A Review on Automatic Marker Identification Methods in Watershed Algorithms Used for Medical Image Segmentation

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Abstract

Medical imaging is the process of representing human body parts with the help of modern electronic devices such as computer. Segmenting a region of interest (ROI) from the medical images is an important and challenging task for the clinicians. There are many algorithms proposed for medical image segmentation. Watershed algorithm is a mathematical morphology based method and it can be effectively used for medical image segmentation applications. The main objective of watershed algorithm is to find watershed lines for separating the objects from its background. Because of the noises and other irregularities present in the image, watershed algorithm leads to a problem of over-segmentation. A solution to this problem is the use of internal and external markers for representing foreground and background regions respectively. There are many methods used for finding markers in the medical images. In this paper we present a review on various methods used for marker identification in medical images. This review also includes a small description about different medical imaging modalities, mathematical morphology method and watershed algorithm. For an experimental result, this paper also compares the segmentation accuracy of commonly used marker identification methods.

Keywords: Medical Imaging, Imaging Modality, Mathematical Morphology, Internal Markers, External Markers, Watershed.

1. Introduction

Medical imaging plays an important role in modern medical science field. It helps the doctors for clinical analysis and medical intervention. Medical image analysis is highly computational in nature and requires the use of automated systems. It needs an accurate, fast and robust method for analysis. Now a days, computer assisted surgical planning and advanced image guided technology have become increasingly used in neurosurgery. Many imaging techniques have been developed and are in clinical use. In medical imaging it is called modalities. X-Rays, MRI, PET and CT are the examples of different imaging modalities [1]. All the applications of capturing and storing of medical images are done digitally, however, the interpretation of details of medical images is still time-consuming. This matter is especially observed in regions with abnormal colour and shape which should be identified by radiologists for future studies [2]. The most important and challenging task in medical image processing is segmentation. Image segmentation is the process of partitioning different regions of the image based on different criteria [2]. Image segmentation is typically used to locate objects and boundaries in images. Otherwise we can say that image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain visual characteristics [3]. Image segmentation problem can be formulated as follows: let F represents an image and F= {R_i} be the entire spatial region occupied by an image. That is, F can be partitioned in to n sub regions R_1, R_2… R_n. Given image F = {R_i}, the segmentation problem is to determine connected subset R_i (R_i ⊂ F), such that

\[ \bigcup_{i=1}^{n} R_i = F, \quad R_i \cap R_j = 0 \quad (i \neq j) \]  

Since the doctors are highly depends on the segmentation results for diagnosing, it should be accurate and robust. Since the presence of artifacts and other noises in the medical images, the segmentation task is more complex and challenging. There is no common standard segmentation method available for medical images. According to the modality and type of the images, many algorithms are proposed for medical image segmentation. Thresholding, region based techniques, edge based segmentation, clustering methods, and hybrid segmentation are some of the examples of medical image segmentation [4]. Watershed algorithm comes under the category of region based methods. It is based on the technology of mathematical morphology [5]. The intuitive idea underlying the watershed notion comes from the field of topography. Imagine our image as a lake and holes pierced in local minima. Water will fill up basins starting at these local minima, and, at points where waters coming from different basins would meet, dams are built. As a result, the surface is partitioned into regions or basins separated by dams, called watershed lines [6]. In the literature we can see different types of watershed segmentation methods- Vincent-Soille watershed
algorithm [7], Meyer’s watershed algorithm [8], Cost-based watershed [9-11], and Topological watershed [12]. Although watershed algorithm is a well-known and effective approach for medical image segmentation, the main problem with the algorithm is the over segmentation. It is due to the noise and other irregularities present in the medical images. One solution to this problem is the use of markers. A marker is a connected component belonging to an image. Two types of markers are used for watershed segmentation-internal markers and external markers. Internal marker associated with the objects of interest and external marker associated with the background. There are many methods are proposed for identifying internal and external markers. In this paper we present a review about marker identification methods in medical images.

The rest of the paper presented as follows, next section discusses different medical image modalities, section 3 describes mathematical morphology, watershed algorithm explained in section 4. Section 5 covers different marker based watershed algorithms, experimental results included in the section 6 and finally conclusions are made in the section 7.

