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Application of Active Contours Driven by Local Gaussian Distribution Fitting Energy to the Computed Tomography Images

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ABSTRACT

This paper presents the application of active contours region-based method of image segmentation to Computed Tomography (CT) images. Previous researchers applied this region based method on Magnetic Resonance Image (MRI), in vivo images and synthetic images which contain intensity inhomogeneities. In this paper, a different modality known as Computed Tomography (CT) scan was applied. CT scan also produces images containing intensity inhomogeneity, and it is predicted that this method provide good segmentation results. The main objective of applying this method is to check its applicability on CT images. The segmentation process begins by finding the area of interest (black region). Results from this experiment are then used in estimating time of death. Experimental results show that this method has successfully segmented the black region when some parameters changed, provided that the regions are closed to each other. If the black regions are located far from each other, then this method will only segment certain areas.

Keywords: Local Gaussian distribution, computed tomography images, segmentation

INTRODUCTION

Segmentation is one of the basic tasks involved in digital image processing. Digital image processing involves the processes of creating, processing, communicating and displaying images (Gonzalez & Woods, 2008). It can be used to convert signals from image sensor to digital images, increase clarity of images by removing noise and other artefacts, extract the size, scale or the number of objects in a scene, prepare images

for display or printing, and compress images for communication across a network (Mathwork, 2013). There are many types of images that can be used in segmentation process such as medical images from different modalities, for example, Magnetic Resonance Images (MRI), Computed Tomography Images (CT) and Ultrasound.

In real world images, there are some difficulties in segmenting medical images due to intensity inhomogeneity. Intensity inhomogeneity is pondered to be the multiplicative low-frequency variation of intensities. It is caused by anomalies of the magnetic fields of the scanners (Rajapakse & Kruggel, 1998) such as the presence of intensity inhomogeneity in CT images due to the effects of beam hardening while MRI intensity inhomogeneity arises from radio-frequency coils or acquisition sequences.

This paper focuses on segmenting Computed Tomography (CT) images by using Active Contours driven by local Gaussian distribution fitting energy. The main objective of doing this segmentation is to check the applicability of this method on CT images as there is a future research related to this paper, which is finding the area of segmented region.

This paper is organised in several sections. Section 2 discusses the materials and method used in this paper. This section includes the procedure for CT image segmentation. Meanwhile, experimental result and discussion are presented in Section 3, and finally conclusions are illustrated in Section 4.

Active contour was introduced by Kass, Witkin, and Terzopoulos (1988). Currently, active contours model is widely used in image segmentation. This method produces good results because the model can be achieved by subpixel accuracy. Besides, this model also provides closed and smooth contours on surfaces (Wang, He, Mishra, & Li, 2009).

There are two categories of active contour which are parametric and geometric (Mumford, & Shah, 1989). Parametric active contour model is represented explicitly as parametric curve while geometric active contour model is based on the theory of curve evolution and geometric flows. Basically, active contours can be classified into two classes; edge-based models and region-based models. Edge-based models focus on employing local image gradients to attract contours towards object boundaries, while region-based model focuses on employing global image information in each region such as the distribution of intensities, colours, textures and motions to move the contours towards the boundary. Examples of region-based model are Mumford-Shah functional model (Mumford & Shah, 1989), Chan-Vese Model (Chan, & Vese, 2001), local Binary Fitting (Tsai, Yezzi, & Willsky, 2001) and local Gaussian distribution (Wang et al., 2009).

MATERIALS AND METHODS

Region-based Geometric Active Contour

The Chan-Vese algorithm is an example of the geometric active contour model and it was the first region-based model. This model uses the technique of mean curvature motion. The aim is to evolve the contour in such a way that it stops on the boundaries of the foreground region. Basically in the region based model, it is assumed that there are two regions in each image,

which are, foreground region and background region. This model is known as the Chan-Vese's Piecewise Constant model. It is defined by the energy functional, $F(c_1;c_2;C)$ and that energy functional consists of the energy inside and outside the contour. There are also two additional parameters and that energy functional is defined as follows:

$$F(c_1,c_2,C) = \rho_1 \int_{C_{in}} |f(x,y) - c_1|^2 \, dxdy + \rho_2 \int_{Cout} |f(x,y) - c_2| dxdy + \kappa.Length(C) + \mu.Area(C) \quad (1)$$

Where,

$\rho_1, \rho_2, \kappa, \mu$	:	fixed positive integers
$f(x, y)$	:	pixel in the image
c_{in}	:	the region inside the contour
c_{out}	:	the region outside the contour
c_1	:	the mean intensity of region inside the curve of evolution
c_2	:	the mean intensity of region outside the curve of evolution

The main objective of this region-based GAC is to determine contour, $F(c_1;c_2;C)$ that minimise the energy functional. This energy functional can be minimised by transforming (1) to the level set function.

