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A Study of Left Ventricular (LV) Segmentation on Cardiac Cine-MR Images

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ABSTRACT

Left ventricular segmentation from cardiac images has high impact to have early diagnosis of various cardiovascular disorders. However, it is really a challenging task to segment left ventricular images from magnetic resonance image (MRI). In this paper, we explore several state-of-the-art segmentation algorithms applied on left ventricular (LV) segmentation on cardiac cine-MR images. Both adaptive and global thresholding algorithms along with region-based segmentation algorithm have been explored. Edge-based segmentation is disregard due to the absence of edge information in the employed dataset. For evaluation, we explored a benchmark dataset that was used for the MICCAI 3D segmentation challenge. We found that the cardiac MRI global thresholding has proved to be much efficient and robust than the adaptive thresholding. We achieved more than 92% accuracy for global thresholding, whereas, about 78% accuracy for the adaptive thresholding approach. The use of entropy or histogram to characterize segmentation in place of the intensity value of the pixel has a vital effect on segmentation efficiency. It is evident that the intensity information is corrupted by acquisition procedure, as well as the structure of organs. Due to the lack of boundary information in cardiac cine-MRI, clustering and region-based segmentation have produced more than 93% segmentation accuracy. For the case of soft clustering, the increased accuracy is found as 96%. However, more explorations are required, specially based on deep learning approaches on very large datasets.

Keywords: MRI; cine-MRI; Left Ventricular Segmentation; cMRI; Medical Imaging

INTRODUCTION

Healthcare is a prime topic in the modern era due to the advancements of technologies and demands (Ahad et al. 2018). Various issues are explored, e.g., medical support systems for patients, computer-aided assistance to physicians, elderly support system and smart home, study on autism, and so on [e.g., in (Syeda et al. 2017; Irtija and Ahad, 2018; Saha et al. 2018)]. Magnetic Resonance Imaging (MRI) related research areas have encompassed a huge number of researchers all over the World. The magnetic resonance images from different body locations are studied extensively [e.g., (Hossain et al. 2016; Anadh et al. 2015; Alam and Kobashi, 2016; Morita et al. 2015; Kobashi et al. 2015)]. However, challenges remain as we demand for better accuracy, smarter methods, and faster approaches with big data. Advanced cardiac imaging techniques have made a possible rapid, precise and accurate estimation of heart function.

With the advancement in cardiac imaging using cardiac cine magnetic resonance (CMR), high-resolution multiphase 3D images of a complete cardiac cycle can be obtained easily. Since high-resolution CMR produces a large amount of data, it is necessary to extract particular desired data for extensive patient studies. The extraction becomes difficult due to the problem of determining tissue boundaries and anatomical boundaries. To extract a meaningful amount of information, accurate determinations of the boundaries are essential. However, due to the blurriness of intensity distinction between neighboring tissues due to the partial volume effect, the difficulties of determining boundaries increases. Moreover, the same type of neighboring tissues that belong to different anatomical structure increases the confusion. All these challenges make it essential to find out proper segmentation technique to extract required data for the further medical process.

Segmentation of this type of data should be automatic to save the time required in the manual process. Recently, several automatic segmentation methods are proposed to segment cardiac images. Some of them are used to calculate mass and volume, blood ejection fraction, contraction, wall motion analysis and 3D visualization of cardiac anatomy. But automatic 3D wall motion and left ventricular (LV) segmentation have shown superior result than others. Due to the low contrast and signal to noise ratio (SNR) of the right ventricle (RV), myocardium or other essential anatomical parts, its segmentation is not necessary.

In the field of cardiology, cine magnetic resonance imaging (cine-MRI) is primarily used. The imaging procedure includes the acquisition of short-axis (SA) and long-axis (LA) sequences that cover the entire cardiac cycle. The data acquired in this process is too large for further studies. Hence, the required data need to be extracted from this large amount of data. For this purpose, image segmentation is used to extract the required part from the huge amount of available information. Image segmentation is one of the essential image processing methods (Gongalez and Woods, 2008). Segmentation basically deals with the property of intensity value. Segmentation can be categorized as edge-based segmentation and region-based segmentation. Thresholding is another point for segmentation. The basic idea of thresholding is to separate region of interest (ROI) from the background by selecting an optimal gray-level thresholding value. Thresholding is divided into two types, namely – (i) global thresholding (where a fixed optimal threshold is used for the entire image); and (ii) adaptive thresholding (where the optimal threshold changes over the pixels of the image) (Gongalez and Woods, 2008).