2. Medical Imaging Modalities

Based on the application there are two types of medical imaging modalities- anatomical modality and functional modality. Anatomical modality represents structural properties and functional modality represents different functionalities of human body. X-Rays, CT, MRI, Ultrasound are the examples of anatomical modality and PET, SPECT and fMRI are the examples of functional modality [1].

2.1 X-Rays

X-Rays were discovered by the German scientist W. C. Rontgen in 1895. He accidently identified these rays and he called that un-known rays as X-Rays. For his discovery, Roentgen was awarded the Noble Prize in 1901. The position of X-Rays is between Ultraviolet rays and gamma rays in the electromagnetic spectrum. The X-Rays pass through the patient’s body and are detected either by a film or an ionization material placed on the opposite side. X-Rays are coming from an X-Ray tube which consists of two electrodes. X-Rays are mainly used to represent hard parts in the body like bones. Since the dense structures like bones are absorbs the X-Rays and they appear whiter than the other structures. All other medical imaging techniques are discovered after X-Rays intervention [13].

2.2 CT

Computer Tomography (CT) also known as “CAT scanning” (Computed Axial Tomography) imaging technique is mainly used to study the anatomy of the human body. The idea behind the CT scan is that the scanning of the same cross-section with sufficient images, allows reconstructing the anatomic details of the cross-section [14]. CT was invented in 1972 by British engineer Godfrey Hounsfield. Since CT scanning is very faster method, it helps to eliminate artifacts from patient motion such as breathing or peristalsis. CT images of brain is used to identify different deceases such as Alzheimer’s, brain tumors, bleeds, injuries to the brain and other major brain diseases.

2.3 MRI

Magnetic resonance imaging (MRI) is a modern technology, mainly used for anatomical medical imaging. The main advantage of MRI is that it is free from radiation and therefore it is harmless to the patient. MRI makes the use of the property of nuclear magnetic resonance (NMR) to image nuclei of atoms inside the body [15]. The inventor of magnetic resonance imaging is Raymond Vahan Damadian in 1977. He identified that the tumor can be detected using nuclear magnetic resonance, because of the high relaxation time of the tumor tissue [16]. The MRI machine consists of a super conducting electromagnet, gradient coils and RF coils.

2.4 Ultrasound

Ultrasound imaging uses high frequency sound waves to produce images of body tissues and organs. A special device called transducer is used for imaging. The sound waves enter to the body and reflected back like an echo to the transducer. This reflection of the sound signal is used for the construction of the images. Ultrasound images are mainly used to for the study of soft tissues [17]. It is commonly used to the study of development of fetus during pregnancy period.

2.5 PET

Positron emission tomography (PET) is a type of nuclear medicine. A radioactive isotope called tracer is injected to the patient’s body and that will emits a particular particle called positron. The positrons are captured by a scanning device, which produces pictures and provides molecular information. It is mainly used to study the various tissues in the body for identifying certain conditions. It is also used to detect the status of the treatment in a patient’s body. The main risk of PET scan is that the injection of
radioactive isotopes to the body. It may leads to some problems to the tissues in the human body [18].

2.6 SPECT

Single-photon emission computed tomography (SPECT) is another type of nuclear imaging technology. Like PET in SPECT, a radioactive isotope, tracer is injected to the blood. Here the radioactive isotopes are capable of emission of gamma rays, which can be detected by a scanner. The computer connected to the scanner will convert it to an image. The main difference with the PET scan is that it will project the blood stream rather than the other tissues [19]. It is cheaper and will produce the images with higher resolutions.

2.7 fMRI

Functional magnetic resonance imaging or functional MRI (fMRI) is an example of functional medical imaging modality. It is used to measure the activities of brain. When a part of the brain is active, that part requires more blood. Then the flow of the blood to that region is increased and consumes more oxygen. fMRI can be used to show which part of the brain is involved in a particular mental process. The principle behind the fMRI is same as MRI, but instead of creating the images of organs and tissues, it is used to track the blood flow in the brain to identify the activities of brain [20]. These changes in the blood flow are used to create the images with the help of computers.

