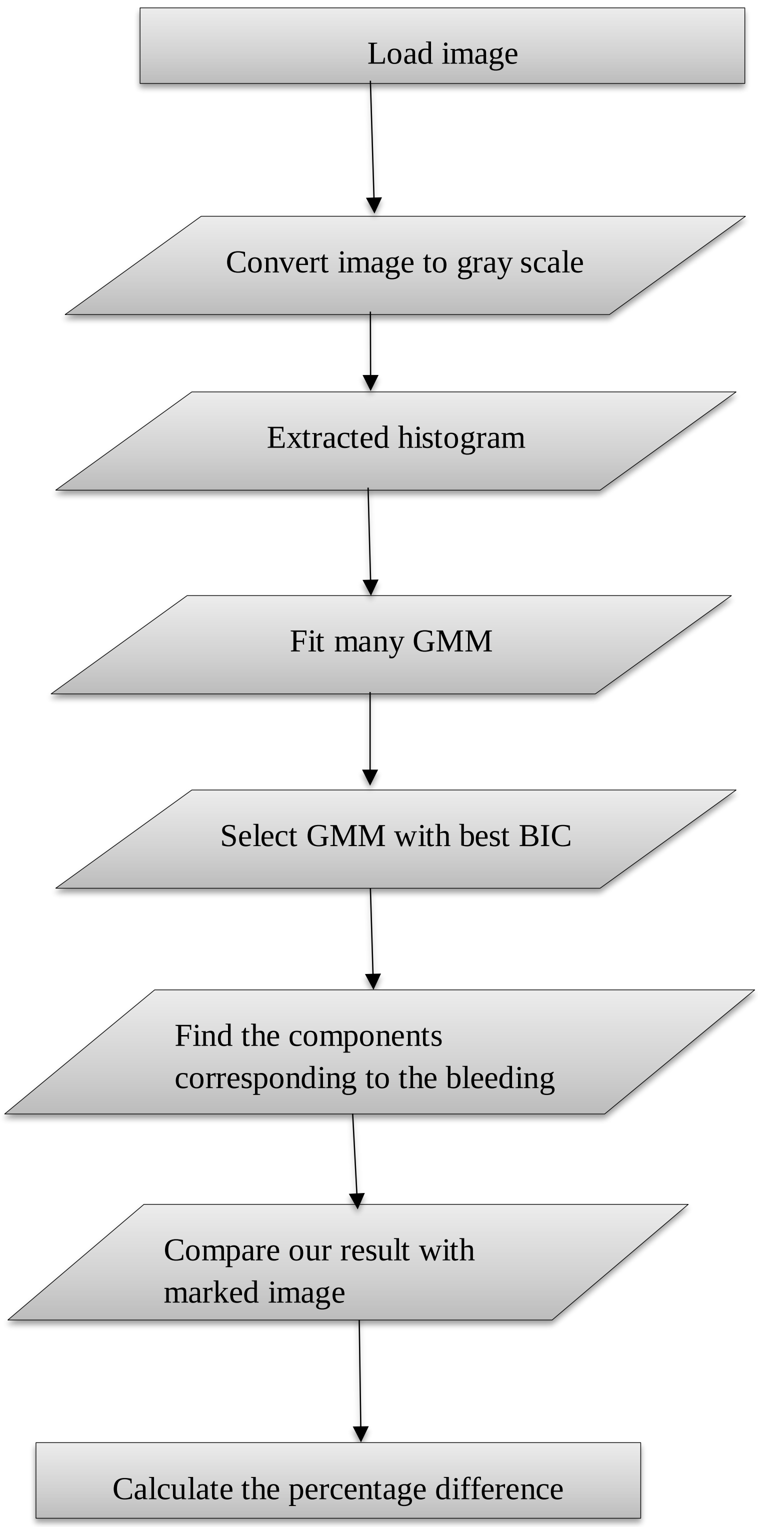


Figure 3. 2 Diagram of pseudo code for the proposed method

The stages of Method of GMM: -

- Read image.
- Convert image to gray scale.
- Extracted histogram
- Fit many GMM.
- Select GMM with best BIC.
- Find the components corresponding to the bleeding region.
- Compare our bleeding segmentation with marked image.
- Calculate the percentage difference.

3.3 Preprocessing

Preprocessing is used to enhance the nature of an image. In this study, preprocessing techniques are developed to split the tissues and detect the bleeding tissues corresponding to the intensity. In preprocessing, first, we convert the image into a grayscale image to make it contrast. After that, divided the original image (marked) into three colors red, green and blue to get the information of ground truth and extract the boundaries of red color. We used many operations such as morphological operation to enhance the region of bleeding when it extracted from the original image.

