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*Full Length Research Paper*

# Light refraction based medical image segmentation

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**Image segmentation is the most important and first step in pattern recognition and image analysis. In this paper, an automatic segmentation algorithm based on light refraction was proposed for medical images. In the proposed algorithm, similarity percents of the pixels were calculated by using the amount of shift while occurred light through a transparent sheet and re-enters the same environment. The proposed algorithm is similar to region growing algorithm where the seed points are automatically selected and grown and does not require any prior knowledge of the number of regions existing in the image. So, it decreases the computational load required for the other image segmentation methods. The proposed algorithm is demonstrated by application to real medical images. Results have showed that proposed algorithm extract all segments effectively.**

**Key words:** Light refraction law, image segmentation, medical images.

## INTRODUCTION

Image segmentation is an important step for image processing and computer vision algorithms. Segmentation refers to the process of partitioning a digital image into multiple regions. In other words, segmentation is to simplify and change the representation of an image into something that is more meaningful and easier to analyze (Shapiro and Stockman, 2001). Medical imaging is a most commonly used technique in radiology to visualize the structure and function of the body (Pham et al., 2000). Successful numerical results in segmented medical image can help physicians and neurosurgeons to investigate and diagnose the structure and function of the body in both health and disease (Chang et al., 2007). Also, accurate segmentation is needed in clinical applications for doctors. But, segments in the medical images may not be manually obtained in accurate and efficient way. In other words, manual segmentation of medical images is a challenging and time-consuming task. Therefore, computer aided segmentation is very important to determine healthy results in medical images.

In recent years, the segmentation of medical images has been a big area of intense research (Bezdek et al., 1993). Some of the applications of image segmentation are locating tumors, measuring tissue volumes, diagnosis etc. (Hoad and Martel, 2002). There are several issues related to medical image segmentation. One of the general problems is choosing a suitable approach for isolating different objects from the background and each other. The segmentation algorithms do not perform well if the gray levels of different objects are quite similar. Issues related to segmentation involve choosing good segmentation algorithms, measuring their performance, and understanding their impact on the scene analysis system (Demirci, 2006). Researchers have been proposed many approaches for segmentation to medical images, such as atlas-based (Kaus et al., 2001; Prastawa et al., 2004; Leemput et al., 1999), region-based (Nanayakkara et al., 2006), knowledge based (Clark et al., 1998; Duta and Sonka, 1997 ), wavelet transform (Mallat 1989; Qian et al., 1999), artificial intelligent (Li et al., 2001; Dokur and Olmez, 2008; Saha and Bandyopadhyay, 2007; Gonzalez et al., 2007) and fuzzy c-means (Kannan 2008; Cai et al., 2007; Szilagyi et al., 2007; Zhang and Chen, 2004; Phillips et al., 1995; Rezaee et al., 2000) etc.

The fuzzy c-means method is one of the best-known and more important image segmentation methods. But, it has some drawbacks like using other methods. These drawbacks are that adjacent clusters frequently overlaps in colour space and causing incorrect pixel classification and clustering becomes more difficult when the number of clusters is unknown, as it is typical for segmentation

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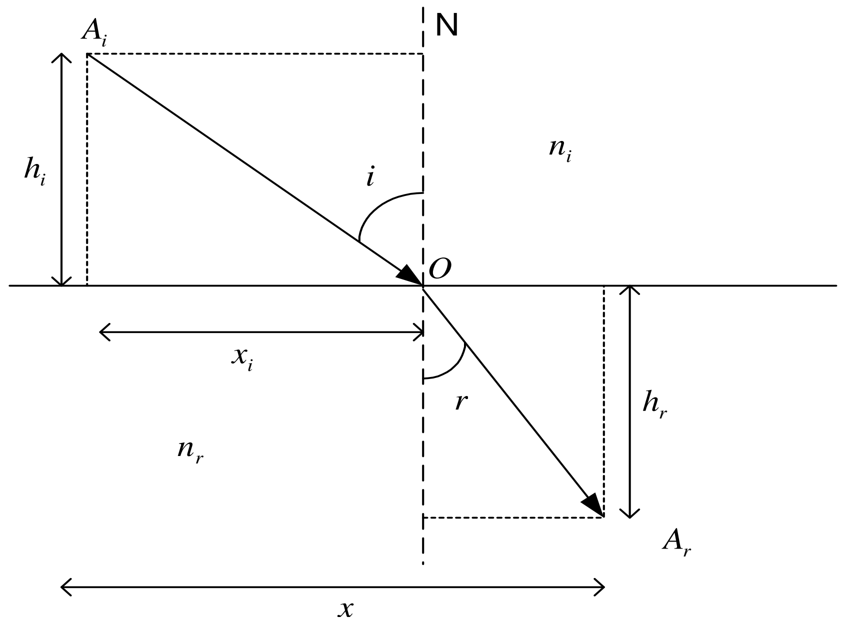