3. Mathematical Morphology

Mathematical morphology is a tool for extracting image components that are useful in the representation and description of region, shape such as boundaries, skeletons, and convex hull [21]. The operations in the mathematical morphology performed on the basis of shapes in the image. Morphological methods probe an image with a small shape or template called a structuring element (SE). Erosion and Dilation are fundamental morphological operations. They are mathematically defined as,

\[ \text{Dilation, } A \ominus B = \{ z \in (B) \text{ } z \subseteq A \} \]  
\[ \text{Erosion, } A \oplus B = \{ z \in (B) \text{ } z \cap A \neq \emptyset \} \]

Opening and closing are morphological operations based on dilation and erosion and they are defined as,

\[ \text{Opening, } A \ominus B = (A \ominus B) \oplus B \]  
\[ \text{Closing, } A \oplus B = (A \oplus B) \ominus B \]

Opening generally used to smoothes the contours but, as opposed to Opening, it generates fuses narrow breaks and long thin gulfs, eliminates small holes and fills gaps in the contours [3]. Mathematical morphology based methods are used in different medical image processing applications [22-29].

4. Watershed Algorithm

Image segmentation is an important step in the medical image processing. It is the process of extraction of a region of interest from a medical image. Many algorithms and methods are available for medical image segmentation. Watershed algorithm is an efficient method used for this. The main idea behind the watershed algorithm is the mathematical morphology. The watershed algorithm is proposed by by Digabel and Lantuejoul in 1977 [30] and later it is improved by Li et al. in 2003 [31]. The basic idea used in watershed transform comes from topography. In the topographic view, there are three different types of points-points belonging to regional minimum, points at which a drop of water, if placed at the location of any of those points, would fall with certainty to a single minimum, is called as catchment basin or watershed, points at which water would be equally likely to fall to more than such minimum, is called as divide lines or watershed lines. The main stage of watershed algorithm is to find the watershed lines. Suppose that a hole is created on each regional minimum and let the water to rise through the holes at a uniform rate. When the water level is reached at the highest peak point the process is stopped. Now the landscape is divided in to different regions separated by dams or watershed lines. When applying this concept in to image segmentation, the entire image will be divided in to different regions based on the intensity values and separated by watershed lines. Figure 1 represents the modelling of watershed algorithm.
The mathematical background of watershed algorithm is described as follows. Let $M_j$, $j = 1$ to $R$ be the different regional minima of an input image $f(x, y)$. Assume that $C(M_j)$ be the set of points in a catchment basin associated with the regional minimum $M_j$. $T[n]$ represents the set of coordinates $(p, q)$ of the image in which $f(p, q) < n$. Mathematically we can represent it as

$$T[n] = \{(p, q) | f(p, q) < n\} \quad (6)$$

That is $T[n]$ is a set of coordinates of the image $f(x, y)$ lying below the plane $f(x, y) = n$. $\text{min}$ and $\text{max}$ denote the minimum and maximum value of $f(x, y)$. The flooding starts from the range of $n = \text{min} + 1$ to $n = \text{max} + 1$. Let $C_n(M_j)$ represents the set of coordinates in the catchment basin associated with minimum $M_j$ that are flooded at stage $n$. $C_n(M_j)$ can be viewed as a binary image represented as

$$C_n(M_j) = \begin{cases} 1, & \text{If } (x, y) \in C(M_j) \text{ and } (x, y) \in T[n] \\ 0, & \text{Otherwise} \end{cases} \quad (7)$$

$C[n]$ represents the union of the flooded catchment basins at the stage $n$.

$$C[n] = \bigcup_{j=1}^{R} C_n(M_j) \quad (8)$$

$$C[\text{max} + 1] = \bigcup_{j=1}^{R} C(M_j) \quad (9)$$

From the equations we can show that $C[n-1]$ is a subset of $C[n]$ and $C[n]$ is a subset of $T[n]$. Therefore $C[n-1]$ is a subset of $T[n]$. For finding the watershed lines, we initialize $C[\text{min}+1] = T[\text{min}+1]$. The algorithm then recursively finds $C[n]$ from $C[n-1]$. The calculation of $C[n]$ from $C[n-1]$ as follows. Let $H$ be the set of connected components in $T[n]$. Then for each connected component $h \in H[n]$, there may be three possibilities.