Level Set Equation

In level set function, there is a curve C known as the contour which divides the image into two regions. If the contour is defined as closed curves, it can be implicitly represented with higher-dimensional function. The first is the inside region denoted by C_{in} and the second is the outside region denoted by C_{out}. The interface of level set function is defined as $\phi(x)=x^2+ y^2=1$, where $\phi(x)=0$. The example is as shown in Figure 1. The signed distance function can be defined as curve function, ϕ (Uppu, 2006). In Matlab, an image is defined in matrix form. Suppose, there is point x_1 for $i=1,2,...,m$ and m represents the number of column for the image. This point can be determined whether it is placed inside or outside the contour C by checking the sign of ϕ.
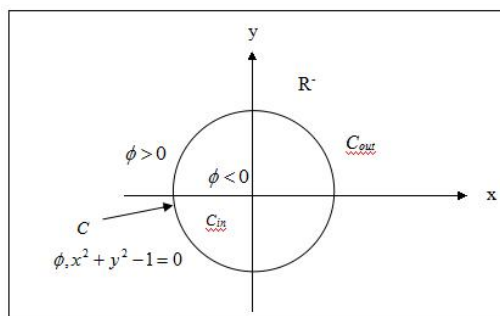

Figure 1. The Initial Contour

Local Gaussian Distribution

Local Gaussian Distribution Fitting (LGDF) is used to model the probability density functions, where the mean and variance are used as varying parameters. In order to effectively exploit information on local intensities, the distribution of local intensities is characterised by the partition of neighbourhood. In this research, local Gaussian distribution is used to obtain local mean and local variance.

In order to obtain the LGDF energy functional for all points in the entire image domain R, the integral of the following equation is minimised to give the following LGDF energy functional:

$$E^{LGDF} = \int_R \sum_{i=1}^{M} \rho_1 \int_{Ri} -W(x-y) \log p_{i,x}(h(y)) dy$$
$$= \int_R E_x^{LGDF} dx \tag{2}$$

In LGDF, there are level set functions which are contained inside and outside the contour region. Both the contour regions are named as foreground and background, respectively. Hence, it implies that the image domain where $R = R_1 \cap R_2$ R_1 denotes as the foreground region, while denotes as the background. Thus, (2) can be written as:

$$E(u_1(x), u_2(x), \sigma_1^2(x), \sigma_2^2(x), C) = \rho_1 \iint_{R\,R_1} -W(x-y) \log p_{1,x}(h(y)) G_\varepsilon(\phi(x,y)) dy dx$$
$$+ \rho_2 \iint_{R\,R2} -W(x-y) \log p_{2,x}(h(y))(1 - G_\varepsilon(\phi(x,y))) \, dy dx \tag{3}$$
$$+ \kappa \int_\varepsilon |\vartheta(\phi(y)|\nabla(\phi(y)) dx dy$$

Then, adding the term *Length (C)* to (3) transforms the LGDF energy functional to the level set function. Therefore, the LGDF energy functional becomes:

$$E(u_1(x), u_2(x), \sigma_1^2(x), \sigma_2^2(x), C) = \rho_1 \iint_{R\,R_1} -W(x-y) \log p_{1,x}(h(y)) G_\varepsilon(\phi(x,y)) dy dx$$
$$+ \rho_2 \iint_{R\,R2} -W(x-y) \log p_{2,x}(h(y))(1 - G_\varepsilon(\phi(x,y))) \, dy dx \tag{4}$$
$$+ \kappa \int_R |\vartheta(\phi(y)|\nabla(\phi(y)) dx dy + \mu \int_R \frac{1}{2}(|\nabla \phi(x)| - 1)^2 dx dy$$