The high-resolution 3D data acquired by cardiac cine-MRI is large. The required portion of data needs to be extracted from this large amount of data. For this purpose, image segmentation is used to extract the required portion from the huge amount of available cine-MRI information. However, the segmentation becomes daunting due to: (i) the overlap of intensity distribution within the cardiac regions, (ii) partial volume effect, (iii) presence of the same tissue in different anatomic structure, (iv) lack of edge information, (v) different shapes of endocardial and epicardial contours across phases and slices, and (vi) inter-subject variability of the factors. Due to these challenges, it becomes very difficult to segment required portion from cine-MRI. Several methods have been proposed in recent years to extract anatomical parts from MRI for further use. But, due to low signal to noise ratio (SNR) and contrast found at the time of data acquisition, segmentations of anatomic parts (such as right ventricle (RV) and myocardium) are not possible. However, automatic left ventricular (LV) segmentation demonstrates a better result than other cardiac segmentation. Automatic segmentation of LV from cine-MRI is very important for cardiac analysis. Applications for which fully segmented LV is required are (Suinesiaputra et al. 2014): (i) quantitative analysis of heart function analysis, (ii) global and regional cardiac function analysis, (iii) clinical parameters such as ejection function (EF), left ventricle myocardium mass (MM) and stroke volume (SV) computation, (iv) accurate calculation of endocardial and epicardial contour of the left ventricle, (v) detection of heart diseases, chances of stroke and heart failure detection, etc.

The objective of this research is to find better segmentation method for left ventricle detection from cine-MRI. The dataset used for this research is cardiac MRI dataset used for MICCAI 2009's 3D segmentation challenge for clinical application (Sunnybrook Cardiac dataset used for the 2009 MICCAI's challenge). The data is then filtered using moving average filter. After that several segmentation methods such as adaptive thresholding, maximum entropy, Otsu's method, active contours without edges, k-means clustering, and fuzzy-c means clustering are used to segment LV from MRI. Finally, to evaluate the accuracy of the segmentation, the Dice coefficient matrix is used.

The paper is organized as follows: Section 1 introduces the idea of cine magnetic resonance imaging, image segmentation, and research issue. In Section 2, we briefly describe the background of this research. Section 3 contains a brief description of the dataset, segmentation and evaluation schemes used in the work. In Section 4, experimental analyses are presented. Finally, we conclude the paper in Section 5.

RELATED WORKS

With the current development of medical imaging, medical image processing gained popularity and great significance in the diagnosis of diseases. Medical image analysis, image recognition, and image understanding greatly depend on the segmentation of the medical image. The main purpose of medical image processing is to divide the image into meaningful regions of interest for further processing, which makes it the most popular topic in medical image processing. But lack of edge information and overlapping of regions make the task difficult. Researchers have been working for years for better segmentation algorithm to overcome the difficulties. Different segmentation algorithms have been proposed by researchers over the years. This section provides information about the year's research in the field of medical image segmentation.

In the field of cardiology, cine magnetic resonance imaging is used primarily. In this technique, numerous evenly spaces short time frames in the cardiac cycle are produced by co-ordination fast gradient eco-MRI sequence with retrospective ECG-gating. These images are high resolution multiphase 3D image that can describe the complete cardiac cycle. The wall motion of ventricles, valve motion and blood flow pattern in the heart and great vassals can be visualized by placing these images in a cinematic display (SLiman et al. 2014; Khalifa et al. 2013; Sliman et al. 2013; Elnakib et al. 2014; Petitjean and Dacher, 2011).

Several methods have been proposed in recent years to extract anatomical parts from cardiac cine-MRI for further use. But due to low contrast and signal to noise ratio found in the time of data acquisition segmentation of anatomic parts such as right ventricle (RV) and myocardium is not possible. While automatic left ventricular (LV) segmentation shows a better result than other cardiac segmentation. Many methods have been proposed for automatic and semi-automatic segmentation of LV from cardiac cine-MRI or in multiple views. Due to multiple time breath-hold and movement of a patient during the MRI procedure, 3D segmentation methods require registration processing steps.

Years of research prove that in the case of medical image segmentation, especially MRI image, thresholding has shown a better result than edge- or region-based segmentation. A number of survey papers show that most of the basic thresholding techniques use global thresholding. But fixed thresholding value fails in the case of illumination variation. To overcome the problem of illumination variation, adaptive thresholding is used instead of using fixed thresholding values. Due to its robustness to illumination variation, a number of adaptive thresholding methods are proposed by Parker (1991), Chan et al. 1998, Yang and Yan (2000), Bradley et al. 2007.

