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Souhil Larbi BOULANOUAR

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Dr. Lamri SAYAD	Université Mohamed Boudiaf de M'sila	Président
Dr. Allaoua HEMMAK	Université Mohamed Boudiaf de M'sila	Rapporteur
Pr. Hocine BELOUADAH	École Normale Supérieure de Bou Saâda	Examinateur
Dr. Noureddine CHIKOUCHE	Université Mohamed Boudiaf de M'sila	Examinateur
Dr. Mohamed BENOUIS	Université Mohamed Boudiaf de M'sila	Examinateur

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New Hybrid Method for Segmentation of MRI Medical Images

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Dr. Lamri SAYAD	University Mohamed Boudiaf of M'sila	President
Dr. Allaoua HEMMAK	University Mohamed Boudiaf of M'sila	Reporter
Pr. Hocine BELOUADAH	ENS of Bou Saâda	Examiner
Dr. Noureddine CHIKOUCHE	University Mohamed Boudiaf of M'sila	Examiner
Dr. Mohamed BENOUIS	University Mohamed Boudiaf of M'sila	Examiner

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GENERAL INTRODUCTION

General Introduction

Medical imaging techniques are very useful in diagnosing and treating various medical issues. They are non-surgical techniques that are used for investigating inside the patient's body without the need to open it. Over the past decades, researchers have focused on developing and enhancing these techniques, the most important and widely used imaging techniques include X-Ray, Computed Tomography (CT) and Magnetic Resonance Imaging (MRI), each one of them comes with its own different advantages and disadvantages. X-Ray and CT scans can imaging dense tissues in a very good way, but these medical imaging techniques depend on using high-energy electromagnetic radiation, which could harm the staff and damage the patient's healthy tissues and increase the chances of getting cancer in the future. Magnetic Resonance Imaging (MRI) is a diagnostic technology based on exciting the body's protons and receiving the resultant energy to generate Two-Dimensional (2D) and Three-Dimensional (3D) cross-sectional images without using harmful radiation. Generally, an MRI scanner is comprised of three main components, a main magnet surrounds the patient and is considered the most expensive component, gradient system that has a small strength magnetic field used for signal localization and a Radiofrequency (RF) system that consists of an RF transmit coils and an RF receiver coils. Doctors and radiologists are using MRI in many applications such as detecting tumors, strokes, cysts and anomalies of the brain and spinal cord, it is also a helpful tool for surgery planning. The first MRI scans took several hours to produce an image, meanwhile in nowadays and with the huge development in both software and hardware, MRI scans can be performed within minutes and produce very good image quality [1].

Brain MR images are extremely complex and contain very sensitive and critical information about a patient's health that doctors must discover. Because of that, the process of segmentation has been introduced to improve the visualization and facilitate the delineation of different brain anatomical structures. Generally, image segmentation could be defined as the process of dividing a digital image into various sets of regions that have the same characteristics [2]. Medical image segmentation divides and identifies anatomical organs and structures of the human body, it is a challenging and difficult task in image processing because of the high complexity and variability in medical imaging modalities, such as X-ray, CT and MRI. Our study's goal is to segment brain MR images to facilitate for doctors the measuring and visualizing of the brain tissues, Cerebrospinal Fluid (CSF), Gray Matter (GM) and White Matter (WM). MRI scans are affected by a variety of artifacts, including noise, density inhomogenity and partial volume effects. These artifacts have negative effects on the quality of the segmentation process.

During the last years, researchers have introduced many segmentation techniques to overcome the Magnetic Resonance Imaging (MRI) artifacts and to improve the quality of the segmentation results such as clustering, edge detection, thresholding, region growing, and other techniques, each has its own set of benefits and limitations. The field is still open for improving the current techniques and proposing new ones.

Clustering techniques work on the concept of partitioning data or digital image into a set of groups, or clusters, the pixels of the same cluster are similar while they are dissimilar to pixels of other clusters. In the last few years, researchers have proposed many clustering techniques including hierarchical clustering methods, partitional clustering methods, non-iterative partitional methods and other techniques. However, k-means and fuzzy c-means algorithms are the most commonly used for the medical images segmentation.

Fuzzy C-Means Clustering (FCM) algorithm is a soft clustering method based on fuzzy sets theory, FCM is considered as an unsupervised technique that divides the data or the digital image into a number of clusters [3]. What distinguishes this algorithm over the rest is that the data or the image's pixels can belong to more than one cluster at the same iteration with a certain probability value called membership value. Fuzzy C-Means (FCM) clustering algorithm has shown great efficiency in brain MRI segmentation and produced remarkable results. However, FCM suffers from many drawbacks, such as the sensitivity to imaging artifacts such as noise, density inhomogeneity and partial volume, the sensitivity to the initial cluster centers and the need to determine the cluster centers number. To solve these problems, many FCM variants have been proposed in the literature. The researchers also used the techniques of hybridization and optimization to improve the standard FCM and to overcome its drawbacks.

Combinatorial Optimization (CO) is the problem of finding the best solution among many possible but finite solutions, it's applied in various fields including computer vision, image processing, artificial intelligence, machines learning, software engineering and applied mathematics. The Fuzzy Clustering Problem (FCP) is a Combinatorial Optimization (CO) problem that seeks to find the best clusters (best separation) among many possible sets of clusters. The optimization problems could be solved by exact and approximate methods, the exact methods are ensured to find a provably optimal solution but they are unsuitable for high complexity optimization problems because of the huge execution time needed for solving these types of problems. On the other hand, the approximate methods consume a reasonable execution time and they are very suitable for solving complex optimization problems [4].

Metaheuristic algorithms are the most used approximate optimization techniques in the last few decades, they have achieved great success in solving many challenging combinatorial optimization problems in different fields. Compared to heuristic methods, metaheuristic methods are often problem-independent techniques that can be applied to a broad range of problems, it can also find high-quality solutions with less computational effort and resources. As an example of the metaheuristic algorithms, we mention, Simulated Annealing (SA), Artificial Bee Colony (ABC), Genetic Algorithm (GA), Firefly Algorithm (FA), Particle Swarm Optimization (PSO), Bat Algorithm (BA) and many other. There are several classifications for metaheuristic algorithms, firstly, they could be classified according to their origins into nature-inspired vs. non-nature inspired, secondly, they could be categorized into memory usage vs. memory-less methods based on the use of search history, thirdly, they classified into single-point method vs. population-based method.

Bat Algorithm (BA) is a bio-inspired metaheuristic algorithm proposed in 2010 by Xin-She Yang [5], bat algorithm works on the concept of microbats echolocation behavior to find their prey, it has received significant attention by researchers in recent years due to its great ability for solving different kind of optimization problems.

In our thesis, we developed a new hybrid method for brain MRI segmentation called Modified Fuzzy Bat Algorithm for Fuzzy C-Means MFBAFCM, our hybrid method combines the Bat Algorithm (BA) with the standard Fuzzy C-Means (FCM) clustering algorithm to overcome its drawbacks. Firstly, we introduced some existing adjustments to the Standard Bat Algorithm (BA) to be suitable for solving fuzzy clustering problems and called it Fuzzy Bat Algorithm (FBA). Secondly, we modified the Fuzzy Bat Algorithm (FBA) to be more efficient and named it Modified Fuzzy Bat Algorithm (MFBA), the modification was made by replacing all bats, its fitness value does not change four times sequentially by new solution, this solution generated by calculating the average of the best five solutions achieved. Finally, we used the MFBA to get better initial cluster centers for the standard FCM algorithm by using a new fitness function that combines intra cluster distance with fuzzy cluster validity indices. The experimental results on several brain MR images corrupted by different levels of intensity non-uniformity and noise, show that our proposed method MFBAFCM produces better results than the standard FCM and some other recent published works.

Our thesis consists of five chapters, the details of these chapters are as follows:

The first chapter provides an overview of medical imaging techniques. First, we have mentioned the X-Ray and Computed Tomography (CT) scanners, which were the first medical imaging technologies and they have provided great services to the medical field. Second, the first chapter focused on Magnetic Resonance Imaging (MRI), we have discussed the main components and the process of the MRI system then the imaging sequences and the clinical applications of MRI, in addition to the Magnetic Resonance Imaging (MRI) artifacts.

The second chapter offers a summary of MRI segmentation. We have defined the segmentation in the digital image, then in the brain MR images. Furthermore, the second chapter gives a detailed presentation on MRI segmentation techniques.

The third chapter discusses the previous work on MRI segmentation based on clustering and metaheuristic methods. Moreover, we have presented the metaheuristic optimization and the hybridization techniques.

In the fourth chapter, we have given a detailed explanation of the methods used in our study, which are Fuzzy C-Means (FCM) clustering algorithm and Bat Algorithm (BA). We have mention their basics, pseudo codes, applications, limitations and their improved versions.

In the fifth and the last chapter, we present our contribution in the brain MRI segmentation, we have proposed a hybrid method based on Modified Fuzzy Bat Algorithm (MFBA) and the Fuzzy C-Means (FCM) clustering algorithm named MFBAFCM. Furthermore, the fifth chapter discusses the experimental results on our method MFBAFCM compared with the standard FCM and other tested methods.

CHAPTER 1

MEDICAL IMAGING OVERVIEW

Chapter 1

Medical Imaging Overview

1.1 Introduction

In the past years, a huge contribution has been made to medicine by medical imaging, which can generate a number of different and detailed images representing human anatomy. The most important and widely used imaging techniques include X-ray, Computed Tomography (CT) and Magnetic Resonance Imaging (MRI). Each technique comes with its own different benefits and risks. The medical images have very high sensitivity to different human tissue properties because of the difference in imaging principles. For example, X-ray and CT can provide very good image quality when looking at dense tissues (such as bones). On the other hand, the images resulting from the soft tissues will be poor and not clearly. In contrast, MR images can give an excellent contrast between different forms of soft tissues. However, it is unable to illustrate the physiological processes. These medical images are often used to assist in the diagnosis and treatment of different diseases. The details of medical imaging techniques are introduced in the following subsections.

1.2 X-Ray Radiography

Radiography introduced to the medical field with the discovery of X-ray by Wilhelm Conrad Roentgen in 1895, it is a medical imaging technique for the diagnostic process, which uses X-rays to visualize human anatomy [6]. An X-ray is a form of high-energy electromagnetic radiation that can pass through solids and ionize gases. Its wavelength ranges from 0.01 to 10 manometers. The imaging process starts by producing beams of X-rays that penetrate the patient's body. The exposed organs and tissues absorb an amount of energy depending on their densities and compositions, and then a detector captures the remaining X-ray energy and uses it to create a 2D image. Despite the fact that X-ray is the oldest medical imaging technique, it is still commonly used for disease screening due to its low cost and wide availability. However, the high level of radiation-emitted can expose patients and staff to skin reddening, hair loss and even harmful diseases like cancer. Figure 1.1 shows the X-ray scanner system.

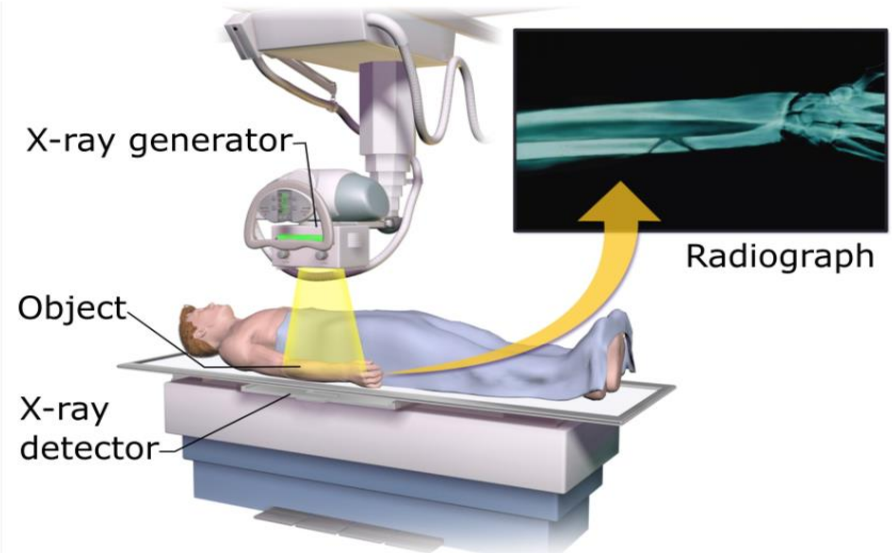


Figure 1.1: The system of X-ray scanner. This image was obtained from [7].

shoulder knees Head

Figure 1.2: Examples of X-ray images. These images were obtained from [8].

1.3 Computed Tomography (CT)

Cormack is the first who described Computed Tomography (CT) as an imaging technique in 1963, then in 1972 Hounsfield performed the first clinical CT scanner. CT consider as a medical imaging technique that makes use of computer processed X-rays measurements taken from different angles to produce tomographic (cross sections) of the human body [9], The scanner device includes a moving table and a rotating frame that has an X-ray tube and a detector, both are mounted on opposite sides. A series of projectional X-ray images were taken while the X-ray tube and detector rotated around the patient to cover all the angles. The CT image will be reconstructed by a computer from a large number of X-rays images (slices). In clinical, CT images are commonly used for diagnostic and therapeutic purposes of various organs, such as lung, brain and heart, this is because CT images are quick, painless, have global view of veins and provide a good soft tissue contrast as well as high spatial resolution. However, it has a lot of disadvantages as the high level of radiation which could damage the healthy tissues and increase the possibility of getting cancer later, and it also can not detect intra-luminal abnormalities and can not be performed without contrast (allergy, toxicity). Figure 1.3 shows the system of computed tomography scanner.

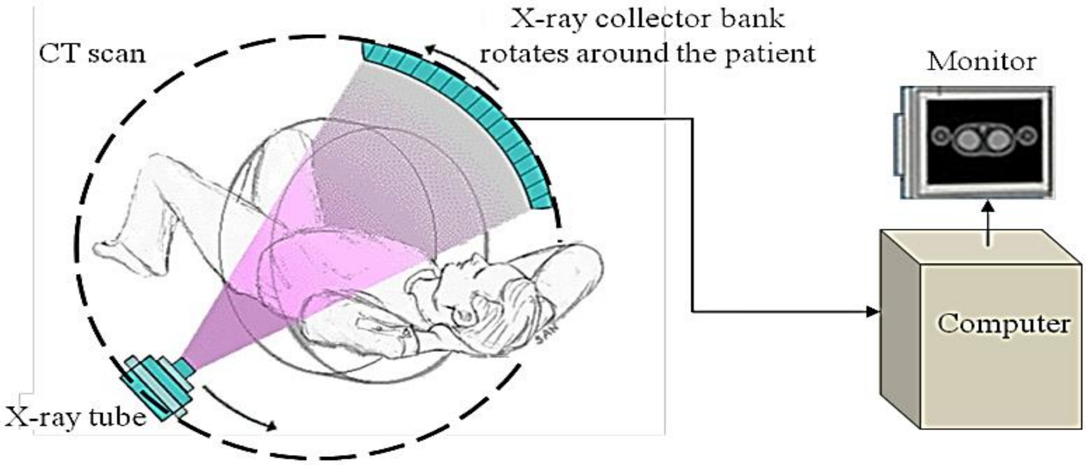
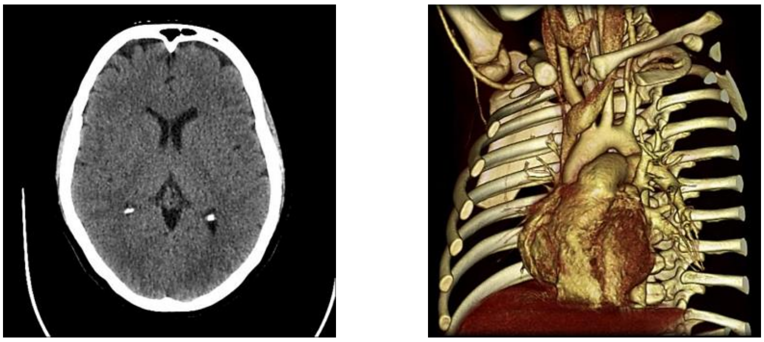


Figure 1.3: The system of CT scanner. This image was obtained from [1].



2D Brain 3D mediastinal anatomy

Figure 1.4: Examples of Computed Tomography (CT) images. These images were obtained from [8].

1.4 Magnetic Resonance Imaging

1.4.1 Introduction

In the early 1980s, Magnetic Resonance Imaging (MRI) entered the medical field. Since then, MRI has experienced huge progress related to the growing number of its clinical applications. MRI has become an indispensable diagnostic imaging technique and continues to play this role until nowadays. This great success is the result of the good characteristics of anatomical MRI, it is capable of generating high quality two-dimensional (2D) as well as three dimensional (3D) cross-sectional images inside of the human body without using harmful radiation. MRI is a non-invasive technology and commonly used for diagnosis, detection and treatment of various diseases. It is a technology based on exciting the protons found in the water and detecting the result energy to generate the cross-sectional images. We notice now that the MRI machine has become an important equipment in modern hospitals. Tens of thousands of MRI scanners are installed across the world, and tens of millions of MRI examinations are being performed each year [10].

Figure 1.5: Magnetic resonance imaging scanner. This image were obtained from [11].

1.4.2 The MRI Hardware

In general, MRI scanner is comprised of three main components:

1.4.2.1 Main Magnet

A large and expensive magnet surrounding the patient. It is a cylindrical and mostly superconducting magnet that has a set of metal coils. The MRI system uses the liquid helium to cool these coils to near absolute zero and reduces their resistance to zero to become superconducting and provide the magnetic field needed for MR. Imaging magnets have a high field strength B_0 to provide a strong tissue magnetization and, thus, a high Signal-to-noise ratio (SNR) for good image quality [12]. The MR scanner can be classified according to its magnetic field strength to:

a) Low-field MRI Scanners: called open MRI scanners, which means the patient isn't completely surrounded by the magnet Figure 1.6 (b). It requires less space and less expensive. It has a range of 0.2T up to 1T. Since the magnet of low-field MRI scanners does not traverse around the entire body, these kinds of scanners produce poor images quality and take long time to scan. These scanners are useful for avoiding claustrophobia and overweight problems [13].

b) High-field MRI Scanners: called closed MRI scanners, which means surrounding the patient by a magnet. These scanners produce magnetic fields that have a range of 1T-3.0T. In small hospitals, a 1.5T MRI scanner is considered the standard clinical machine, while the 3.0T MRI scanner is faster and provides better quality images, especially with the small organs and tissues such as brain and heart vessels. However, closed MRI scanners can be unsuitable for claustrophobic patients and have weight restrictions.

c) Ultra High-field MRI Scanners: Ultra high-field MRI uses a magnet strength of 7T or higher. These closed MRI scanners are considered as the most powerful machines currently available in the medical field. They are faster and more effective in the diagnosis process than the high-field MRI scanners. However, they are still uncommon in hospitals due to their high cost and they have very huge SAR (the amount of energy absorbed from RF waves by the patient) because of the strong magnetic field. Various magnets used for MRI machine is shown in Figure 1.6.

(a) (b)

Figure 1.6: Various magnets used for MRI: (a) 1.5T high-field closed magnet MRI system, (b) 0.3T low-field open MRI system. These images were obtained from [14].

1.4.2.2 Gradient System

In gradient system, there are three gradient coils x, y and z they have small strength magnetic field comparing with the main magnetic, these magnets are very important in signal localization. They generate linear fields that are superimposed over a strong uniform magnetic field, which is generated by the main magnet. Adjusting the gradient magnets allows the MRI machine to focus on a specific part of the body and create images "slices" for it [15].

1.4.2.3 Radiofrequency (RF) System

The Radiofrequency (RF) system is the main part of the MRI scanner. Generally, an RF system consists of an RF transmit coils and RF receiver coils. The radiofrequency transmit coil transmits RF waves to generate the MR signal and excite the protons, while the RF receiver coil receives the resonance signal leaving the patient. Typically, the RF receiver is placed near the body's part that is being scanned during the exam to optimize the received signal. According to the imaging part, there are different coils such as heads, wrists, knees, and necks [12]. The system of MRI machine is shown in Figure 1.7.

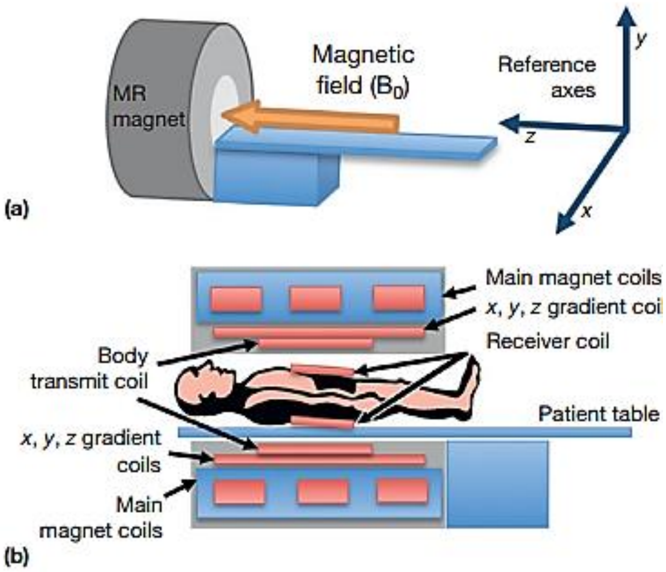


Figure 1.7: The Magnetic Resonance Imaging (MRI) system (a) the direction of the main magnetic field (B_0). (b) Schematic diagram showing the main coils in a typical MRI system. These images were obtained from [16].

1.4.3 Process of the MRI System

Up to 60% of our whole bodies are made up of water, the oxygen atom is connected to two hydrogen atoms in each of the billions of water molecules that make up our bodies. Proton, which is a little component of hydrogen atoms behaves as a tiny magnet and has extreme sensitivity to magnetic fields, the Magnetic Resonance Imaging (MRI) scanner benefits from this sensitivity to produce good quality medical images to assist in the diagnosis and treatment of different body disease. The basic steps of MRI scanner are as follows [1]:

The first step: doctors must remove any metal from patients' bodies. After that, the patient is placed in a strong unified magnetic field B_0 produced by the main magnet.

The second step: To focus and isolate a certain part of the body, the gradient coils adjust the magnetic field into smaller regions with different magnetic strengths. When the patient lies inside the magnetic field, the hydrogen atoms (protons) in his body become aligned with the magnetic field.

The third step: Radiofrequency (RF) transmit coil sends radio waves B_1 that match or resonate with the magnetic field, causing the protons to absorb amount of the energy and tilt away from the direction parallel to the magnetic field, which means entering the excited state.

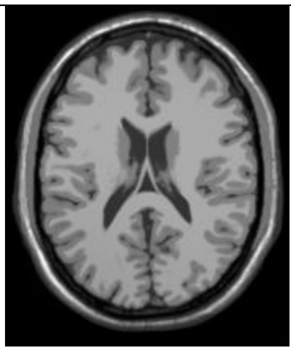
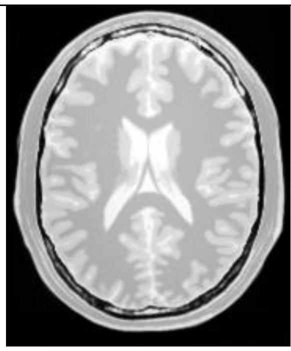
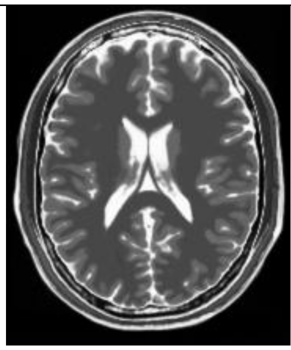
The fourth step: When the Magnetic Resonance Imaging (MRI) scanner's radio waves stop being emitted, the excited protons release the energy and go back to their position (it is called relaxation). The RF receiver coil picked up this energy then sent a signal to a MRI scanner 's computer, which uses a developed software to convert the data obtained from the imaging into an image of a specific body part.

1.4.4 MRI Sequences

The most used MRI sequences are T1-weighted, T2-weighted and Proton-Density PD weighted. There are two important parameters that control most of these sequences, which are Repetition Time (TR) and Echo Time (TE).

Repetition Time (TR) refers to the time between successive pulse sequences applied to the same slice, while Echo Time (TE) indicates the amount of time between transmitting the RF pulse and the receipting of the echo signal. The important values in determining the relative contrast of various tissues are TE and TR, where combining short TR and short TE will lead to T1 weighted images, long TR and long TE will generate T2 weighted images, long TR and short TE lead to proton-density- weighted images [17]. Some different MRI modalities are shown in Table 1.1. Each MRI sequence contains specific information, so the choice between different sequences depends on the case studied.

Table 1.1: Different MRI modalities.

	Short TR (500 msec)	**Long TR (4000 msec)**
Short TE (14 msec)		
	T1 weighted	PD weighted
Long TE (90 msec)	**Poor contrast**	
		T2 weighted

1.4.5 Clinical Applications of MRI

Unlike X-ray and computed tomography (CT) scans, MRI doesn't use harmful radiation. Due to that, it's considered as the safest and the favorite imaging machine by many doctors, especially with the soft tissues or non-bony parts of the body. During the past years, the MRI machine has proven its effectiveness in early diagnosis and detecting different diseases, including various organs. With the brain, MRI can distinguish between White Matter (WM), Grey Matter (GM) and Cerebrospinal Fluid Flow (CSF), which used to diagnose tumors and aneurysms. With the spinal cord, it helps to find cancer, blood vessel damage and spinal cord injuries. It also helps with the heart and the bones by looking for heart disease, bone infections, damage to joints …etc.

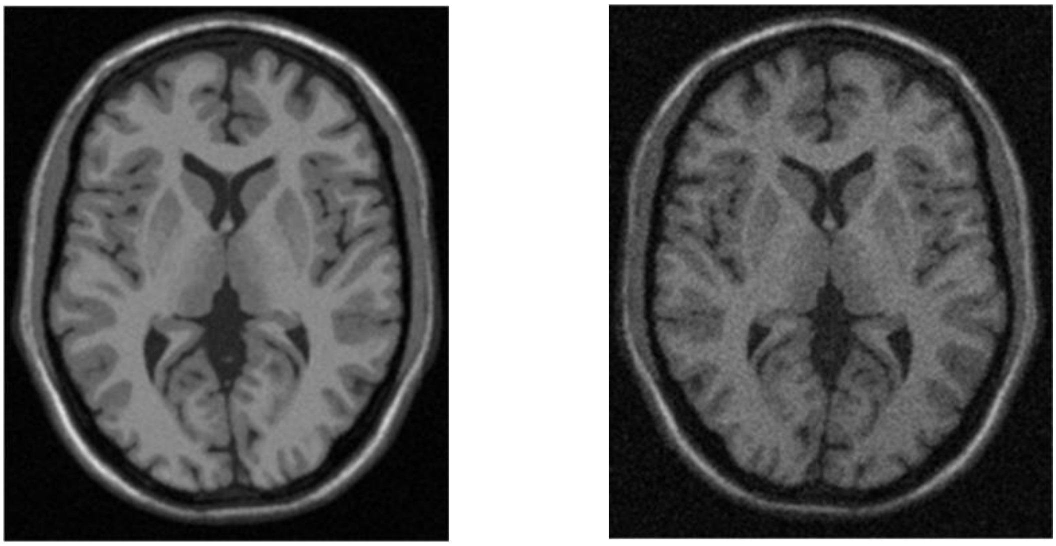
An MRI can be done to check the health of other organs such as the liver, kidneys, and pancreas, prostate…etc. In the surgical field, the 3D MR images of different organs and structures of the body provide global vision and help doctors to simulate and plan surgeries. However, MRI scans involve some drawbacks, such as: the long scan and post processing time (the exams can take more than 60 minutes), the scan is relatively expensive and can make some people feel claustrophobic and also the loud noise during the scan experienced by the patients.

1.4.6 MRI Artifacts

MRI produces several specific artifacts, which can defined as a feature appearing in an image during the scan that must not appeared, some of these artifacts have a bad effect at the quality of the MRI exam while others do not, but can make a big confuse to the doctors., be familiar with them is necessary for a correct diagnosis. Generally, artifacts can be classified into three categories. First, patient-related artifacts like motion artifacts, flow and metal artifacts. Second, signal processing-dependent artifacts like gibbs artifacts, partial volume, wrap-around and chemical shift artifact. Third, machine (hardware)-related as RF inhomogeneity, RF noise, external magnetic field (B_0) inhomogeneity, bounce point artifact …etc. [18]. We will focus on three principal artifacts:

1.4.6.1 Motion Artifact (Noise)

In Magnetic Resonance Imaging (MRI), motion artifact considered as the most popular artifact [19]. It causes either ghosts or blurred images in the phase-encoding direction. The main reasons for this artifact are voluntary motions, involuntary motions, and physiologic motions, which could cause a huge significant on the sharpness of the images. These motions can cover and reduce the visibility of certain features within the image. The patient's voluntary motions may be controlled by explaining the process of the machine and the importance of keeping still and calm. However, handling with children may be more difficult, and sedation might be necessary. Involuntary motions, generally happen because of mental illness such as Parkinson’s disease or Huntington's chorea, they are harder to handle. Patient's physiologic motions are caused by different factors, such as respiration and cardiac action, and it's harder to handle. Short sequences help reduce the likelihood of motion artifacts.



(a) (b)

Figure 1.8: Motion artifact (Noise) in brain MR images (a) normal brain MRI image, (b) noisy brain MR image. These images were obtained from [20].

1.4.6.2 Chemical Shift Artifact

It is a patient-related artifact and a common finding on some MRI sequences. It happens in the frequency-encoding phase because of the slight differences in the resonance of fat and water's protons. The protons of fat resonate at a slightly lower frequency than those of water [18].This artifact caused a mismapping of fat and water pixels, which appeared as white or dark bands around mostly organs and structures that contained water and were surrounded by fat, such as the liver, optic nerves, kidneys, muscles… etc. Reducing the signal from the fat by some suppression techniques and adjusting imaging parameters can be helpful for reducing this artifact. Figure 1.9 shows an example of a chemical shift artifact.

1.4.6.3 Surface Coil Artifact

Surface coil is a specific type of RF receiver coil, it's small to be placed near the imaged part of the body. The signal strength is very strong near the surface coil, which cause very intense image signal. However, as the distance from the surface coil is increased, the signal drops rapidly and causes shading and a large loss of image brightness. A post-processing filter is considered an effective solution to overcome this artifact. Figure 1.10 shows an example of surface coil artifact.