**Figure 1.** Refraction of light.

applications. Also, the fuzzy c-means method requires prior knowledge of the number of regions existing in the image. Otherwise, false results may be the case.

In this paper, light refraction law based on an automatic segmentation method is proposed for medical images. The proposed segmentation algorithm is similar to region growing algorithm where the seed points are automatically selected and grown. Also, it does not require any prior knowledge of the number of regions existing in the image. Therefore, it reduces the computational complexity required by the other methods. Also, it is shown that the proposed algorithm has efficient segmentation results on real medical images.

## SIMILARITY OF PIXELS

Basically, segmentation is clustering of the similar pixels under same label in the image. Therefore, we need a mathematical judgment of how two pixels are similar or belong to the same object (Guvenc et al., 2008). In this study, the similarity of the pixels is calculated by using light refraction law. Light is electromagnetic radiation of a wavelength that is visible to the human eye. Light always travels at a constant speed in the same medium. The equation for speed of light in a material is:

$$v = \frac{c}{n} \tag{2}$$

Where, $n$ is index of refraction and $c$ is speed of light in a vacuum. Light speed changes and bends when it travels from one medium to another and occur refraction. This happens when it depends on the refraction indices of the mediums. All mediums have different refraction index. Index of refraction is an important property to distinguishable of mediums. In Figure 1, it is observed that, an incoming light wave comes onto $A_i$ point from $i$ medium, and enters $r$ medium and moves to $A_r$ point. Light's refraction rule is found as follows, by taking derivative of time passed through the movement of light from point $A_i$ to point $A_r$.

$$\frac{\sin(i)}{\sin(r)} = \frac{n_r}{n_i} \tag{1}$$

Here, the $i$ is the angle of incidence, $r$ is the angle of refracted light, $n_i$ is the index of refraction of incoming light's medium, and $n_r$ is the refractive index of refracted light. As shown in Equation 2, the ratios of sinus of angle of incidence to sinuses of angle of refractions, gives refractive index ratio of the mediums (Jackson, 1975). Then a design shown in Figure 2 has been constituted. Here, it is considered that the pixel with bigger entry angle is outside medium and the smaller one is located inside a transparent plate with d length. As the light ray comes through the parallel transparent plate, as shown in Figure 2, it refracts and gets closer to normal. When light gets through transparent plate and comes back the same environment, the parallel shift amount of $x_k$ occurs. The occurring shift amount is calculated as the square below.

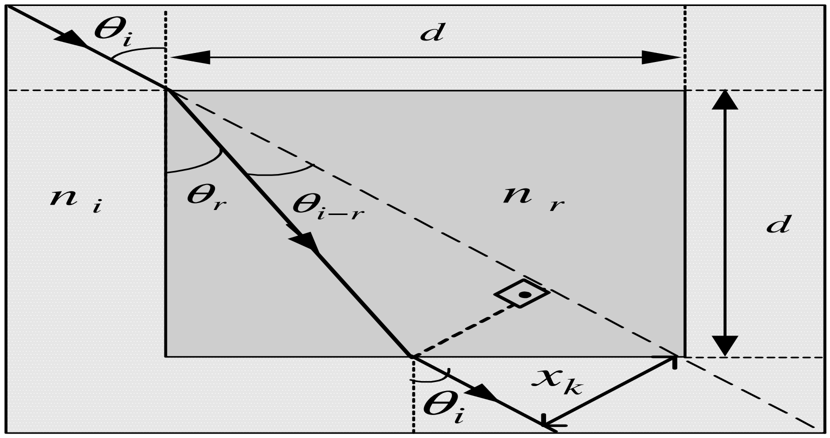


**Figure 2.** Designed state for transition of the light from the transparent plate.

| | | |
|---|---|---|
| x-1, y-1 | x-1, y | x-1, y+1 |
| x, y-1 | x, y | x, y+1 |
| x+1, y-1 | x+1, y | x+1, y+1 |