Normal thresholding methods only use the intensity value of the gray-level of the image. But most of the case, intensity information is not enough for good segmentation. Later, it is proved that the entropy of the image can provide better information than using only intensity value in the case of medical image processing. Researchers have proposed several variants of entropy-based segmentation methods. Using Shannon's classical entropy theory (Shanon, 1948), Andrew et al. 1989 propose a maximum entropy method. Feng et al. 2005 proposed an experimental computationally efficient 2D maximum entropy-based method to segment infrared images which is later used to segment underwater images. Guo and Li (2007) and Qi (2014) describe a multi-thresholding maximum entropy method using adaptive swarm optimization (APSO) algorithm. The optimal threshold value can be obtained by comparing the entropy values of possible maximum gray levels (Shin (2008)). For automatic image annotation, Jeon & Manmatha (2004) demonstrate a maximum entropy model that uses a large number of predicates. However, addition of spatial information in the entropy-measure drastically improves the performance.

Kass et al. (1988) first introduce the concept of active contour. The concept uses snakes, which is energy minimizing splines that guide external constraints forces that influence image forces. Later, Chan and Vas (2001) introduce a new method active contour without edges using Mumford-Shah function (Mumford & Shah, 1989). This method uses the concept of active contour for the images without defined edge boundaries. Yun & He (2012) develop a new model using Chan-Vas algorithm for partial derivatives. Boykov & Veksler (2006) use graph cuts to divide foreground pixels from the background. Afterward, Morar et al. (2012) combine active contour with graph cut method to create a better segmentation method that can detect an object without edges.

Histogram-based thresholding has become popular in recent years. The most used histogram based global thresholding method is Otsu's method proposed by N. Otsu (1979). The global threshold in this method is selected by maximizing between-class variance. But for a grayscale image, it is challenging to compute a single threshold value. So, multi-threshold schemes are preferred than bi-level thresholding method in the case of complex pictures. 1D histogram-based threshold results in the same threshold for different pictures. To solve this problem, Abutaleb (1989) extend 1D histogram thresholding into a 2D histogram. Later, Lui & Li (1993) propose an automatic 2D Otsu thresholding method, which is a little bit time-consuming. Gong et al. (1998) then introduce a faster recursive 2D algorithm. Histogram thresholding method is further extended into 3D thresholding by Jing et al. (2003), which is improved by Fan et al. (2007).

For unsupervised data segmentation, the most popular methods are clustering-based segmentation methods. Among them, k-means clustering is a simple yet very efficient one. K-means clustering is related to some other clustering and location-based methods. Some of these use Euclidean distance to minimize the distance to the nearest k-center problem (Kolliopoulos & Rao, 1999). An asymmetric approximation k-means clustering method is proposed by Matousek (2000). Most of the k-means clustering problems exploit iterative method for finding a locally minimal solution. There are a number of variants for k-means clustering (Kolliopoulos & Rao, 1999; Matousek (2000); MacKay (2005); Dhanachandra et al. 2015). Yadle et al. (2010) propose an enhanced k-means algorithm that has an improved initial center. This enhanced method can find the initial center without any additional input. This makes the algorithm fast and less complex. Later, Nazeer and Sebastian (2001) introduce more efficient and accurate k-means algorithm. This method reduces complexity by first finding initial centroid and then assigning data to the perspective cluster.

In the case of medical imaging, fuzzy c-means (FCM) clustering is more popular than k-means clustring due to its ability to divide data into more than one cluster (Christ & Parvati (2011); Zhou et al. 2009). The FCM clustering is achieved by minimizing cost function in an iterative manner. The cost function relies on the distance of pixels to the cluster centers (Dey et al. 2016). As the pixels of the image are highly correlated, the spatial relationship of neighborhood pixels is an important characteristic of FCM. Pedrycz and Waletzky (Pedrycz & Waletzky (1997)) use the available classification information and applied it to optimize their procedure. Ahmed et al. (2002) allow influencing the pixel label by the labels of the immediate neighborhood by modifying the FCM algorithm. The modified version provides a better result than the conventional FCM in the case of a noisy image. The purpose of this study is to find the appropriateness of different segmentation schemes to segment left ventricular (LV) from cardiac cine-MRI.

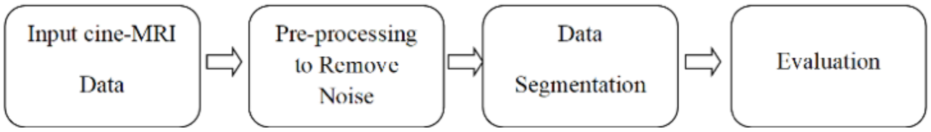

FIGURE 1. Basic block diagram of cine-MRI segmentation

METHODOLOGY

The focus of the research is to segment left ventricular (LV) from cardiac cine-MRI. Due to the presence of noises occurs during the acquisition process a simple moving average filter is applied to the input image before segmentation. Six different segmentation algorithms, namely – adaptive thresholding, maximum entropy, active contour without edges, Otsu's method, k-means clustering, and fuzzy c-means clustering are then applied to the filtered data. To evaluate the accuracy of the segmentation Dice similarity coefficient is used. The entire process is illustrated by a block diagram in Figure 1.