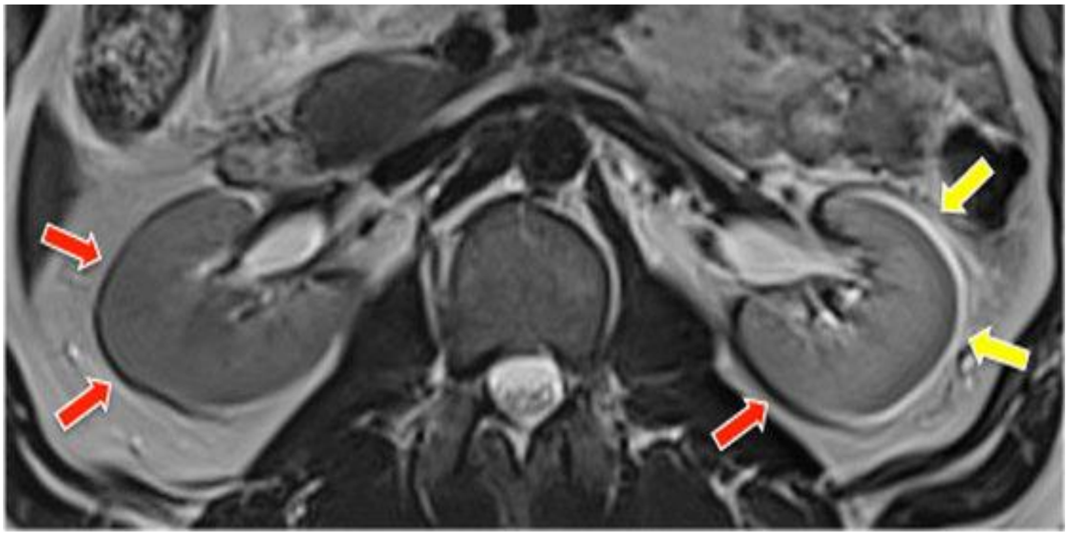


Figure 1.9: MR image with chemical shift artifact on a kidney, the red flashes refer to the dark bands, while the yellow flashes refer to the white bands. This image were obtained from [21].

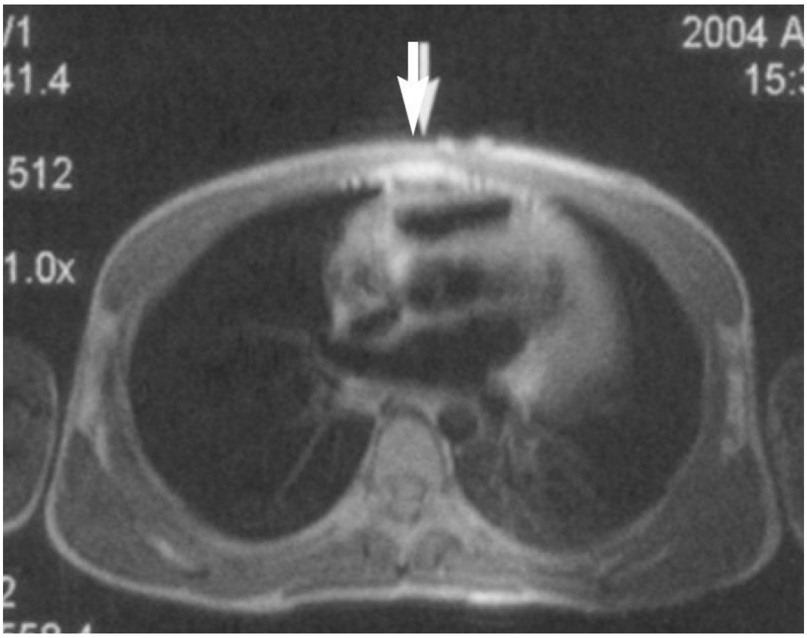
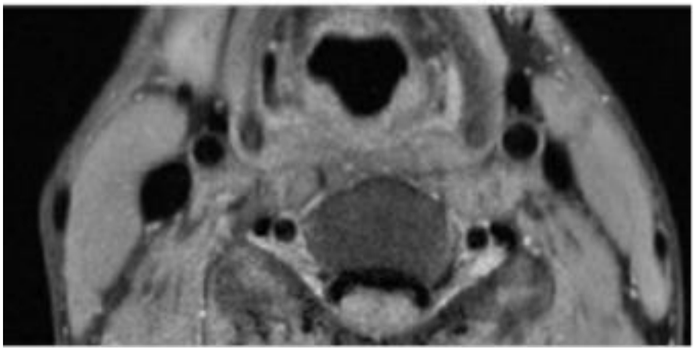


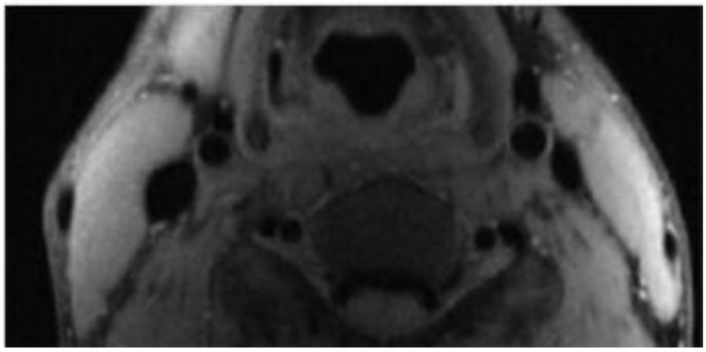
Figure 1.10: High signal at anterior thoracic wall adjacent to surface coil. This image were obtained from [18].

1.4.6.4 Intensity Inhomogenity Artifact

Intensity inhomogenity is also called Intensity Non-Uniformity (INU), it is smooth spatially function that modifies the intensity within homogeneous areas. Intensity Inhomogenity is a challenging problem in Magnetic Resonance Imaging (MRI), especially with brain MR images, it is caused by the bias field which is low frequency signal that corrupts MR images. This artifact will negatively affect segmentation and classification algorithms, especially those that depend on the gray level values of image pixels [22]. Figure 1.11 shows an example of an intensity inhomogenity artifact.



(a)



(b)

Figure 1.11: Example of intensity inhomogenity artifact (a) normal MR image, (b) MR image corrupted by intensity inhomogenity artifact. These images were obtained from [10].

1.4.6.5 Partial Volume Artifact

The partial volume artifact represents a voxel (or pixel) that has contributions from several tissue types, in other words, it indicates the lack of contrast between two neighboring tissues as a result of the absence of high resolution, which means that one voxel (or pixel) contains more than one tissue type [10].

1.5 Conclusion

In this chapter, we have introduced an overview of medical imaging techniques. We have presented the X-ray and CT machines, which have provided great services to the medical field. We have provided a detailed presentation of the MRI machine, which has proven its effectiveness in early diagnosis and detecting various diseases. Even with the great development of MRI during the past years, its resulting images still suffer from some bad effects, which are related to either the patient, the signal or the machine itself. These artifacts have a bad influence on doctors' judgments and decisions. Due to that, MR images sometimes need some treatment and processing, especially the brain images.

One of the essential processing operations is segmentation, which helps especially in differentiate between the different tissues of the brain: White Matter (WM), Grey Matter (GM) and Cerebrospinal Fluid Flow (CSF), which is what we will focus on in our study. In the next chapter, we will present an overview of the MRI segmentation techniques.

CHAPTER 2

MRI SEGMENTATION

Chapter 2

MRI Segmentation

2.1 Introduction

Digital image processing depends on computer algorithms to achieve various tasks such as analysis, manipulation and interpretation. Image segmentation is an exemplary and a hotspot subject in image processing, it aims to create a content based separation by dividing an image into set of regions. MRI segmentation is a critical step and has an essential role in the medical field, because of its complexity and diversity, the segmentation of MR images, specially the brain MR images continues to be a challenging problem and various techniques and approaches has developed to improve the segmentation process. The details of the image segmentation, MRI segmentation and their different techniques are discussed in the following subsections.

2.2 Image Segmentation

It is easy for humans to identify various objects, track movements recognize forms, determine contours and do other tasks that are considered very complicated for machine and need a lot of effort and resources to be achieved. The big challenge for computer vision experts is to comprehend human visual function and replicate it using algorithms. To face this challenge, an important step must be done which is identification of homogeneous regions within an image, this procedure is known as image segmentation, which defined as the process of partitioning an image into a set of meaningful and disjoint regions based on some criteria [2].

For example, in 2D digital image that contains an animal face in front of a black background, it would be easy for a human to distinguish the face from the background, and then detect the hair, the mouth and the eyes from the face. However, when it comes to the machines it will be quite difficult and it will need a segmentation algorithms. The first step of these algorithms is to input an image that consists of vague set of pixels. The second step focuses on using different approaches and techniques to split and group a certain set of pixels that share similar parameters or characteristics, such as intensity and texture. The image segmentation algorithms are based on grouping neighboring pixels that have the same or similar gray values, this divide the image into a set of non-overlapping regions. In the final step, the segmentation algorithms use these regions to specify boundaries, draw lines, and separate the objects in an image from the rest and create a segmented image or set of segmented images each one contains specific object. Figure 2.1 shows a block diagram of image segmentation process.

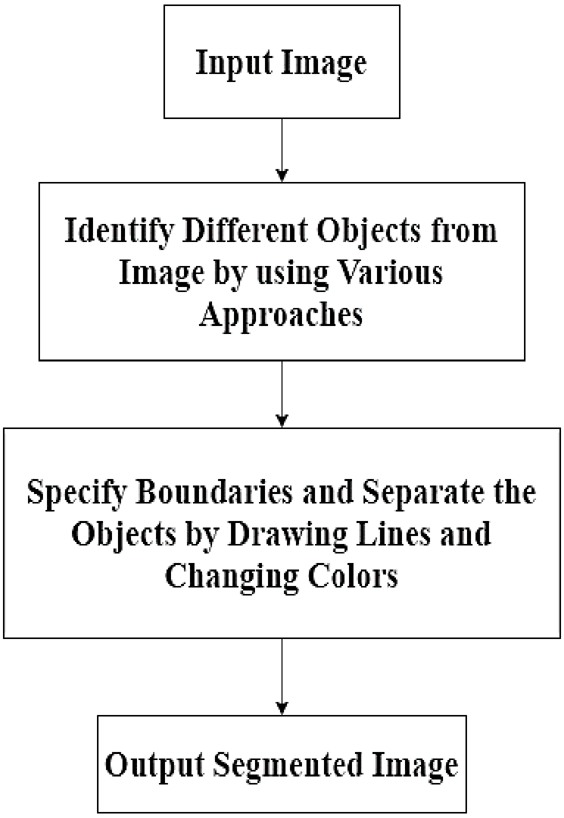


Figure 2.1: Block diagram of image segmentation process.

2.3 MRI Segmentation

In the past years, medical image segmentation technology has grown rapidly because of its importance, although much progress has been made in this field, there is still space for more development and improvement. In digital image processing, medical image segmentation considered as a subfield of image segmentation that has many important applications in the field of medical image analysis and diagnostics, it segments and identifies anatomical organs and human body structures of different medical image modalities such as X-ray ,Computed

Tomography (CT) and Magnetic Resonance Imaging (MRI). The purpose of the MRI segmentation is to improve the visualization and detection processes and make them more effective and efficient, furthermore, it provides critical information about the volumes and the shapes of organs and anatomical structures, it also makes things simpler for doctors in diagnosis and making decisions [23].

2.3.1 Brain MRI Segmentation

The human brain is a complex organ protected within the skull and controls all the body's functions such as thinking, moving, breathing, vision and many others. The brain sends and receives information or messages in the form of chemical and electrical signals through the five senses from and to the outside, some of these messages are transmitted to their destination via the spine, while others are kept within the brain.

The brain has three main parts, the cerebrum, brainstem and cerebellum [24]. First the cerebrum, the front of brain that consider the biggest part of the brain, it is composed of the gray and white matter. Secondly the brainstem, the middle of brain that its main role is connecting the cerebrum with the spinal cord, it is composed of the medulla oblongata ,midbrain and the pons. Thirdly the cerebellum, that situated in the back of the head, the cerebellum is essential for motor control and involved in cognitive skills such as attention and language.

The general anatomy of the human brain is shown in Figure 2.2.

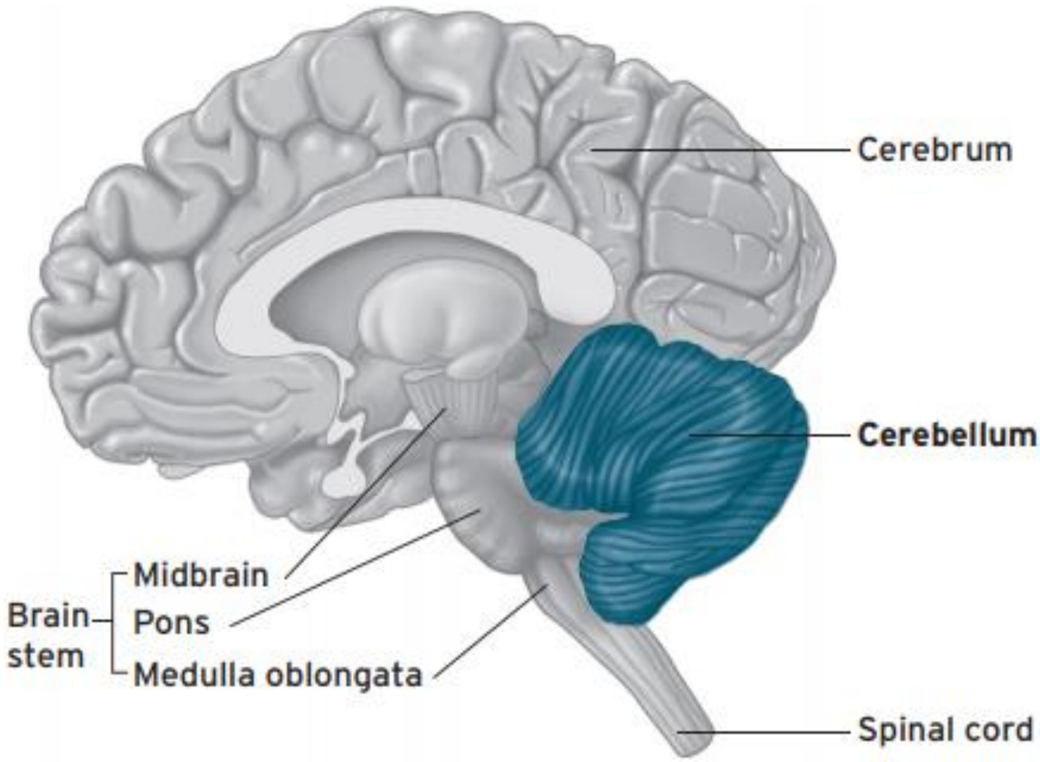


Figure 2.2: General anatomy of the human brain [24].

Brain tissues such as White Matter (WM), Gray Matter (GM), and Cerebrospinal Fluid (CSF) have a sensitive information about the health of the patient, the aim of our study is to segment the GM, WM and CSF of brain MRI scans. Figure 2.3 shows an example of the brain MRI tissues segmentation.

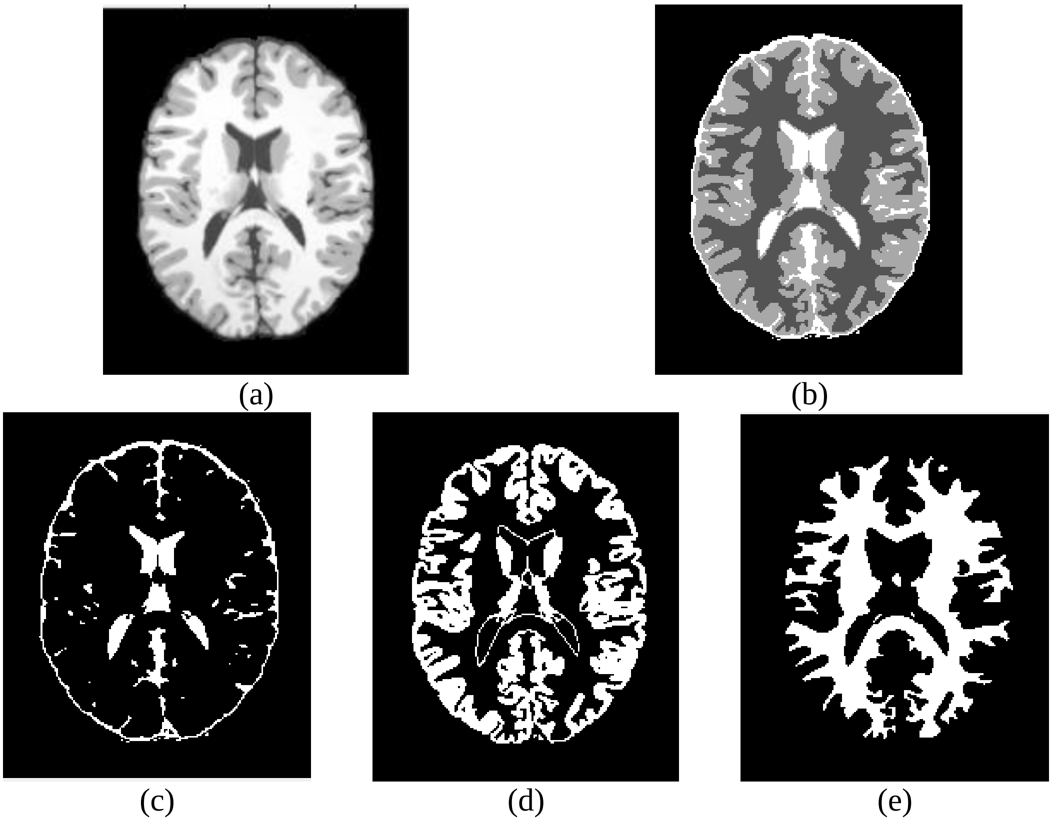


Figure 2.3: Example of the brain MRI segmentation, (a) original brain MR image, (b) global segmented image, (c) segmented image of the CSF brain image (d) segmented image of the GM brain image, (e) segmented image of the WM brain image.

MRI segmentation is a difficult task and has many problems and challenges that effect the quality of the segmentation process, such as high variability in the images, noise, density inhomogenity and partial volume effects. A lot of segmentation approaches and techniques have been proposed to overcome these challenges.

2.4 MRI Segmentation Techniques

In recent years, a great improvement have been made in the MRI segmentation field, several common methods and approaches have been proposed in the recent literature to improve the segmentation process. Because of the huge difference between different types of the MRI scans, there is no single method that could be considered as better technique for all MRI scans. As an example for the image segmentation techniques, we mention [25] thresholding, region growing, clustering, edge detection and other techniques. In this section, we will discuss different techniques and methods that have been used to segment MR images, especially brain MR images which are shown in Figure 2.4.

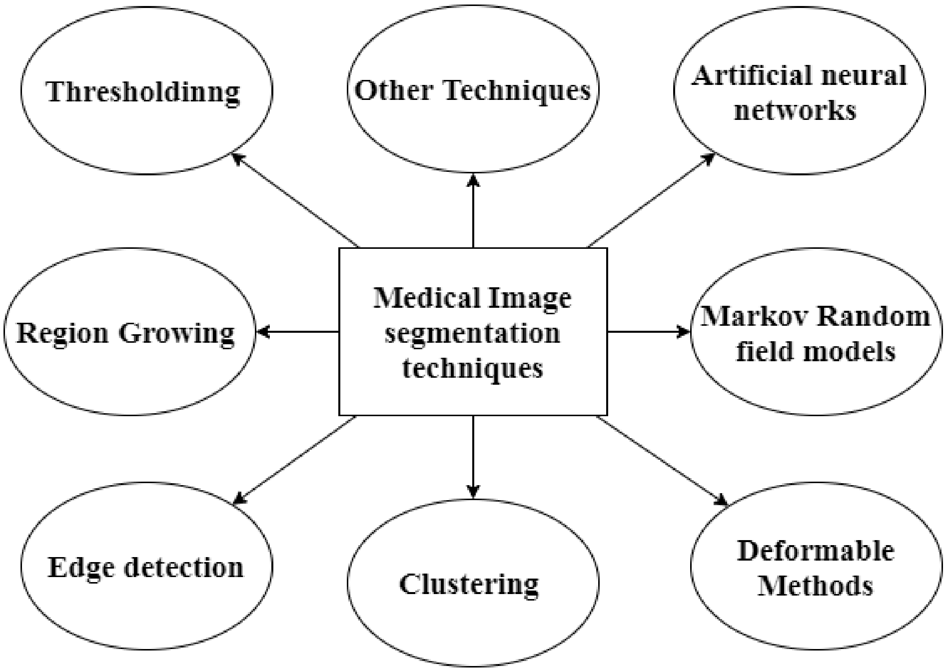
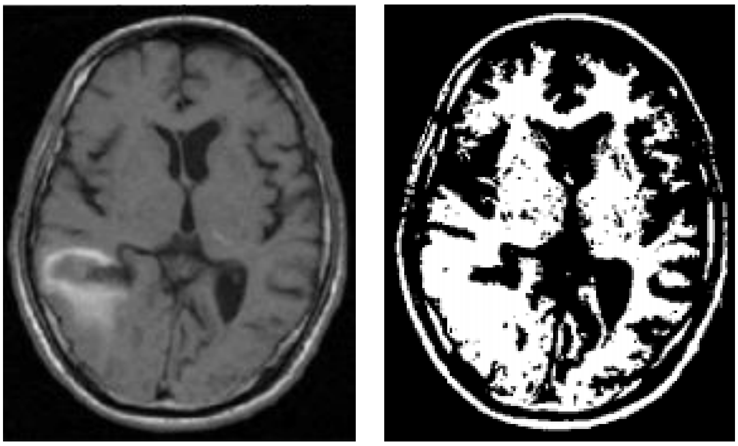


Figure 2.4: Medical image segmentation techniques.

2.4.1 Thresholding Approach

Thresholding is considered the primary approach to image segmentation and the most effective method to eliminate the image background for foreground context analysis. This method aims to convert the grayscale image into a binary image by defining an intensity value called the threshold value, which is used to separate the different regions of the image. The segmentation process done by setting exactly all pixels whose intensities values is above the threshold value into one class and setting all other pixels which are under the threshold value into another class, multithresholding is the process in which more than one threshold value is used [26]. The thresholding results are negatively affected by the noise, strategies of smoothing the image and thresholding with edge detection are useful to reduce the impact of noise on thresholding. In addition, there are many thresholding methods used to achieve the segmentation, Sezgin and Sankur [27] classified these thresholding methods into six categories based on the exploited information, which are histogram shape-based methods, entropy-based methods, clustering-based methods, object attribute-based methods, local methods, and spatial methods.

Much research has been done with thresholding methods, in [28] the authors suggested a soft thresholding approach for medical images. The approach was based on a membership function and used the image histogram to classify each image pixel into a different region, the approach operates automatically and using spatial operations is what made the approach more effective. Another thresholding segmentation method was presented in [29], the method used Particle Swarm Optimization (PSO) algorithm to determine the best threshold value with Dynamic Inertia Weight (DW-PSO). This method effectively controlled the local and global search in the process of optimal searching. The segmentation results achieved by using (DW-PSO are better than those achieved using the standard PSO.



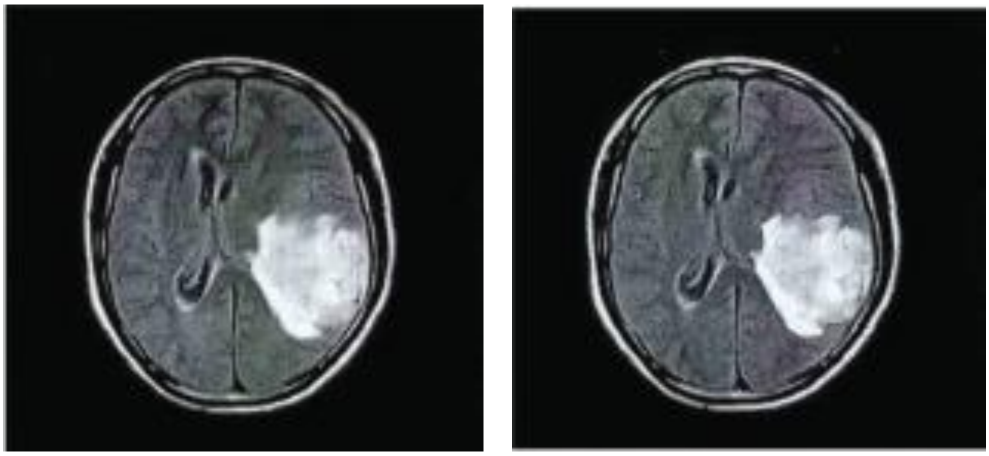
(a) (b)

Figure 2.5: Example of the thresholding segmentation, (a) original grayscale image, (b) segmented image. These images were obtained from [29].

2.4.2 Region Growing Approach

This method works on the concept of extracting regions of interest depending on some predefined condition, such as intensity, shape size, colour or edge details of the image. The process of segmentation first needs to define initial (seeds) points manually for each region, then group all neighboring pixels to the initial point based on the predefined condition. For example, growing the region with pixels has the same intensity values as the initial point or growing the region until meeting an edge in the image. This method is commonly used for extracting tumor regions in the medical field. The main disadvantage with this method is that the quality of segmentation results depends on the initial points, which are selected manually. In addition to this method, there are two more important segmentation approaches based on regions, which are the Region Split and Merge approach and the Watershed approach [30].

Now we will present some of the recent region's growing approaches proposed in the medical field. An automatic seeded region growing approach is proposed for breast MRI tumor segmentation [31], The method is based on the image clustering by the PSO algorithm that in turn is involved in selecting the seed point and threshold value. The method shows good results in segmenting MRI scans of breast tumor compared with other tested approaches. Another segmentation method for brain MRI scans is described in [32]. The method is based on the region growing, it first removes the noise by using an algorithm of anisotropic diffusion filtering to filter the images, then selects the seed points by using the central of RIO, the threshold value is increased through the segmentation processes. The method shows higher performance in reducing the noise and segmenting the brain MR images. An example of the region growing segmentation is shown in Figure 2.6.



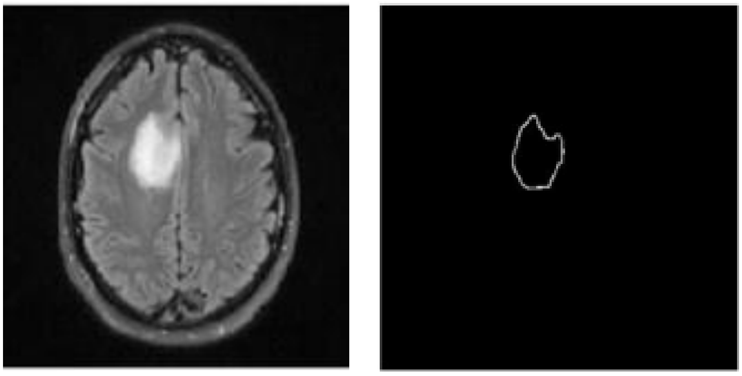
(a) (b)

Figure 2.6: Example of the region growing segmentation, (a) original grayscale image, (b) segmented image. These images were obtained from [32].

2.4.3 Edge Detection Techniques

These approaches are the main tools for image segmentation due to their great efficacy in detecting and outlining objects and backgrounds in an image. Edge detection is the most common way of detecting discontinuity in intensity values of grayscale image, this discontinuity could be in the form of a point, line or edge and separated between two regions having different intensity levels. Edge detection approaches are considered the base technique for other segmentation methods. They also suffer from the bad influence of the noise that needs to be removed before starting the edges detection.

In the literature, several edge detection techniques are proposed for image segmentation [33]. such as Roberts edge detection, Canny Edge Detection, Kirsh edge detection, and other techniques. The authors in [34] presented an MRI segmentation algorithm based on thresholding and edge detection techniques. The goal of this hybrid algorithm is to use the characteristics of an image to find the best threshold value. The approach combines edge detection with an algorithm of modified p-tile, it uses the first for getting information about the shape of objects in an image and uses the second algorithm as the global thresholding. The obtained information from edge detection is very useful for keeping the shape of the original image objects. The results show that this hybrid algorithm has better object segmentation than the conventional algorithm. Another method has been introduced in [35] to detect brain tumor edges in MR images. The method starts by removing the noise with the Balance Contrast Enhancement Technique (BCET) to get better results in the edge detection, then uses the Fuzzy c-Means (FCM) algorithm to segment the MR images.in the final step, it applies the method of canny edge detection to extract the shape and size of fine edges. The obtained results show significant resistance to noise and improve the accuracy of segmentation. Figure 2.7 shows an example of the edge detection segmentation technique.



(a) (b)

Figure 2.7: Example of the edge detection based on fuzzy C-means clustering (a) original grayscale image, (b) segmented image. These images were obtained from [35].

2.4.4 Clustering Approach

Clustering approaches are generally unsupervised methods, image clustering is the task of dividing an image into a predefined number of groups called clusters. All pixels within a specific cluster share the same characteristics and they are more similar to each other than to those in other clusters. Clustering algorithms need initial parameters such as the number of clusters or initial centroids, they are also sensitive to noise and intensity inhomogeneity. There are many clustering techniques in the literature, such as hierarchical clustering methods, partitional clustering methods (centroids-based clustering), non-iterative partitional methods and other techniques. However, k-means and fuzzy c-means algorithms are the most widely used segmentation methods for medical images.

The standard K-means clustering was presented by Stuart Lloyd of Bell Labs in 1957 [36]. In this method, each cluster has a mean or cluster center called the centroid, the clustering is carried out by calculating iteratively the centroid for each cluster, the segmentation is done by categorizing each pixel in the cluster that has the closest centroid. In K-means algorithm, each pixel within an image belongs to only one centroid at a time, this is why it is called "hard clustering". Figure 2.8 shows an example of the K-means process.

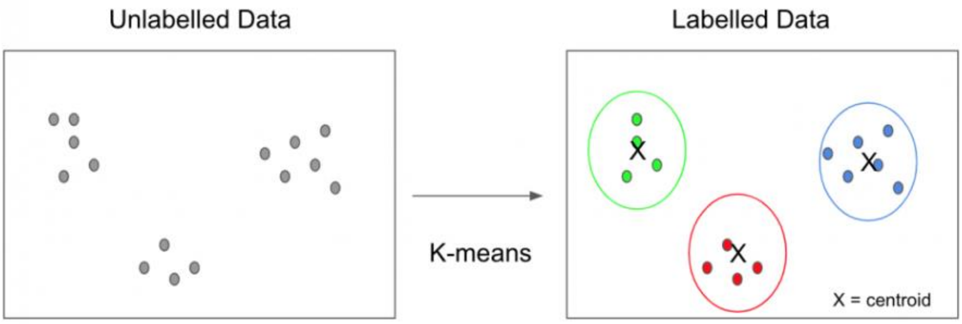
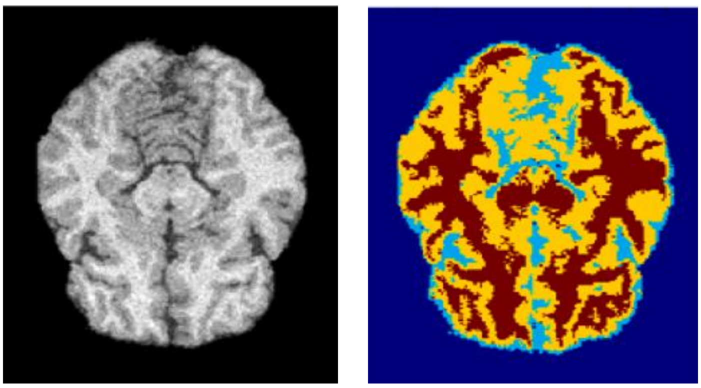


Figure 2.8: Example of the K-means process.