3.4 Morphological Operation

Morphology is related to shape, size and the structure of an object. Morphological operations can likewise be connected to grayscale images to such an extent that their light transfer capacities are obscure and along these lines, their outright pixel values are of no or little interest. Morphological operation depends just on the relative requesting of pixel values, not on their numerical values. Some of the mathematical morphological operators are as dilation, erosion, opening and closing. Opening comprises of an erosion took after by a dilation and can be utilized to wipe out all pixels in areas that are too little to contain the structuring element. For this situation, the structuring element is regularly called a probe, since it is testing the picture searching for little objects to Filter out of the picture. Closing comprises of a dilation took after by erosion and can be utilized to fill in gaps and little gaps. In the wake of opening and closing recreation operation, we are taken the supplement of gray scale picture to compute the provincial maxima. Ascertaining the provincial maxima of these remade images is done to get smooth edge foreground objects. Later, we overlaid these markers on the original images.

3.5 Segmentation of Pre-Processed Image

Segmentation is very significant in the medical image analysis. The exact location of required an object and boundaries in images is done through image segmentation. image segmentation is a procedure of apportioning the image into non-intersecting regions so that every region is homogeneous. Pixels in a region are comparative as indicated by some homogeneity criteria, for example, color, intensity or textures, to find and distinguish objects and boundaries in an image. After preprocessing, the image will be segmented to identify required objects in CT scan and to extract values needed as input. In this study, I used Gaussian Mixture Model-based segmentation algorithm versus *k*-means algorithm. The goal of Gaussian Mixture Model-based segmentation algorithm to distinctive the different intensities in an image in order to separate the distinct regions and make a comparison with the *k*-means method.

3.6 Image Segmentation by *k*-means Clustering

k-means clustering is computationally very efficient and gives satisfactory results if the clusters are compact and well separated in the feature space, but the quantity for clusters must be indicated a priori. The *k*-means algorithm may or may not converge to the global minimum. It is more sensitive to that initially selected cluster centers. The *k*-means algorithm can be run multiple times to alleviate the latter issue.

We can view image segmentation as the apportioning of the watched intensities into similar groups. Then, a clustering method could be employed to segment images into regions or clusters.

The application of the *k*-means algorithm to image segmentation is reasonably straightforward. First, we will write our 2-D or 3-D image in a column-ordered vector format. This can be done by stacking each column after the previous one. Let us call our $M \cdot N \times d$ sample vector $\mathbf{v}$, each element of which comprises the gray-level intensity in that case of a gray-level image (d =1) or R, G, and B values in that case of a color image (d = 3). Note that the column ordering results in the loss of spatial information.

Hence, *k*-means clustering disregards the contextual or spatial information. *k*-means algorithm for image segmentation includes the following steps:

1. Initialize the number of classes K and centroids μj

2. Assign each pixel or voxel to the group whose centroid is the closest.

3. After all pixels have been assigned, recalculate the centroids.

4. Repeat steps 2 and 3 until the centroids no longer change.

As we already mentioned, the *k*-means clustering algorithm minimizes the sum of the within-cluster variances

$$Q = \sum_{j=1}^{k} \sum_{i=1}^{n} \left\| v_i^j - \mu_j \right\| 2 \qquad (3.1)$$

Where v_i^j is i th sample of j th class K_j and μ_j the center of the j th cluster defined as the mean of $v_i \in K_j$. In calculating the centroids, different distance measures can be employed, although Euclidian distance is perhaps the most common. MATLAB's *k*-means algorithm offers a number of different distance measures, including the Euclidian distance. The replicate option of the algorithm allows us to repeat the algorithm a number of times and choose the solution with the lowest total sum of distances over all replicates.

In *k*-means clustering, the distances are calculated from a pixel to the centroid and the dataset is grouped into a preselected number (K) of clusters. The initial centroids are chosen randomly. Then, each spectrum is assigned to the cluster whose centroid is nearest. New centroids are computed, being the average of all spectra in the cluster. The two previous steps are repeated until the solution converges. The results of the *k*-means cluster analysis are the centers of each cluster and the cluster membership map. *k*-means clustering belongs to the partitional methods. Their advantages include that they are fast and applicable to large datasets. Disadvantages include that the selection of the number of clusters is not easy and, often, different results can be obtained depending on the starting points (centroids) of the clustering process.

3.7 Gaussian Mixture Modeling Based Segmentation

Mixture modeling arose as a technique for pdf estimation and found significant applications in various biological problems. The first step in the application of this approach to an image segmentation problem would sensibly be obtaining an image histogram. The histogram gives us a rough idea about the pdf of pixel values. Even though pdf estimation is a tricky problem in itself, the histogram remains a useful/practical tool of great value if the histogram estimate of the pdf is not obtained carefully, some modes may disappear or may appear falsely. Luckily, in the case of image data, we mostly know what the pixel values can be. For instance, while dealing with a grayscale image of 256 intensity values, it is obvious that we should set the histogram bin centers at 0, 1… 255.