The cine magnetic imaging used in the process was mainly designed for MICCAI 2009's 3D segmentation challenge for clinical application (Suinesiaputra et al. 2014). The dataset contains 45 cine-MRI images with manual segmentation of patients (32 males and 13 females) from age limit of 27-88 years. Among those patients, 9 of them had normal heart conditions, 13 were suffering from hypertrophy, 12 had suffered from heart failures with infarct, and rest of the 12 patients were with heart failures without infarct. Cine steady free precession (SSFP) MR short-axis (SA) images are obtained with a 1.5T GE Signa MRI. All the images are taken in 20 cardiac phases of heart cycle with a temporal resolution during a 10~15 seconds breath hold. They are the scanned from the ED phases. From atrioventricular ring to apex 6-12 SAX images are obtained with properties: thickness = 8mm, gap = 8mm, FOV = 320mm×320mm and matrix = 256×256 (Ngo & Carneiro (2014)). All the images of ED and ES phases along with the endocardial trabeculations and papillary muscles in the ventricular cavity are drawn by an expert cardiologist. Then these are confirmed by another cardiologist (Suinesiaputra et al. 2014).

The main motivation for the creation of the dataset was to fully segment left ventricle (LV) automatically from the cardiac MRI. The segmentation faces several challenges such as, an overlap of intensity distribution within the cardiac regions, lack of edge information, different shapes of endocardial and epicardial contours across slices and phases, and inter-subject variability of the factors. The cardiac cine-MRI data is attenuate to noise due to acquisition procedure, patient movement and variable time breath holding time. Before segmentation, it is required to remove these noises. For this purpose, a simple moving average filter is used before segmentation.

A moving-average filter is used when several realizations of a given event is not available. In this case, temporal statistics is used in the case of ensemble statistics, which make the procedure ergodic. As moving-average filter uses only a few samples of the signal along the time axis, the temporal window moves at various points of time to obtain the output. This is also called moving-window averaging filter. The general form of moving averaging filter is:

$$y(n) = \sum_{k=0}^{N} b_k x(n-k) \quad (1)$$

where, x is the input and y is the output of the system. The values of b_k are tap weights or filter coefficients, k = 0,1,2, ..., N, where is the order of the filter. The values of tap weights include the effect of dividing the number of samples by (N+1) (Rangyaan 2015). Image segmentation is one of the most important tools of image segmentation. Several state-of-art image segmentation methods are available. In this paper, we exploit six important approaches that are presented below in short.

ADAPTIVE THRESHOLDING

In the field of image segmentation, thresholding plays a central role. This is simple, fast and has intuitive properties. Image thresholding creates a binary image for the given digital image by setting all the pixels with intensities above-defined thresholding value as foreground value and others as background value. Instead of using one single global threshold for the entire image, adaptive thresholding used different threshold value for each pixel of the image (Bradely & Roath (2007); Gonzales & Woods (2008)).

Adaptive thresholding is a sophisticated version of image thresholding. It results in a strong illumination gradient, by accommodating the changing in the lighting condition of an image. Adaptive thresholding allows thresholding images whose global intensity histogram does not have distinctive peaks by selecting an individual threshold for each pixel by the range of intensity values of its neighborhood pixels.

Adaptive thresholding takes a grayscale or color image and converts it into a binary image in the simplest implementation. A threshold value for each pixel is calculated. If the pixel value is above the threshold value it is considered as foreground, otherwise, it is considered as background. The approach to find the threshold value for each pixel is to statistically examine the intensity values of the local neighborhood pixels. The statistics used for thresholding depends largely on the input image that can be mean, median or mean of maximum and minimum. The window size or the size of the neighborhood must be carefully selected for segmentation. The window size must be large enough to cover sufficient foreground and background pixels but not too large window to violate the assumption of appropriately uniform illumination (Gonzales & Woods (2008)).

MAXIMUM ENTROPY

Entropy is a measure of randomness in an image. It describes the amount of information which is needed by compression algorithm to code. In the case of grayscale threshold segmentation, entropy can be characterized to distinguish between foreground and background. One of the admired approaches that use entropy to characterize thresholding is the maximum entropy. It is a gray-level global thresholding method, which is based on the maximum entropy principle (Andrew et al. 1989; Qi (2014)).

ACTIVE CONTOUR WITHOUT EDGES

Active contour (AC) models develop a curve to detect objects in an image. The curve starts around the detected object and moves towards the interior normal by halting at the boundary of the object. This segmentation method has been applied extensively in the case of medical image processing (Chan & Vase, 2001; Gao & Yang, 2012). Active contour without edging is used to detect an object in an image whose boundaries are not defined by gradients. The energy that can be set as minimal partition problem is minimized. Chan-Vase active contouring algorithm based on curve evaluation is formulated by Mumford-Shah function for segmentation and level set. Mumford-Shah model (Mumford & Shah, 1989) is energy-based model wish use piecewise smooth representation of an image for segmentation via an energy function.