Meanwhile, fuzzy c-means clustering based on the fuzzy set theory, and unlike K-means, each pixel within an image could belong to more than one centroid. It is called "soft clustering" [37]. In the fourth chapter, we will discuss the FCM algorithm in more detail.

In this section, we will present a brief review of some contributions made in medical image segmentation by clustering. The authors in [38] proposed a segmentation method of brain MR images by using a fuzzy c-means approach and statistic histogram information. Their method focused on the determination of an optimal number of clusters needed for the segmentation process automatically. The results demonstrated that the method is faster and more accurate than the classic FCM approach and the FFCM algorithm. To decrease the effect of noise and improve the accuracy of the segmentation process, Balafar .M et *al.* in [39] proposed a new method based on Fuzzy C-Mean (FCM), dominated grey levels in the image and a wavelet approach for reducing the noise. In the clustering stage, dominant grey levels are used as cluster centers. Another approach presented in [40] reduces the noise in MRI segmentation by using neural networks to improve the standard FCM. The method designs a MLP neural network and trains it to label the uncertain pixels resulting from the FCM. An obvious improvement has been seen with the proposed method. To detect brain tumors in MR images, a brain MRI segmentation method has been proposed in [41]. The method works by combining between K-Means and Fuzzy C-Means (FCM). It uses the results of K-means and clusters them again. The experimental results showed that the proposed method is more accurate than the standard algorithms. Li, M et *al.* proposed a segmentation method for brain MR images [42]. They improve the traditional FCM by introducing the regularization of the neighborhood influence and bias field to overcome the issue of intensity inhomogeneity in MR images. Another approach was proposed [43] for brain structure segmentation of MR images. This approach is based on modifying the objective function of the FCM by using double estimation by incorporating both the original and denoised images. The results on both simulated and real MR images showed the effectiveness of the proposed algorithm in reducing noise. An example of brain MRI segmentation based on a clustering approach is shown in Figure 2.9.

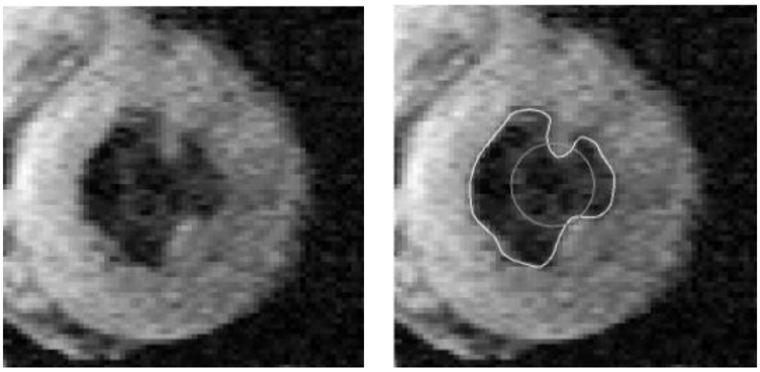


(a) (b)

Figure 2.9: Example of clustering segmentation of brain MR images (a) original grayscale image, (b) segmented image. These images were obtained from [43].

2.4.5 Deformable Methods

Medical images face various artifacts like noise, density inhomogenity and partial volume, which decrease the effectiveness of the segmentation techniques and create incorrect boundaries in the segmentation results. To overcome these difficulties, deformable models have been introduced in medical image segmentation. A deformable method is a curve or surface defined within an image domain to detect object boundaries. It works by initializing a closed shape or curve and putting it next to the target object to outline their boundaries, the closed curve moves within the image by using internal forces computed from the closed curve itself and external forces coming from the image data. Figure 2.10 illustrates the process of deformable model on MR heart image. In Figure 2.10.b, the deformable model initialized a closed curve as a circle than this circle deformed under the influence of internal and external forces to the inner boundary of the left ventricle [44]. Usually, deformable models are classified into two categories, Parametric Deformable Models (active contours) and Non-Parametric Models (geometric active contour).



(a) (b)

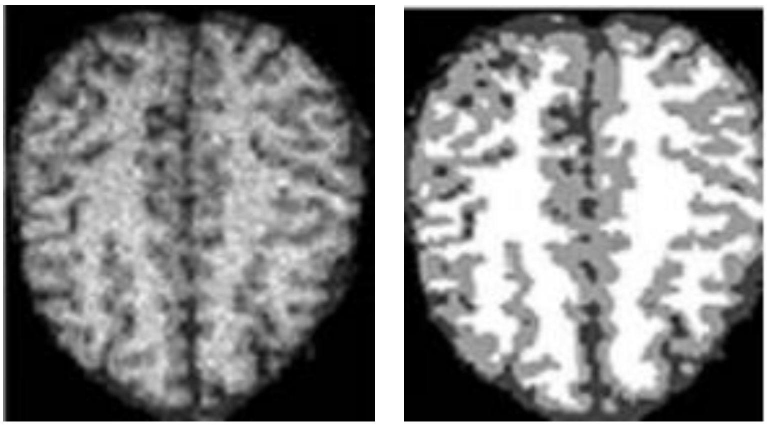
Figure 2.10: Detecting of the inner wall of the left ventricle from a MR image using active contours (a) original grayscale image, (b) initial and final deformable model result. These images were obtained from [44].

In recent years, many works have been used deformable models in medical images segmentation, in [44] a new approach based on deformable models and spatial relations has been introduced to segment MR images of brain structures. The approach proposes a new framework by integrating spatial relations as fuzzy subsets of the image domain in deformable model to construct an external force by three methods. The experiment results show that the proposed method improves the segmentation of the brain structures with low contrast. P. Yan and A.A. Kassim presented a segmentation approach to extracting organ contours from medical images in [45]. The approach is based on a deformable model that uses dynamic programming technique to find the minimal path on the image. The results show the effectiveness of the proposed approach in edge discontinuities and reducing of noise. Similar work has been proposed in [46]. A tumor segmentation method for brain MR images has been proposed in

[47]. The approach combining between deformable models and fuzzy clustering by starting an initial tumor segmentation using fuzzy clustering technique, than feed its results to the deformable model to continue the segmentation process and extract tumor boundaries, the proposed method used gradient vector field as an external force. Lahssene.Y.Y et *al.* proposed in [48] a medical image segmentation approach based on a constrained geometric deformable model called Selective Binary Level Set (SBLS). The experimental result demonstrates the efficiency of the proposed method on global and local segmentations.

2.4.6 Markov Random Field Models

Markov Random Field (MRF) model is a simple stochastic process that could be used for image segmentation, MRF inspired by the Ising model [49]. MRFs model spatial interactions between neighboring or nearby pixels. These local correlations provide a mechanism for modeling a variety of image properties. MRF methods have been widely used for medical image segmentation because of their ability to protect the edges by parameter approximation [50]. A hybrid technique works on concept of Particle Swarm Optimization (PSO) algorithm and Hidden Markov Random Fields (HMRF) has been proposed by Guerrout et *al.* in [51]. The proposed technique depends on using Hidden Markov Random Fields (HMRF) for modeling the segmentation and integrating the PSO algorithm to solve the problem of function minimization that results from using HMRF. The authors got good results, however there are a lot of parameters in the proposed technique that need to be investigated further for better results. Another segmentation method for brain MR images has been proposed in [52]. The proposed hybrid method is based on combining Hidden Markov Random Field (HMRF) and clustering methods and aims to improve the segmentation runtime. An example of the experimental result shown in Figure 2.11 proves the efficiency of the proposed method in brain MRI segmentation.



(a) (b)

Figure 2.11: Example of segmentation of brain MR image by (MFCM + PRE + HMRF) Method (a) original grayscale image, (b) segmented image. These images were obtained from [52].

2.4.7 Artificial Neural Networks (ANN)

ANN is a broadly used machine-learning model. It is a mathematical model of neurons that simulates biological learning. ANN consists of different types of layers, an input layer for data entry, followed by one or more hidden layers, than ending by an output layer to show the results. These layers contain nodes, and these nodes are connected by communication links with weights. Generally, the ANN model aims to classify or identify objects. The ANN is trained by processing examples, each example has an input and a result, the weights associated with nodes are adjusted by the learning rule. Neural network algorithms face huge problems in determining ANN architectures such as network size, type, and number of layers.

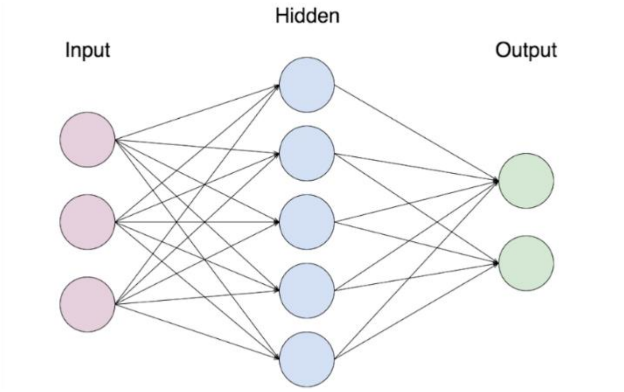


Figure 2.12: A simple artificial neural network structure.

A deep model of neural networks called a Convolutional Neural Network CNN consists of several convolutional layers proposed by combining image-processing and deep learning technologies [53], CNN has good extraction and patterns detecting capabilities. Generally, CNN networks could identify the category of the entire image but could not identify the category of each pixel, Long et *al.* [54] as shown in Figure 2.13, proposed a deep model of neural networks called Fully Convolutional Network (FCN) that modified the CNN architecture to obtain the classification and prediction of each pixel to allow the segmentation process.

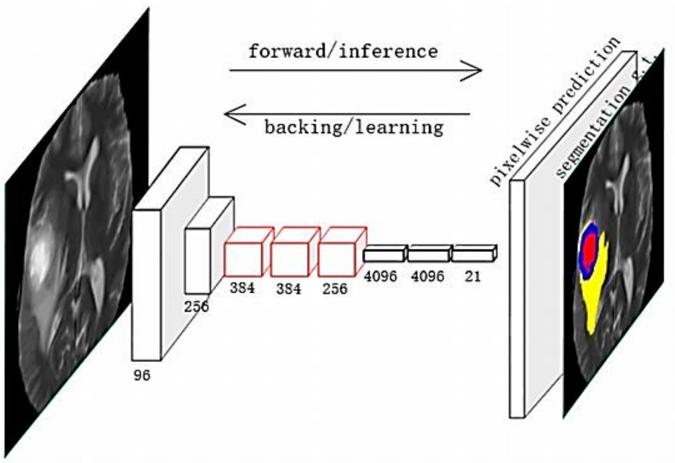


Figure 2.13: Fully convolutional network structure. This image were obtained from [54].

A deep learning segmentation approach has been proposed by Zhou et *al.* [55]. The proposed approach used FCN in a 2.5D for segment 3D CT images and used pixel-to-label training, the approach merged its segmentation results with other FCNs results to obtain the final the segmentation. The experimental results show high accuracy in segmentation large organs than that of small ones. In [56], Ronneberger et al proposed a deep learning segmentation approach for biomedical images called U-Net network. It is based on a fully convolutional network and is composed of U channel and skip-connection. U-Net is widely used in medical image segmentation and it has many variants, Çiçek et *al.* [57] proposed a 3D U-Net model to richer the U-Net structure with spatial information. Another methods based on U-Net have been proposed in [58-60].

2.4.8 Other Techniques

There are many other techniques proposed in order to segment medical images such as atlas guided approach, graph cut approach and Lattice Boltzmann Method (LBM). Each one has its advantages and drawbacks.

2.5 Conclusion

We have presented in this chapter an overview of medical image segmentation techniques. We have mentioned image segmentation, which is considered basic step in image processing. We have focused on medical image segmentation and its techniques, which are very important in order to clarify and improve the quality of medical images and handling with different artifacts. Even with the big development in medical image segmentation during the past years and the huge number of its techniques, there is still no single approach that can handle all types of medical images and perform flawless segmentation on all of them.

In our study, we will combine the clustering segmentation method with a metaheuristic algorithm to achieve better segmentation results. In the next chapter, we will discuss and present some of the previous work on the hybridization between metaheuristic algorithms and segmentation methods.

CHAPTER 3

STATE OF THE ART : MRI Segmentation based on Clustering and Metaheuristics

Chapter 3

State of the Art :

MRI Segmentation based on Clustering and Metaheuristics

3.1 Introduction

In the past years, computer vision researchers have made significant contributions in the medical field, especially in the segmentation process. Many techniques and approaches has been proposed to achieved good segmentation results and to overcome different kinds of artifacts, but until now there is no method could consider as the best brain MRI segmentation method, because of that, the existent methods need to be optimized. In our study, we have chosen to combine and hybrid clustering technique with metaheuristic algorithm for brain MRI segmentation optimization. The details of the optimization, metaheuristics concepts, hybridization and previous recent work about the hybridization of MRI segmentation are discussed in the following subsections.

3.2 Metaheuristic Optimization

Before diving into a detailed discussion of metaheuristics, first we have to introduce and explain the optimization process and its basics. The Optimization is a process related to the domain of applied mathematics and statistical analysis, it's is required in different fields such as computer vision, image processing and machines learning. Generally, optimization is the problem of finding the best solution (global solution) out of all possible solutions (local solutions) in defined search space and with specified parameters. calculating the solutions needs a mathematical equation called the objective function and finding the best solution need to minimize or maximize the values of the objective function results .Technically [4], it could described an optimization problem P as a triple (S,Ω,f), where:

- *S* refers to the search space defined over a set of variables X_i, $i = 1, \ldots, n$.
- Ω refers to a set of constraints among the variables.
- $f : S \rightarrow IR+$ refers to the objective function that assigns a positive cost value to each solution of *S*.

The aim from the optimization process is to find a solution $s \in S$ such that:

- To minimize the objective function : $f(s) \leq f(s'), \forall s' \in S$
- To maximize the objective function : $f(s) \geq f(s'), \forall s' \in S$

Figure 3.1 shows an example of the optimization in a search space, sometimes we face optimization problems that need several objective functions to be solved, this is known as multi-objective optimization. The available techniques for solving optimization problems are classified into two different categories: exact and approximate methods. The exact methods are guaranteed to find a provably optimal solution, but at the cost of a huge run-time, which makes them unsuitable for high complexity optimization problems. Meanwhile, the approximate methods are used for solving complex optimization problems in reasonable run-time and will eventually find a good solution, in other words, we can say that in approximate methods, the optimality is sacrificed for the sake of limited run-time [61].

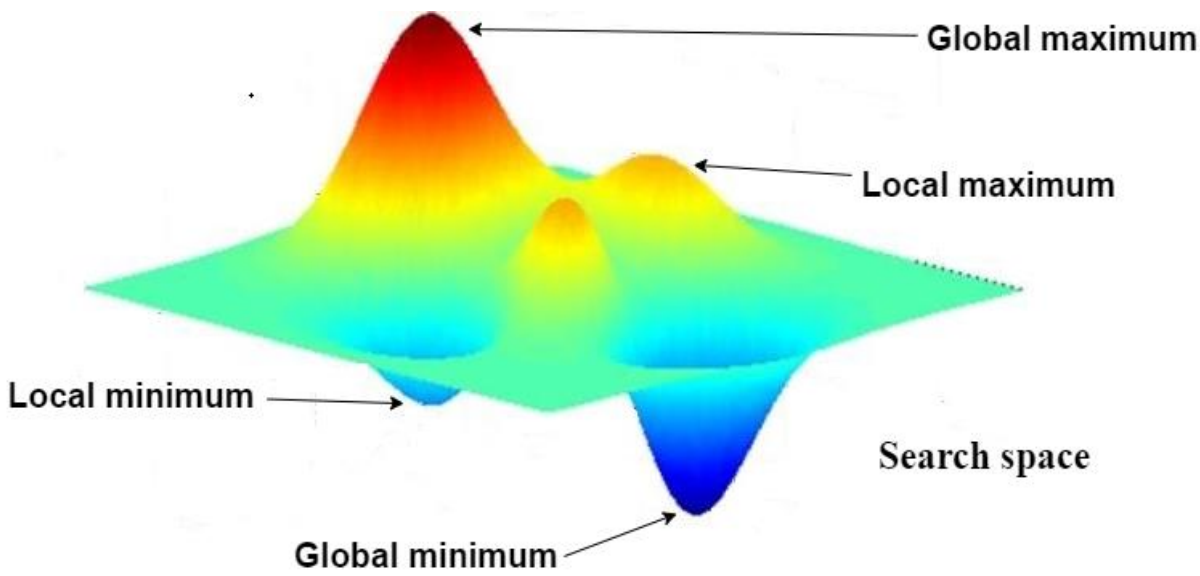


Figure 3.1: Example of the optimization.

3.2.1 Overview of Metaheuristics

Approximate methods could be categorized into two basic techniques, which are heuristic and meta-heuristic. Heuristic methods are usually problem dependent, which indicates that they are proposed for solving given problems.

In the 70ies, a new type of approximate method called metaheuristics was evolved in an attempt to integrate fundamental heuristic approaches into higher level frameworks and improve the exploration of search space. The word metaheuristic is a combination of two old Greek terms, meta which meaning "upper level", while heuristic means "to find" [62]. I. Osman and G. Laporte formally defined metaheuristic as an iterative process that uses learning strategies, combining different concepts and guides a subordinate heuristic to improve the quality of the obtained solutions and enhancing the exploration of search space [63]. In many metaheuristic methods, the process of searching for an optimal solution starts by calculating the values of several search space points to discover new promising zones. Then the searching continues by investigating these promising areas in order to find the local-optimum, after that, the method identifies the best local optimum among the local ones that are found in the different zones and hopes to be the best solution that the metaheuristic methods are looking for. Compared to heuristic methods, metaheuristic methods are often problem-independent techniques that can be applied to a broad range of problems. They can also find high-quality solutions with less computational effort and resources.

Metaheuristic methods can be classified in different ways [4]:

First, they are classified based on their origins into nature-inspired vs. non-nature inspired. Nature-inspired methods could be also categorized into Swarm-based, Bio-inspired, Physics/Chemistry-based, Human-based and Plant-based. Non-nature-inspired ones such as iterated greedy (IG) and Simulated Annealing (SA).

Second, metaheuristic methods are classified into memory usage vs. memory-less methods based on the use of search history (experience). Memory is explicit used in Tabu Search (TS) method and it could be treated the population of Genetic Algorithm (GA) as a kind of memory.

Third, they could be categorized according to the number of solutions manipulated at one iteration into single-point method vs. population-based method. Single-point methods (trajectory method) such as, Iterated Local Search (ILS) and Tabu Search (TS) are leaning to the local searching space, meanwhile the population-based methods such as BAT algorithm and Simulated Annealing (SA) are inclining towards the global searching space. Table 3.1 presents some of popular metaheuristic methods.

Metaheuristic methods have received significant attention by researchers in recent years due of its great ability for solving different kind of optimization problems. The importance of these methods depends on several factors such as [79]:

Table 3.1: List of some popular metaheuristic methods

Metaheuristic methods	**Main category**	**Authors and year of publication**
Genetic Algorithm (GA)	Population-based	John Holland (1975) [64]
Simulated Annealing (SA)	Single-solution	Kirkpatrick, S et *al.* (1983) [65]
Tabu Search (TS)	Memory usage/ Single-solution	Fred W. Glover (1989) [66]
Particle Swarm Optimization (PSO)	Nature-inspired (Swarm-based)	Kennedy, J and Eberhart, R (1995) [67]
Differential Evolution (DE)	Population-based	Storn, R., & Price, K. (1997) [68]
Variable Neighborhood Search (VNS)	Single-solution	Mladenović, N.; Hansen, P (1997) [69]
Harmony Search (HS)	Population-based	Zong W. Geem et *al.* (2001) [70]
Artificial Bee Colony (ABC)	Nature-inspired (Bio-inspired)	Karaboga, D. (2005) [71]
Ant Colony Optimization (ACO)	Nature-inspired (Bio-inspired)	Dorigo, M et *al.* (2006) [72]
Firefly Algorithm (FA)	Nature-inspired (Bio-inspired)	Eusuff, M. et *al.* (2006) [73]
Chemical Reaction Optimization (CRO)	Nature-inspired (Physics/Chemistry-based)	Lam, A. Y. S., & Li, V. O. K. (2010) [74]
Cuckoo Search (CS)	Nature-inspired (Bio-inspired)	Yang, X.-S., & Suash Deb. (2009) [75]
Bat Algorithm (BA)	Nature-inspired (Bio-inspired)	Yang, Xin-She (2010) [5]
Artificial Root Foraging Algorithm (ARFA)	Nature-inspired (Plant-based)	Ma, Lianbo et *al.* (2014) [76]
Lion Optimization Algorithm (LOA)	Nature-inspired (Bio-inspired)	Yazdani, M. & Jolai, F. (2016) [77]
Heap-Based Optimizer (HBO)	Nature-inspired (Human-based)	Askari, Q et *al.* (2020) [78]

- Usable in various science fields, rely on simple techniques and easy to implement.
- Metaheuristic methods are not problem-specific and could be used for high complex optimization problems.
- Improving the exploration of searching space by include techniques to prevent being stuck in limited areas and using search history (experience) to guide the search.

3.3 The Hybridization

3.3.1 Concept of Hybrid Algorithms

In recent years, a huge number of non-traditional algorithms have been proposed in the literature. These proposed algorithms combine different algorithmic components, they are known as hybrid algorithms. The basic purpose behind the hybridization is to obtain higher-performing structures and benefit from the complementary characteristics of various algorithm techniques. In a hybrid algorithm, a combination of two or more algorithms works together to efficiently solve a predefined problem [80].

3.3.2 Hybridization Categories

In the hybrid algorithm that called **Unified purpose hybrids**, all the algorithms used are concerned with solving the problem directly by using different components of each algorithm to improve another algorithm. Meanwhile, in other hybrid algorithms, known as **Multiple purpose hybrids**, only one algorithm is concerned in solving the problem, while the other sub-algorithms are responsible for initializing and tuning its parameters, Figure 3.2 illustrates the difference between the two categories.

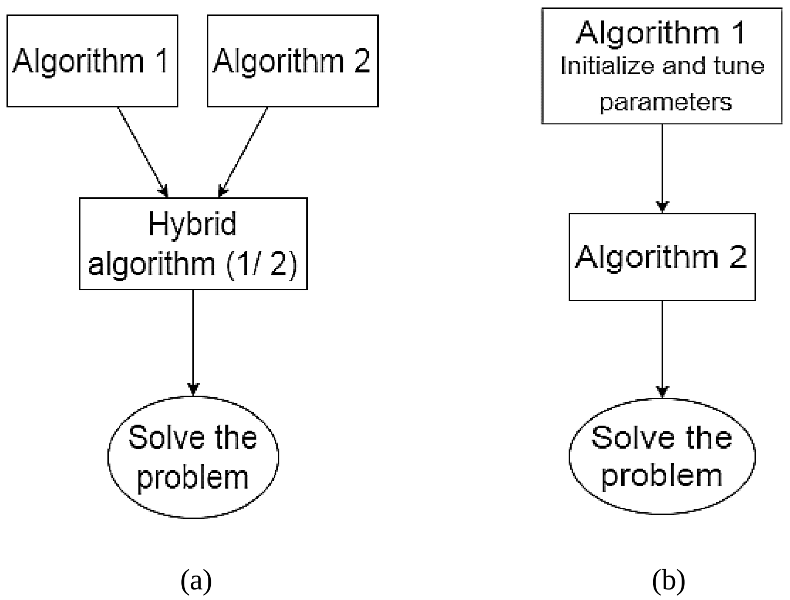


Figure 3.2: Hybridization categories, (a) presents structure of unified purpose hybrids, (b) presents structure of multiple purpose hybrids.

There is another classification based on weight of contribution of each algorithm, this divides the hybrid algorithms into two different categories [81], which are:

3.3.2.1 Collaborative Hybrids

In this category, the participate algorithms are executing sequentially or in parallel and they have equal contribution in solving the problem in the simplest case. There are three possible structures illustrated in Figure 3.3, which are:

- Multi-stage: each algorithm have its own population, the algorithm of the first stage is the global optimizer, while the local search is performed by the algorithm of second stage.
- Sequential: each algorithm have its own population, all algorithms are executed with the same number of iterations alternately until reaching convergence criteria.
- Parallel: the algorithms are executed simultaneously and manipulating on the same population one of the algorithms may be executed on a pre-specified percentage of an algorithm.

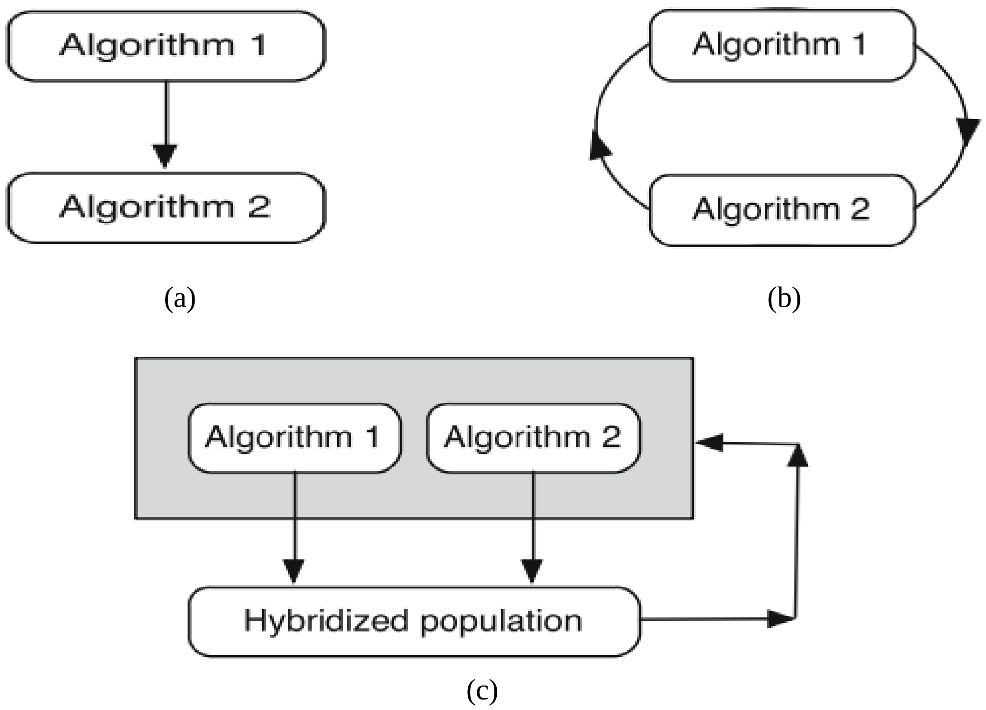


Figure 3.3: Collaborative hybrids, (a) presents multi-stage structure, (b) presents sequential structure, (c) presents parallel structure. These images were obtained from [81].

3.3.2.2 Integrative Hybrids

In this category, the participated algorithms does not have equal contribution, there is a primary algorithm which is dominant in solving the problem and a secondary algorithm that is involved by 10–20 %. This involves incorporation of a manipulating operator from a secondary algorithm into a primary algorithm. There are two possible approaches based on the manipulation of the population illustrated in Figure 3.4, which are:

- Full manipulation: at each iteration, the whole population is manipulated.
- Partial manipulation: only a part of the entire population is manipulated at every iteration. Selecting the right part is a significant issue in ensuring the effectiveness of this hybrid structure.

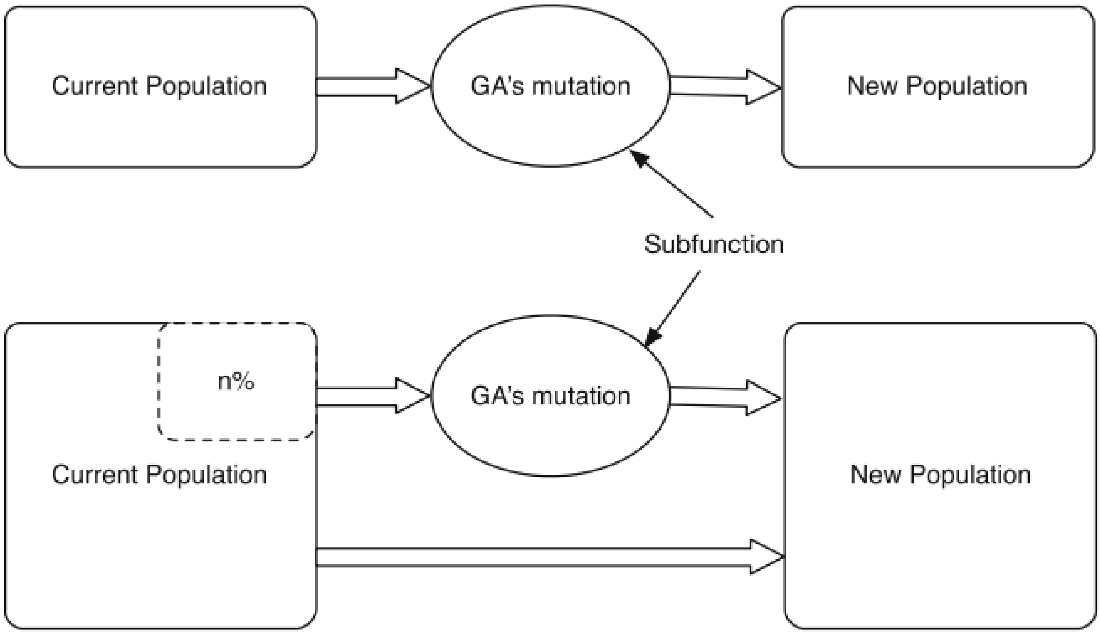


Figure 3.4: Integrative structure of a hybrid algorithm, with full and partial manipulations. These images were obtained from [81].

3.4 State of the Art- MRI Segmentation based on Clustering and Metaheuristic Algorithms

The hybridization concept in MRI segmentation does not change very much, It is also a combination of two or more algorithms including segmentation algorithm such as thresholding, region growing, clustering, edge detection … etc. and optimization algorithms such as the metaheuristics PSO, BA, GA, HS… etc. In this section we will focus on the previous works concerning the methods of MRI segmentation, specially brain MRI segmentation based on Fuzzy C-Means (FCM) clustering algorithm and different metaheuristic algorithms specially the bio-inspired algorithms.