**Figure 3.** A pixel with spatial coordinates in image.

$$x_k = d \times \frac{\sin(\theta_i - \theta_r)}{\cos(\theta_r)} \quad (3)$$

As shown in Equation 3, the occurring shift amount depends on the thickness of the media, and refraction and input angles of light. If the lights angle of input and output are equal to each other, this means that, these two environments are same, and also "0" is obtained from the equations. While this d thickness ensures the change in the amount of shift between 0 - 1, it also sets the edge transition degrees in the image. As value of the d thickness gets closer to 1 the harder edges occurs. Therefore, the value of similarity between two pixels is calculated as;

$$S_k = 1 - x_k \qquad k=1, 2, 3\ldots\ldots 8 \quad (4)$$

Also, the minimum value of similarity ratios between the central pixel to be processed and neighboring pixels give us the similarity map of the image.

$$S = \min(S_1, \ldots\ldots, S_8) \quad (5)$$

In this study, entry angle and the refractive angle is limited between 1 - 90 degrees. If the gray level colour value of P1 is greater than the gray-level colour value of P2, the input angle of the light refraction angle will be calculated as in Equation 6 and 7.

$$g = {}^{89}\!/_{255} \times P1 + 1 \quad (6)$$

$$k = {}^{89}\!/_{255} \times P2 + 1 \quad (7)$$

If the gray level colour value of P1 is smaller than the gray level color value of P2, light input angle shall be calculated as in Equation 8 and refractive angle shall be calculated as in Equation 9. (3)

$$g = {}^{89}\!/_{255} \times P2 + 1 \quad (8)$$

$$k = {}^{89}\!/_{255} \times P1 + 1 \quad (9)$$

Here, the $g$ is entry angle and $k$ is refractive angle.

## AUTOMATIC SEGMENTATION METHOD

A pixel and its neighbours in an image could be represented as shown in Figure 3. The value of membership functions are calculated for all neighbours with Equation 4. In the proposed algorithm, the direction of calculation of similarity percent is the same as clockwise direction and a dynamic array which has the same size of the image is used to hold the region numbers of pixels. Initially, the array is filled with −1. If the value in the array is