By differentiating energy functional in (4), with respect to $u_i(x)$ and $\phi_i(x)^2$, while considering $\phi(y)$ as a constant, both mean intensities and variance intensities can be defined as follows:

$$u_i(x) = \frac{W(y-x) f(y) M_{i,\varepsilon}(\phi(y)) dy}{W(y-x) M_{i,\varepsilon}(\phi(y)) dy} \tag{5}$$

$$\sigma_i(x)^2 = \frac{W(y-x)(u_i(x) - f(y))^2 M_{i,\varepsilon}(\phi(y)) dy}{W(y-x) M_{i,\varepsilon}(\phi(y)) dy} \tag{6}$$

Procedure for CT Image Segmentation

An image segmentation method, which is local Gaussion distribution fitting energy, was applied to the CT images. The CT images were taken from Hospital Kuala Lumpur for testing purposes. After undergoing the segmentation process, the segmented region was obtained. The aim of this method is to introduce a localised energy functional using a truncated Gaussian Kernel. Wang et al. (2009) used double integral for the energy minimisation. This method also assumes that the mean and variance of the local Gaussian distribution are spatially varying parameters. Generally, the procedure is as follows:

Step 1:   View the image in Dicom Viewer.

Step 2:   Reduce the image pixels to 256×256 using Adobe Photoshop.

Step 3:   Read image in Matlab.

Step 4:   Update local means and local variances in (5) and (6).

Step 5:   Update the location of the region of interest to locate the initial contour.

Step 6:   Repeat step 4 until the criteria is met.

Step 7:   Display the result.

The difference between this paper and the previous research is that this paper focused on the black region area. Previously, Wang et al., (2009) focused on the white region and applied on synthetic images, MR images and in vivo images. Our focus is to segment the black region in CT images since the black region can be seen clearly in the CT images.

The method of Wang et al. (2009) has successfully segmented the black region when the region is near to each other and the initial contour is on the region itself. The initial contour needs to be set manually. This means that each image uses different initial contours and the position of the initial is not same. Then, the evolution of the contour changes at each iteration until it reaches the zero level set.

For image iteration, different images require different amounts of iteration. The iteration is set by running the LGDF coding several times with different numbers of iteration. This is done to determine the suitable values which the contour stop evolves. After all the images have been segmented, the results will be used for calculating the area of the black region, which is the next process of this research.

RESULTS AND DISCUSSION

The CT images data originated from Hospital Kuala Lumpur. Dicom Viewer is used to view the images. Then, the CT images are converted into bitmap image file (BMP) and the image pixels are reduced to since LGDF coding cannot read large image pixels. Then, the edited images are read in MATLAB until the results are obtained.

For all the images in this paper, there is a default setting of the parameters which are σ=3, μ=1, timestep Δt=0.1 and v=0.001×255×255. Other parameters will change according to the images. This means that different images will use different parameters.