3.4.1 FCM based Genetic Algorithm (GA)

A new hybrid MR images segmentation approach was proposed by Ghassabeh, Y. A et *al.* in [82]. Their approach is based on improving the traditional Fuzzy C-Means (FCM) clustering algorithm by using Genetic Algorithm (GA) to find and compute the optimal two parameters

λ and ζ, these two parameters motivate the traditional FCM to take into account pixels' location and their neighborhood for reducing the effect of noise . Experimental results demonstrated the efficiency of the proposed IFCM algorithm in segmenting noisy brain tissue images and computing the two parameters of λ and ζ compared with traditional FCM and the algorithms that use Artificial Neural Networks (ANN) to compute the two parameters. Another hybrid technique introduced for MRI segmentation in [83], the proposed method takes advantage of the GA searching capability with techniques of crossover and mutation to find an optimal initial centroid value of the FCM clustering algorithm. The results show that the proposed GA-based FCM method for brain MRI segmentation provides better performance as compared to the other tested techniques. A similar hybrid approach using Genetic Algorithm (GA) to initialize the centroid value of an improved FCM called EFCM for MRI segmentation has been proposed in [84].

Since the objective function of the conventional FCM algorithm considers only the pixel intensities and does not take into account pixels' location, a new version of FCM called Kernel Intuitionistic FCM (KIFCM) was proposed in [85], it modified the Euclidean distance and used the kernel trick. After that, the authors developed a new DNA-based genetic algorithm to enhance the KIFCM clustering process by obtaining the optimal parameters that affect the calculation of the membership degrees and cluster centroids. The methodology has been successful in reducing noise and improving the segmentation accuracy of both synthetic and clinical MR images compared to other methods.

Das, S., & De, S in [86] developed the standard genetic algorithm by modifying the crossover technique and initialization of the population ,they named it MfGA. After that, the authors used the MfGA algorithm to improve the initial input of the standard fuzzy c-means algorithm. The result shows that the proposed method produces better performance compared with standard FCM. Das, S. et *al.* in [87] used some quantum computing, such as quantum gate and entanglement to improve MfGA that used for optimize the initialization of the standard FCM algorithm in order to segment the color MR images. The quantum computing concept has a good effect on accelerating the traditional MfGA and improving the segmentation process. An algorithm called SAGAKFCM was proposed for brain MRI tissue segmentation in [88]. First, the algorithm improved the standard FCM algorithm to be more resistant to the noise effect by introducing the gaussian kernel function and naming it KFCM. Then, they combined between the two metaheuristic methods, Simulated Annealing (SA) and Genetic Algorithm (GA) to enhance the initialization of the centroid value of the KFCM algorithm. The proposed algorithm took advantage of the strong abilities of both the SA and GA algorithms in local and global search respectively. The authors succeeded in minimizing the iterations' number and time complexity compared to the standard FCM algorithm, in addition to enhancing the quality of segmentation of brain MRI tissue compared with other tested methods like ARKFCM and FCMLSM.

3.4.2 FCM based Particle Swarm Optimization (PSO)

The Cerebrospinal Fluid (CSF) has sensitive information about brain health. Detecting the CSF in MR images is a hotspot in the literature, P. Tamije Selvy et *al.* [89] have proposed a hybrid method named ADTVFCM-PSO for extraction of the CSF in brain MR images. The segmentation process starts by enhancing the input image by CLAHE technique, then improving the standard FCM to ADTVFCM by integrating noise elimination mechanisms that are TV and Anisotropic Diffusion (AD). After that, the authors used the Particle Swarm Optimization (PSO) algorithm for the global optimization. The proposed method PSO-ADTVFCM created a swarm of particles, ADTVFCM algorithm calculated the cluster center for each particle, finally the global optimal solution was achieved by the swarm g_best value. The results demonstrated the proposed method has better performance than the tested methods. Mekhmoukh and Mokrani [90] proposed a hybrid brain MRI segmentation technique named IKPCM. Their technique is based on a modified version of the standard FCM named KPCM and the Particle Swarm Optimization (PSO) algorithm. They first made use of the PSO algorithm and its ability in the global search to initialize KPCM cluster centers, then they modified the calculation method of KPCM membership function, taking neighborhood pixels and outlier rejection into account in order to reduce the noise. Their proposed technique concludes by finalizing the segmentation with a level set. The experimental result illustrates that IKPCM has succeeded in improving segmentation quality and decreasing the noise effect. Another hybrid brain MRI segmentation method proposed in [91] to overcome FCM drawbacks, the authors used Fuzzy Particle Swarm Optimization (FPSO) to initial cluster centers standard FCM and they use new fitness function by combining between fuzzy cluster validity indices. The results show the efficiency of the proposed algorithm compared with standard FCM.

In [92], the authors introduced a hybrid MRI segmentation approach based on the pParticle Swarm Optimization (PSO) algorithm and Kernel Fuzzy C- Means (KFCM). The proposed approach depends on the PSO algorithm for improving the KFCM cluster centers' initialization step. After that, the proposed approach was modified to the level set model for better segmentation results. The results proved the effectiveness of the proposed approach KFPSO compared with other tested methods. A hybrid approach FCM-PSO has been proposed in [93] to take advantage of the good ability of the FCM algorithm in separating regions and from excellent global searching capability of the PSO algorithm. This method was used for brain MRI segmentation and it achieved good results compared to other methods such as the standard FCM, FCM-FPSO, BBO-FCM. Another similar approach was proposed in [94]. Pham, T. X et *al.* introduced a new hybrid algorithm for brain MRI segmentation named called PSO-KFECSB [95], this algorithm is based on two existing algorithms, the improved PSO algorithm named LHNPSO and the Fuzzy Entropy Clustering (FEC) algorithm. First, the authors improved the objective function of the FEC algorithm by involving bias correction and neighborhood pixel information to resist the noise effect and named it KFECSB.,then they briefly enhanced

LHNPSO to be faster in global searching and used it to optimize the objective function of KFECSB. The experiments demonstrated the efficiency of the proposed method in segmenting both real and simulated brain MR images and in reducing the noise compared with the other five methods.

3.4.3 FCM based Ant Colony Optimization (ACO)

A combination of Fuzzy C-Means (FCM) and Ant Colony Optimization (ACO) has been proposed in [96]. The hybrid combination takes advantage of the ACO ability in global searching to obtain the optimal initial centroid value for the Fuzzy C-Means (FCM) clustering algorithm. Experimental results demonstrated the effectiveness of the proposed method in reducing noise and improving the accuracy of brain MRI segmentation compared to the existing methods. Time consumption is a main factor in the optimization problems. Because of that , G. Zou in [97] suggested a hybrid brain MRI segmentation method that seeks to reduce running time as well as improve the segmentation performance. The suggested method is based on using the ACO algorithm to initialize the cluster centers of the FCM clustering algorithm and determine their number. The author improved the Markov random field model by involving the observation field information such as pixels distance gray values in the new potential function. After that, he combined it with the FCM algorithm to create a new better clustering objective function. From the obtained experimental results, the suggested hybrid method has efficiently improved brain MRI segmentation and reduced the run-time and noise effect. For MRI segmentation, a hybrid ant fuzzy algorithm called HAFA has been presented by Bozhenyuk et *al.* [98]. The hybrid method is based on Fuzzy c-means FCM and Ant Colony Algorithm (ACA). The proposed method modifies the membership function of each pixel considering different image characteristics such as color and geometric distance, making the segmentation more accurate for noisy MR images. The HAFA method ensured finding the optimal solution, nevertheless, the run-time could not be defined due to parameters initialization sensitivity.

3.4.4 FCM based Firefly Algorithm (FA)

In an effort to overcome Fuzzy c-means drawbacks in brain MRI segmentation, a hybrid method was developed in [99] based on combining between FCM and FA. The developed method aims to automate the segmentation process of the normal and abnormal brain MR images and enhance the initialization of FCM cluster centers and the determination of their number. The FA feeds FCM with the optimal cluster centers by inspecting the search space (grayscale image). The experimental results show that the developed method FAFCM succeeded in determining the types of brain MR images (normal and abnormal) and improved the quality of segmentation. Another brain MRI segmentation method based on FA/FCM has been proposed in [100]. Segmentation of brain MRI tissues into White Matter (WM), Gray Matter (GM) and Cerebrospinal Fluid (CSF) is a hotspot issue in medical field, Ghosh, P et *al.* [101] proposed a hybrid method works on the concept of a modified FCM algorithm and a chaos theory based firefly algorithm. First, the authors reformulated the FCM membership function by considering pixels location and neighborhood pixels information in addition to applying Total Variation (TV) denoising to reduce the effect of noise and intensity inhomogeneity. Then, they used chaotic maps to tune the parameters of the FA and improve its searching ability. Finally, the proposed method C-FAFCM used the chaotic firefly algorithm to provide the optimal cluster centers to the modified FCM and avoid to be sucked in local optima. The experimental results on different brain MRI datasets and types (simulated and real) show the efficiency of the proposed method in segmentation accuracy and reducing noise and intensity inhomogeneity effects compared with FAFCM and, En-FAOFCM.

3.4.5 FCM based Artificial Bee Colony (ABC)

In [102], M. Taherdangkoo et *al.* replaced the Genetic Algorithm (GA) that was used in [82] with the A algorithm. The results show that using the ABC algorithm accelerated and improved the segmentation quality of the MR images tissue. A new hybrid strategy introduced by M. Shokouhifar and G. S. Abkenar in [103] for segmentation of MRI brain tissues into WM, GM and CSF. The authors proposed a new parameter called a noise threshold λ, this parameter distinguishes between noisy and normal pixels and is used for a modified membership function of the standard FCM. For choosing the right and the optimal value of noise threshold λ, artificial bee colony algorithm ABC has been used due to its efficient ability in the searching. The results illustrate that the proposed method produced better brain MRI segments, reduced the noise and faster than the other tested methods. A hybrid approach for brain MRI segmentation called SFCM-MeanABC has been presented in [104]. The presented approach used the SFCM clustering algorithm, which modified the membership function of the standard FCM by considering neighboring pixels information. To avoid being trapped in local optima, the proposed approach used an improved version of ABC called Mean Artificial Bee Colony (MeanABC) that optimized the process of finding the optimum cluster centers by modifying the search equation. The experiment results demonstrated the superiority of the proposed SFCM-MeanABC approach in segmenting brain MR images and in reducing the noise compared with SFCM-ABC and other tested methods. Other method used spatial information presented by Lin, J.S., Wu, S.Hin [105], and another similar hybrid brain MRI segmentation approach developed the original ABC by considering the mean of the previous best solutions [106]. The experimental results of the last hybrid approach on 20 volumes of real brain MRI images illustrate better performance in the segmentation process with faster global searching and more reducing the noise compared with other improved ABC.

3.4.6 FCM based Harmony Search (HS)

A new hybrid method called DCHS for dynamic segmentation of brain MRI was suggested in [107] by Alia, O. M et *al.* The proposed method is based on a combination of Fuzzy C-Means (FCM) and improved Harmony Search (HS) algorithms. The authors improved the conventional HS algorithm by integrating the Variable Length Encoding (VLE) technique into the harmony memory vectors to determine the number and optimal cluster centers automatically. In the DCHS method, every single harmony memory vector represented a possible solution (cluster centers), and to evaluate the optimality of that solutions during the iterations, the DCHS algorithm used the PBMF-index as a fitness function. Finally, the FCM algorithm used the optimal solution found as an initial cluster centers. Experimental results on both synthetic and clinical brain MR images demonstrate the efficiency of the proposed DCHS method in determining the right number of cluster centers and in performing the segmentation dynamically compared with other clustering algorithms such as FVGA and FVGAPS. Another hybrid segmentation approach for brain MR images combined between standard FCM and Harmony Searching (HS) algorithms has been proposed in [108] by the same authors Alia, O. M et *al.* A hybrid brain MRI segmentation method was proposed by Yang et *al.* in [109]. The proposed method is based on the Harmony Searching (HS) algorithm and the conventional FCM algorithm. Their method improved the FCM cluster centers initialization by introducing rough set theory to the Harmony Searching (HS) algorithm. The experimental results proved the effectiveness of the proposed method compared with the standard HS algorithm and conventional FCM.

3.4.7 FCM based Other Metaheuristics

Das, S., and Konar, A developed a new method for fuzzy automatic segmentation in [110]. The developed method uses an improved Differential Evolution (DE) algorithm to determine the necessary number of cluster centers and the optimal cluster centers location. The obtained results on several image types including brain MR images, show that the developed method reduced noise and achieved better segmentation accuracy than FVGA and standard FCM. A hybrid MRI segmentation method called HAFSA was presented by Li Ma et *al.* [111]. Their presented method enhanced the artificial fish swarm algorithm (AFSA) by considering neighborhood pixels information and integrating the metropolis criterion technique to improve the convergence rate and resist noise. Their presented method had good segmentation results on MR images and reduced the noise compared with standard FCM and SFCM.

Other hybrid segmentation approach based on whale optimization algorithm WOA and FCM algorithm [112]. The hybrid approach takes advantage of global searching ability of the whale optimization algorithm to improve the local searching ability of standard FCM and to overcome the FCM drawbacks and integrated noise detection and reduction technique. Experimental results on both real and simulated MR images illustrate the efficiency of the proposed approach in terms of segmentation performance and noise reduction compared with other existing approaches.

3.5 Conclusion

A state of the art for MRI segmentation based on clustering and metaheuristics has been given in this chapter. We have introduced first an overview about the optimization and its basics, which have considered challenge and useful process in image segmentation. Then we presented the metaheuristics optimization and discussed its categories and we mentioned some popular metaheuristic algorithms. We also explained the concept of hybridization and its categories. Finally, we present a detailed state of the art for recent hybrid methods of MRI segmentation based on the FCM clustering algorithm and metaheuristics.

In our work, we will use a clustering approach called FCM that has shown good success in medical image segmentation and combine it with the Bat Algorithm (BA) to achieve better results. In the next chapter, we will provide a detailed explanation of both FCM clustering algorithm and the Bat Algorithm (BA).

CHAPTER 4

THE METHODS USED: FCM Algorithm & Bat Algorithm

Chapter 4

The Methods Used:
FCM Algorithm & Bat Algorithm

4.1 Introduction

Due to the huge contribution made by the hybridization in the image processing field and spatially in MRI segmentation, we propose a hybrid method for brain MRI segmentation based on a clustering approach for the segmentation and a metaheuristic method to optimize and improve the segmentation process. The Fuzzy C-Means (FCM) clustering algorithm is considered among the popular clustering algorithms for brain MRI segmentation. It is used in many researches because of its efficiency in grouping similar pixels into one cluster. However, the FCM algorithm has many drawbacks that need to be considered. The Bat Algorithm (BA) is a bio-inspired metaheuristic algorithm that has recently been used in many optimization problems and become the center of attention in many fields. The details of the Fuzzy C-Means (FCM) algorithm and the Bat Algorithm (BA) are discussed in the following subsections.

4.2 Fuzzy C-Means (FCM) Overview

4.2.1 Fuzzy Sets Theory

In the past, classical set theory (mathematical problems) was based on the concept of yes-or-no (true-or-false), which means that it depends on an absolutely solution. However, in real life, not all set theory problems can be solved by the yes-or-no concept, a lack of information could lead to uncertainty. Due to that, a new theory called fuzzy sets based on a more-or-less concept introduced by Lotfi Zadeh in 1965 [113], which is a set of objects with a membership (characteristic) function for determining a specific membership degree for each object among the set. This membership degree has a value between 0 and 1. Many concepts with various properties like complement, intersection, union and intersection are included and established in these fuzzy sets.

For example, in the classification of a set of adult people into TALL or SHORT classes, let us consider that the height of all the people in the set ranges from 1.4 m to 2 m. It is easy to classify people who have exactly 1.4 m and 2 m into the short people class and tall people class respectively, but the problem appears with people who have 1.55 m, 1.7 m or 1.85 m. The height of 1.55 m is close to being in the short people's class but not as the 1.4 m height, and the height of 1.7 m could not be classified into only one class. With fuzzy sets theory, we can define two fuzzy classes, TALL and SHORT then use a membership function range between 0 and 1 to specify the degree of height of each person. Figure 4.1 shows two membership function for TALL and SHORT classes for determining the membership grade of each person in the two classes. We can see that the people who are 1.55 m have a SHORT membership value equal to 0.75 and a 0.25 TALL membership value. Meanwhile, people who are 1.7 m have the same membership value, which is 0.5.

The theory of fuzzy sets has spread widely because of its great effectiveness in solving various kinds of problems. It has been used in different fields such as operations research, human sciences, linguistics, control engineering, management science, computer science and others [114]. Using fuzzy sets theory for categorizing and clustering objects into different clusters with a membership grade is a very useful and challenging process at the same time.

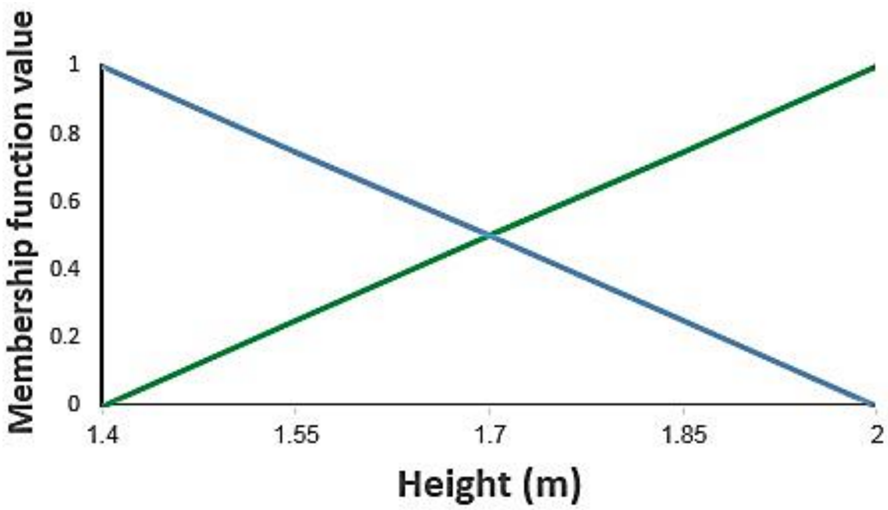


Figure 4.1: Example of fuzzy sets theory, two membership functions for determining grade value of a person based on height, blue line presents a membership function named SHORT while in the green one called TALL

4.2.2 Fuzzy C-Means (FCM)

Fuzzy C-Means (FCM) is considered the most widely used clustering algorithm in the literature, it was first proposed by Dunn [115] and then improved by Bezdek [116]. Unlike K-means, FCM works on the concept of fuzzy sets theory, where the data can belong to various clusters at the same iteration by using membership values (soft clustering). This method is an unsupervised learning approach that is capable of partitioning identical data elements based on their level of similarity, which decreases the similarity among elements between various groups and increases the similarity of elements within a group [3].

4.2.2.1 FCM Basics

The algorithm aims to minimize the cost function by dividing the image data into several partitions called c ($2 \leq c \leq N$). The Fuzzy C-Means (FCM) algorithm uses fuzzy memberships to assign pixels $x = \{x1,x2,x3,,,,,,xn\}$ for each category. The cost function defined by (Eq. 4.1) as follows [117]:

$$J = \sum_{i=1}^{N} \sum_{j=1}^{c} u_{ji}^{m} \left\| x_i - z_j \right\|^2 \tag{4.1}$$

With the following constraints:

$$\forall i \in \{1..N\}, \forall j \in \{1..c\} \sum_{j=1}^{c} u_{ji} = 1;\ 0 \leq u_{ji} \leq 1; \sum_{i=1}^{N} u_{ji} > 0 \tag{4.2}$$

- u_{ji} is the membership of pixel x_i in the *j-th* cluster
- z_j is the j-th cluster center
- ‖.‖ is a norm metric
- m (m>1) is a constant controls the fuzziness of the resulting partition

The membership functions and cluster centers are updated by (Eq. 4.3) and (Eq. 4.4) respectively as follows:

$$u_{ji} = \left(\sum_{k=1}^{c} \left(\frac{\left\| x_i - z_j \right\|}{\left\| x_i - z_k \right\|} \right)^{2/(m-1)} \right)^{-1} \tag{4.3}$$

$$z_j = \sum_{i=1}^{N} u_{ji}^{m} x_i \cdot \left(\sum_{i=1}^{N} u_{ji}^{m} \right)^{-1} \tag{4.4}$$

4.2.2.2 FCM Algorithm

The FCM is an iterative algorithm starting with a random cluster centers, then converges to a solution for z_j representing a saddle point or the local minimum of the cost function. By comparing the changes in the cluster center or the membership function at two successive iteration steps, the convergence can be detected [118]. The FCM algorithm steps are presented as follows in Algorithm 4.1:

Algorithm 4.1: The standard Fuzzy C-Means (FCM) algorithm

Input: Data (original image)
Parameters: c, m, *itermax* and ε
Randomly initialize cluster centers z_j
for $t \leftarrow 1$ to *itermax* **do**
    Update u_{ij} by (Eq.4.3)
    Calculate z_j by (Eq. 4.4)
    Calculate the objective function by (Eq. 4.1)
    if $| J^{(t)} - J^{(t-1)} | < \varepsilon$ **then**
        Break
    end if
end for
Output: U and Z (segmented image)

4.2.3 FCM Applications

During the last years, Fuzzy C-Means (FCM) algorithm has been implemented in many fields, and for solving different problems, as an indicator to the huge application of FCM, the list resulting from typing " Fuzzy c mean " on Google Scholar site contains approximately 2,930,000 results. Table 4.1 contains some of application of standard FCM and other improved versions in different fields.

4.2.4 FCM Drawbacks

Despite the great use of the Fuzzy C-Means (FCM) algorithm in solving many problems in various fields, FCM have many drawbacks such as [142]:

- Long computational time.
- Sensitivity to the initial cluster centers.
- Necessary to specify cluster centers number.
- Sensitivity to imaging artifacts such as noise, density inhomogeneity and partial volume.

Table 4.1: List of some FCM application

Field	Application
Medical	Medical image segmentation [119] Brain tumors detection [120] Detecting lung cancer [121] Classification of ECG arrhythmias [122] Epileptic spikes detection [123]
Internet	Web page recommender system[124] Wireless sensor networks [125] Internet portals [126]
Communication	Cognitive radio networks [127] Churn management [128] Wireless sensor networks [129] Energy detection [130]
Management and marketing	Transboundary water management [131] Customer clustering [132] Supply chain management [133]
Security	Intrusion detection system [134] Security assessment [135] Intrusion detection system [136]
Industrial	Industrial gas turbine modeling [137] Mechanical fault detection [138] Measuring industry data [139] Power flow management [140] Tunnel boring machine analysis[141]

4.2.5 Improvements to Fuzzy C-Means (FCM)

To overcome the drawbacks of the standard fuzzy c-means algorithm, many improved versions have been introduced in the literature. Chumsamrong, W. et *al.* [143] proposed an improved FCM algorithm to reduce the noise effect by involving the neighboring pixels information. Their proposal got better segmentation results, but it had little bad effect on the edges. A new modified FCM named BCFCM has been proposed in [144]. The authors modified the standard FCM objective function to take into account immediate neighborhood pixels information in the clustering. The experimental results show the efficiency of BCFCM in MR images segmentation compared with standard FCM. However, it is a very time-consuming algorithm. Szilagyi, et *al.* [145] introduced enhanced FCM algorithm named EnFCM to accelerate and improve BCFCM. S.C. Chen and D.Q. Zhang [146] also suggested two improved methods called FCM_S1 and FCM_S2 to reduce the execution time of BCFCM by replacing the neighborhood pixels concept with the extra mean-filtered image and median-filtered image, which can be computed in advance.

A fuzzy kernel c-means FKCM algorithm has been proposed by Zhong-dong Wu et *al*. [147]. The FKCM algorithm modified the conventional FCM by using the Mercel kernel function to map the input data with nonlinear relationships into a higher dimensional feature space. The proposed algorithm could deal with both spherical and non spherical shapes. Another modified FCM algorithms based on kernel function have been introduced in [148-152]. Dubey et *al*. [153] suggested an improved FCM algorithm named a Rough Set based Intuitionistic Fuzzy C-Means (RIFCM), They worked on using an intuitionistic fuzzy roughness measure in order to get optimal initial values of cluster centroids. Furthermore, they proposed a new intuitionistic fuzzy complement function. The experiment results on brain MR images show that RIFCM reduces the noise and gets good segmentation results.

4.3 Bat Algorithm (BA) Overview

4.3.1 Biological Inspirations of Bats

Bats are the only mammals that can fly, and they are found in nature in very large numbers, about one fifth of all the world's mammals. Bats are found in most parts of the world, especially in the tropics and subtropics zones, and they can live in deserts, farms, forests, and even industrial areas, except for the Arctic and Antarctic. Their exceptional ability to fly at night and navigate in full darkness tremendously assisted them in locating and finding their prey. Their search technique is based on echolocation. In 1794, Lazzaro Spallanzani was the first scientist who explained how bats could fly in the darkness. Then, after 150 years, Donald Griffin and Sven Dijkgraaf described the echolocation in more detail. The echolocation process starts with the bats emitting high-frequency sounds through their mouths or noses that transcend the highest range of human hearing, then listening to the reflected echo to determine the shape, size and distance of surrounding prey or objects (objects in its environment). Even though it's impossible for humans to capture these frequencies, developed devices can analyze and make them understandable [154]. Figure 4.2 explains the bat’s echolocation.

There are three types of echolocation signals illustrated in Figure 4.3, which are:

- Frequency Modulated (FM), short and the most popular signal type that covers wide frequency range.
- FM-CF, consists of short sloped modulated followed by a constant but longer frequency band.
- FM-CF-FM, the longest fixed sound signal that usually precedes and is followed by short Frequency Modulated.

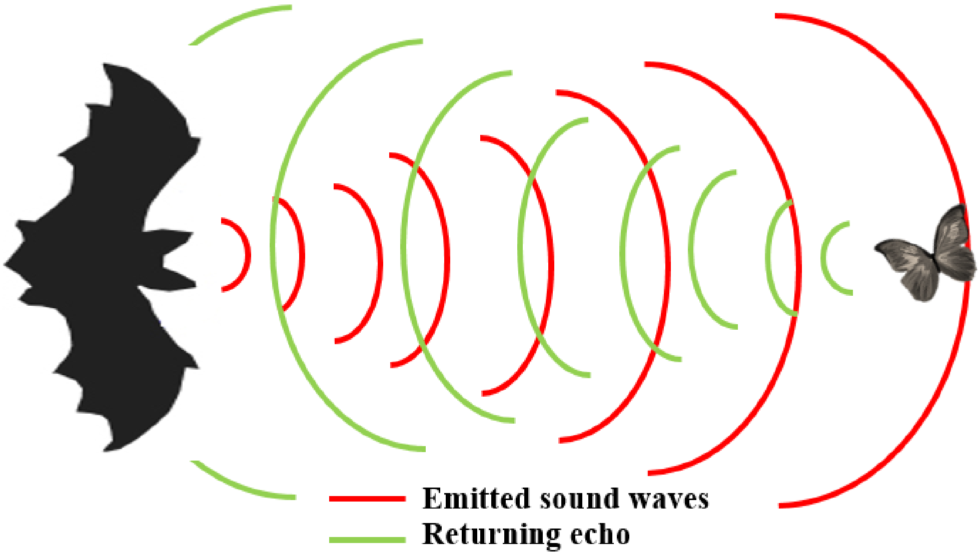


Figure 4.2: Bat's echolocation

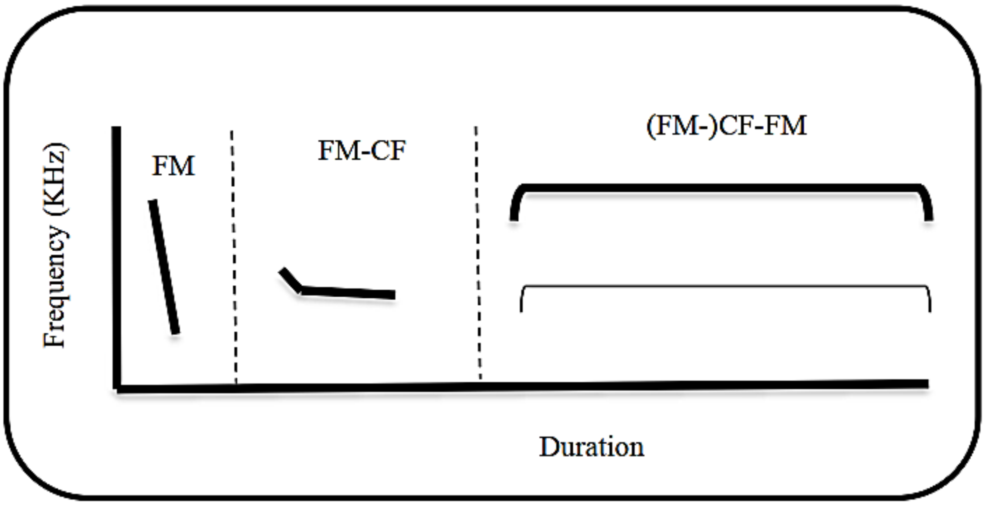


Figure 4.3: Bats echolocation Types, This image were obtained from [154].

4.3.2 The Standard Bat Algorithm

In 2010, Xin-She Yang [5] proposed a bio-inspired metaheuristic algorithm named the Bat Algorithm (BA). BA works on the concept of microbats' echolocation behavior to find their prey. The micro-bat emits signals in the searching space, then collects and analyzes the reflected echoes from a prey to determine its type, orientation and speed. During the past few years, BA has proved its efficiency in solving various optimization problems in different fields.

4.3.2.1 Echolocation Capability of Bats

To design the algorithm and create the mathematical equations, Yang proposed several rules to simulate the bat's echolocation behavior [5]:

- All bats make use of echolocation technique to find their preys and sense their environment. Bats can also distinguish in remarkable way between obstacles and prey/food.
- Bats fly randomly with velocity v_i at position x_i with wavelength λ, frequency f and loudness A to search for prey.
- Wavelength (λ) and frequency (f) of emitted sound pulse are related due to the fact λf is constant, so a range of [f_{min} ; f_{max}] is corresponds to a range of [λ_{min} ; λ_{max}].
- According to the proximity of their target, bats can automatically adjust the wavelength (or frequency) and the rate of pulse emission r $\in$[0;1].
- Loudness decreases from high value A_0 to a positive low constant value A_{min}.