A. $h \cap C[n-1]$ is empty.
B. $h \cap C[n-1]$ contains one connected component of $C[n-1]$.
C. $h \cap C[n-1]$ contains more than one connected component of $C[n-1]$.

Further flooding would leads to the merging of these catchment basins. One pixel thick dam can be constructed by dilating $h \cap C[n-1]$ with a $3 \times 3$ structuring element of $1$s and constraining the dilation to $h$.

5. Marker Based Watershed Algorithm

Though the watershed algorithm is an effective method for medical image segmentation the direct application of the watershed transform leads to the problem of over-segmentation. It is due to the noises and other irregularities in the image [32]. Figure 2 represents over-segmentation problem of watershed algorithm. There are many methods are proposed for avoiding this over-segmentation problem. One of the efficient methods is proposed by Meyer [8]. He used markers before segmenting the image. A marker is a connected component belonging to an image. We can use two types of markers, called external and internal markers. Internal marker belongs to the object of interest and external marker belongs to the remaining background area.

Identifying external and internal markers from an image is the important stage in the marker based watershed algorithm. There are many methods are proposed for the detection of the markers. In this paper we made a review on different approaches to find the markers in the medical image segmentation applications.

5.1 Clustering Based Methods

Clustering is the process of organizing data instances into different groups. Clustering methods are also used to identify the markers for the watershed algorithm. M. A. Gonzalez and V. L. Ballarin proposed a novel method for the detection of internal marker based on clustering techniques [33]. They used K-Means [34] clustering algorithm for internal marker identification and then morphological erosion is applied for the detection of external markers. K means follows a numerical, unsupervised, non-deterministic and iterative method for partitioning images into K clusters. Here K indicates the number of clusters to be identified. They proposed a two-step watershed algorithm for the segmentation of bone narrow biopsies. In the first step classical watershed segmentation algorithm is applied on to the bone narrow biopsy medical images. Then the over segmented images
are clustered using K-Means clustering algorithm based on the features mean and standard deviation. The final internal markers were obtained by applying morphological opening and closing operators with a 4x4 structuring element [35]. The external markers are obtained by the morphological erosion of the internal markers complements.

M. C. Jobin Christ and R. M. S. Parvathi implemented marker based watershed transform on MR brain images after applying clustering methods such as K-means clustering [34] and Fuzzy C-means clustering [36]. They used a particular type of segmentation map, which produces more prominent results than the segmentation maps produced by the conservative watershed algorithm [37]. Sae Hwang and M. Emre Celebi proposed an efficient method for the detection of markers from the Wireless Capsule Endoscopy (WCE) images [38]. They used the method for the detection of polyps from WCE images. After Gabor filter applied on the images, they implemented clustering using K-Means clustering algorithm. The clustering centroids are used as the internal markers.

5.2 Template Based Methods

Shengzhou Xu et al. proposed an automatic marker identification method for lesion segmentation from mammogram images based on the template matching technique [39]. Template matching is a method used for classifying an object by comparing portions of images with another image [40]. In the first stage they estimated the rough region of the lesion using template matching and a thresholding method. Then the Euclidean distance from each pixel in the rough region to the nearest zero pixel is calculated to form a distance image. From the distance image, a point with highest distance value is selected to be the center of the internal marker. External marker is identified by applying morphological dilation on the internal markers.

5.3 Histogram Quantization and Biological Seed Modeling

Joe Chalfoun et al. suggested a novel method for marker identification for cell segmentation from multiple imaging modalities [41]. The method used for the separation of touching cells from the microscopic images. They developed two different methods for the automatic detection of seed points: (1) histogram quantization with seed size constraint, and (2) nucleoli seed detection, which incorporate biological insight to locate cell nuclei and their clustering. First method computes markers as the function of histogram percentile binning quantization with the seed size constraint. Instead of using every pixel values in the histogram, they used binned pixel intensities, which reduce the over-segmentation problem. The quantization method also avoids the over-segmentation. In the second method, biological modeling of individual cells is incorporated into the seed selection stage. The nucleoli are filtered by using a threshold size ST and the circular shape threshold CT. Multiple nucleoli within the nucleus can be clustered using another threshold value DN. the Euclidian distance between respective nucleoli centroids is less than DN, then these nucleoli belong to the same cell.