Table 1
Results of the segmented images of the black region based on local Gaussian Distribution fitting energy
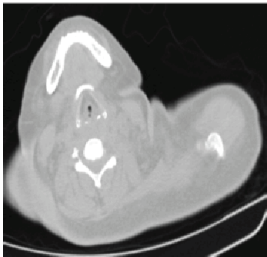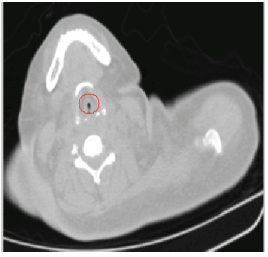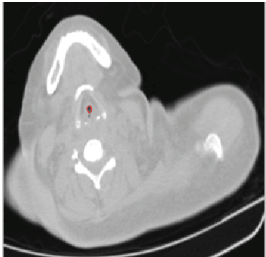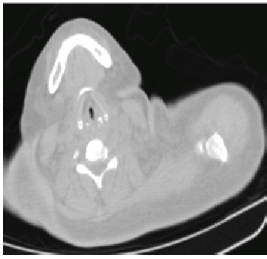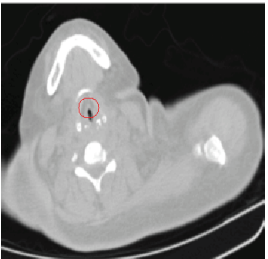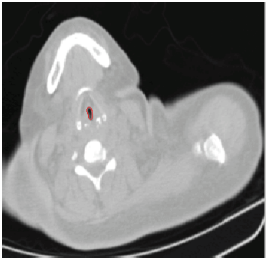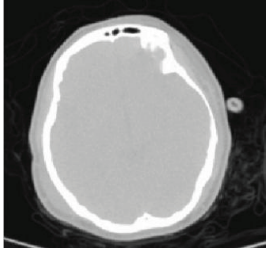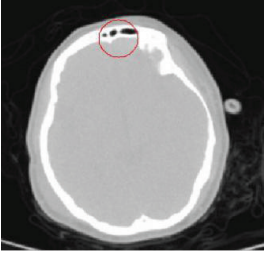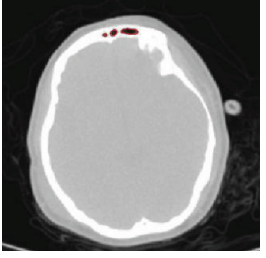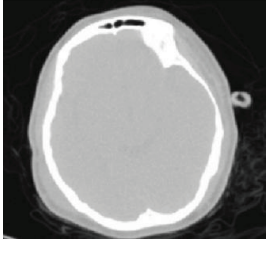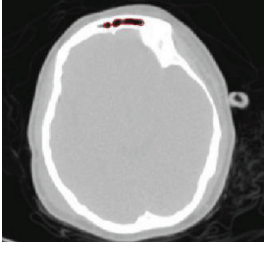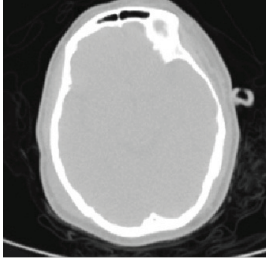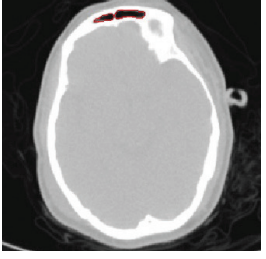
Images	Original images	Initial Contour	Segmented images
Image 1			
Image 2			
Image 3			
Image 4			
Image 5			

Table 1 shows the results of segmented images. The process of segmentation starts with initial contour and will iterate until the black region is fully segmented. The successful results are shown under segmented images and it is clearly seen that this method is able to segment the images when the region of interest is close to each other. The results for iteration and CPU time are recorded in Table 2. It was observed that the iteration took less than 10 seconds for each image to finish the segmentation process. It is a good sign since this method can abbreviate computation time.

Table 2
Number of iteration and CPU time (in s)

Image	Number of Iteration	CPU time
Image 1	40	1.431318
Image 2	40	1.300227
Image 3	100	3.315977
Image 4	140	8.279270
Image 5	140	3.961400

CONCLUSIONS

In this paper, we have presented the application of active contours driven by local Gaussian distribution fitting energy to the CT images. Based on the results given in the previous section, the method proposed by Wang et al. (2009) was found to have successfully segmented the black region provided that the regions are close to each other (as in Figure 2) and make some changes on several parameters. If the images have more than one black region and are located far from each other (as in Figure 3), this method only could segment certain areas of the CT images. Thus, it is a necessity to make an improvement to the model in order to make it applicable with CT images and will definitely give good results.
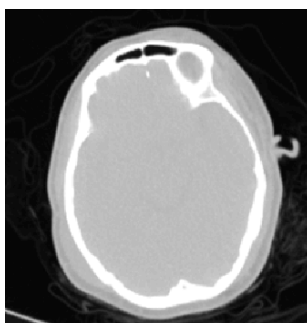

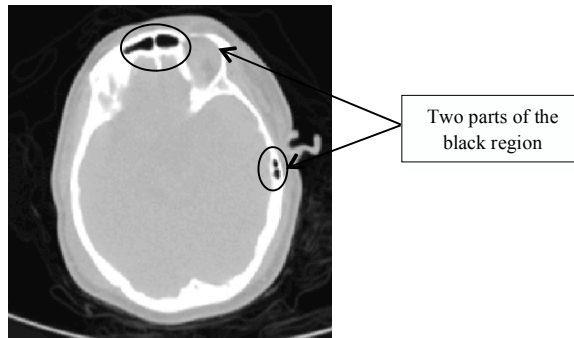*Figure 2*. CT images with more than one black region (near to each other)

Figure 3. CT images with two black regions (far from each other)

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