4.3.2.2 The Structure of Bat Algorithm (BA)

a) Initialization of bat population: The bat algorithm consider the search space as an area containing food/prey sources, and aim to locate or hunt the best quality one. BA used swarm consists of N bats for his searching process, this swarm randomly generated from real-valued vectors with dimension d. Then, the objective function evaluates the quality of the food/prey sources obtained.

b) Generation of frequency, velocity and new solutions: During the bat algorithm iterations, the position x_i and the velocity v_i of each bat should be defined and subsequently updated according to these rules [155]:

$$f_i = f_{min} + \beta\ (f_{max} - f_{min}) \tag{4.5}$$

$$v_i^t = v_i^{t-1} + \left(x_i^t - x_*\right) f_i \tag{4.6}$$

$$x_i^t = x_i^{t-1} + v_i^t \tag{4.7}$$

Where β ∈ [0,1] and represents a random value, x_* is the current global best location (solution) achieved by evaluating all swarm's bats and f_i presents a frequency value of the ith bat, it ranges between f_{min} and f_{max}. According to the problem type, BA uses either f_i (or λ_i) to adjust the velocity change while fixing the other factor λ_i (or f_i).

c) Local search capability of the algorithm: For each bat, a new solution is generated locally using random walk given by (Eq. 4.8).

$$x_{new} = x_{old} + \varepsilon \overline{A}^{t} \tag{4.8}$$

Where x_{old} indicates a high quality solution chosen among the best solution, ε is a random value lies between -1 and 1, $\overline{A}^{t}$ represents the average of all the bats' loudness at this time.

d) Loudness and pulse emission rate As the BA iterations proceed, the loudness *A* and pulse emission rates *r* are updated as a bat gets closer to its target, A and r can be decreased and increased as following to (Eq. 4.9), (Eq. 4.10) respectively when bat gets closer to its target.

$$A_i^{t+1} = \alpha A_i^t \tag{4.9}$$

$$r_i^{t+1} = r_i^0 \left(1 - e^{-\gamma t}\right) \tag{4.10}$$

In simple problems, α and γ are constants and $\alpha = \gamma$, r_i^0 represents initial pulse emission rate value of the *i*th bat. With α ranges between 0 and 1 , $\gamma > 0$, we have

$$A_i^t \longrightarrow 0,\ r_i^t \longrightarrow r_i^0 \text{ as } t \longrightarrow \infty \tag{4.11}$$

4.3.2.3 Pseudo Code of Bat Algorithm

Based on the bats echolocation behavior, the basic steps of the Bat Algorithm (BA) can be described as follows in Algorithm 4.2 [5]:

4.3.2.4 Bat Algorithm Efficiency

During the past years, researchers have proposed and developed many metaheuristic algorithms in order to solve optimization problems in an efficient way. By analyzing bat algorithm, updating equations and key features, the efficiency of the bat algorithm can be summarized by the three following points: frequency tuning, parameter control and automatic zooming [156].

a) Frequency tuning: Bat Algorithm sharing the capability of using frequency variations to solve optimization problems with other swarm algorithms like particle swarm optimization and harmony search, Therefore, BA may possess the advantages of other swarm-intelligence-based algorithms.

b) Parameter control: Unlike many other metaheuristic algorithms that use fixed parameters, BA uses parameter control technique that allows the values of parameters (*A* and *r*) to change as the iterations proceed.

c) Automatic zooming: BA have the ability to automatic zooming or focusing on the promising region. This helps to swap from exploration to local intensive exploitation which leads to quick convergence rate to the global optimal solution in the early stages of the algorithm iterations.

Algorithm 4.2: The standard Bat Algorithm (BA)

Input: Data (original image)
Parameters: *Np* number of the population, *itermax*, f_{max}, f_{min}
Define the objective function F(x)
Initialize x_i and velocity v_i for each bat
Initialize pulse frequency *fi* pulse rate *ri* and loudness *Ai* for each bat
Repeat
  for i⟵1 to Np **do**
    Create new solution through adjust frequency by (Eq. 4.5), update velocity by (Eq. 4.6) and update location by (Eq. 4.7)
    if (rand $>r_i$) **then**
      Choose a solution among the best solutions, generate a local solution near the selected best solutions by (Eq. 4.8)
    end if
    Generate a new solution randomly
    if (rand $< A_i$ **and** $F(x_i) < F(x_*)$) **then**
      Accept the new solution
      Decrease A_i and increase r_i by (Eq. 4.9) (Eq. 4.10) respectively
    end if
  end for
  Rank the bats and find the current best x_*
Until t > *itermax*
Output: best solution x_* (segmented image)

4.3.2.5 Bat Algorithm Limitations

Even with the great ability of the bat algorithm to accelerate the convergence rate, especially if its parameters are well-tuned, bat algorithm suffer from some drawbacks, such as [157]:

- Bat Algorithm have a huge difficulty in escaping from the local optima because to his inability to produce a mutation in addition to lack of diversity of the population.
- All bats move toward the best solution, which causes them to fall into local optima easily.

- Using simple linear equations to update the value of loudness and pulse rate, which decreases the bat algorithm's exploration ability.
- In the bat algorithm, the bats don't move to a new location unless the new location is better than the current global solution, which limits the movement process.

4.3.2.6 Applications of Bat Algorithm

The Bat algorithm has been used in different fields because of its efficiency in solving different optimization problems. Some of the major applications are presented as follows:

a) Image Processing: Akhtar, S et *al.* in [158] implemented the bat algorithm (BA) for full human body pose estimation in video sequences. The BA parameters are tuned to be suitable for tracking whole-body human problems. The results show that the tracking accuracy of BA is better than Particle Swarm Optimization (PSO), Annealed Particle Filter (APF) and Particle Filter (PF). A modified bat algorithm called Bat Algorithm with Mutation (BAM) developed by Zhang, J. W and Wang, G. G in [159]. The BAM used for solving image matching problems. The results proved the efficiency of BAM compared with standard BA and other optimization methods, DE and SGA in addition to that, their proposal BAM succeeded in accelerating the global convergence rate. Alihodzic, A., & Tuba, M.in [160] improved the standard bat algorithm for multilevel image thresholding problem. The authors adjusted BA by integrating some elements from the Artificial Bee Colony (ABC) algorithm and DE. The results show that the improved bat algorithm proposed has better accuracy than the other five tested methods, including the standard BA.

b) Clustering: A new method called KMBA has been proposed by Komarasamy, G. & Wahi, A [161]. The proposed method uses the bat algorithm to determine the optimal number of clusters and to initialize the center clusters of the K-Means Clustering algorithm. The results show that KMBA achieved better clustering than other tested methods. A combination between the Bat Algorithm (BA) and the Fuzzy C-Means (FCM) clustering algorithm for optimizing the location of rural kiosk proposed in [162] by Gupta, R et *al.*. Lipare, A et *al.* in [163] proposed a method called FC-RBAT that used both Fuzzy C-means (FCM) and BA, the first used for load-balanced clustering and the second used for energy-efficient routing.

c) Classifications: Mishra S et *al.* [164] suggested a new model named Bat-FLANN for microarray data classification. The suggested model Bat-FLANN use bat algorithm to adjust the Functional Link Artificial Neural Network weights. Compared with FLANN and PSOFLANN, the suggested model Bat-FLANN illustrates great efficiency in the microarray data classification. A new method for medical data classification called Bat based Fuzzy Classification (BFC) presented by Binu, D and Selvi, M in [165]. The BFC is based on using the bat algorithm for optimizing rules while the classification of test data is done by the fuzzy system. The results proved the efficiency of the BFC by achieving 75.21% and 76.67% accuracy with lung cancer data and Indian liver data respectively.

d) Other application: Bat algorithm has been used in fuel and energy [166], attribute reduction [167]. cloud computing [168] , load balancing [169] and other application.

4.3.2.7 Bat Algorithm Variants

The Bat Algorithm (BA) has received great attention since it was proposed by Yang (2010) and has been used in many fields. Many researchers have developed the original version of bat algorithm either by improving it with different techniques or by hybridizing it with other metaheuristics.

a) Improved version: Multi-objective optimization problems are considered complex problems that need efficient optimization algorithms. Because of that, Yang (the founder of BA) extended his original Bat Algorithm (BA) version to MOBA [170] and improved it to be able to solve multi-objective optimization problems. An enhanced BA named FLBA proposed by Khan et *al.* [171] for office workplace management. The proposed fuzzy logic bat algorithm FLBA modified the velocity equation and combined incorporated the fuzzy logic mechanisms with the parameters of the bat algorithm. A discrete version of the original bat algorithm named Binary Bat Algorithm (BBA) suggested by Nakamura et *al.* in [172]. BBA is used to solve feature selection and classification problems. Xie et *al.* [173] presented an enhanced BA named DLBA by combining between differential operations and the levy flights technique. Another improved BA version based on the levy flights technique was proposed in [174 -175]. An improved bat algorithm introduced by Fister et *al.* [176] named the Quaternion Bat Algorithm (QBA). The authors used quaternions to represent microbats in the algorithm. Kiełkowicz K, Grela D have improved the standard bat algorithm by modifying the velocity equation and presenting a new system for accepting the new solutions [177].

b) Hybrid version: Wang G, Guo L in [178] developed a hybrid algorithm combining between bat algorithm and Harmony Search (HS) algorithm. The authors increased the diversity of the population and decreased falling into the local optima by integrating the Harmony Search (HS) algorithm mutation feature into the position update equation of the bat algorithm. The experimental results show the efficiency of the hybrid algorithm when compared with both BA and HS. For solving numerical optimization problems, Nguyen, T.-T et *al.* [179] introduced a hybrid algorithm combining an Artificial Bee Colony (ABC) and a Bat Algorithm (BA). After *Ri* iterations, the hybrid algorithm replaced some poorer BA agents with some of the best ABC individuals, and on the contrary, the worst ABC individuals will be replaced by better BA agents with the proposed communication strategy. The result illustrates that the proposed hybrid algorithm had a better performance than both BA and ABC. A new hybrid algorithm called BADE for solving constrained problems has been proposed by Meng X et *al.* [180]. the proposed BADE algorithm combining between bat algorithm and differential evaluation, the authors improved the bat algorithm by using the neighborhood bats velocities to modify the velocity update equation and making use of the DE mutation feature. Another hybrid algorithm based on DE has been presented by Yildizdan, G. and Baykan, Ö. In [181]. Tawhid MA and

Dsouza KB suggested a new hybrid algorithm named HBBEPSO for problems of feature selection [182]. Their suggested algorithm is based on the binary bat algorithm and an improved PSO, HBBEPSO combines both capabilities, fast convergence rate and exploration search space of the improved PSO algorithm and the bat algorithm respectively. To reduce electricity bills and optimize energy usage, Latif, U et *al.* in [183] proposed a hybrid algorithm based on GA and BA. Saraswathi, M. et *al.* [184] took advantage of the bat algorithm's echolocation ability and combined it with cuckoo search parasitic behavior and developed a new algorithm called the hybrid cuckoo bat algorithm for obtaining the optimal path for the mobile robot. Another hybrid algorithm based on cuckoo search and bat algorithms is presented in [185].

4.4 Conclusion

We have discussed in this chapter the two algorithms, Fuzzy C-Means (FCM) clustering and the Bat Algorithm (BA) that we have used in our study. At first, we have presented the Fuzzy c-means algorithm in detail, which is commonly used in MRI segmentation in the literature. We have mentioned Fuzzy Sets Theory (FST) and focused on the FCM algorithm, FCM application, FCM drawbacks and some improved FCM algorithms. Secondly, we have presented an overview of the metaheuristic Bat Algorithm (BA), which has proved its efficiency in solving optimization problems. We have mentioned the biological inspirations of bats, the standard bat algorithm, bat algorithm efficiency, limitations, application and bat algorithm variants.

In this study, we will combine between FCM clustering algorithm with a Bat Algorithm (BA) to achieve better segmentation results on brain MR images. In the next chapter, we will discuss and present our contribution in brain MRI segmentation.

CHAPTER 5

OUR CONTRIBUTION IN BRAIN MRI SEGMENTATION

Chapter 5

Our Contribution in Brain MRI Segmentation

5.1 Introduction

Magnetic Resonance Imaging (MRI) plays an important role in clinical diagnosis, because of that, it has attracted increasing attention in recent years. The symptoms of many diseases correspond to the brain's structural variants. The detection of various diseases has become easier through the MRI segmentation methods. There are various MRI segmentation techniques in the literature, fuzzy c-means (FCM) is considered among the popular clustering algorithms for medical image segmentation. However, FCM is sensitive to the noise and falls into local optimal solution easily because of the random initialization of the cluster centers. In our study, we propose a hybrid method based on Modified Fuzzy Bat Algorithm (MFBA) and the FCM clustering algorithm named MFBAFCM for brain MRI segmentation. This developed approach uses the MFBA to get better initial cluster centers for the FCM algorithm by using a new fitness function that combines intra cluster distance with fuzzy cluster validity indices. The experimental results on several brain MR images corrupted by different levels of intensity non-uniformity and noise, show that the proposed method produces better results than the standard FCM and some other recent published works.

5.2 Our Contribution

5.2.1 Motivation

Medical imaging has made a great contribution to the medical field in recent years, it is able to generate a wide range of detailed 2D and 3D images of the body structures. The most used imaging techniques are X-ray, CT, and MRI. In our thesis, we studied the Magnetic Resonance Imaging (MRI) because of its capability to produce excellent image quality of the human anatomy, especially the brain MR images. These medical images assist radiologists to examine the inside of the patient's body without the need for surgeries, Magnetic Resonance Imaging (MRI) also helps to diagnose and detect diseases or injuries early. However, sometimes MR images corrupted by various artifacts such as the noise, intensity non-uniformity and partial volume, which have negative effects on the quality of the MRI.

MR images contain sensitive information about the health of the patients, it is difficult for doctors to monitor and detect all of this information. Because of that, MR images need to be segmented. Brain MRI segmentation is a very important step in medical image analysis, it enhances the doctor's ability to detect the tiny information. The MRI segmentation helps to detect boundaries and extract different objects, these objects could be organs, tissues, bones, and others. In the last few years, various segmentation techniques have been proposed in the literature, each technique has its advantages and drawbacks. In our study, we chose a clustering technique called Fuzzy C-Means (FCM) clustering algorithm.

FCM algorithm, as we discussed previously, is commonly used in brain MRI segmentation due to its fuzzy ability and efficiency. However, it has many drawbacks that negatively affect the segmentation process.

To improve the Fuzzy C-Means (FCM) algorithm, we chose a metaheuristic algorithm named Bat Algorithm (BA) to optimize the segmentation process, Bat Algorithm (BA) has been widely used in the literature and has proved its efficiency as we saw in the fourth chapter. We proposed a hybrid algorithm named FBAFCM for segmenting the Gray Matter (GM), White Matter (WM) and Cerebrospinal Fluid (CSF) of brain MRI scans.

5.2.2 Fuzzy Bat Algorithm (FBA)

The standard bat algorithm could not be used for solving fuzzy clustering problem directly, it needs some adjustments to be suitable for these kinds of problems. Pang et *al.* [186] proposed a Fuzzy Particle Swarm Optimization (FPSO) algorithm to solve an NP-hard problem, which is Traveling Salesman Problem (TSP). They represented PSO particles position X and velocity V by a fuzzy matrices, and they redefined the formulas operators to be suitable for fuzzy matrices. M. Semchedine A. Moussaoui in [91] used the FPSO and proposed a new objective function based on validity indices for brain MRI segmentation. In our study, we benefited from the previous works and applied the FPSO principles to the standard Bat Algorithm (BA) and proposed another objective function based on intra cluster distance and cluster validity indices.

5.2.2.1 Representation of FBA

The representation of Fuzzy Bat algorithm (FBA) is as following:

- The position of bat *X*, represented by matrix *c* rows and *N* columns and it is similar to the membership matrix *U*, where u_{ij} is the membership function of the *i*th pixel with the *j*th cluster

$$X = \begin{bmatrix} U_{11} & \cdots & U_{1N} \\ \vdots & \ddots & \vdots \\ U_{c1} & \dots & U_{cN} \end{bmatrix} \tag{5.1}$$

- The velocity V also represented by matrix c rows and N columns.

$$V = \begin{bmatrix} U_{11} & \cdots & U_{1N} \\ \vdots & \ddots & \vdots \\ U_{c1} & \dots & U_{cN} \end{bmatrix} \tag{5.2}$$

- Wavelength λ and frequency f_i, loudness *A* and pulse emission rates *r* represented by real numbers.

5.2.2.2 Redefined FBA Formulas

The equations (Eq. 4.5), (Eq. 4.9) and (Eq. 4.10) do not need redefining because they do not include any position *X* or velocity *V*. Meanwhile, the rules of updating the velocity (Eq. 4.6), position (Eq. 4.7), and generating a local solution (Eq. 4.8), will be redefined as following:

$$V_i^t = V_i^{t-1} \oplus (X_i^t \ominus X_*) \otimes f_i \tag{5.3}$$

$$X_i^t = X_i^{t-1} \oplus V_i^t \tag{5.4}$$

$$X_{new} = X_{old} \oplus \varepsilon \overline{A}^t \tag{5.5}$$

Where the symbol $\oplus$ is used to indicate the addition between matrices, the symbol $\ominus$ indicates the subtraction. Meanwhile, the symbol $\otimes$ refers to multiplication between the matrix and real number.

5.2.2.3 Pseudo Code of Fuzzy Bat Algorithm (FBA)

After the adjustments that have made on the standard bat algorithm, the steps of the Fuzzy Bat Algorithm (FBA) are as follows in Algorithm 5.1:

Algorithm 5.1: The Fuzzy Bat Algorithm (FBA)

Input: Original image
Parameters: *Np* number of the population, *itermax*, f_{max}, f_{min}
Define the fitness function F(X) by (Eq. 5.10)
Initialize X_i and velocity V_i for each bat
Initialize pulse frequency f_i ,pulse rate r_i and loudness A_i for each bat
Repeat
  for i←1 to *Np* **do**
    Create new solution through adjust frequency by (Eq. 4.5), update velocity by (Eq. 5.3) and update location by (Eq. 5.4)
    if ($rand > r_i$) **then**
      Choose a solution among the best solutions, generate a local solution near the selected best solutions by (Eq. 5.5)
    end if
    Generate a new solution randomly
    if ($rand < A_i$ **and** $F(X_i) < F(X_*)$) **then**
      Accept the new solution
      Decrease A_i and increase r_i by (Eq. 4.9) (Eq. 4.10) respectively
    end if
  end for
  Rank the bats and find the current best X_*
Until $t > itermax$
Output: Segmented image

5.2.3 Modified Fuzzy Bat Algorithm (MFBA)

Through our experiments on Fuzzy Bat Algorithm (FBA), we noted that all bats move toward the best solution and do not move unless the new location is better than the current best solution which causes the falling into local optima easily. To increase the diversity of the FBA population and reduce the full dependency on the best solution, we proposed a small modification on FBA by replacing all bats, its fitness value does not change four times sequentially by new solution, this solution generated by calculating the average of the best five solutions achieved.

The fitness value is calculated by a fitness function (objective function) that we will introduce later in next subsection. Choosing the number of times that the fitness value remains unchanged and defining the number of the best solutions used for generating the new solution is made by experiments (Table A.1, Table A.2 and Table A.3). With this modification, each bat in MFBA will have:

- X_i: ($c \times N$ matrix) represents the position of a bat.
- V_i: ($c \times N$ matrix) represents the velocity of a bat.
- f_i: a real number represents the frequency of a bat.
- A_i: a real number represents the loudness of a bat.
- r_i: a real number represents the pulse emission rate of a bat.
- rep_i: a parameter for each bat to count how many times the same fitness value is repeated sequentially

The steps of the Modified Fuzzy Bat algorithm (MFBA) are as follows in Algorithm 5.2:

5.2.4 Proposed Method

5.2.4.1 Cluster Validity Indices

The cluster validity indices are necessary to evaluate the quality of the clustering process. The main point is to determine whether the partitions resulted from the clustering algorithm correctly presented the data or not. We describe four indices, which are presented as follows:

a) Partition Coefficient (PC): A useful index can measure the amount of "overlapping" between clusters. PC index value lies between 1/c and 1, it is defined by Bezdek [116] as follows:

$$PC = \frac{\sum_{i=1}^{N}\sum_{j=1}^{c}\left(u_{ji}\right)^2}{N} \tag{5.6}$$

b) Classification Entropy (CE): CE and PC indices are similar, classification entropy can only measure the fuzziness of the cluster partition [187].

$$CE = \frac{-\sum_{i=1}^{N}\sum_{j=1}^{c}u_{ji}\log\left(u_{ji}\right)}{N} \tag{5.7}$$

Algorithm 5.2: The Modified Fuzzy Bat Algorithm (MFBA)

Input: Original image
Parameters: *Np* number of the population, *itermax*, f_{max}, f_{min}
Define the fitness function F(X) by (Eq. 5.10)
Initialize X_i , V_i randomly and initialize $rep_i \leftarrow 0$ for each bat
Initialize pulse frequency f_i, pulse rate r_i and loudness A_i for each bat
Repeat
  for i←1 to *Np* **do**
    Create new solution through adjust frequency by (Eq. 4.5), update velocity by (Eq. 5.3) and update location by (Eq. 5.4)
    if ($rand > r_i$) **then**
      Choose a solution among the best solutions, generate a local solution near the selected best solutions by (Eq. 5.5)
    end if
    Generate a new solution randomly
    if ($rand < A_i$ **and** $F(X_i) < F(X_*)$) **then**
      Accept the new solution
      Decrease A_i and increase r_i by (Eq. 4.9) (Eq. 4.10) respectively
    end if
    if $(F(X_i^t) - F(X_i^{t-1})) = 0$ **then**
      $rep_i \leftarrow rep_i + 1$
    else
      $rep_i \leftarrow 0$
    end if
    if $rep_i = 4$ **then**
      Replacing X_i by average of the best five solutions achieved
    end if
  end for
  Rank the bats and find the current best X_*
Until $t > itermax$
Output: Segmented image

c) Partition Index (SC): It represents a set of individual cluster validity measures normalized through division by the fuzzy cardinality of each cluster [188].

$$SC = \sum_{j=1}^{c} \frac{\sum_{i=1}^{N} (u_{ji})^m \left\| x_i - z_j \right\|^2}{N \sum_{k=1}^{c} \left\| z_k - z_j \right\|^2} \tag{5.8}$$

d) Separation Index (S): For partition validity, the separation index S uses a minimum-distance separation [188].

$$S = \frac{\sum_{j=1}^{c} \sum_{i=1}^{N} (u_{ji})^m \left\| x_i - z_j \right\|^2}{N \min j,k \left\| z_k - z_j \right\|^2} \tag{5.9}$$

To end up with a better partition and regions, the three indices CE, SC and S should be minimized. Meanwhile, the PC value should be maximized.

5.2.4.2 Fitness Function

The fitness function (objective function) is the important part in the optimization problems, it is the responsible of valuates how close is a given solution to reach the aimed result. We propose a new fitness function that combines intra cluster distance with fuzzy cluster validity indices, it is defined as follows:

$$F(X) = \frac{intra\_cluster + SC}{PC} \tag{5.10}$$

Where SC is the partition index presented in (Eq. 5.8), PC is the partition coefficient presented in (Eq. 5.6), and the intra cluster (α distance) [91] is calculated using the equation given below:

$$Intra\_\text{cluster} = \frac{1}{N} \sum_{i=1}^{N} \sum_{j=1}^{c} \left\| x_i - z_j \right\|^2 \tag{5.11}$$

5.2.4.3 Modified Fuzzy Bat Algorithm for Fuzzy C-Means (MFBAFCM)

The purpose of the study is to propose and develop a new hybrid method, in order to improve the brain MRI segmentation process and overcome the shortcomings of the standard FCM. Our contribution consists of two steps:

- The first step: the Modified Fuzzy Bat Algorithm (MFBA) algorithm is used to get the best solution X_* by minimizing the fitness function F(X) that given in (Eq. 5.10).
- The second step starts by extracting the optimal cluster centers from the best solution X_* by (Eq. 4.4), then use them as the initial seed of the standard FCM.

Bearing in mind that the fitness is minimized when the value of PC is high and the value of (intra_ cluster + SC) is low. The steps and flow chart of the MFBAFCM algorithm are as follows:

Step 1: input the original image, set the initial values of the parameters *c*, *m*, *itermax*, ε, *Np*, λ, f_{max} and f_{min}.

Step 2: initialize bat population X_i, velocity V_i, r_i and A_i, then start MFBA.

Step 3: for each bat, adjust frequency, update velocity and locations by (Eq. 4.5), (Eq. 5.3), (Eq. 5.4) respectively.

Step 4: depending on a random number and a pulse rates r_i, a local search is done by generating a local solution around one of the best by (Eq. 5.5).

Step 5: generate a new solution randomly.

Step 6: depending on loudness A_i, a random number, the fitness of the new solution and the best solution, the new solution is accepted while A_i is decreased and r_i is increased, by (Eq. 4.9) (Eq. 4.10).

Step 7: replace all bats, its fitness value does not change four times sequentially by the average of the best five solutions achieved.

Step 8: rank the bats and find the current best solution X_*.

Step 9: repeat steps 3 to 8 until reaching the maximum number of MFBA iterations.

Step 10: end of MFBA, extract the initial cluster centers *Z* from X_* by (Eq. 4.4), note that the best solution X_* is similar to the membership matrix *U*.

Step 11: start the FCM algorithm.

Step 12: use the membership matrix *U* that is resulted by FCM to reshape the segmented image.

Step 13: Output the segmented image.

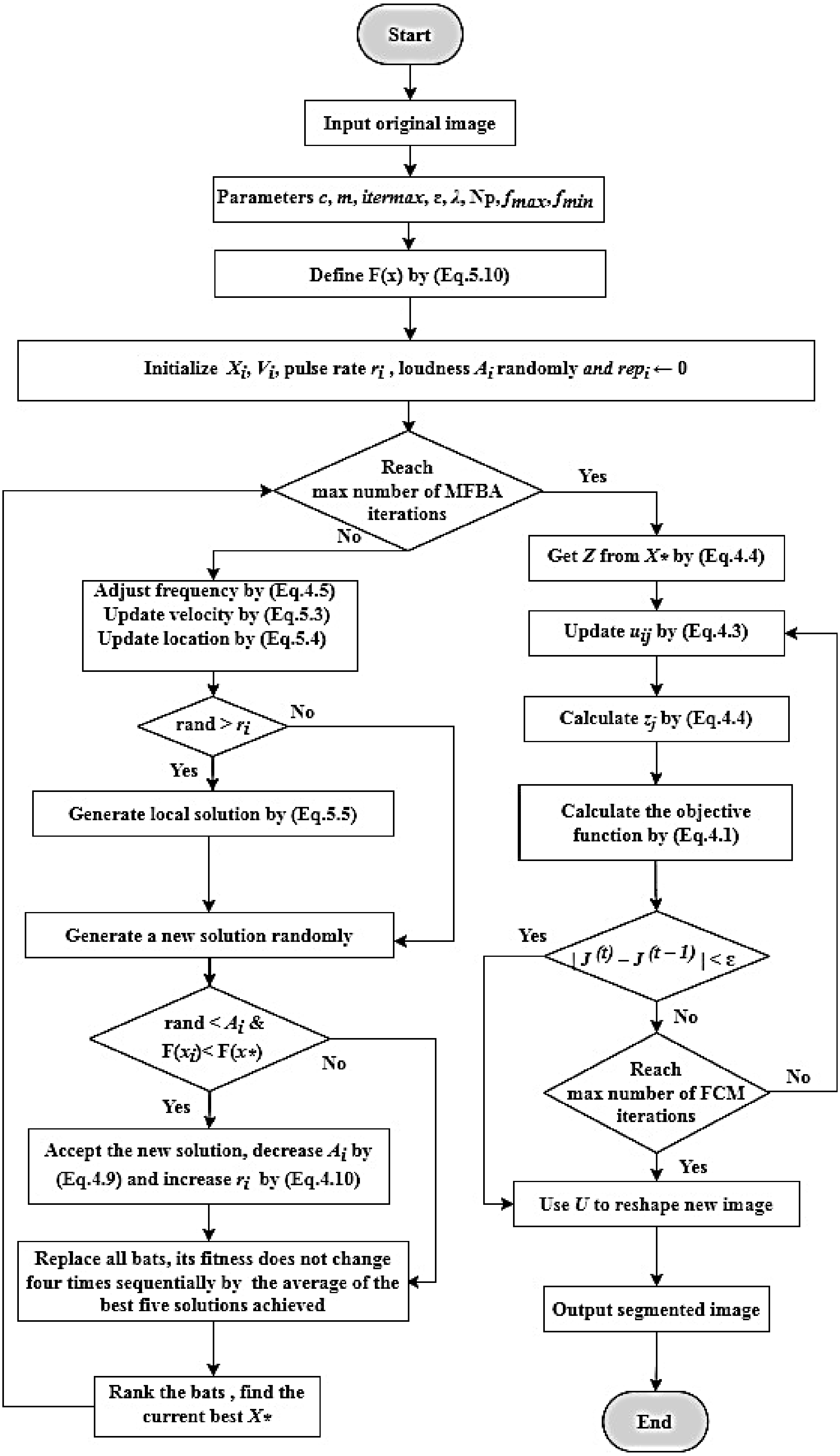


Figure 5.1: MFBAFCM flow chart

Algorithm 5.3: The Modified Fuzzy Bat Algorithm for Fuzzy c-Means (MFBAFCM)

Input: Original image
Parameters: *Np*, *itermax_FCM*, *itermax_MFBA*, λ, f_{max}, f_{min}, *c*, *m*, and ε
Define F(X) by (Eq. 5.10), initialize X_i , V_i , f_i , r_i ,A_i randomly and $rep_i \leftarrow 0$ for each bat
Repeat
  for i←1 to *Np* **do**
    Create new solution through adjust frequency by (Eq. 4.5) update velocity by (Eq. 5.3) and update location by (Eq. 5.4)
    if ($rand > r_i$) **then**
      Choose a solution among the best solutions, generate a local solution near the selected best solutions by (Eq. 5.5)
    end if
    Generate a new solution randomly
    if ($rand < A_i$ **and** $F(X_i) < F(X_*)$) **then**
      Accept the new solution
      Decrease A_i and increase r_i by (Eq. 4.9) (Eq. 4.10) respectively
    end if
    if $(F(X_i^t) - F(X_i^{t-1})) = 0$ **then**
      $rep_i \leftarrow rep_i + 1$
    else
      $rep_i \leftarrow 0$
    end if
    if $rep_i = 4$ **then**
      Replacing X_i by average of the best five solutions achieved
    end if
  end for
  Rank the bats and find the current best X_*
Until t > *itermax_MFBA*
Extract the initial cluster centers Z from X^* by (Eq. 4.4)
for *t*←1 to *itermax_FCM* **do**
   Update u_{ij} by (Eq. 4.3)
   Calculate z_j by (Eq. 4.4)
   Calculate the objective function by (Eq. 4.1)
  if $| J^{(t)} - J^{(t-1)} | < \varepsilon$ **then**
    Break
  end if
end for
Use U to reshape the new image.
Output: the segmented image

5.2.4.4 Determination of MFBAFCM Parameters

a) MFBA step parameters:

- **Number of the bat algorithm population *Np* :** we chose a fixed number of the bat algorithm population which is 20 individuals.
- **Maximum number of MFBA iterations *itermax_MFBA*** : we chose a fixed number of *itermax_MFBA* which is 100 iterations.
- **The maximum frequency f_{max} and minimum frequency f_{min}:** according to our experimental and the founder of bat algorithm X.-S. Yang, experiments [5], we determine $f_{min} = 1$, $f_{max} = 2$.
- **The initial loudness A^0 and the initial pulse emission rate r^0:** in our study, we determine $A_0 = 0.9$, $r_0 = 0.1$.
- **Wavelength λ and α:** by our experiments and as we mention in chapter 4 , we chose $\alpha = \gamma = 0.9$.

b) FCM step parameters:

- **Maximum number of FCM iterations *itermax_FCM*** : we chose a fixed number of *itermax_FCM* which is 100 iterations.
- **The fuzziness parameter m :** efficient of FCM depends on the determination of parameter m which corresponds to the degree of fuzziness of the solution**,** according to [189] a good results obtained with $m = 2$
- **Parameter ε**: according to [190], well performance achieved with $\varepsilon \in [0.01, 0.0001]$, in our study we determine $\varepsilon = 0.001$.
- **The cluster number**: the number of cluster $c = 4$ (White Matter (WM), Gray Matter (GM), Cerebrospinal Fluid (CSF) and Background).