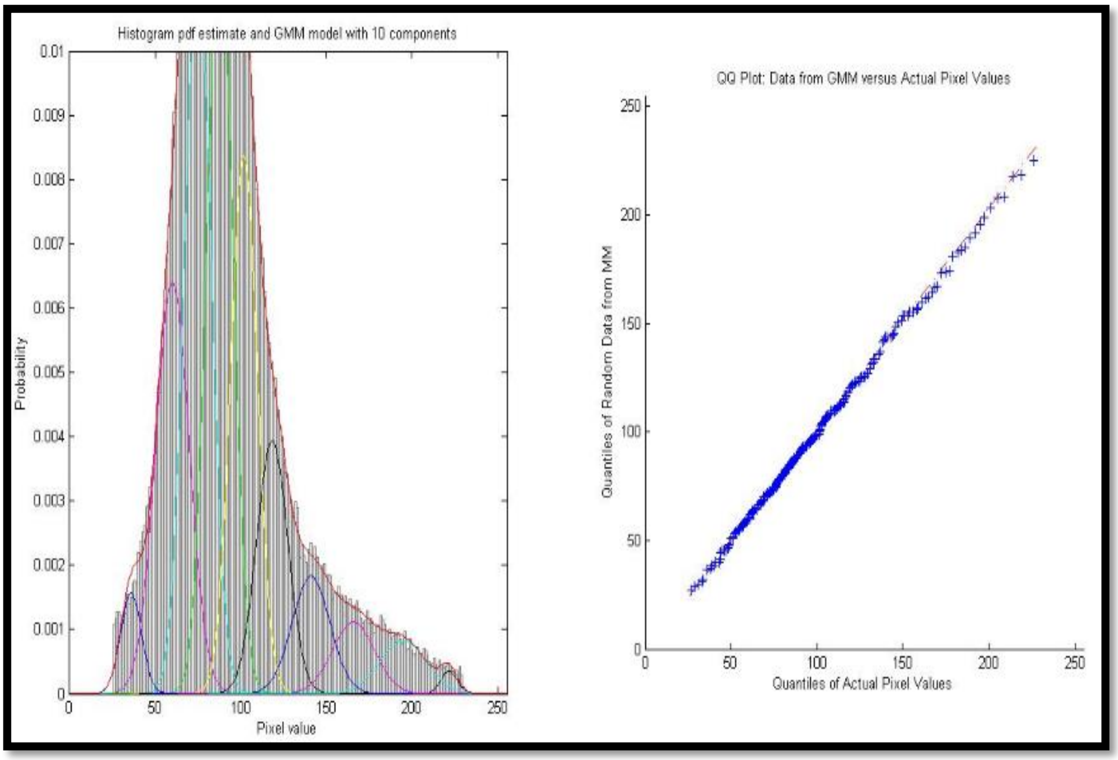


Figure 3. 3 Histogram of data

When we look at the histogram of the CT image of Figure 3.2, we observe that there are many modes.

One should have $\sum_{i=1}^{k} w_i = 1$ to make sure that $f(\boldsymbol{x})$ is a valid pdf. That is, if we know $k-1$ weights, the last weight is determined automatically. Therefore, the total number parameters to be estimated in equation (3.2) is $M = km + k - 1$.

$$f(x) = \sum_{i=1}^{k} w_i f_{i(w|\theta_i)} \tag{3.2}$$

wi, representing the "weight" or "mixing coefficient" of the ith component pdf, One practical/ popular way to estimate the unknown parameters of a mixture model, that is, θ, is to select it in a such way that it maximizes the likelihood function. This is called the maximum likelihood (ML) estimate of $\boldsymbol{\theta}$.

$\boldsymbol{\theta_{ML}} = arg_\theta \max\ L(\theta).$

The ML estimate of θ can be found numerically using various optimization algorithms. One particular popular optimization method that is widely used in mixture modeling is the expectation maximization (EM). The EM is an iterative method for optimizing the likelihood function when some information is missing. In our case, missing information is the class membership of the observations, that is, the pixel values. The EM algorithm for mixture modeling can be summarized as follows:

1. Initialization: Start with a proper initial estimate of the mixture parametersθ. Assuming that we know the number of components k , this initialization can be accomplished by using one of the available nonparametric clustering algorithms. For instance, the data can be classified into k classes using the k-means algorithm and the initial values of the parameters can be estimated from the clustered data. Instead of using random initial parameter estimates, using this approach improves convergence of the EM algorithm significantly.
2. Expectation step: Compute the class conditional pdf's $f_i\left(x_j \,|\theta_i\right)$ using the current estimated value of θ and determine or estimate the posterior probability that an observation x_j belongs to class i as

$$Pr.(\,\theta_i \mid x_j\,) = \hat{h_{ij}} = \frac{w_i f_i\,(x_j\,|\theta_i)}{f\,(x_j)}\ ; i = 1,2,\ldots\ldots k; j = 1,2,\ldots\ldots n \tag{3.3}$$

Where the dominator $f(\boldsymbol{xj})$ is given by Equation (3.2).