5.4 Thresholding Based Methods

Thresholding is a technique which is used to partitioning an image into foreground and background regions [3]. Threshold value can be identified either automatically or manually. Xiaopeng Wang et al. proposed a method for marker extraction from MRI or CT brain tumored images based on thresholding [42]. After performing some pre-processing steps they calculated internal markers on the basis of a threshold value T. Since the tumor cells have the larger intensity value, pixel value larger than T is labeled as internal markers. The external markers are identified by calculating watershed transform of the Euclidian distance of the internal markers.

Hui Zhu et al. suggested a novel method for marker extraction on the basis of h-minima [43] and minima imposition to make a marked image before watershed transformation [44]. They implemented this method for the extraction of contour from MRI brain images. The h-minima operator is used to identify the set of all markers with depth greater than the threshold value h. Minima imposition is a morphological filtering method which is used to create minima at the locations corresponding to the markers. Jierong Cheng and Jagath C. Rajapakse proposed a marker extraction method based on adaptive H-minima transform [45]. They used this method to separate clustered nuclei from fluorescence microscopy cellular images. Chanho Jung and Changick Kim suggested a novel method to extract the markers from medical images for segmenting cervical and breast cell images using H-minima transform [46].

Ahmed Wasif Reza et al. proposed a marker identification method for the extraction of features from retinal images [47]. They used the method of extended minima transformation for the marker extraction. The extended minima calculate the regional minima of the h-minima transform. It determines a group of high intensity pixels belonging to the foreground such that pixels in each region create a connected component and all the pixels in the connected component have the same intensity value. External markers are identified by marking the exact midway between the internal markers. Rowayda A and Sadek implemented a marker extraction method for MRI
brain image segmentation [48]. Internal markers are extracted using extended minima transform and external markers are extracted using an outer distance transform. S. N. Geethalakshmi and T. Jothy proposed a marker detection method for medical image segmentation based on optimal thresholding algorithm [49]. In optimal threshold algorithm, projected data is used to find the threshold value instead of local image data [50]. They used a projection Distance Minimization (PDM) measurement for this purpose. The internal markers are the pixels with gradient value less than the optimal threshold value and external markers are the pixels with gradient value greater than the optimal threshold value.

Petros S. Karvelis et al. proposed a novel method for marker identification used for the segmentation and classification of Multiplex fluorescent in situ hybridization (M-FISH) chromosome images [51]. They used the dynamic approach of thresholding for the marker detection [52]. It selects the minima values above a threshold value. Yongqiang Tan et al. suggested a method for marker identification for segmenting the lung cancer from CT or MR images based on a threshold and using distance transform on the reference slice [53]. To determine the threshold for separating the internal markers from the background a Gaussian mixture model is used. The regions with higher density than the threshold value were considered as the pixels in the internal marker. Other marker extraction methods in the medical images using thresholding is given in the references [54- 56].

5.5 Atlas Based Methods

Alas based segmentation is a type of segmentation which is commonly used in medical image processing applications. In this method, prior knowledge about the size, shape, anatomy and features of different soft tissues, organs are used in the form of reference images or atlases [57]. Justyna Wlodarczyk et al. proposed an automatic marker identification method based on atlas segmentation [58]. They used the method for the segmentation of wrist bones from MR Images. Their segmentation process includes three stages: segmentation of the distal parts of ulna and radius, segmentation of the proximal parts of metacarpal bones and segmentation of carpal bones. For each segmentation markers of the bones and markers of the background determined first and based on this markers bone segmentation is carried out.