5.3 Experimental Results

The experiments has been carried out using a computer with Intel Core i3, 4GB RAM, and were performed in MATLAB 2018b compiler. Firstly, we have compared between MFBAFCM with both traditional FCM and FBAFCM on brain MR images. Secondly, we have compared between MFBAFCM with other recent methods.

5.3.1 Performance Measures

There are many performance measures to evaluate the quality of the image segmentations. We used in this study jaccard and dice similarity indices.

5.3.1.1 Jaccard Similarity Index (JS*):*

In the segmentation process, jaccard similarity index (coefficient) measures the dissimilarity between observed and expected images [191], a comparison is made between pixels of the ground truth (R_g) and resulting image (R_t), it is defined as:

$$Jaccard = \frac{R_t \cap R_g}{R_t \cup R_g} \tag{5.12}$$

5.3.1.2 Dice Similarity Index (DS):

The dice similarity index (coefficient) is a powerful performance measure that can be used in the segmentation process to measure the extent of spatial overlap between observed and expected images [191], it is defined as:

$$Dice = \frac{2 \times \left| R_t \cap R_g \right|}{\left| R_t \right| + \left| R_g \right|} \tag{5.13}$$

The both dice and jaccard similarity indices values are bounded by 0 and 1, a better performance is achieved when the results are higher.

5.3.2 Images Database

We have used in our study a simulated brain MR images downloaded from Brainweb [20]. The testing images are from T1 modality, size of 181x217x181, voxel size 1x1x1 mm3, we have chosen T1 modality for its great clarity and the reliance of most researches on it. The Brainweb simulated brain MR images are corrupted by different levels of Intensity Non-Uniformity (INU) (0%, 20%, 40%) and different levels of noise (0%, 3%, 5%).

5.3.3 Comparative Study with Standard FCM and FBAFCM

5.3.3.1 Comparative Study by using Cluster Validity Indices

We have compared between the Modified Fuzzy Bat algorithm for Fuzzy c-Means (MFBAFCM) with both traditional FCM and Fuzzy Bat algorithm for Fuzzy c-Means (FBAFCM) on 60 simulated brain MR images from 60th to 120th, which are corrupted by different levels of Intensity Non-Uniformity (INU) (0%, 20%, 40%) and different levels of noise (0%, 3%, 5%). The results of FCM, FBAFCM and MFBAFCM on T1 are given in terms of four indices values PC, CE, SC and S respectively given in (Eq. 5.6), (Eq. 5.7), (Eq. 5.8) and (Eq. 5.9).

After 20 independent runs of simulation, the cluster validity indices results of standard FCM, FBAFCM and MFBAFCM in different levels of Intensity Non-Uniformity (INU) (0%, 20%, 40%) and Noise (N) (0% 3%, 5%) are summarized in Table 5.1, Table 5.2 and Table 5.3, where the best values are shown in bold.

Table 5.1 Cluster validity indices results of FCM, FBAFCM and MFBAFCM on 0% noise and (0%, 20%, 40%) INU

(INU)	index	FCM	FBAFCM	MFBAFCM
0%	PC	0.91234	0.96785	**0.98837**
	CE	0.14722	0.07462	**0.04329**
	SC	0.44540	0.41994	**0.39324**
	S	0.000015	0.000012	**0.000010**
20%	PC	0.91800	0.96074	**0.98490**
	CE	0.15074	0.08006	**0.04403**
	SC	0.45143	0.42854	**0.39396**
	S	0.000016	0.000012	**0.000010**
40%	PC	0.91025	0.95573	**0.97985**
	CE	0.15487	0.08880	**0.04400**
	SC	0.45963	0.43007	**0.39473**
	S	0.000017	0.000014	**0.000011**

Table 5.2 Cluster validity indices results of FCM, FBAFCM and MFBAFCM on 3% noise and (0%, 20%, 40%) INU

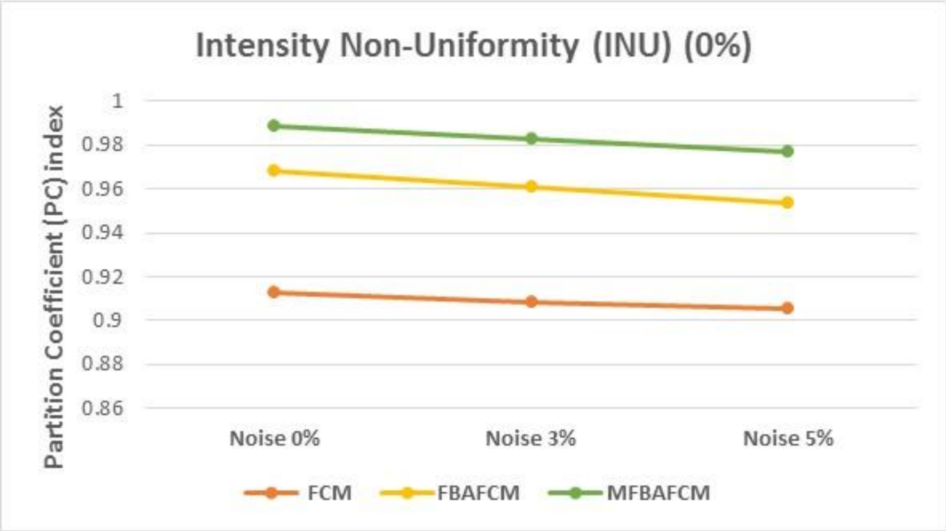
(INU)	index	FCM	FBAFCM	MFBAFCM
0%	PC	0.90834	0.96046	**0.98266**
	CE	0.15706	0.08599	**0.04464**
	SC	0.45039	0.41940	**0.39803**
	S	0.000016	0.000013	**0.000010**
20%	PC	0.90354	0.95993	**0.98008**
	CE	0.15940	0.08606	**0.04929**
	SC	0.45143	0.42854	**0.39396**
	S	0.000017	0.000012	**0.000010**
40%	PC	0.90093	0.95582	**0.97205**
	CE	0.15885	0.09462	**0.05002**
	SC	0.46193	0.43772	**0.40847**
	S	0.000018	0.000014	**0.000012**

Table 5.3 Cluster validity indices results of FCM, FBAFCM and MFBAFCM on 5% noise and (0%, 20%, 40%) INU

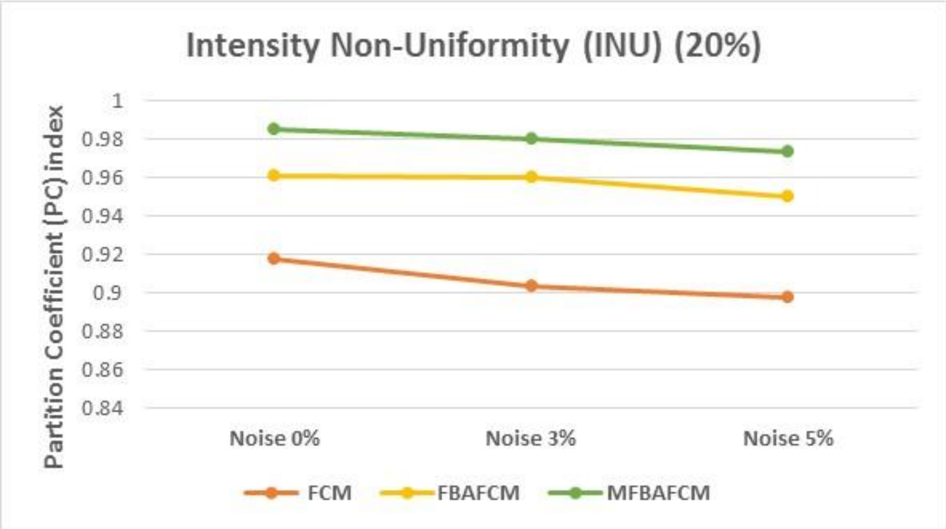
(INU)	index	FCM	FBAFCM	MFBAFCM
0%	PC	0.90542	0.95324	**0.97669**
	CE	0.16006	0.08597	**0.04995**
	SC	0.46579	0.43805	**0.40921**
	S	0.000019	0.000014	**0.000012**
20%	PC	0.89800	0.95048	**0.97338**
	CE	0.16272	0.08806	**0.05118**
	SC	0.47699	0.44632	**0.41136**
	S	0.000019	0.000015	**0.000014**
40%	PC	0.87500	0.94786	**0.97140**
	CE	0.18344	0.10798	**0.05400**
	SC	0.47703	0.44901	**0.41381**
	S	0.00002	0.000016	**0.000014**

Table 5.1, Table 5.2 and Table 5.3 show that the PC values of MFBAFCM are larger than both FBAFCM and the traditional FCM in different levels of INU (0%, 20%, 40%) and noise (0% 3%, 5%). Meanwhile, the CE, SC and S values of MFBAFCM are smaller than both FBAFCM and the traditional FCM. These results indicate that our proposed method MFBAFCM provides better-separated clusters than other tested methods FCM and FBAFCM, which leads to having more accurate segmented MR images.

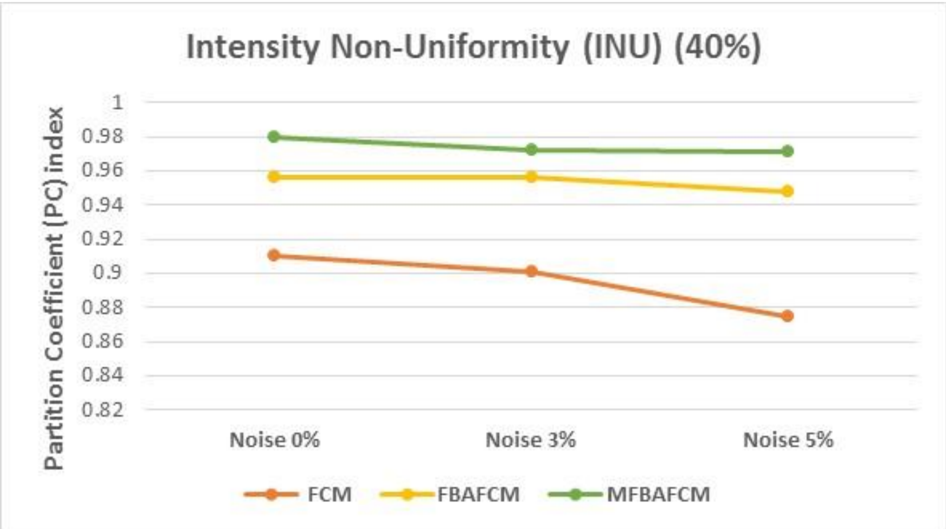
The graphical interpretations of Tables 5.1 to 5.3 are represented in Figure 5.2 to Figure 5.5, these figures illustrate the changes in the values of the four PC, CE, SC and S on different levels of Intensity Non-Uniformity (INU) (0%, 20%, 40%) and noise (0% 3%, 5%). We notice that in different levels of INU and N, the MFBAFCM's PC values are higher than both FBAFCM and the FCM. Meanwhile, MFBAFCM's CE, SC and S values are lower than both FBAFCM and the FCM. This leads to the superiority of the proposed method MFBAFCM over both FBAFCM and traditional FCM in terms of cluster validity indices.



(a)

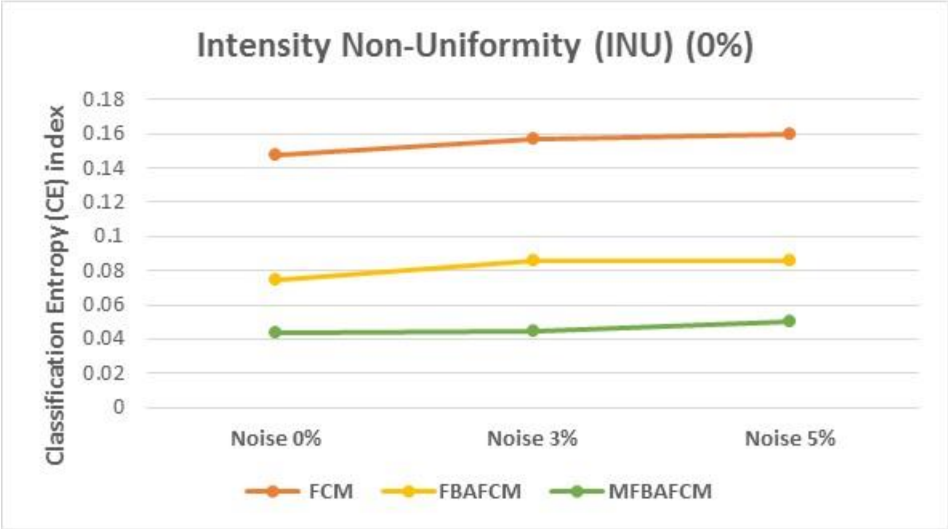


(b)

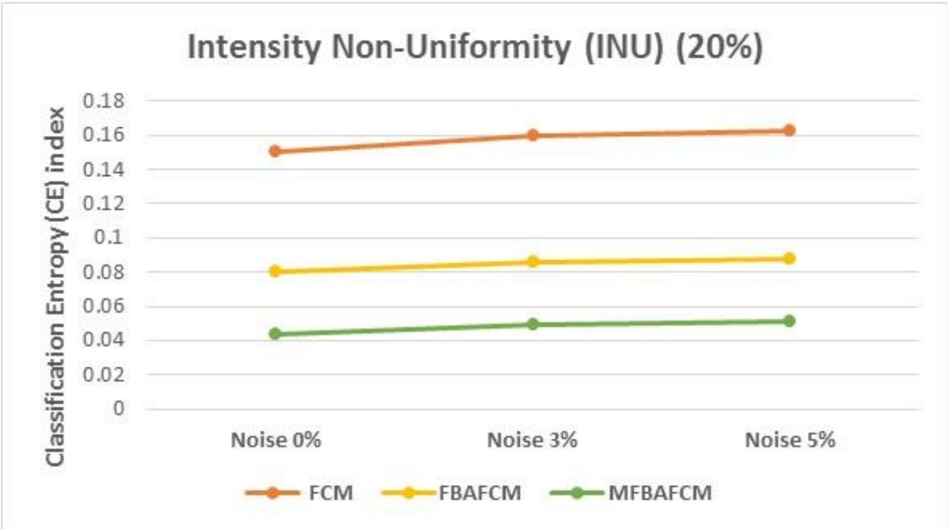


(c)

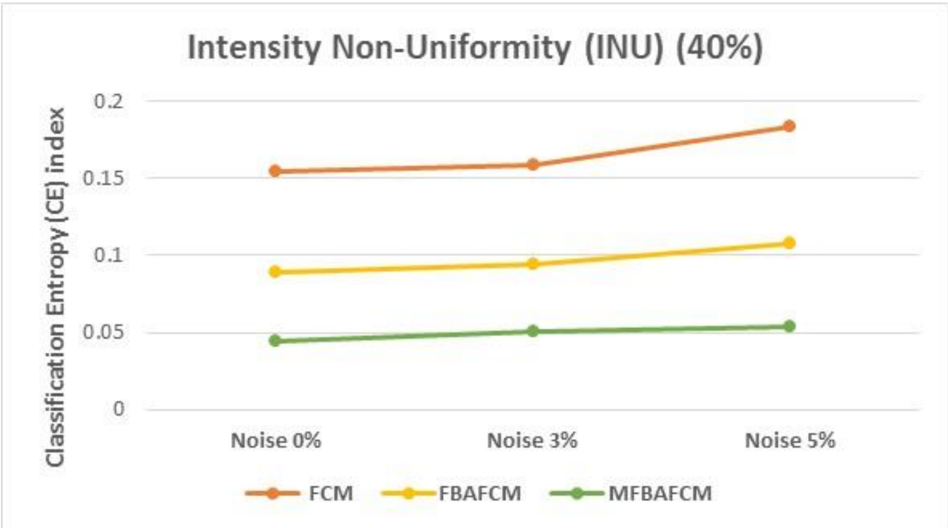
Figure 5.2: Graphical comparison of the PC index value between FCM, FBAFCM, MFBAFCM, (a) INU = 0%, (b) INU = 20%, (c) INU = 40%.



(a)

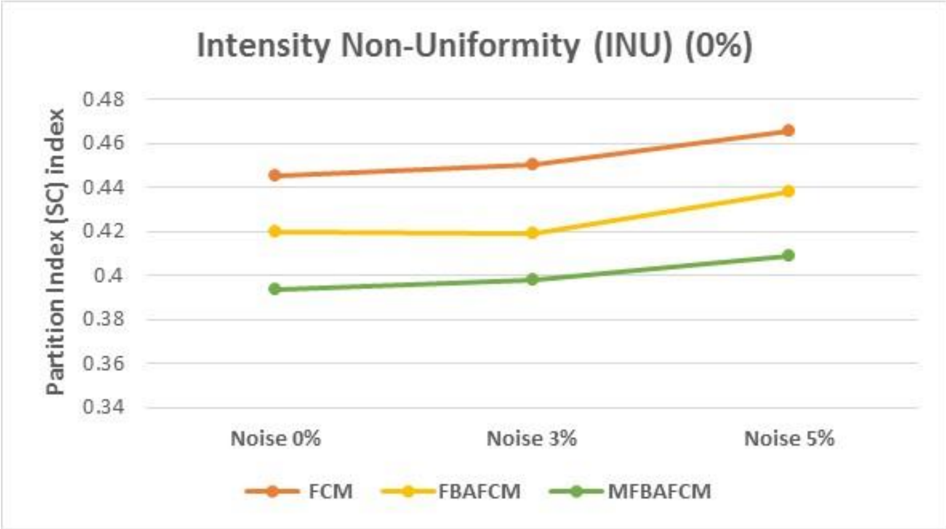


(b)

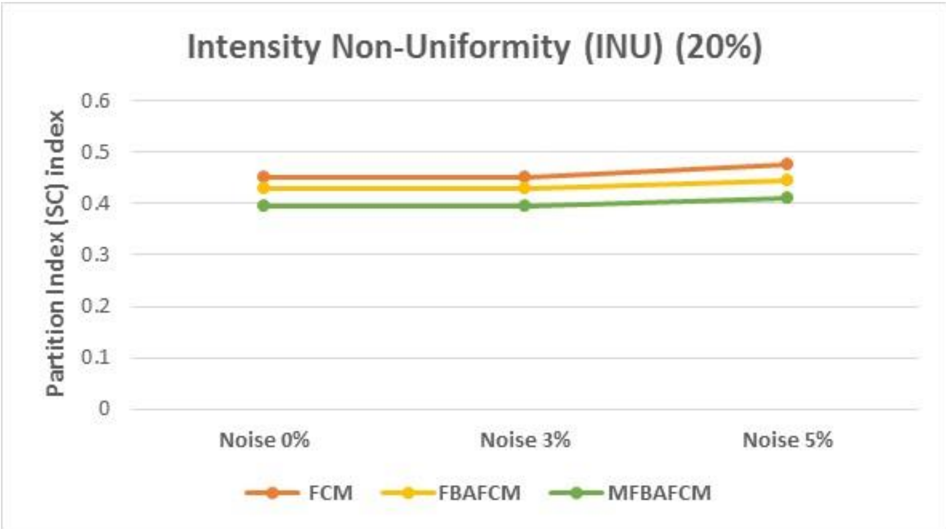


(c)

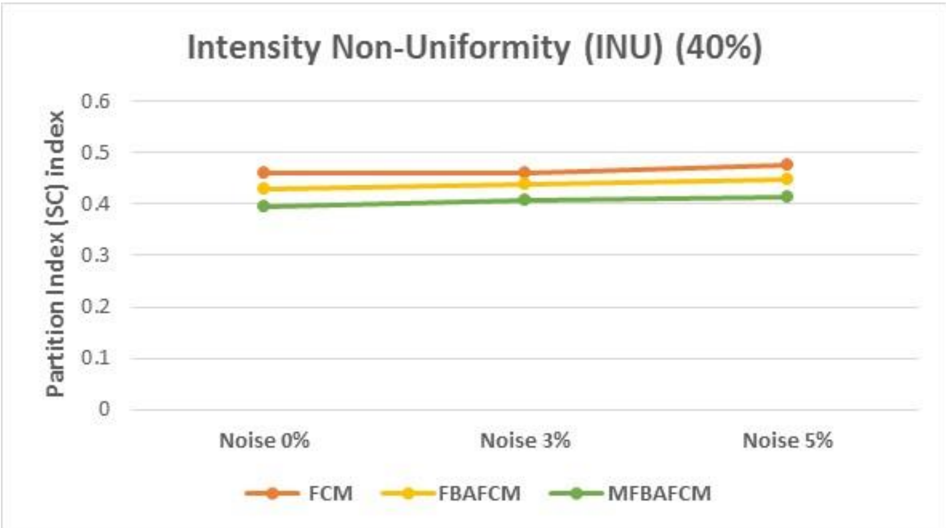
Figure 5.3: Graphical comparison of the CE index value between FCM, FBAFCM, MFBAFCM, (a) INU = 0%, (b) INU = 20%, (c) INU = 40%.



(a)

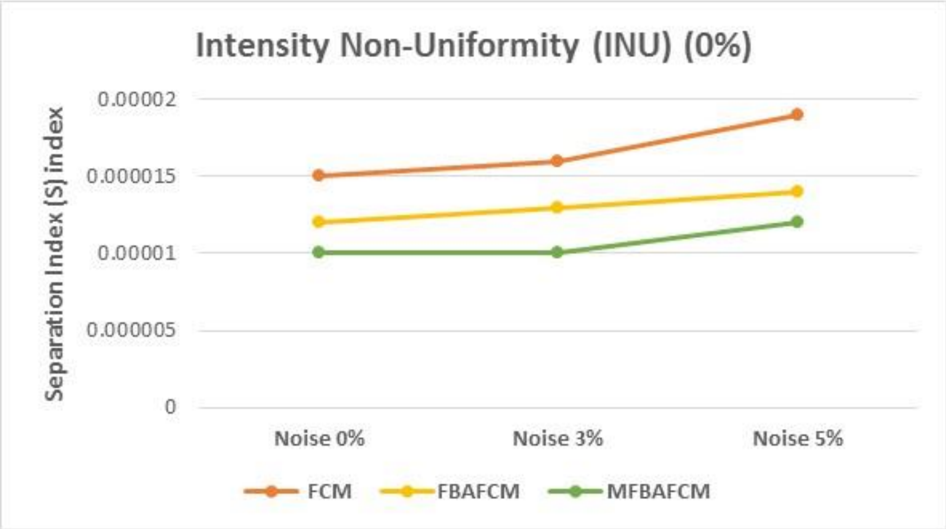


(b)

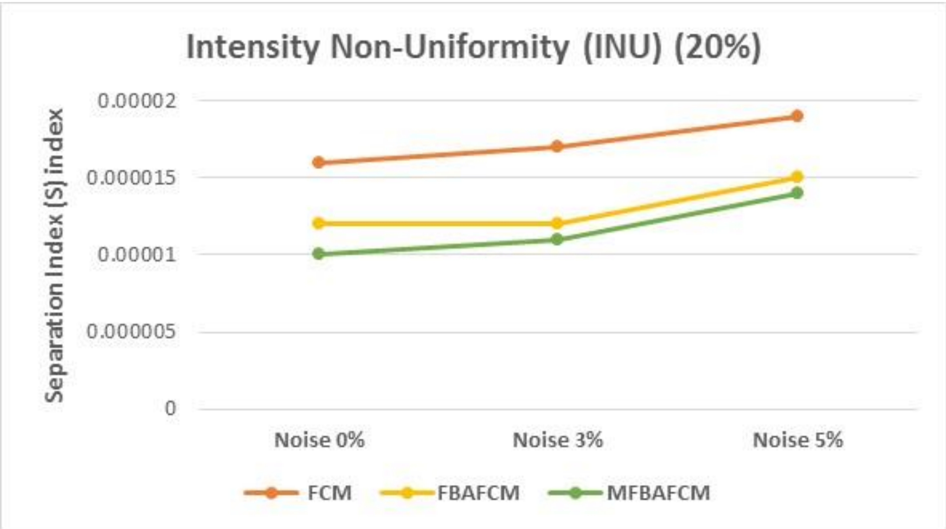


(c)

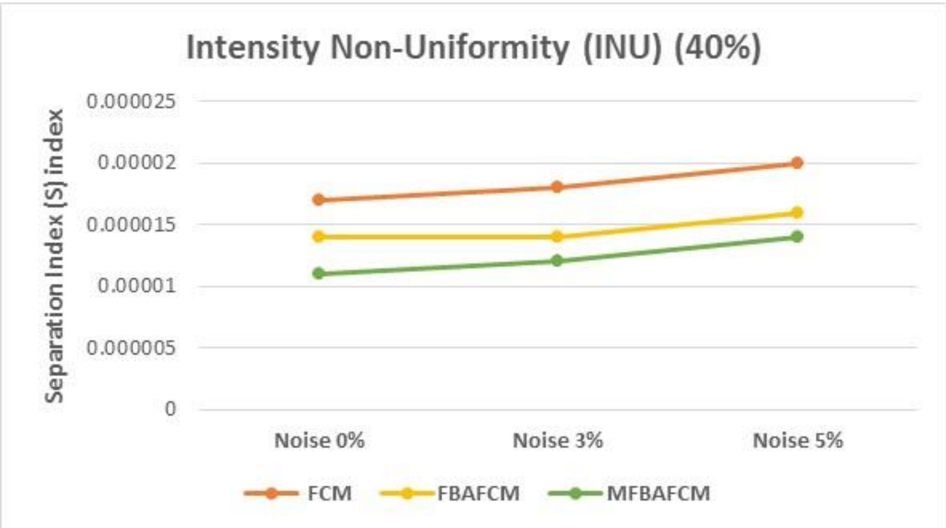
Figure 5.4: Graphical comparison of the SC index value between FCM, FBAFCM, MFBAFCM, (a) INU = 0%, (b) INU = 20%, (c) INU = 40%.



(a)



(b)



(c)

Figure 5.5: Graphical comparison of the S index value between FCM, FBAFCM, MFBAFCM, (a) INU = 0%, (b) INU = 20%, (c) INU = 40%.

5.3.3.2 Comparative Study by Using Performance Measures

After 20 independent runs of simulation, the results of the comparison between FCM, FBAFCM and MFBAFCM in terms of jaccard and dice similarity indices values respectively given in (Eq. 5.12) and (Eq. 5.13) are reported in Table 5.4, Table 5.5 and Table 5.6.

Table 5.4 Jaccard and dice similarity indices results of FCM, FBAFCM and MFBAFCM on 0% noise and 20% INU

Index	Tissue	FCM	FBAFCM	MFBAFCM
Jaccard	CSF	0.84031	0.90830	**0.94817**
	GM	0.89387	0.94427	**0.97602**
	WM	0.92261	0.95000	**0.98143**
Dice	CSF	0.90039	0.95797	**0.97255**
	GM	0.93108	0.96006	**0.98801**
	WM	0.95309	0.97800	**0.99130**

Table 5.5 Jaccard and dice similarity indices results of FCM, FBAFCM and MFBAFCM on 3% noise and 20% INU

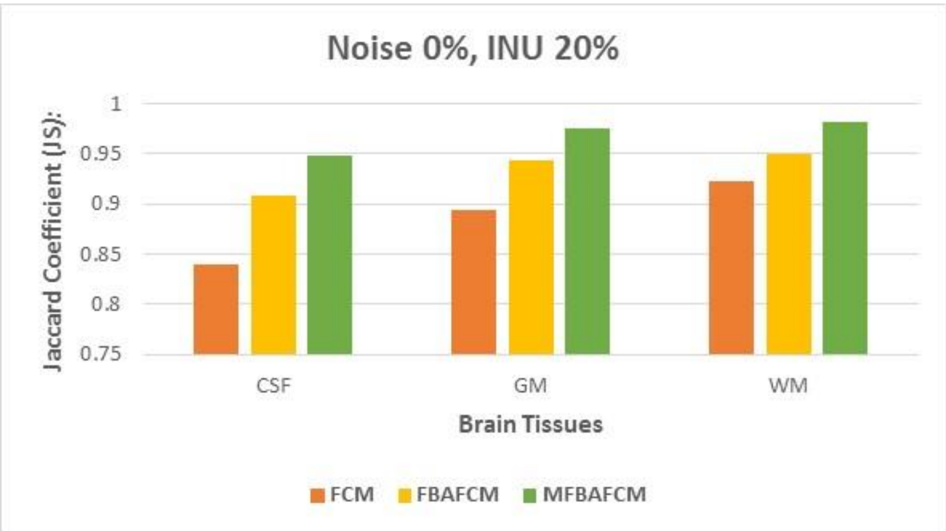
Index	Tissue	FCM	FBAFCM	MFBAFCM
Jaccard	CSF	0.82663	0.89833	**0.92906**
	GM	0.85775	0.91590	**0.95092**
	WM	0.89052	0.93885	**0.96710**
Dice	CSF	0.88059	0.92266	**0.94744**
	GM	0.90995	0.95104	**0.96906**
	WM	0.92890	0.96600	**0.97804**

Table 5.6 Jaccard and dice similarity indices results of FCM, FBAFCM and MFBAFCM on 5% noise and 20% INU

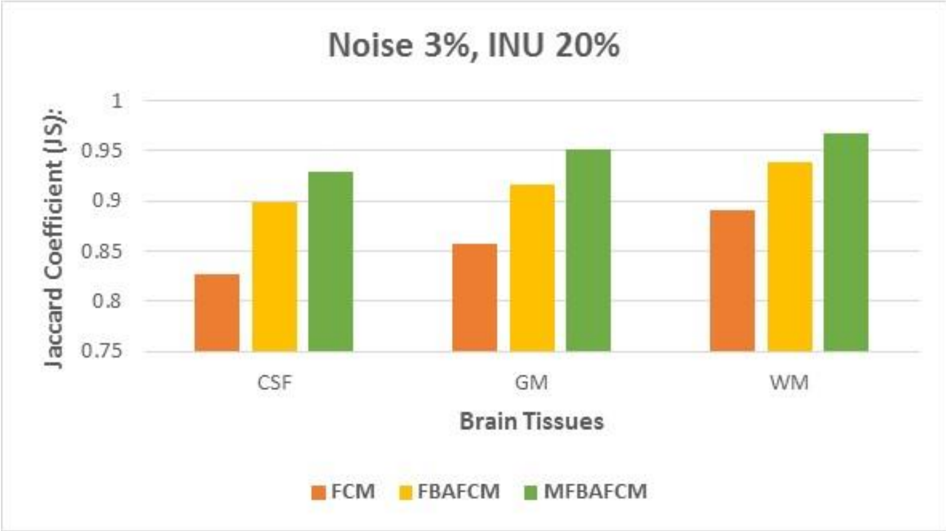
Index	Tissue	FCM	FBAFCM	MFBAFCM
Jaccard	CSF	0.78904	0.88810	**0.90330**
	GM	0.83073	0.90004	**0.93011**
	WM	0.87125	0.92100	**0.95002**
Dice	CSF	0.86559	0.90069	**0.92901**
	GM	0.88600	0.92044	**0.94903**
	WM	0.90337	0.94693	**0.96003**

Table 5.4, Table 5.5 and Table 5.6 show that the jaccard and the dice similarity indices values of MFBAFCM are higher than those of FBAFCM and FCM in different noise levels (0% 3%, 5%) and 20% of INU, which indicates that the proposed algorithm MFBAFCM is more efficient against the noise and provides better segmentation performance than both FBAFCM and FCM.