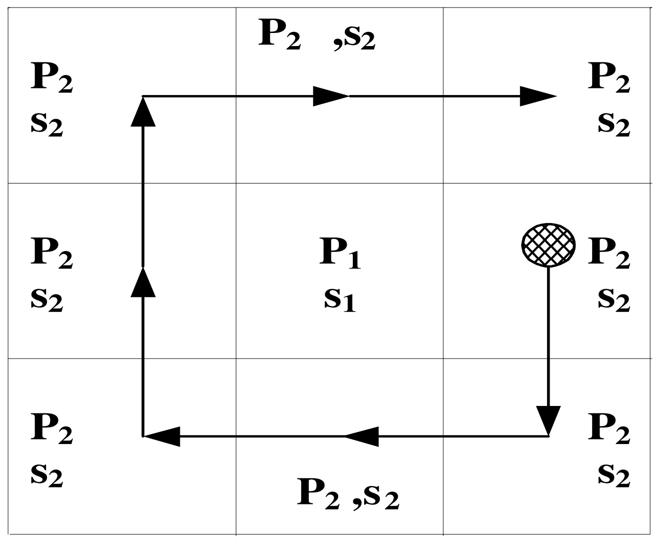


**Figure 4.** A pixel in image mask used for similarity percert.

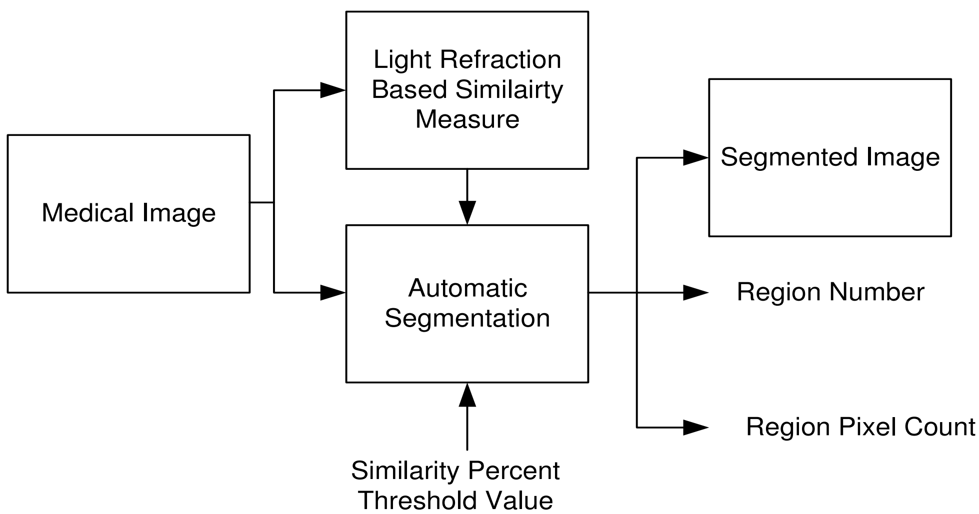


**Figure 5.** Proposed method.

negative, it means the pixel has not assigned to any region yet and the similarity percent value must be calculated. Then similarity percent value is compared with the similarity percent threshold value to decide whether the neighboring pixel belongs to the same region. If true, then the region number of P1 is assigned to P2 and the next pixel is checked. If the value in the array is positive, it means the corresponding pixel has already been assigned to any of previous region and there is no need to further consider it. Then, the mask has shown in Figure 4 is moved through the image from left to right and from top to bottom for ending the region labeling.

The light refraction based automatic image segmentation method could be described as a system whose inputs are a medical image and the similarity percent threshold value, as shown in Figure 5. The outputs of the system are a segmented image, the region numbers and region pixel counts.

## EXPERIMENT RESULTS

Once the proposed algorithm was tested with the MR head and knee images which are two images of size 367 x 342 and 186 x 186 with 255 gray levels, respectively. Figure 6(a) is the original image of MR head image. Figure 6(b) shows the similarity image obtained by means of Equation 6. Figure 7(a) is the original image of MR knee image. Figure 7(b) shows the similarity images obtained by means of Equation 6. It has been noticed from applications that the medical images could be transferred into similarity image with the light refraction law. The transformed image is a gray scale image where