OTSU'S METHOD

Otsu's method is one of the most successful global image thresholding methods, due to its computational simplicity. It is an automatic clustering-based image thresholding method that reduces gray level image into a binary image. The algorithm calculates optimum thresholding to separate background pixels from foreground pixel for which inter-class variance is maximized. In addition, it obtains 1D array by performing computations on the histogram of the image.

K-MEANS CLUSTERING

K-means image clustering method is one of the most popular unsupervised methods to segment region of interest from the background of an image based on vector quantization. This algorithm partitions the pixel element of the image into assigning a set of *k* levels. It puts *N* data point in *I*-dimensional space into *k* clusters where each cluster is parameterized by its mean vector (MacKay (2205)).

The clustering method is divided into two phases. The initial step computes *k* centroid, whereas, the second phase takes the points of the cluster that is nearest to the centroid. The points are assigned by the using minimum Euclidian distance between the cluster center and the data point. The sum of distances of objects in the cluster is minimized at the centroid of that cluster. It is an iterative method, which minimizes the sum of distances from each object to its cluster centroid (Dhanachandra et al. 2015). The biggest advantage of k-mean clustering is its fast and simple implementation. But the initial centroid is randomly chosen, which creates a different result for different centroid. Therefore, the initial centroid must be carefully chosen to acquire the desired segmentation (Dhanachandra et al. 2015).

FUZZY C-MEANS CLUSTERING

Fuzzy C-means algorithm is one of the most popular soft partitioning unsupervised clustering methods in the field of medical image segmentation. The basic idea of clustering method is to ensure each data point belongs to more than one cluster. The algorithm segments a given dataset in such a manner that it is grouped into N clusters where all the data points belong to almost every cluster to a certain limit (Christ & Parvati, 2011; Zhou et al. 2009). Among most of the segmentation methods, this algorithm can extract more information from an original image. But the only disadvantage is that it ignores spatial information, thereby making it more receptive to noise and various artifacts.

DICE INDEX

Image segmentation is a very important step in medical image processing. It is essential to have a standard evaluation method to compare the quality of segmentation. The most popular image segmentation evaluation method is the use of the Dice similarity coefficient. It measures the contour overlap, to find the accuracy of segmentation. Dice coefficient or Dice index (DICE) is one of the most used validation methods in medical image segmentation (Dice (1945)). It uses a direct comparison between automatic segmentation and ground truth segmentation. It is a convention to employ DICE for measuring repeatability or reproducibility of MRI segmentation. The calculation of DICE is measured by:

$$\mathrm{DICE} = \frac{2\,|S_g \cap S_t|}{|S_g| + |S_t|} \tag{2}$$

where, S_g is ground truth segmentation and S_t is test segmentation. The Jaccard index (JAC) is the intersection between two sets divided by their union:

$$\mathrm{JAC} = \frac{|S_g \cap S_t|}{|S_g \cup S_t|} \tag{3}$$

JAC is always larger than DICE, except {0,1}, where they are equal. The relation between them is:

$$\begin{aligned}\mathrm{JAC} &= \frac{|S_g \cap S_t|}{|S_g \cup S_t|} \\ &= \frac{2\,|S_g \cap S_t|}{2\,(|S_g| + |S_t| - |S_g \cap S_t|)} \\ &= \frac{\mathrm{DICE}}{2-\mathrm{DICE}}\end{aligned} \tag{4}$$

Similarly,

$$\text{DICE} = \frac{2\ \text{JAC}}{1+\text{JAC}}$$

The closer the value to DICE to 1, the higher is the accuracy of the segmentation. There are a number of segmentation methods available that have been used by researchers for segmenting region of interest (ROI) from an image for different applications. In medical image processing, specifically in the case of cardiology, it is very important to segment ROI from unnecessary available data automatically. Due to low contrast and signal to noise ratio in cardiac cine-MRI, only left ventricular holds meaningful amount of information in the image. For years, researchers have been working for segmenting left ventricular segmentation from cardiac MRI. Evan the dataset used in this research was specifically designed for a challenge to segment left ventricular from cardiac cine-MRI (Suinesiaputra et al. 2014).

RESULTS AND ANALYSIS

This section provides the experimental result and analysis of left ventricular segmentation using the above-mentioned methods. This section also provides a comparison between the segmentation methods and their accuracy to segment left ventricular from cardiac cine-MRI. The evaluation is done by using the most popular MRI segmentation evaluation method.