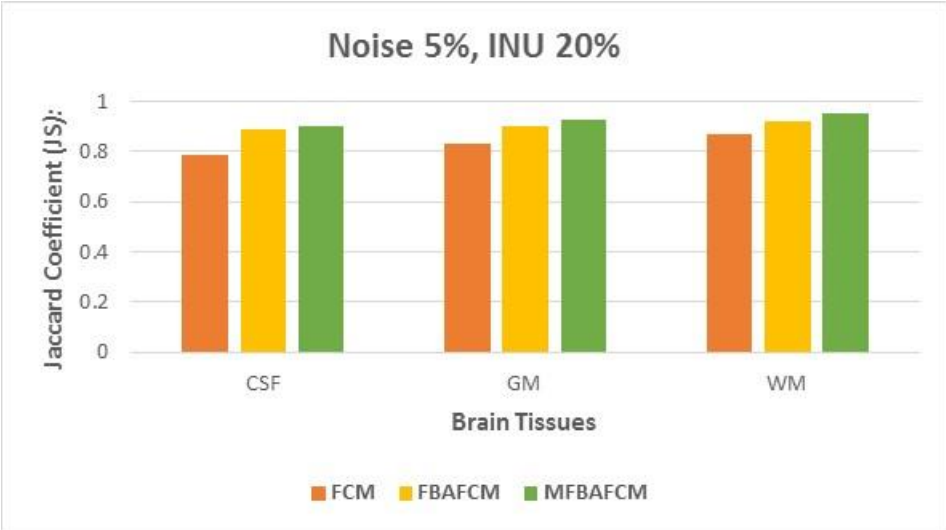
Figure 5.6 and Figures 5.7 display the graphical interpretations of Table 5.4, Table 5.5 and Table 5.6, these figures illustrate the changes in the values of jaccard similarity (JS) and dice similarity (DS) indices on level of Intensity Non-Uniformity (INU) (20%) and different levels of noise (0% 3%, 5%). The Figure 5.6 and Figure 5.7 prove the efficient performance of the proposed method MFBAFCM over both FBAFCM and traditional FCM on brain MRI tissue segmentation in terms of jaccard and dice similarity indices.



(a)

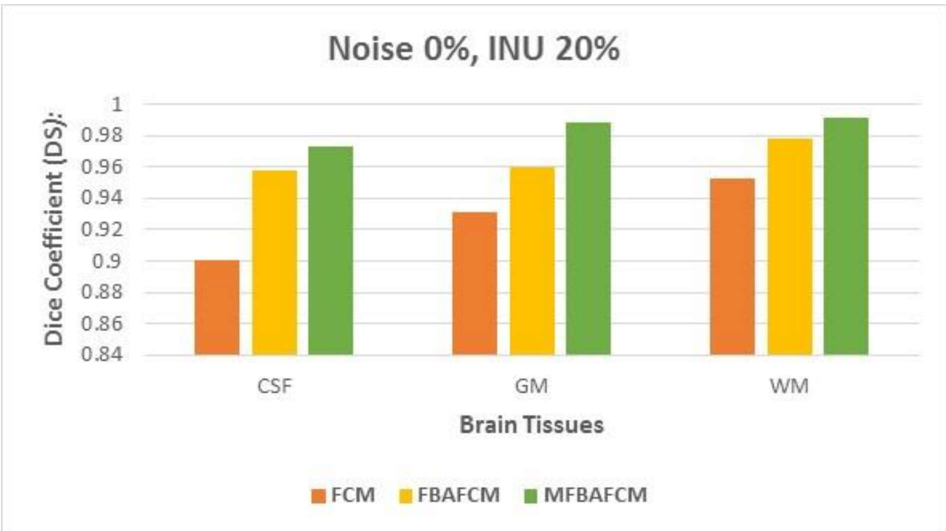


(b)

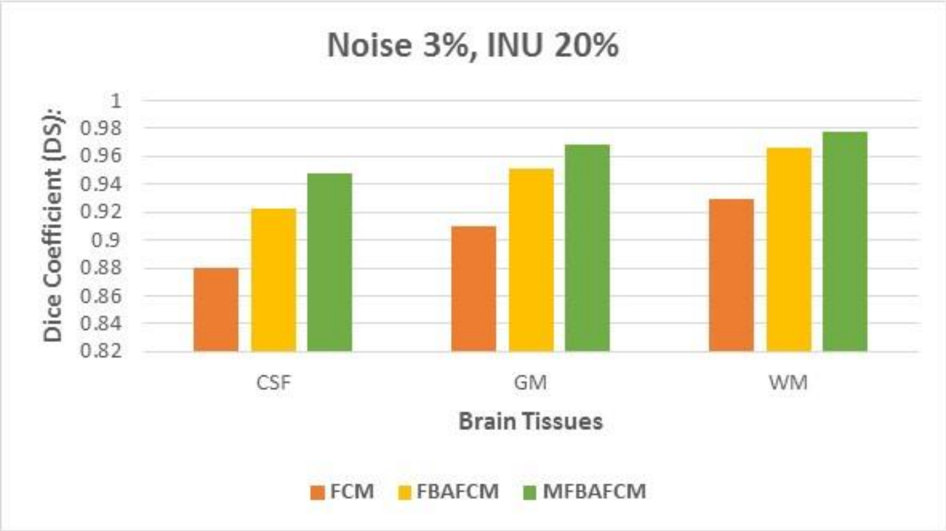


(c)

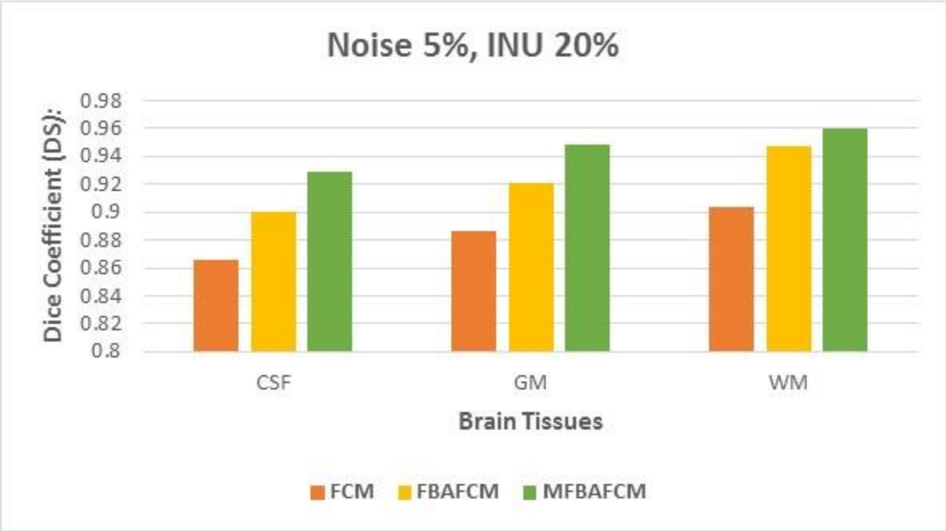
Figure 5.6: Graphical comparison of the jaccard similarity index (JS) values between FCM, FBAFCM, MFBAFCM, (a) noise = 0%, (b) noise = 3%, (c) noise = 5%.



(a)



(b)



(c)

Figure 5.7: Graphical comparison of the dice similarity index (DS) values between FCM, FBAFCM, MFBAFCM, (a) noise = 0%, (b) noise = 3%, (c) noise = 5%.

Figure 5.8 to Figure 5.10 display a comparison results of brain tissue segmentation on simulated brain MR images with different noise levels (0%, 3%, 5%) respectively. The details of these images are as follows:

- Figure 5.8 (a)(b), Figure 5.9 (a)(b) and Figure 5.10 (a)(b) show the original brain MR images and brain MR images without skull.
- The segmentation results obtained by FCM are shown in Figure 5.8 (c)(d)(e), Figure 5.9 (c)(d)(e) and Figure 5.10 (c)(d)(e).
- Figure 5.8 (f)(g)(h), Figure 5.9 (f)(g)(h) and Figure 5.10 (f)(g)(h) show the segmented images provided by FBAFCM.
- Figure 5.8 (i)(j)(k), Figure 5.9 (i)(j)(k) and Figure 5.10 (i)(j)(k) show the segmented images provided by MFBAFCM.
- Figure 5.8 (l)(m)(n), Figure 5.9 (l)(m)(n) and Figure 5.10 (l)(m)(n) show the ground truth images of CSF, GM and WM.

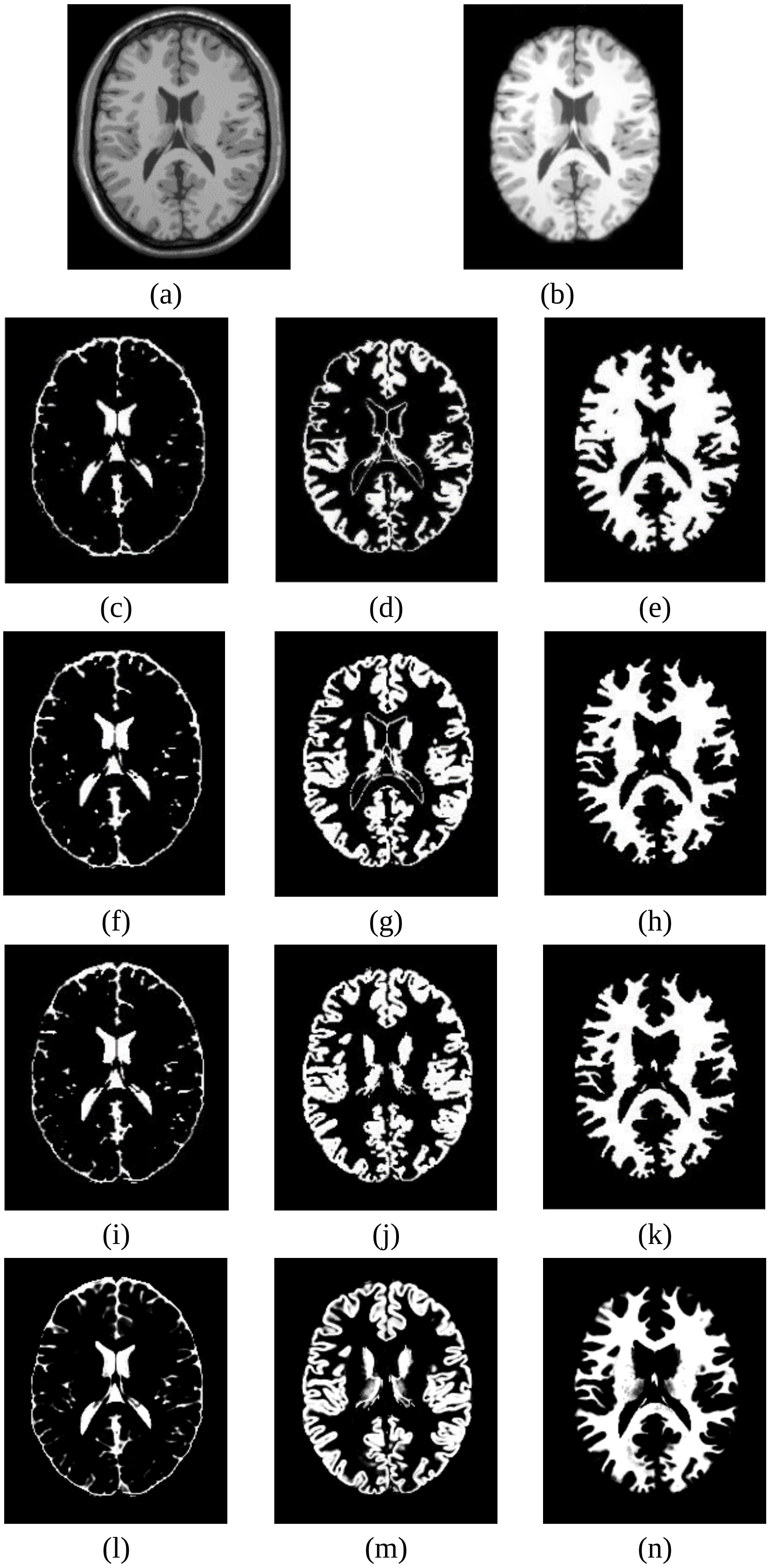


Figure 5.8. The segmentation results of the CSF, GM and WM (from left to right) by the FCM, FBAFCM, MFBAFCM on a T1-weighted brain MR image with 0% noise and 0% INU, (a) original brain MR image, (b) brain MR image without skull. (c)–(e): FCM algorithm; (f)–(h): FBAFCM algorithm; (i)–(k): MFBAFCM algorithm; (l)–(n): ground truth.

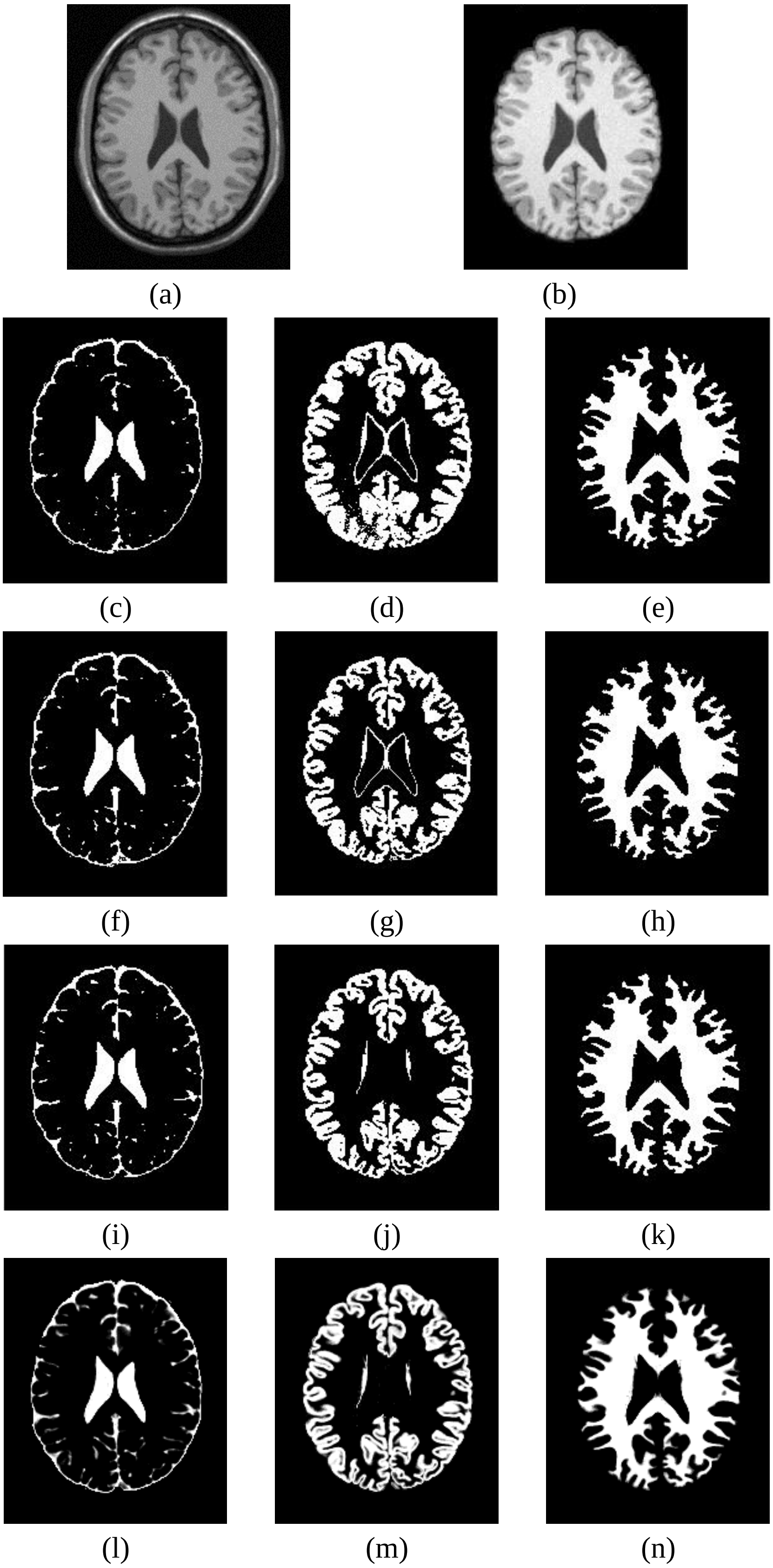


Figure 5.9. The segmentation results of the CSF, GM and WM (from left to right) by the FCM, FBAFCM, MFBAFCM on a T1-weighted brain MR image with 3% noise and 20% INU, (a) original brain MR image, (b) brain MR image without skull. (c)–(e): FCM algorithm; (f)–(h): FBAFCM algorithm; (i)–(k): MFBAFCM algorithm; (l)–(n): ground truth.

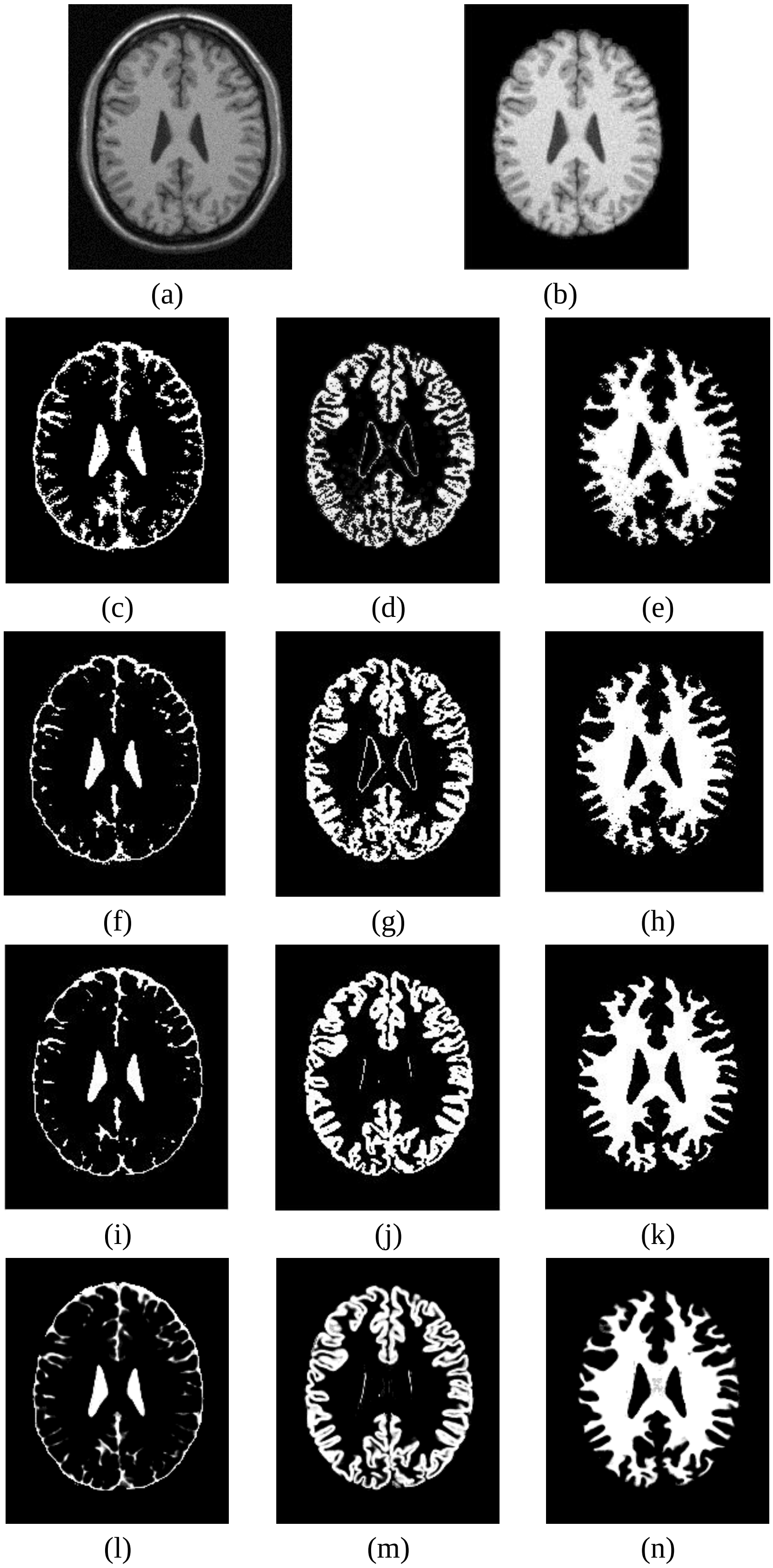
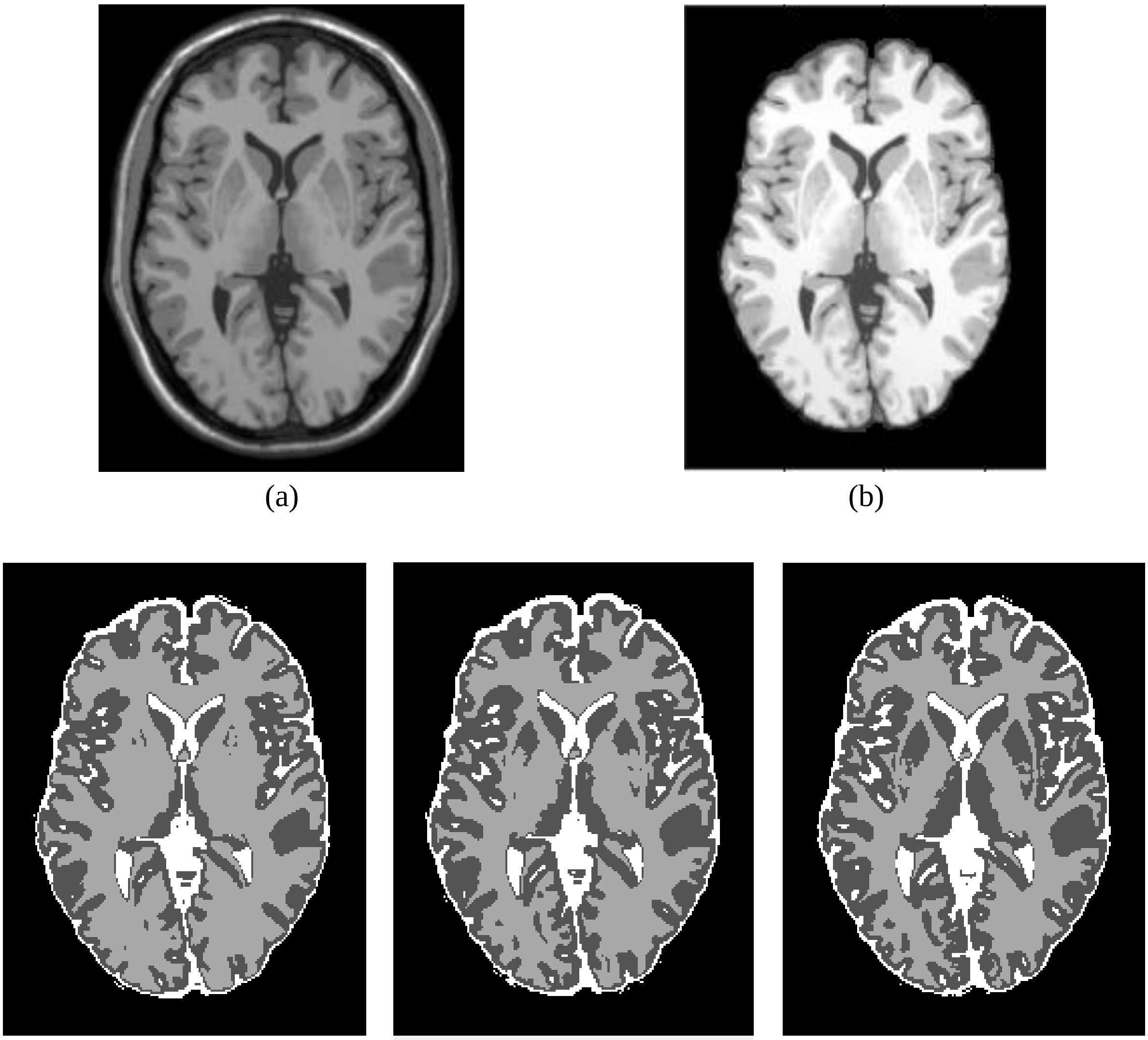


Figure 5.10 The segmentation results of the CSF, GM and WM (from left to right) by the FCM, FBAFCM, MFBAFCM on a T1-weighted brain MR image with 5% noise and 40% INU , (a) original brain MR image,(b) brain MR image without skull. (c)–(e): FCM algorithm; (f)–(h): FBAFCM algorithm; (i)–(k): MFBAFCM algorithm; (l)–(n): ground truth .

Figure 5.8, Figure 5.9 and Figure 5.10 clearly show the superiority of our method MFBAFCM over other tested methods in the segmentation process.

A global segmentation of simulated brain MR images is shown in Figure 5.11 and Figure 5.12. A visual examination of these figures might give an indication that the MFBAFCM algorithm provides more detail and achieves better segmentation results than its counterparts, FBAFCM and FCM.



(a) (b) (c) (d) (e)

Figure 5.11 The segmentation results by FCM, FBAFCM, MFBAFCM on a T1-weighted brain MR image with 0% noise and 0% INU, (a) original brain MR image, (b) brain MR image without skull. (c): FCM algorithm; (d): FBAFCM algorithm; (e): MFBAFCM algorithm

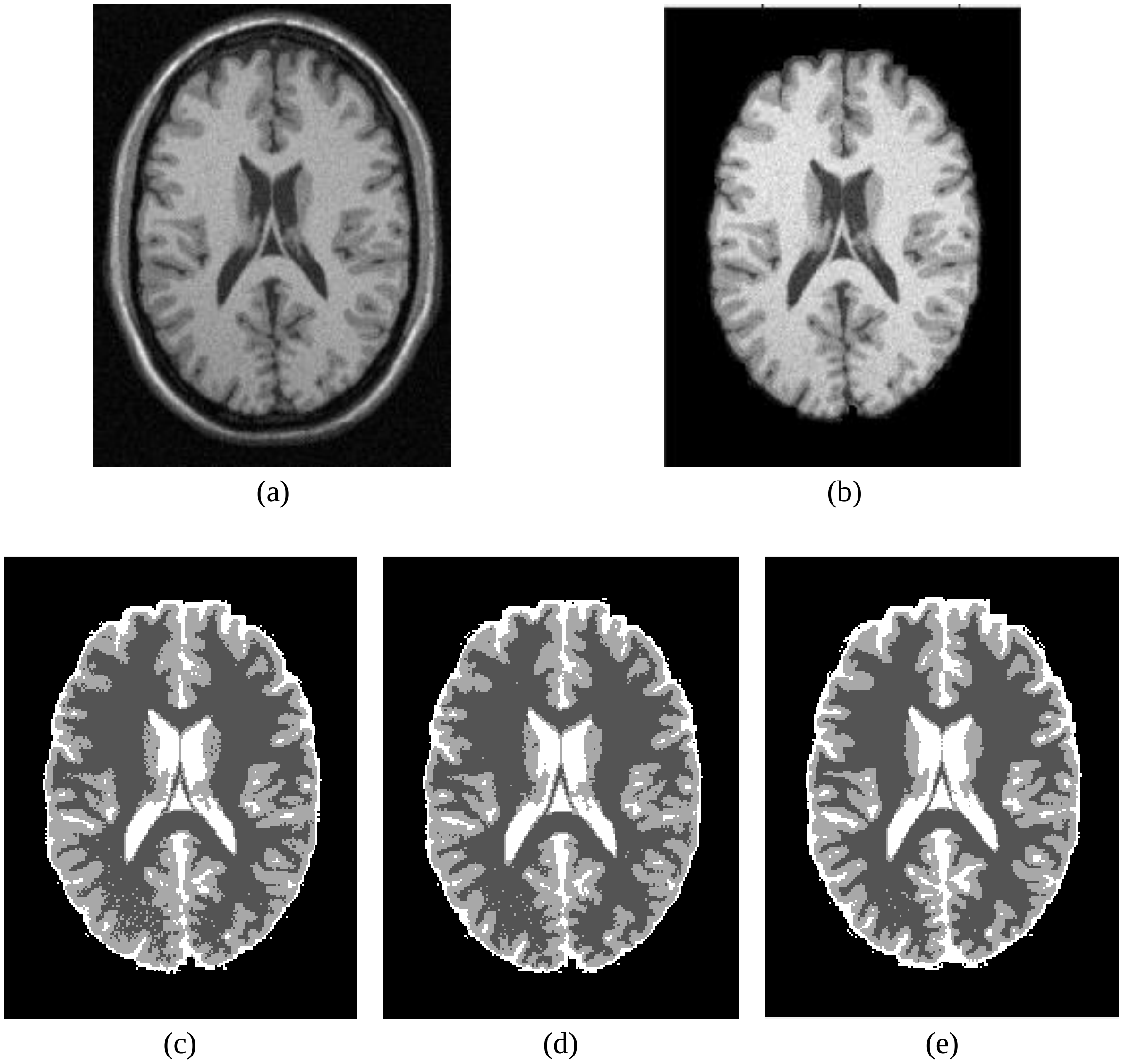
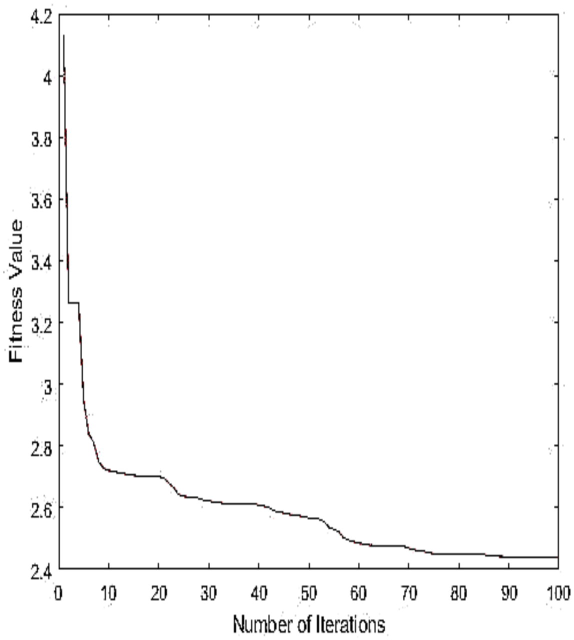


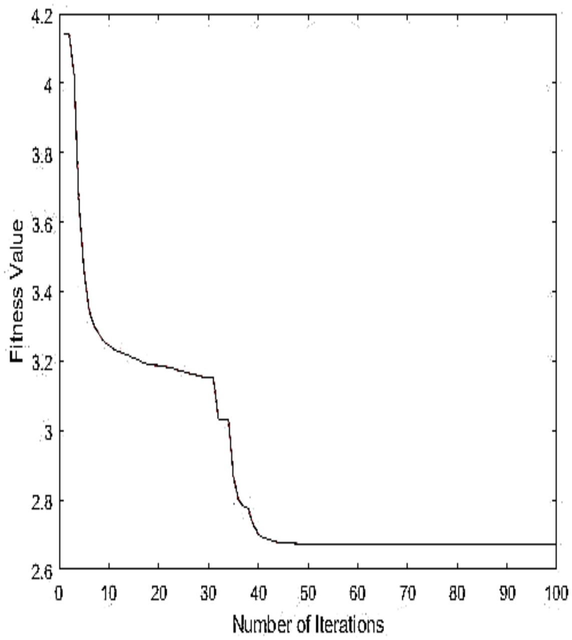
Figure 5.12 The segmentation results by the FCM, FBAFCM, MFBAFCM on a T1-weighted brain MR image with 5% noise and 40% INU, (a) original brain MR image, (b) brain MR image without skull. (c): FCM algorithm; (d): FBAFCM algorithm; (e): MFBAFCM algorithm;

5.3.3.3 Comparative Study Depending on Fitness Values

The fitness function's definition is an important step in determining the effectiveness of any algorithm. The fitness function determines how close a solution found is to the optimal solution. Figure 5.13 illustrates the comparison between MFBAFCM and FBAFCM on 10 simulated brain MR images (Table A.4) by evaluating the fitness values in term of iterations' number



(a)



(b)

Figure 5.13 Comparison between MFBAFCM and FBAFCM. (a) Fitness value of MFBAFCM algorithm in term of iterations' number, (b) Fitness value of FBAFCM algorithm in term of iterations' number

Figure 5.13 illustrates that MFBAFCM gets better fitness values than FBAFCM in less number of iterations, this proving that MFBAFCM is faster and gets better brain MRI segmentation performance than FBAFCM.