Here, we have used the Bayes' formula, which simply states that

$$posterior = \frac{prior \times likelihood}{evidence}.$$

We then compute the new or updated $\hat{w_i}\ s$, i.e., class weights or prior probabilities, by averaging the posterior probabilities for each class as

$$\hat{w_i} = \frac{1}{n}\sum_{j=1}^{n}\hat{h_{ij}} \tag{3.4}$$

3. Maximization step: Given the estimated weights $\hat{w_i}\ s$ from the expectation step. For the normal mixtures, the updates on the mean vector $\hat{\mu_i}$ and the covariance matrix $\hat{\Sigma_i}$ are as follows:

$$\hat{\mu_i} = \frac{1}{n}\sum_{j=1}^{n}\frac{\hat{h_{ij}}x_j}{\hat{w_i}}\,,\quad \hat{\Sigma_i} = \frac{1}{n}\sum_{j=1}^{n}\frac{\hat{h_{ij}}(x_j-\hat{\mu_i})(x_j-\hat{\mu_i})t}{\hat{w_i}} \tag{3.5}$$

4. Iterate (i.e., repeat the expectation and maximization steps) until the relative updates/changes in mixture parameter estimates are smaller than a small preset tolerance level or a certain number of iterations is reached.

Once a mixture model is fitted to our image's pdf, we can then assign pixels to different classes on the basis of the final estimated posterior probabilities. In our sample case, it was easy to determine the number of modes in the pdf of pixel values. However, sometimes we may not be quite sure about the number of modes in the pdf, as there may be some modes blocking other modes; that is, some overlapping modes may appear as a single mode. Therefore, we may try fitting several mixture models to our data's pdf with different number of components. Then, we can check the maximum value that likelihood or log-likelihood function attains. As we increase the number of parameters in the model, typically, the situation improves; that is, we can come up with a better model/fit and, consequently, the maximum of the likelihood function keeps increasing.

That is, if we use too few model parameters, the model/ fit will not be satisfactory enough in terms of explaining the composition of our pdf. On the other, if we use too many model parameters, we may produce an over fit, meaning we may be bringing in components that do not really exist. Therefore, we must determine an optimal number of model parameters (or optimal number of mixture components in our case) that will adequately explain our pdf. One popular method for evaluating/ determining the quality of fit is the Bayesian Information Criterion (BIC) proposed by Schwartz:

$$BIC = -2L(\theta) + M \ \log(n) \tag{3.6}$$

Where $L(\theta)$ is the maximized value of the log-likelihood function, and M and n are the number of model parameters and pixels, respectively. This criterion has two components acting in opposite sense: the first one, $-2L(\theta)$, decreases as M increase, whereas the second term is directly proportional to M. Therefore, by minimization of BIC, we can catch the balance point at which adding more parameters does not decrease the first term of the BIC much.

So we can summarized the functions of GMM method :

Gaussian function

$$P(X) = N(X|\mu, \Sigma) \tag{3.7}$$

GMM function

$$P(X) = \sum_{k=1}^{K} \pi_k \, N(X|\mu_k, \Sigma_k) \tag{3.8}$$

Where N: Gaussian == “Normal” distribution.

μ: Mean.

$\sum$: Covariance.

π_k : Mixing coefficient

This mixture model is a well-known method that has been widely used as a tool for image segmentation. Its success is attributed to the fact that the model parameters can be efficiently estimated by adopting various techniques such as EM algorithm, or gradient-based optimization techniques. Other advantages are its simplicity and ease of implementation. However, the major disadvantage of GMM is that the model assumes that each pixel is independent of its neighbors. It is well known that pixels in an image are similar in some sense and cannot be classified consistently based on feature attributes alone. Thus, the segmentation result of GMM is extremely sensitive to noise.

These ideas are implemented in the MATLAB function named GMixFit_Segment_Sawsan_automatic. Here, Im_in is the input image to be segmented, which is a grayscale image. Im_out is the output, that is, the labeled/segmented image and K is the number of classes/segments in the image. Before proceeding with the estimation of mixture parameters, if it is needed, data could be preprocessed or transformed to make its distribution approximately normal.

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Results

Results that obtained from the implementation as shown in the following Table 4.1 shows the comparison between the original image (marked images) and the results of our segmentation. We used two methods (GMM versus *k*-means) and make a comparison between them as result, we got that our proposed method (GMM) for detecting the bleeding region is superior to *k*-means.

The legend for Table 4.1 is as follows:

The first column: The case number.

The second column: Database image name.

The third column: Number of mixture components.

The fourth column: Indices of components corresponding to the bleeding region for *k*-means method.

The fifth column: Percentage Error between the original image (marked image) and segmented result image for *k*-means method.

The sixth column: Indices of components corresponding to the bleeding region for GMM method.

The seventh column: Percentage Error between the original image (marked image) and segmented result image for GMM method.

Percentage of difference equation (%)

$$f = 100 \times \frac{|Original\ image - segmented\ image|}{Original\ image} \quad (4.1)$$

Table 4.1 Segmentation Results for K-Means and GMM methods.