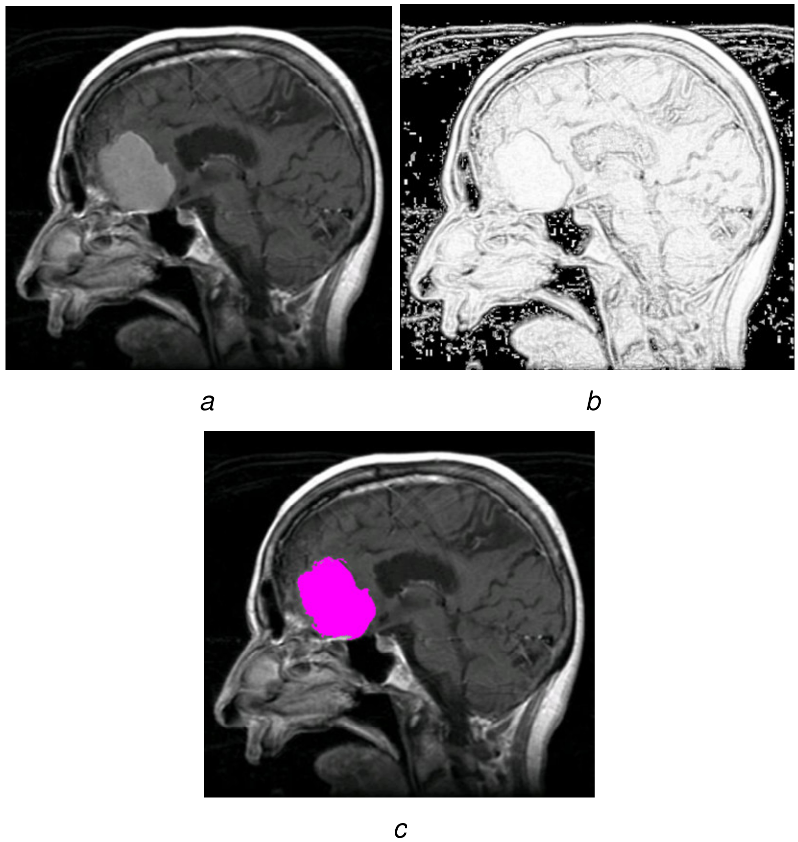


**Figure 6.** A MR image of the head (a) Original image (b) Similarity image (c) Segmented tumor image.

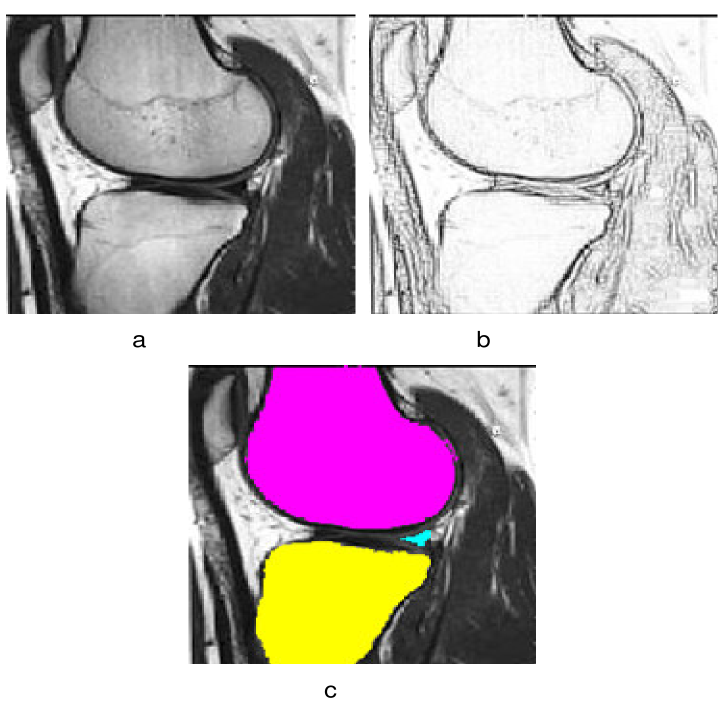


**Figure 7.** A MR image of the knee (a) Original image (b) Similarity image (c) Segmented femur, tibia and meniscus image.

the gray levels show the edginess strength. As a result of this, very small variations in a medical image could be detected. Figure 6(c) shows the image which is segmented tumor by proposed method with pink colour. Figure 7(c) shows the image which is segmented femur, tibia and meniscus by proposed method with pink, yellow and green colour, respectively.

The goals of the brain and knee medical images experiments were to determine and separate the tumor and femur, tibia, meniscus segments from background in image. From segmentation results, tumor segment which is in the brain contains 3761 pixels and femur, tibia and meniscus segments which are in the knee contains 8484, 5249, 75 pixels, respectively. This helps surgeons for an operation and radiologist to estimate its size and progression. As could be seen from the results, the proposed method could successfully segment the objects. The proposed method in the experiments has been implemented in C++. The running time is nearly 100 ml/s per image with a computer with a CPU of 2.4GHz and 512MB RAM.

## CONCLUSION

Images are very important parts of medicine which are frequently used by physicians and doctors to investigate and diagnose of the structure and function of the body. In this paper, an automatic segmentation method is proposed for medical images. It is similar to region growing algorithm where the seed points are automatically selected and grown. In the proposed algorithm, similarity percents of the pixels were calculated by using the amount of shift while the occurred light through a transparent sheet and re-enters the same environment.

The proposed segmentation algorithm does not require any prior knowledge of the number of regions existing in the image. Therefore, it reduces the computational complexity required by the other image segmentation methods. The experimental results show that the proposed segmentation algorithm gives sufficient segmentation results. The further research for calculating the similarities of neighboring pixels with neural networks is still in progress.

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