5.3.4 Comparative Study with Other Methods

To evaluate the quality and the performance of our MFBAFCM method, we made a comparative study with both LGMM [192] and HMRF-PSO [51] on the basis of dice similarity (DS) index. We have used the slices (85, 88, 90, 95, 97, 100, 104, 106 110) from Brainweb database corrupted by different levels of Noise (N) and Intensity Non-Uniformity (INU). Table 5.7 describes the dice similarity index results of LGMM, HMRF-PSO and MFBAFCM on (0%, 3%, 5%) noise and (0% 20%) INU.

Table 5.7 Dice similarity index results of LGMM, HMRF-PSO and MFBAFCM on (0%, 3%, 5%) noise and (0% 20%) INU

(N,INU)	**Tissue**	**LGMM** [192]	**HMRF-PSO** [51]	**MFBAFCM**
(0%,0%)	GM	0.69000	0.95000	**0.97000**
	WM	0.66000	0.98000	**0.99000**
	CSF	0.75000	0.95000	**0.96000**
	Mean	0.70000	0.96000	**0.97300**
(3%,20%)	GM	0.90000	0.94000	**0.95000**
	WM	0.94000	0.96000	**0.97000**
	CSF	0.89100	**0.94000**	**0.94000**
	Mean	0.91000	0.95000	**0.95300**
(5%,20%)	GM	0.91000	0.91000	**0.93000**
	WM	**0.95000**	**0.95000**	**0.95000**
	CSF	0.88000	0.92000	**0.93000**
	Mean	0.91000	0.93000	**0.93600**

Table 5.7 shows that the dice values of MFBAFCM are larger than HMRF-PSO and LGMM in different noise levels (0%, 3%, 5%) as for different INU levels (0%, 20%) indicating that the proposed algorithm MFBAFCM can produce more accurate segmented brain MR images than other tested techniques.

Another comparative study was made between our method MFBAFCM with both MFCM [193] and RIFCM [153] in terms of dice similarity (DS) and jaccard similarity (JS) indices. We have used the slice (No. 91) from Brainweb database corrupted by different levels of Noise (N) (1%, 5%) and 0% Intensity Non-Uniformity (INU). Table 5.8 and Table 5.9 describe jaccard and dice similarity indices results of MFCM, RIFCM and MFBAFCM on (1%, 5%) noise and 0% INU respectively.

Table 5.8 Jaccard similarity index results of MFCM, RIFCM and MFBAFCM on (1%, 5%) noise and 0% INU

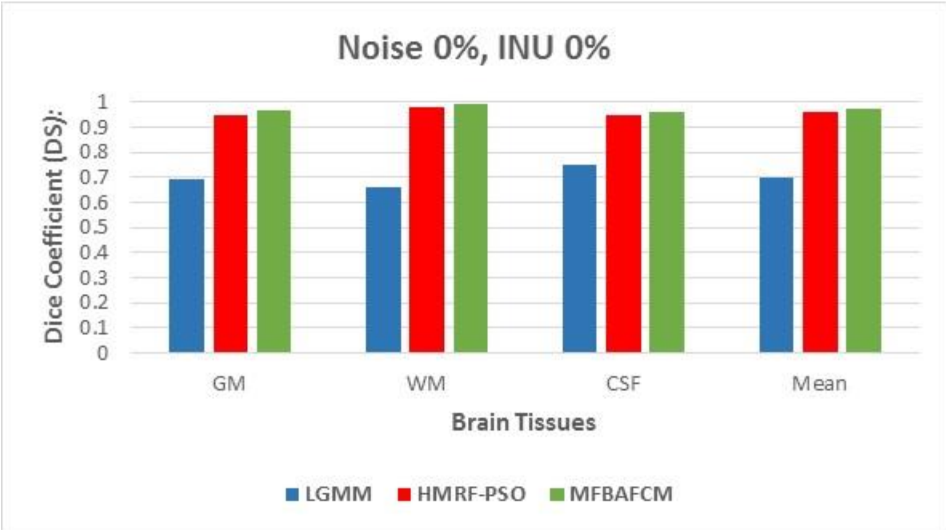
N	**Tissue**	**MFCM** [193]	**RIFCM** [153]	**MFBAFCM**
1%	CSF	0.88530	0.89920	**0.93060**
	GM	0.92180	0.97030	**0.97880**
	WM	0.96760	0.95640	**0.96910**
5%	CSF	0.85830	0.91160	**0.92020**
	GM	0.88850	0.95650	**0.96150**
	WM	0.94670	0.94560	**0.95730**

Table 5.9 Dice similarity index results of LGMM, HMRF-PSO and MFBAFCM on (1%, 5%) noise and 0% INU

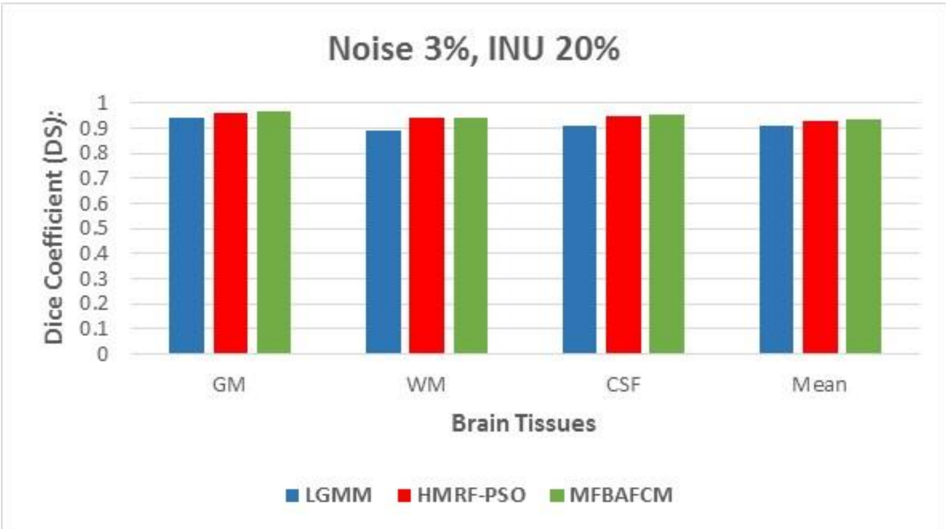
N	**Tissue**	**MFCM** [193]	**RIFCM** [153]	**MFBAFCM**
1%	CSF	0.93910	0.94690	**0.95800**
	GM	0.95930	0.98490	**0.98860**
	WM	**0.98350**	0.97770	0.98330
5%	CSF	0.92360	0.95370	**0.96840**
	GM	0.94100	0.97770	**0.98160**
	WM	0.97260	0.97200	**0.98600**

Table 5.8 and Table 5.9 show that jaccard and dice similarity values of MFBAFCM are larger than RIFCM and MFCM in different noise levels (1%, 5%), indicating that the proposed algorithm MFBAFCM can provide better and more accurate segmentation results than other tested methods.

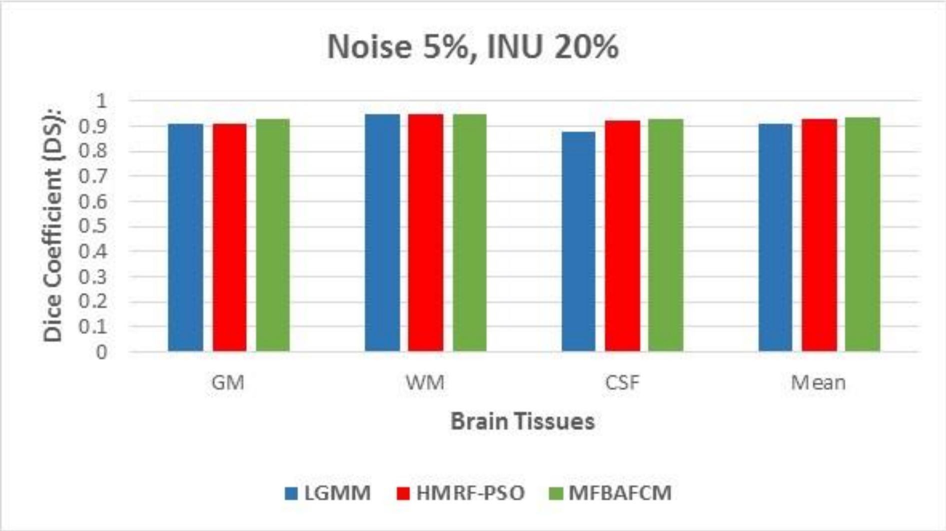
The graphical interpretations of Tables 5.7 are represented in Figure 5.14, this figure illustrates the changes in the values of dice similarity index (DS) on different levels of Intensity Non-Uniformity (INU) (0% 20%) and different levels of Noise (N) (0% 3%, 5%). We notice that the Dice Similarity (DS) values of MFBAFCM are larger than both HMRF-PSO and LGMM in different noise and INU levels, which proving that the suggested approach MFBAFCM outperforms both LGMM and HMRF-PSO in brain MRI tissue segmentation.



(a)



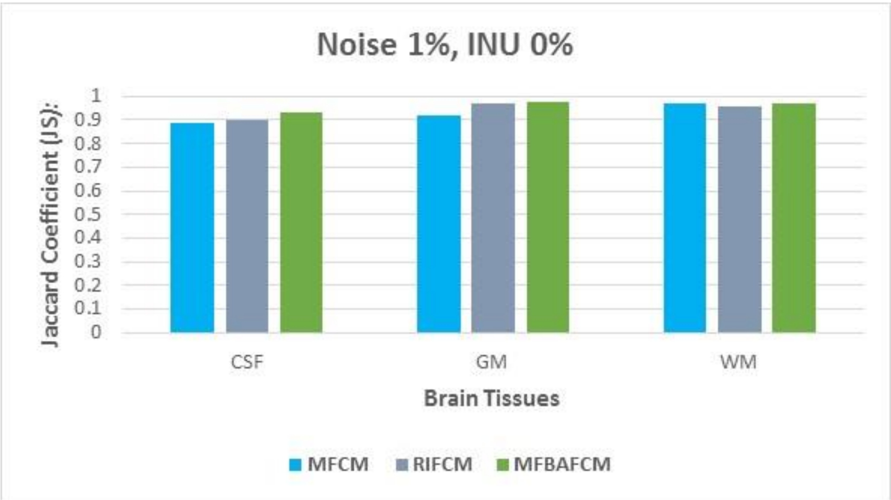
(b)



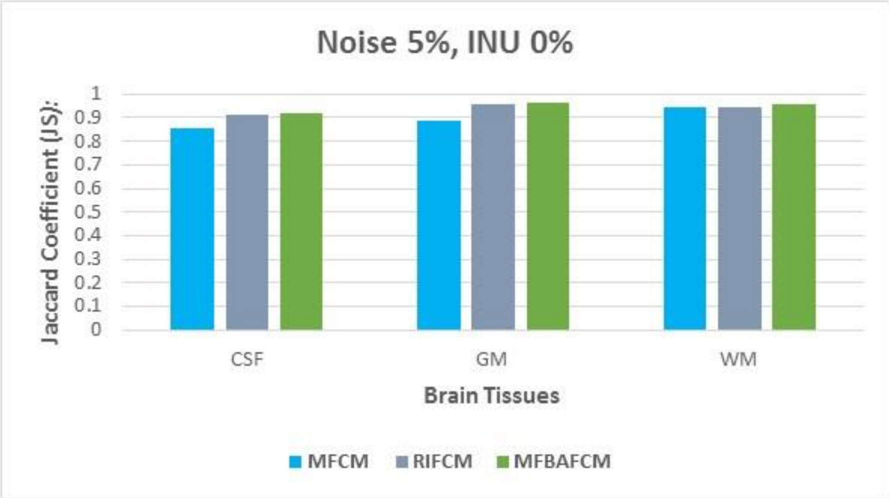
(c)

Figure 5.14: Graphical comparison of the dice similarity index (DS) values between LGMM, HMRF-PSO, MFBAFCM, (a) noise = 0% and INU = 0%, (b) noise = 3% and INU =20%, (c) noise = 5% and INU =20%.

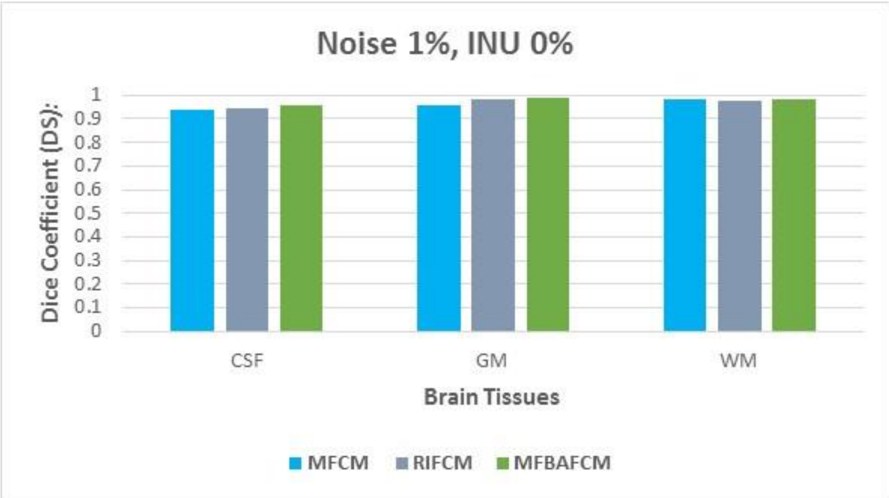
Figure 5.15 illustrates the graphical interpretations of Table 5.8 and Table 5.9, this figure shows the changes of the values of jaccard similarity (JS) and the dice similarity (DS) indices on level of intensity non-uniformity INU (0%) and different levels of noise (1%, 5%). The figure 5.15 demonstrates the efficiency of the proposed method MFBAFCM compared to MFCM and FIFCM.



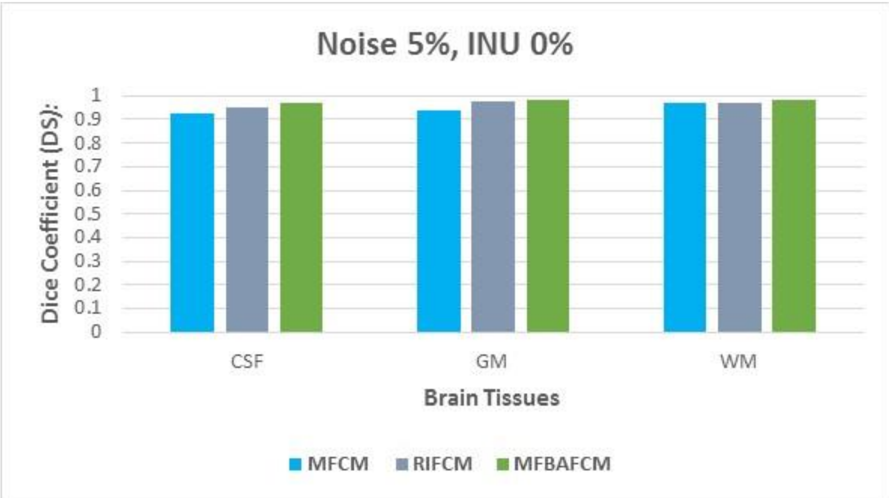
(a)



(b)



(c)



(d)

Figure 5.15: Graphical comparison of the jaccard similarity (JS) and dice similarity (DS) indices values between MFCM, FIFCM, MFBAFCM, (a) jaccard similarity values on noise = 1%, INU = 0% , (b) jaccard similarity values on noise = 5% and INU =0%, (c) dice similarity values on noise = 1% INU = 0% (d) dice similarity values on noise = 5% and INU = 0%.   .

5.4 Conclusion

In our study, we have proposed a Modified Fuzzy Bat Algorithm (MFBA) and its obtained results are taken to improve the initialization step of the FCM algorithm. This operation is done by using new fitness function that combines intra cluster distance with fuzzy cluster validity indices. The results show that the proposed algorithm MFBAFCM can segment brain MR images more accurately than RIFCM, MFCM, HMRF-PSO, LGMM, FBAFCM and traditional FCM algorithm in different levels of Intensity Non-Uniformity (INU) and noise.

GENERAL CONCLUSION

General Conclusion

In the last few years, the subject of brain MRI segmentation has been a hotspot in medical and image processing fields. Due to that, it has piqued the interest of numerous researchers, who have proposed many approaches to improve the segmentation process and solve its problems. This great interest is what motivated us to dig into this area and to propose our contribution in brain MRI segmentation.

In our thesis, we have begun by providing an overview of medical imaging techniques that are very important to assist in the diagnosis and treatment of different disease, they could create a variety of distinct and detailed 2D or 3D images of human anatomy. Magnetic Resonance Imaging (MRI) is a widely used medical imaging technique that could generate high quality images inside of the human body without using harmful radiation, it has become an indispensable diagnostic technique because of its good anatomical characteristics. We have focused on the brain MRI due to its huge importance in the diagnosis process and determining the health of patients. Despite the huge advancements in Magnetic Resonance Imaging (MRI), the images produced still suffer from some artifacts. These artifacts have a bad influence on doctors' judgments and decisions. As a result, the images produced from MRI machine sometimes need some treatment and processing [10].

After deep research into the MRI segmentation techniques, we have concluded that each segmentation technique comes with its own advantages and disadvantages, and there is no single technique that could be considered the best one. In our study, we chose a clustering technique called the Fuzzy C-Means (FCM) clustering algorithm due to its great efficiency in brain MRI segmentation. However, the Fuzzy C-Means (FCM) algorithm has several drawbacks, such as the sensitivity to the initial cluster centers and to the various imaging artifacts, including noise, density inhomogeneity and partial volume [117]. These drawbacks must be overcome to obtain better segmentation results. The exploitation of metaheuristic methods in the field of brain MRI segmentation has been commonly used in the literature, as we detailed in the third chapter.

Our contribution is based on creating a new hybrid method for segmenting brain MR images into the three tissues, White Matter (WM), Gray Matter (GM), and Cerebrospinal Fluid (CSF). We have improved the Fuzzy C-Means (FCM) clustering algorithm to overcome its drawbacks by using a bio-inspired metaheuristic method called Bat Algorithm (BA), which shows great performance in solving different kinds of optimization problems, such as the fuzzy clustering problem. We proposed a hybrid method called the Modified Fuzzy Bat Algorithm for Fuzzy C-Means (MFBAFCM) that consists of two basic steps.

- In the first step: we converted the standard Bat Algorithm (BA) to the Fuzzy Bat Algorithm (FBA) to make it capable of solving the fuzzy clustering, then we modified the Fuzzy Bat Algorithm (FBA) to be faster and better in brain MRI segmentation and called it Modified Fuzzy Bat Algorithm (MFBA). Finally, we used the MFBA to get better initial cluster centers by using a new fitness function that combines intra cluster distance with fuzzy cluster validity indices.

- In the second step: the MFBAFCM uses the initial cluster centers that were obtained from the first step for the standard FCM algorithm initialization, and then FCM algorithm produces the segmented brain MR images.

The experimental results on several simulated brain MR images prove that our proposed algorithm MFBAFCM has better performance in the segmentation process compared to the standard FCM algorithm, FBAFCM and other tested methods in different levels of intensity non-uniformity and noise.

Our future work will focus on:

- Finding a better fitness function to make our method MFBAFCM more efficient against the high levels of intensity non-uniformity and noise.

- Investigating and using the improved FCM algorithm versions for enhancing the segmentation results.

- Trying to combine between two or more metaheuristic methods to improved the exploitation and exploring process.

- Using the Convolutional Neural Network (CNN) on the brain MRI segmentation

Annex A

Experiment results of MFBAFCM & FBAFCM

Table A.1, Table A.2 and Table A.3 are presented the fitness values of MFBAFCM with various number of times that the fitness value stays without changing and number of the best solutions used for generating the new solution, we have used the slices (74, 80, 84, 89, 90, 93, 97, 100 102, 105) from Brainweb database. In Table A.1, the images are corrupted by 0% noise and 0% INU, images of Table A.2 are corrupted by 3% noise and 20% INU, and in Table A.3, the images are corrupted by 5% noise and 40% INU.

Table A.1 Fitness values of MFBAFCM with various number of times the fitness value remains unchanged and number of the best solutions that used for generating the new solution (0% noise and 0% INU)

		Number of times that the fitness value remains unchanged							
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Number of the best solutions used for generating the new solution	**1**	3.624	3.320	2.949	2.725	2.608	2.661	2.729	2.879
	2	3.470	2.960	2.703	2.721	2.570	2.621	2.690	2.743
	3	3.079	2.602	2.228	2.150	2.159	2.219	2.260	2.338
	4	2.792	2.249	1.969	1.901	1.943	1.980	2.012	2.110
	5	2.538	1.848	1.648	**1.639**	1.684	1.808	1.834	1.865
	6	2.644	1.849	1.721	1.673	1.698	1.770	1.905	1.988
	7	2.792	1.902	1.882	1.724	1.732	1.839	1.964	1.995
	8	2.885	2.107	1.969	1.817	1.854	1.946	2.037	2.028

Table A.2 Fitness values of MFBAFCM with various number of times the fitness value remains unchanged and number of the best solutions that used for generating the new solution (3% noise and 20% INU)

		Number of times that the fitness value remains unchanged							
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Number of the best solutions used for generating the new solution	**1**	3.759	3.509	3.186	2.967	2.940	2.932	2.995	3.338
	2	3.506	3.117	2.860	2.897	2.803	2.783	2.842	2.993
	3	3.172	2.869	2.483	2.403	2.511	2.523	2.663	2.753
	4	2.936	2.557	2.250	2.034	2.127	2.328	2.451	2.493
	5	2.949	2.328	2.094	**1.849**	1.902	2.036	2.102	2.218
	6	2.993	2.317	2.099	1.910	1.986	1.992	2.089	2.228
	7	3.026	2.329	2.149	1.969	2.026	2.103	2.248	2.327
	8	3.174	2.428	2.259	2.037	2.152	2.301	2.396	2.441

Table A.3 Fitness values of MFBAFCM with various number of times the fitness value remains unchanged and number of the best solutions that used for generating the new solution (5% noise and 40% INU)

		Number of times that the fitness value remains unchanged							
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Number of the best solutions used for generating the new solution	**1**	4.688	4.374	4.083	3.801	3.770	3.855	3.868	3.892
	2	4.484	4.302	3.962	3.539	3.422	3.518	3.576	3.602
	3	4.007	3.924	3.180	2.802	2.813	2.837	2.953	2.980
	4	3.702	3.425	2.886	2.663	2.712	2.764	2.866	2.814
	5	3.204	2.995	2.621	**2.602**	2.638	2.760	2.806	2.808
	6	3.503	3.034	2.655	2.604	2.600	2.771	2.787	2.803
	7	3.775	3.290	2.681	2.639	2.689	2.659	2.790	2.796
	8	3.813	3.437	2.789	2.773	2.695	2.704	2.726	2.731

Table A.4 Images used in the comparison between fitness values of MFBAFCM and FBAFCM

	Noise	**INU**	**Slice number th**
Image 1	0%	20%	85
Image 2	3%	20%	73
Image 3	3%	40%	99
Image 4	5%	20%	88
Image 5	5%	20%	104
Image 6	5%	40%	77
Image 7	5%	40%	83
Image 8	5%	40%	89
Image 9	5%	40%	106
Image 10	5%	40%	116

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Scientific Productions

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International Conferences

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ملخص:

في الوقت الحالي، تعد الصور الطبية للتصوير بالرنين المغناطيسي مصدرًا مهمًا للمعلومات للأطباء، يوفر هذا النوع من التصوير تمثيلات عالية الدقة لتشريح الدماغ. تعتبر مشاكل التصوير بالرنين المغناطيسي مثل الضوضاء وعدم انتظام الكثافة (INU) والحجم الجزئي قيدًا رئيسيًا لإجراء تحليل مفصل لصورة التصوير بالرنين المغناطيسي للدماغ. تعد تجزئة صور التصوير بالرنين المغناطيسي للدماغ عملية مهمة تساعد الأطباء على قياس وتصور الهياكل التشريحية للدماغ، تعتبر خوارزمية المتوسطات الضبابية (FCM) من بين خوارزميات التجميع الشائعة لتجزئة صور التصوير بالرنين المغناطيسي للدماغ. ومع ذلك، فإن FCM حساسة لتهيئة مراكز الاقسام. في هذه الأطروحة، قمنا باقتراح طريقة هجينة اسمها MFBAFCM لتجزئة صور الرنين المغناطيسي للدماغ، طريقتنا تستخدم خوارزمية الخفاش الضبابي المعدلة (MFBA) لإيجاد أفضل مراكز اقسام لتهيئة خوارزمية FCM التقليدية بالاعتماد على دالة لياقة جديدة. تظهر النتائج التجريبية على العديد من صور الدماغ بالرنين المغناطيسي التي تم إتلافها بمستويات مختلفة من INU والضوضاء أن طريقتنا المقترحة أنتجت نتائج أفضل من FCM التقليدية وبعض الأعمال الأخرى المنشورة مؤخرًا.

الكلمات المفتاحية: التصوير بالرنين المغناطيسي، التجزئة، المتوسطات الضبابية (FCM)، خوارزمية الخفاش، طريقة هجينة.

Abstract

Nowadays, MRI medical images are a valuable source of information for clinicians, this type of imaging provides high-resolution representations of brain anatomy. The MRI artifacts such as the noise, intensity non-uniformity INU and partial volume effect are a major constraint to perform a detailed analysis of a brain MR images. Brain MRI segmentation is an important process that assists doctors on measuring and visualizing the brain’s anatomical structures, Fuzzy C-Means (FCM) is considered among the popular clustering algorithms for brain MRI segmentation. However, FCM is sensitive to the cluster centers initialization. In this thesis, we proposed a hybrid method named MFBAFCM for brain MRI segmentation, our proposed method uses the Modified Fuzzy Bat Algorithm (MFBA) to get better initial cluster centers for the standard FCM algorithm by using a new fitness function. Experimental results on several brain MR images corrupted by different levels of INU and noise show that our proposed method produced better results than the standard FCM and some other recent published works.

Keywords: MRI, Segmentation, Fuzzy C-Means (FCM), Bat Algorithm, Hybrid Method.

Résume

De nos jours, les images médicales IRM sont pour les cliniciens une source d’informations précieuse, ce type d’imagerie fournit des représentations haute résolution de l’anatomie cérébrale. Les artéfacts des images IRM tels que le bruit, inhomogénéité RF et le volume partiel sont une contrainte majeure pour effectuer une analyse détaillée d'une image IRM. La segmentation des images IRM cérébrales est un processus important qui aide les médecins à mesurer et à visualiser les structures anatomiques du cerveau, c-moyennes floues (FCM) considère parmi les algorithmes de clustering populaires pour la segmentation des images IRM cérébrales. Cependant, FCM est sensible à l'initialisation des centres de cluster. Dans le cadre de cette thèse, nous avons proposé une méthode hybride nommée MFBAFCM pour la segmentation des images IRM cérébrales, notre méthode proposée utilise l'algorithme de chauve-souris floue modifié (MFBA) pour obtenir meilleurs centres de cluster pour l’initialisation de l'algorithme FCM standard en utilisant une nouvelle fonction de fitness. Les résultats expérimentaux sur plusieurs images cérébrales IRM corrompues par différents niveaux RF et de bruit montrent que notre méthode proposée a produit de meilleurs résultats que le FCM standard et certains autres travaux publiés récemment.

Mots-clés : IRM, Segmentation, C-Moyennes Floues (FCM), L'algorithme de Chauve-Souris, Méthode Hybride.