			k-means Method		GMM Method	
	Name of image	# of components	Indices of components chosen as bleeding region	Difference (%)	Indices of components chosen as bleeding region	Difference (%)
1	IMG_1_1	8	6,7,8	14.51%	6,7,8	14.51%
2	IMG_1_2	4	4	28.80%	3,4	27.78%
3	IMG_1_3	4	4	31.45%	3,4	15.61%
4	IMG_1_4	4	4	43.41%	4	23.49%
5	IMG_2_2	4	4	25.86%	4	17.05%
6	IMG_2_3	5	5	21.17%	5	15.53%
7	IMG_2_4	4	4	14.71%	4	15.13%
8	IMG_2_5	4	4	24.41%	4	22.16%
9	IMG_3_1	4	4	13.74%	3,4	11.68%
10	IMG_3_2	9	7,8,9	10.79%	7,8,9	10.85%
11	IMG_3_3	10	8,9,10	13.01%	8,9,10	12.81%
12	IMG_3_4	7	5,6,7	11.33%	5,6,7	11.57%
13	IMG_3_5	7	5,6,7	12.27%	5,6,7	12.49%
14	IMG_3_6	7	6,7	10.91%	6,7	10.69%
15	IMG_3_7	10	8,9,10	10.71%	8,9,10	10.59%
16	IMG_3_8	7	6,7	10.30%	6,7	10.76%
17	IMG_3_9	7	5,6,7	12.68%	5,6,7	12.41%
18	IMG_3_10	4	4	10.51%	3,4	9.35%
19	IMG_3_11	4	4	9.72%	3,4	8.78%
20	IMG_3_12	4	4	12.74%	3,4	9.87%
21	IMG_3_13	10	8,9,10	10.19%	8,9,10	10.15%
22	IMG_3_14	4	4	14.61%	3,4	15.49%

Table 4.1 (Cont'd)

			k-means Method		GMM Method	
	Name of image	# of components	Indices of components chosen as bleeding region	Difference (%)		Name of image
23	IMG_3_15	6	5,6	13.54%	5,6	13.50%
24	IMG_5_1	4	3,4	21.78%	4	13.62%
25	IMG_7_1	3	3	12.32%	3	12.15%
26	IMG_8_1	6	5,6	19.66%	5,6	21.22%
27	IMG_9_2	4	4	18.36%	4	21.88%
28	IMG_9_3	10	8,9,10	20.23%	8,9,10	22.68%
29	IMG_9_4	7	6,7	26.61%	6	25.00%
30	IMG_9_5	5	4,5	41.51%	5	19.63%
31	IMG_10_1	7	6:7	18.87%	6:7	19.32%
32	IMG_12_1	9	7,8,9	11.13%	7,8,9	11.65%
33	IMG_13_1	9	7,8,9	10.82%	8,9	10.43%
34	IMG_15_1	9	8,9	14.77%	8,9	14.47%
35	IMG_17_1	7	6,7	22.37%	6,7	22.63%
36	IMG_18_1	8	7,8	21.02%	7,8	21.07%
37	IMG_19_1	7	6:7	8.83%	6	7.99%
	Average Percent of Difference			17.56%		15.30%
	STDEV			0.08		0.05

Table 4.1 shows the resultant error percentage that is obtained by applying two methods (GMM and *k*-means) in determining the area of EDH and comparing this estimated area against original values provided by the expert physician, i.e. the radiologist. This is the key point for the performance assessment and comparison for different EDH detection/segmentation methods.

We used two methods (GMM & *k*-means) and we made a comparison between them. Our experimental results clearly show that GMM is superior in detecting the bleeding region because the average of the error percent difference between the result and ground truth image for GMM is less than the average of the error percent difference for *k*-means method.

Although GMM is computationally more complex, it yields the more accurate result in EDH detection. The best images/cases where we have less than 10% are IMG_3_10, IMG_3_11, IMG_3_12, IMG_19_1; for these cases (#18, #19, #20, #37).

We have 37 cases most of them as perfect results for GMM the results of error percentage are less than error percentage of *k*-means, but we have some cases in our results for *k*-means are better than GMM this is may be because the image intensity or quality of image needs improvement. when we refer to the resultant table we have found that there are (3, 4, 5, 6, 7, 8, 9, 10) components corresponding to the bleeding region. The table contains some unsatisfactory results, which are possibly due to i) ambiguity and/or error in doctor's mark, ii) relatively poor image quality or iii) difference in bleeding characteristics. From Table 4.1 we observe that the average accuracy of GMM and *k*-means methods reaches to approximately 85% and 82%, respectively.

4.2 Discussion

By using Gaussian Mixture Modeling based segmentation we can detect the epidural hematoma from the brain image. It will be helpful for doctors as well as medical students for better diagnosis and treatment. The results of the system using intensity segmentation "Gaussian Mixture Modeling based segmentation" for an image is enlisted in above table 4.1.

The dataset consists of 37 CT images of the human brain which includes images of EDH. During training, information is extracted from images. After training is completed, whenever an image is taken as input to the algorithm, it is simulated with trained process and goes for testing the data. All these images are tested by the proposed system. During testing, we extract the size of bleeding on the brain images and make a comparison between the result and the ground truth for each image and calculate the difference between the size of bleeding extracted from the image and the size of bleeding on the ground truth. After testing, the proposed system gives 85% accuracy for EDH.

This research study works with the automatic detection and segmentation of epidural hematoma in the brain by using CT scan images. In addition, the importance of CT images and their characteristics within this thesis. And the effect of CAD system in the medical field and the rapid diagnosis of the disease, what is more, this dissertation describes the implementation and application of image preprocessing and histogram techniques together with the evaluation of several different parameters. Image clustering analysis using *k*-means clustering. Afterward, Image segmentation and smoothing techniques such as morphological operation image segmentation and special segmentation based on intensity are outlined and applied of MATLAB's image processing toolbox. All experimental work and procedures performed in a set of CT image of brain injury and implemented in MATLAB R2014.