V. Grau et al. implemented an atlas based marker identification method for the segmentation of knee cartilage and gray matter/ white matter from MRI images [59]. They generated the markers using a statistical atlas. Before the calculation of the markers, for the accurate results they applied two operations on the images: Skeletonization and outlier removal. Soumik Ukil and Joseph M. Reinhardt proposed a marker identification method based on the previous knowledge [60]. Using the markers they implemented watershed algorithm for the segmentation of pulmonary fissures from the lung CT images. The basins generated by the normal watershed algorithm are merged according to the detected markers. The markers are selected using a labeled tree and prior information about the shape and orientation of the fissures and the lungs.

F. Cloppet and A. Boucher implemented an efficient method for marker identification based on prior knowledge for the segmentation of aggregated or overlapping nuclei from the microscopic images [61]. For the marker identification they used previous knowledge about the normal and abnormal nuclei shape. If the nuclei are identified as aggregating nuclei, then marker is the middle of the nuclei and if the nuclei are an overlapping one, then there will be one more marker in the overlapping area along the segment. Then the topographic view of gradient image is flooded from markers.

5.6 Fuzzy Based Methods

Fuzzy logic represents inaccurate, ambiguous information into linguistically expressed knowledge. In fuzzy logic, variables have the values between 0 and 1 [62]. Mariela Azul Gonzalez et al. implemented a fuzzy based method for marker identification from bone marrow biopsies images [63]. Before the identification of the markers, they applied normal watershed algorithm on the images. From each over-segmented images, statistical features such as mean and variance are extracted. A trained expert will selects a number of regions from the over-segmented image. The membership value of each region is identified and pixel wisely applied on to the image. Now the image contains only the values between 0 and 1. Using Otsu’s thresholding [64] method the internal markers are extracted from the image. The external markers are obtained by eroding the resulting image as the complement of the internal markers.

5.7 Morphology Based Methods

Mathematical morphology is a method for extracting region of interests (ROI) from an image on the basis of shape parameter [21]. Erosion and Dilation are the two fundamental operations in mathematical morphology. In the literature, we can see many applications of mathematical morphology. For the watershed algorithm, internal and external markers can be extracted using mathematical morphology based methods. F. Nery et al. proposed a novel method for the extraction internal and external markers based on morphological methods [65]. They used the markers for the segmentation of lungs part
from the PET scan images. In the first stage, they defined internal markers on the basis of low intensity values of the lungs using a threshold value. The non-lung regions are avoided using dilation operation. The final internal markers are identified using a series of morphological operations such as erosion and dilation. The external markers are identified using morphological dilation and the distance transform method.

Muhammad Rizal Mohamed Razali et al. identified the markers of the watershed algorithm for the extraction of dental parts from the X-Ray images [66]. After applying the Otsu’s thresholding algorithm, they used dilation and erosion operations for getting the maximum and minimum values from the images respectively. These values are used as the markers for the watershed algorithm. Devaki, K. and V. Murali Bhaskaran implemented a novel method for the detection of the markers for the fissure segmentation from CT lung images [67]. They used morphological opening operation for the extraction of the internal markers. External markers are identified using distance transform method. Can Fahrettin Koyuncu et al. proposed a marker detection method based on morphology operations [68]. They used the methods for isolating cells from medical images. They used two types of markers—markers from dark pixels and markers from white pixels. For finding markers on the dark pixel, they used an iterative erosion algorithm and for identifying white pixels they used a method based on dilation.

Ahmad EL ALGAOUT and M’barek NASRI proposed a marker identification method based on morphological reconstruction [69]. They identified markers on 6 medical images (X-Ray, MRI): cell, muscle, brain, foot and dental image. Morphological reconstruction can be considered as the repeated dilations of an image [70]. Two images are used in reconstruction operation: marker image and mask image. Marker image is continuously dilated until the contour of the image fits under the mask image. Patel Janakumar Baldevbhai and R.S. Anand implemented a marker identification method for the segmentation of atherosclerosis images using morphological reconstruction [71]. Marker identification for the brain image segmentation using morphological reconstruction is given in the references [72-80].