The cardiac cine images cover the whole cycle by long- and short-axis images. During the image acquisition procedure, a patient has to hold his/her breath several times to cover the whole heart cycle. Again, due to the movement of patient difference in illumination occurs in the images. The angle of view is also responsible for this change. So, due to this illumination verity and several intensity levels, the adaptive thresholding is used in the first place. To calculate the threshold for each pixel, mean of the intensity level of local neighborhood pixels is used. The window size is carefully selected by trial and error method. The size of the window should be large enough to cover sufficient foreground and background pixels, provided that the window size does not violate the assumption of appropriately uniform illumination. Hence, 80 pixels are used as neighbor window size, where we assume the illumination is uniform.

After that Dice similarity coefficient is applied for evaluation of adaptive thresholding for left ventricular segmentation over 45 patient's cine-MRI. The output of the Dice similarity coefficient is 0.7811, which means adaptive thresholding segmented left ventricular from cine-MRI with 78.11% accuracy. The time required for this process is 1 second. Figure 2 shows the result of adaptive thresholding for left ventricular segmentation. In Figure 2(c), the blue line shows the original left ventricle in the image, and the redline depicts the left ventricle according to adaptive thresholding.

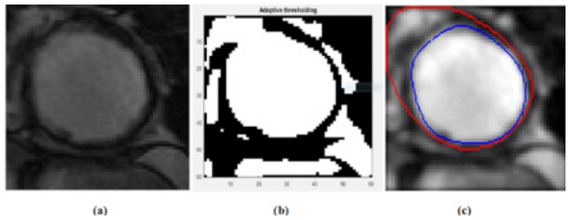

FIGURE 2. (a) Cardiac cine-MRI for left ventricle, (b) binary output of adaptive thresholding and (c) the evaluation of left ventricular segmentation.

Due to the overlap of the intensity distribution within the cardiac region of the dataset, it is not wise to use a segmentation algorithm that is only characterized by intensity values. So a new parameter is used instead of intensity for segmentation, which is entropy. It is a global thresholding method. The threshold value is determined by the maximum probability distribution of image histogram. In this research, the threshold value is 114. This is selected by the maximum entropy of the images used in this case. Figure 3 shows the result of maximum entropy for left ventricular segmentation.

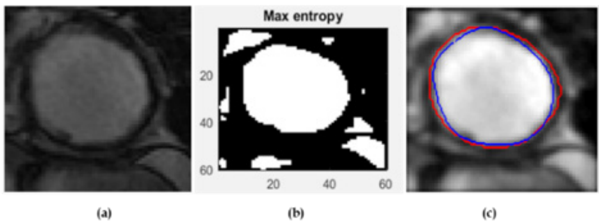

FIGURE 3. (a) Cardiac cine-MRI for left ventricle, (b) binary output of maximum entropy method and (c) the evaluation of left ventricular segmentation.

The output of the Dice similarity coefficient is 0.9220 by using maximum entropy method. It means that the maximum thresholding segmented the left ventricular from cine-MRI with 92.2% accuracy with only 1 second required time in the process. Figure 3(c) blue line shows the original left ventricle in the image and redline the left ventricle according to adaptive maximum entropy.

The lack of edge information in our cardiac cine-MRI makes segmentation impossible for conventional active contour method. So Chan-Vase's active contour without edging algorithm is used for left ventricular segmentation. Due to the overlap of intensity distribution and presence of the same tissue in different organs in the heart, it becomes difficult to detect the edge or boundaries of left ventricular from other organs. But masking using active contour left ventricular have been easily detected from cine-MRI data.

Dice similarity coefficient shows that the output for active contour without edges is 0.9421. Active contour without edges has segmented left ventricular with an accuracy of 94.21%. The complexity of the process elevates the process time into 3 seconds. Figure 4 shows the result of applying active contour without edges for left ventricular segmentation. In Figure 4(c), the blue line shows the original left ventricle in the image and redline the left ventricle according to active contour without edges.

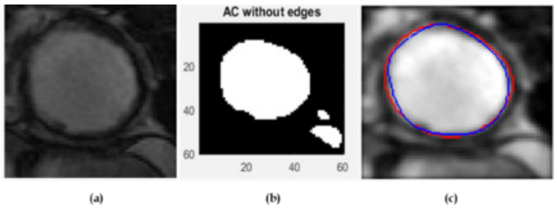

FIGURE 4. (a) Cardiac cine-MRI for left ventricle, (b) binary output of active contour without edges and (c) the evaluation of left ventricular segmentation.