CHAPTER 5

THE CONCLUSION AND THE FUTURE WORK

5.1 Conclusion

Due to the advances in medical imaging technology and wider adoption of electronic medical recording systems in recent years, medical imaging becomes a most important tool in clinical trials and a huge number of medical images are proliferated in hospitals and medical institutions every day.

An automated method has been technologically advanced for the detection hematoma for brain CT images using segmentation method with Gaussian Mixture Modeling based segmentation (thresholding). The brain region identified with a bleeding can be precisely isolated from the brain image. This framework distinguishes hematoma on routine non-improved brain CT images. The proposed framework has been effectively tried on a small size of bleeding for hematoma. The proposed framework encourages the doctors to better analyze human brain hematoma, for supplementary treatment. The average overlap metric, average precision between the results achieved using the proposed approach and the ground truth are 0.85. MRI and CT of the brain are powerful techniques for diagnosis, used by the clinician to detect structural abnormalities responsible for neurological pathology and the disorder. As recently as a few years ago, most of the neurologist only had available to them pictures of several cross sections of a brain on a light board, using their knowledge to formulate a diagnosis or determine the effect of a therapy only based on these images. With an increasing interest in the space of medical image process, semi-automatic and automatic tools are developed to help medical diagnosis.

(CT) and (MR) images are very important for segmentation and classification of medical images for clinical research, diagnosis, and applications, prompting necessity of strong, reliable and adaptive segmentation techniques.

This research deals with improved detection of the brain hematoma at early stages using Gaussian Mixture Modeling based segmentation and *k*-means clustering. The research's main aim was identifying a bleeding region in a brain scan image and auto detection the bleeding region.

So, detection of the bleeding region can be done with the clustering methods. GMM method gives fewer difference rates (better detection performance) than *k*-mean clustering for soft tissues. These types of fully automatic epidural hematoma detection algorithms can be employed in medical diagnosis systems.

Making use Gaussian Mixture Modeling based segmentation versus *k*-means clustering getting the improvement of our proposed method it is the better and able to capitalize on distinctive features in an image to detect the EDH. Our proposed method with combined preprocessing methods is able to capitalize on different features in an image. Since it possesses different processing approaches, the method can distinguish the bleeding in an image.

Computerized frameworks for investigating and ordering medical images have picked up an extraordinary level of consideration as of late. One such example is the problem of detecting whether a brain hemorrhage be existent (the binary classification problem) and if it exists how to extract it. The experiments performed in this work showed that after preprocessing CT Scans, the binary classification problematic was solved with 100% accuracy. Also, the implemented system achieved more than 85% accuracy for the determining the hemorrhage size using a Gaussian Mixture-Model-based thresholding method as a segmentation method. The results are encouraging and a higher accuracy for the extract the bleeding tissue from the others tissue and determining the size of its. the problem can be attained by obtaining a better dataset with high-resolution images taken directly from the CT scanner. Moreover, different feature extraction and feature selection techniques could be employed to improve the performance of the system. Finally, ensemble classifiers for classification will be considered as a future work to accomplish higher accuracy. This will allow the future system to reach a level that will allow it to be a significant asset to any medical establishment dealing with brain hematoma. Epidural hematoma if detected early, has a 95-100% successful treatment rate, therefore early detection is vital. Computer-aided methods have been developed to assist radiologists. The goal of any imaging methodology used in radiology is to detect the injury of brain and diagnosis in early stages because, by dependence on it, the treatments are affected. Investigations show, that in early diagnosis more than 90% can be treated while in late diagnosis less than 50%. The diagnosis and successful treatments often complete with stable monitoring for suspicious. The Computer vision can play important role in Medical Image Diagnosis and has been proved by many existing systems this with highly capable. Despite the great advances in the field of imaging technology, but it is the biggest challenge remains the clinical diagnosis of brain hematoma, especially for the physician, which deals with the disease since its initial stages and diagnostic is the first point of contact with patients, in order to deportation to radiology community. As a result, the diagnosis of the brain hematoma operation has become occupies great importance in recent years, and it became the focus of attention of specialists and diagnostic regimes. The aim of this research is to assist physicians in the diagnosis of brain hematoma through quantitative analysis of the lesion. Diagnostic systems have played an important role in the registration and follow-up the patient's condition and the progression of the disease and ways to treat it. It is still work in progress in order to get effective results and it needs the concerted efforts of doctors and accurate work to provide assistance to researchers in this field.