5.8 Level Set Based Methods

Level set methods are used to manage the problem of curve or surface propagation in an implicit manner [81]. In the level set method, contours are considered as the zero level set of a higher dimensional function, normally called a level set function. That is, representing the varying contours using a signed function whose zero corresponds to the real contour. Shutong Tse et al. proposed a level set based method for the marker identification [82]. They used this method for the segmentation of the brightfield cells from the microscopic images. Instead of one level set segmentation method, they used multiple level set segmentation for the extraction of the markers. Using this method they extracted foreground and background markers from the image.

5.9 Distance Transform Based Methods

Distance transform is a commonly used method in image processing. A distance transform of a binary image identifies the distance from each pixel to the adjacent non-zero pixel [83]. Huigang Yang and Narendra Ahuja implemented a marker identification method for blob or granular object recognition based on distance transform methods [84]. They extracted the markers of the cells through a series of steps. At the initial stage, foreground and background are separated. Then the local density of each foreground pixel is calculated and object pixels with the same patch are grouped into cluster. After that step, distance transform of each pixel to the background is identified. For a circular object, the circular center typically has the largest distance to the background compared with any other pixel in the object. These pixels considered as the local maxima or markers. After all the markers are identified, they clustered the markers that belong to the same object. Hakan Ancin et al. proposed a maker detection method by combining gradient function and distance function [85]. They used the algorithm for the extraction of cells from anisotropic 3-D biological images.

5.10 Other Methods

The methods given in the previous section are the most important and commonly used methods for marker identification in the watershed medical image segmentation. There are some other methods can be found in the literature for marker identification. Petr Dokladal et al. suggested a novel method based on component tree representation [86]. They used this method to extract various head parts from magnetic resonance images. Usha Mittal and Sanyam Anand proposed a marker identification method for medical image segmentation based on convolution and correlation [87]. Chen Pan et al. implemented another method for marker identification based on mean shift procedure [88]. Mean shift procedure is applied after the detection of a mean shift vector [89]. The method is used to extract the blood cells from microscopic images.
6. Experimental Results

For the experimental part, we have applied the commonly used marker identification algorithms on MRI brain tumored images. We have used a database of eighty MRI brain tumored images. The sample images are provided by Govt. Medical College, Thrissur. All the images are of T2 sequence, taken from axial plane. From the methods described in the last section, we selected three algorithms for the marker identification in the tumored part. The methods are clustering based methods, thresholding based methods and morphology based methods. These three methods are separately applied on each image for detecting the markers on the tumor part. Ground truth of the tumored image is created using ITK Snap toolkit [90]. Percentage of accuracy for the marker identification using each method is given in the table.1. Here the accuracy is calculated on the basis of following equation.

\[
\text{Accuracy} = \frac{\text{Number of cases that correctly identified marker on the tumored area}}{\text{Total cases}} \times 100
\]

From these three methods, morphology based method produces more prominent results than the other two methods and thresholding based method has the lowest percentage of accuracy.

### Table 1: Accuracy of the algorithms

<table>
<thead>
<tr>
<th>No</th>
<th>Method name</th>
<th>% of accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Clustering based method</td>
<td>85.00</td>
</tr>
<tr>
<td>2</td>
<td>Thresholding based method</td>
<td>77.5</td>
</tr>
<tr>
<td>3</td>
<td>Morphology based method</td>
<td>93.75</td>
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6. Conclusions

Medical image segmentation is a challenging and complex task. There are many algorithms are proposed for medical image segmentation. Watershed segmentation is a simplest and robust algorithm among them. It is developed on the basis of mathematical morphology. The main problem with the watershed algorithm is the over-segmentation. One of the adaptive solutions to this problem is the use of markers. In this paper we mainly focus on different marker identification methods used for the watershed algorithm in medical image segmentation. We also presented a brief idea about various medical imaging modalities. The methods used to detect markers in one modality are entirely different from another modality. Though all this methods are effective on a particular type of imaging modality, there is no common standard algorithm for the marker detection which is applicable for all medical imaging modalities. Most of the methods used morphological operations in between the marker identification steps. In future, internal and external markers can be efficiently extracted using many emerging technologies such as neural networks. It is not possible to completely replace the physician’s work by an automated procedure, but can be useful for the complex decision making purposes.

References


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