As in cardiac cine-MR images, the same tissue is present in different organs and 1D histogram will show a poor result. Hence, a 2D histogram-based Otsu's method is used. To convert input cine-MR images into binary, threshold value 129 is used. It causes maximum inter-class variance that divides the image into two classes. After that Dice similarity coefficient is applied for an evaluation of Otsu's method for left ventricular segmentation. The output of the Dice similarity coefficient is 0.9321, which proves that left ventricular has a segment with 93.21% accuracy. The whole process required only 1 second. Figure 5 shows the result of applying Otsu's method for left ventricular segmentation. In Figure 5(c), the blue line shows the original left ventricle in the image and redline the left ventricle according to Otsu's method.

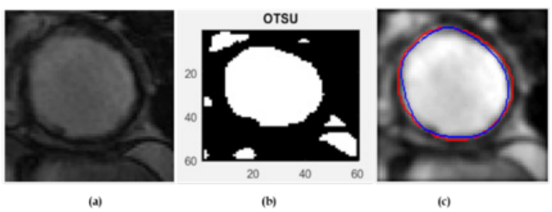

FIGURE 5. (a) Cardiac cine-MRI for left ventricle, (b) binary output of Otsu's method and (c) the evaluation of left ventricular segmentation.

As our cardiac cine-MR images suffer from a lack of edge information clustering-based segmentation can overcome this difficulty. For that reason, k-means clustering is used. Each pixel of the image is assigned to one of the two clusters without any overlap. Vector mean is used to assign pixels into their corresponding cluster. After that Dice similarity coefficient shows that the output for k-means clustering is 0.9345. K-means clustering has segmented left ventricular with an accuracy of 93.45% and only 1 second process time. Figure 6 shows the result of applying k-means clustering for left ventricular segmentation. In Figure 6(c), the blue line shows the original left ventricle in the image, and the redline defines the left ventricle according to k-means clustering.

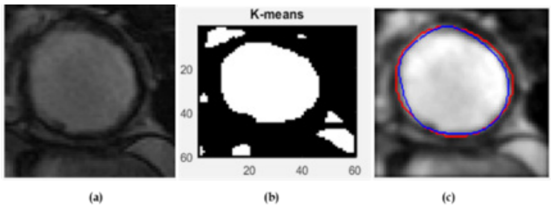

FIGURE 6. (a) Cardiac cine-MRI for left ventricle, (b) binary output of k-means clustering and (c) the evaluation of left ventricular segmentation.

For medical image segmentation fuzzy c-means clustering is preferred over k-means clustering. Even in several cases, fuzzy c-means algorithm is applied after k-means is performed. It is a soft partitioning unsupervised clustering method. Instead of confining each pixel to only one cluster, fuzzy c-means allows every pixel to be part of every cluster to a certain amount. The cardiac cine-MRI data used in this research has partial volume effect. The intensity distribution is overlapped between neighborhood regions. Same tissue is present in different organs. If we want to extract most of the information, then the overlapping must be taken into account. For that three class fuzzy c-means clustering is used so that the involvement of each pixel with its neighborhood can be considered. 25-30 iteration is taken place to divide the pixels into clusters.

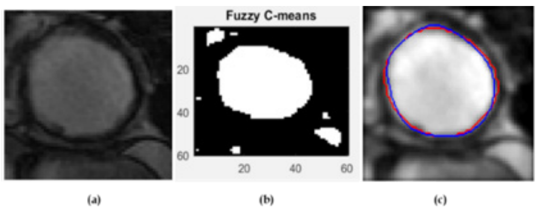

FIGURE 7. (a) Cardiac cine-MRI for left ventricle, (b) binary output of fuzzy c-means clustering and (c) the evaluation of left ventricular segmentation.

After that Dice similarity coefficient is applied for an evaluation of fuzzy c-means algorithm for left ventricular segmentation. The output of the Dice similarity coefficient is 0.9604 for fuzzy c-means. Fuzzy c-means almost perfectly segment left ventricular with 96.04% accuracy. Due to the complexity result from soft partitioning, the process time elevated to 2 seconds. Figure 7 shows the result of applying fuzzy c-means clustering for left ventricular segmentation. In Figure 7(c), the blue line shows the original left ventricle in the image, and the redline depicts the left ventricle according to fuzzy c-means clustering.

DISCUSSIONS

To segment left ventricular from cardiac cine-MRI, six state-of-art methods, such as adaptive thresholding, maximum entropy, active contour without edges, Otsu's method, k-means clustering, and fuzzy c-means clustering are exploited. After segmentation, Dice similarity coefficient is applied to evaluate all the six segmentation methods. Dice coefficient measures the similarity between the ground truth and output segmentation. The value of the Dice coefficient varies among 0 to 1. Higher the value of the coefficient, greater is the similarity with the original object. The accuracy of the segmentation methods can easily be found only by converting Dice coefficient value into a percentage. Table 1 shows the comparison between the six state-of-the-art methods by their accuracy of segmenting left ventricular from cine cardiac MRI.