With the aim of contributing to the development and improvement of some methods in the field of diagnosis, and developing new technologies to be accurate, fast and reliable helped in the diagnostic process; this thesis presented a segmentation technique that can help in the development of a diagnostic system for the brain hematoma. CAD system involves several steps including image acquisition, segmentation or border detection, feature extraction and selection, and classification. In this thesis, we have discussed a segmentation for the brain hematoma by using image processing techniques. The data set used in this thesis has been built and collect it from the medical location web "https://radiopaedia.org/" The dataset consists of 37 CT images of human brain. These images include epidural hematoma CT images (EDH). In this study, CT images are used for diagnosis of the brain hematoma. CT scan is able to image bone, soft tissues and blood vessels all at the same time. CT images are read first. Then brain CT image is converted into jpeg. This image will be uploaded to the system for pre-processing. We get a help from" Prof Dr. Ismail Oran, Ege University, School of Medicine , Department of Radiology, Bornova, Izmir Turkey "to build the ground truth of these images by detecting the bleeding of the brain image and surrounding it by a red color and all results were obtained by using MATLAB version R2014a. After following diagnoses system steps, the first step is image enhancement. As a result, there is a need for robust methods to remove artifacts and detect lesion borders in CT images. Those artifacts may be occluding some of the information about the lesion such as its boundary and texture.

5.2 Future Work

In this study, as an estimation of detection epidural hematoma and extract the size, we have obtained average percentage error rate of 15%, in comparison with the ground truth. This figure seems relatively high. However, as stated earlier, the radiologists may make mistakes while marking the regions or their marking result is only approximate. Therefore, there are some questions regarding the integrity or validity of the ground truth information. In future studies, we are planning to test our methods on other data sets as well, so that we can shed light on some of these "ground truth" issues. The problem of noise can be avoided by obtaining a better dataset with high-resolution images taken directly from the CT scanner. Different clustering techniques (Markov Random Field (MRF) and Fuzzy C-Mean clustering) could be employed to improve the performance of the system. In future after detecting the bleeding region with clustering techniques, we may extract features from the detected region and employ these features for discriminating three types of hematoma (subdural, intracerebral, epidural). We will then assess, or observe the average of percentage error for those cases and if the values do not fall below 5%, we will revise and further develop our algorithms.

REFERENCES

[1] Rao, K.M.M. and Rao, V.D.P., (2006). “Medical image processing. In Proc of Workshop on Medical Image Processing and Applications”.

[2] Loncaric, S.,et al., (1995). "3-D image analysis of intra-cerebral brain hemorrhage from digitized CT films." Computer methods and programs in biomedicine 46.3: 207-216.

[3] Loncaric, S., and Majcenic, Z., (1999). “Multiresolution simulated annealing for brain image analysis”,. In Medical Imaging, International Society for Optics and Photonics, 99:1139-1146.

[4] Cheng, D. C., and Cheng, K. S., (1998). “Multiresolution based fuzzy c-means clustering for brain hemorrhage analysis”. In Bioelectromagnetism, Proceedings of the 2nd International Conference on IEEE :35-36.

[5] Cheng, K. S., Lin, J. S., and Mao, C. W., (1996).“The application of competitive Hopfield neural network to medical image segmentation”, IEEE transactions on medical imaging, 15(4): 560-567.

[6] Cheng,J. Lin, K. and Mao,C.,) 1996).”A fuzzy Hopfield neural network for medical image segmentation”,IEEE Transactions on Nuclea Science,43(4):2389–2398.

[7] Liu, H., Xie, C., Chen, Z. and Lei, Y.,(2006). “January. Segmentation of ultrasound image based on morphological operation and fuzzy clustering”, In Electronic Design, Test and Applications, 2006. DELTA 2006. Third IEEE International Workshop on :4.

[8] Li, Y., Hu, Q., Wu, J., and Chen, Z.,(2009). “A hybrid approach to detection of brain hemorrhage candidates from clinical head CT scans”, In Fuzzy Systems and Knowledge Discovery, 2009. FSKD'09. Sixth International Conference on 1:361-365.

[9] Gong, T.,et al.,(2007)."Classification of CT brain images of head trauma.", IAPR International Workshop on Pattern Recognition in Bioinformatics, Springer Berlin Heidelberg: 401-408.

[10] Balasooriya,U. and Perera,M.,(2012).“Intelligent brain hemorrhage diagnosis using artificial neural networks.”, In IEEE Business Engineering and Industrial Applications Colloquium (BEIAC),:128–133.

[11] Liu, R., et al.,(2008)."Hemorrhage slices detection in brain ct images." Pattern Recognition, ICPR 2008. 19th International Conference on, IEEE,: 1-4.

[12] Datta,A. and Biswas, B.(2011).”A fuzzy multilayer perceptron network based detection and classification of lobar intra-cerebral hemorrhage from computed tomography images of brain”. In 2011 International Conference on Recent Trends in Information Systems (ReTIS), IEEE, :257–262.

[13] Chawla,M. et al.,(2009). “A method for automatic detection and classification of stroke from brain ct images”, In Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), :3581–3584.

[14] Chan,T.,(2007).“Computer aided detection of small acute intracranial hemorrhage on computer tomography of brain”, Computerized Medical Imaging and Graphics, 31(4):285–298.

[15] Liao,C et al.,(2007). “A knowledge discovery approach to diagnosing intracranial hematomas on brain ct” recognition, measurement and classification. In Medical Biometrics,:73–82.

[16] Al-Ayyoub, M.et al.,(2013)."Automatic detection and classification of brain hemorrhages." WSEAS Transactions on Computers ,12(10): 395-405.

[17] Shalikar,A. et al.,(2014).”Mohammad Reza Ashouri, and Mohammad Hossein Nadimi Shahraki. "A CAD System for Automatic Classification of Brain Strokes in CT Images, International Journal of Mechatronics, Electrical and Computer Technology 4(10):67-85.

[18] Sridevi, M. et al.,(2015)."Diagnosis and classification of brain hemorrhage using CAD system." Indian Journal of Scientific Research: 121-126.

[19] Lisboa, P.J., (2002). “A review of evidence of health benefit from artificial neural networks in medical intervention”, Neural networks, 15(1):11-39.

[20] Epidural hematoma, https://en.wikipedia.org/wiki/ ,20. january.2017.

[21] stock-vector-brain-anatomy-human-brain-lateral-view-illustration-isolated-on-white-background.html,http://www.shutterstock.com/pic-168732359/ ,25.january.2017.

[22] Ahmad, M. A., (2012). "Detecting traumatic intracranial bleedings in a brain phantom using microwave technology.".

[23] wpengine.netdna-cdn.com/wp-content/uploads/2014/02/figure2.jpg http://44tmty10gzq314zldj14iuvh.5.february.2017

[24] A.D.Gean,N.J.Fischbein,Headtrauma(Nov.2010).URL http://linkinghub.elsevier.com/retrieve/pii/S10525149100010007.february.2017.

[25] Leon-Carrion, J. et al., (2010)."The Infrascanner, a handheld device for screening in situ for the presence of brain haematomas." Brain Injury: 1193-1201.

[26] Denver, A. M. and DEF, P. B., (2001). “Head and Neck Surgery”.

[27] Sawhney,G.S.,(2007).“Fundamental of biomedical engineering. New Age International”.

[28] Holmes, E.J., Forrest-Hay, A.C.,and Misra, R. R., (2008).” Interpretation of emergency head CT”, a practical handbook. Cambridge University Press.

[29] Gopi,E.S.,(2012).“Digital signal processing for medical imaging using MATLAB”, Springer Science and Business Media.

[30] Sridevi, M.,Naaz, S. and Anjum, K., (2015). “Diagnosis and classification of brain hemorrhage using CAD system”, Indian Journal of Scientific Research:121-126.

[31] Saad,N.M.,et al.,(2015). "Review of brain lesion detection and classification using neuroimaging analysis techniques." Jurnal Teknologi 74(6):73-85.

[32] Hamacher,A.,etal.,(2015)."3D UHDTV contents production with 2/3-inch sensor cameras." SPIE/IS&T Electronic Imaging. International Society for Optics and Photonics,: 939105-939105

[33] Dougherty,G.,(2009). “Digital image processing for medical applications. Cambridge University Press”.

[34] Sonka, M., Hlavac, V. and Boyle, R.,(2014). “Image processing, analysis, and machine vision. Cengage Learning”.

[35] Jan,J.(2005). “Medical image processing, reconstruction and restoration: concepts and methods”, CRC Press.

[36] Acharya,T.andRay,A.K.,(2005). “Image processing: principles and applications”. John Wiley & Sons.

[37] Gonzalez, R.S. and Wintz, P., (1977). “Digital image processing”.

[38] Demirkaya, O., Asyali, M.H. and Sahoo, P.K., (2008). “Image processing with MATLAB: applications in medicine and biology”,CRC Press.

[39] Li,S.,(1995).“Markov random field modeling in computer vision springer”, In Tokyo 95 .

[40] Suri, J. S., Wilson, D., and Laxminarayan, S., (2005). “Handbook of biomedical image analysis “,Springer Science & Business Media, (2).

CURRICULUM VITAE

PERSONAL INFORMATION

Name Surname	: Sawsan Dheyaa MAHMOOD
Date of birth and place	: 22-10-1983, Iraq-Baghdad
Foreign Languages	: ENGLISH
E-mail	: samah7_7@yahoo.com

EDUCATION

Degree	Department	University	Date of Graduation
Graduate	Computer Engineering	Yildiz Technical University	2017
Undergraduate	(computer Engineering and Program)	Diyala University	2006
High School	science	Atared Secondary School	2002

Year	Corporation/Institute	Enrollment
2010 - 2014	University of Tikrit / Iraq	Teacher
2008 - 2010	University of Diyala / Iraq	Teacher

PUBLISHMENTS

Conference Papers

1. Mahmood, S.D. and SERBES, G., (2107). “AUTOMATIC DETECTION OF EPIDURAL HEMATOMA ON THE BRAIN IMAGES USING IMAGE PROCESSING TECHNIQUES “, ICAS 2017” “International Conference on Advances Science, 4 January - 6 January 2017, Istanbul, Turkey.

2. Mahmood, S.D., (2106). “DEFINATION OF IMAGE INTERPOLATION AND THE RESULT OF ALGORITHMS “, ICAS 2016” “International Conference on Advances Science, 31 Aguste - 2 September 2016, Istanbul, Turkey.