TABLE 1. Comparison between segmentation methods

Segmentation Method	Dice Coefficient	Accuracy (in %)
Adaptive thresholding	0.7811	78.11
Maximum entropy	0.9220	92.20
Active contour w/o edges	0.9421	94.21
Otsu's method	0.9321	93.21
K-means clustering	0.9345	93.45
Fuzzy c-means clustering	0.9604	96.04

Figure 8 shows a chart that describes the evaluation of above mention methods and compares their ability to segment left ventricle from cardiac cine-MRI. On the other hand, Figure 9 compares them by their respective binary output of input gray-level MRI data.

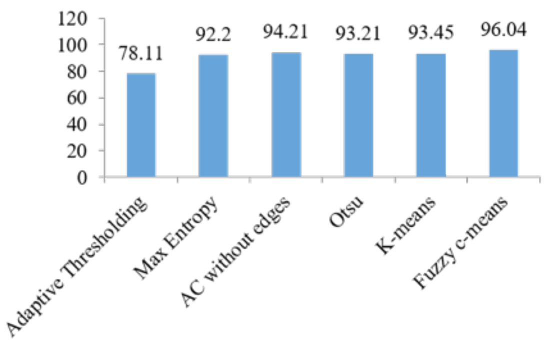

FIGURE 8. Evaluation of segmentation methods on c-MRI (accuracy in %)

The cardiac cine-MRI dataset used in this research has several drawbacks. Partial volume effect, intensity distribution overlap between cardiac regions, the presence of the same tissue in different organs, lack of edge information, inter-subject variability of factors makes the segmentation of left ventricular quite challenging. Even this dataset is specially designed for a competition to overcome these challenges and segment left ventricle successfully (Suinesiaputra et al. 2014).

To overcome the challenge of left ventricle segmentation from cine-MRI, six state-of-the-art methods have been applied. The details of them have been described earlier. At first, a simple adaptive thresholding algorithm has been used based on the intensity level of each pixel compared to its neighborhood pixels. The accuracy of the segmentation is 78.11%. As only intensity level is considered in this case it fails to overcome most of the challenges and extract only a few amounts of data, which shows a poor level of segmentation.

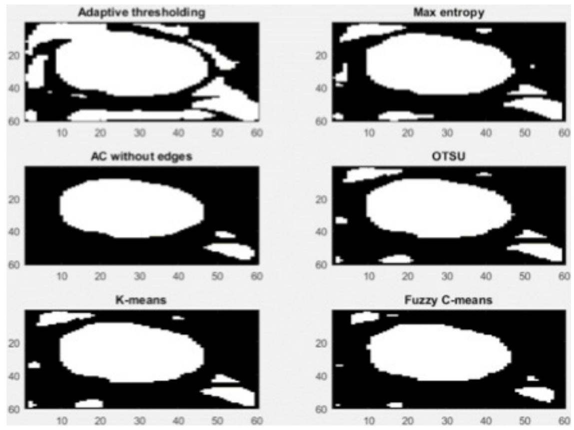

FIGURE 9. Comparison of binary output of the six segmentation approaches

As the intensity level cannot provide enough information for segmentation and can easily be corrupted by overlapping, we used entropy information instead of the intensity value of pixels. For that, we used maximum entropy, a global thresholding algorithm based on the entropy value of an image. It segments left ventricular with 92.2% accuracy. Only the use of entropy instead of intensity level improves the segmentation process highly.

The biggest challenge in left ventricular segmentation is the lack of edge information. Due to overlapping and partial volume effect the boundaries of the left ventricle is not clearly defined. To overcome this lack of information, we used a curve-based segmentation approach active contour without edges. This region-based method is specially designed for such type of cases. Though the accuracy of the segmentation is eventually increased to 94.21%, the complexity of the method elevates the process time into 3 seconds.

To extract more information from data clustering based global segmentation approach is used: the most common approach is the Otsu's method. This method extract region of interest from background by maximizing in-between class of variance. Here direct intensity value is not used but the histogram. As the segmentation is based on normalized histogram of image intensity, not direct intensity level of each pixel the problem overlapping intensity distribution is eradicated. This method successfully segments left ventricular 93.21% accurately.

After Otsu's method the most popular clustering method, k-means clustering is used. This method confined each pixel only in one of the clusters based on vector mean. As by the use of the clustering method, lack of edge-based information is overcome k-means also shows almost the same type of accuracy as Otsu's method for left ventricular segmentation, which is 93.45%. As both Otsu's method and k-means clustering confine each pixel only into one cluster the problem of overlapping intensity distribution is still alive. To solve this fuzzy c-means clustering is used. Instead of using hard clustering, fuzzy c-means uses soft clustering for partitioning by taking into account the extent of the presence of data into each pixel, which drastically improves the segmentation accuracy into 96.04%. However, it also increases the processing time into 2 seconds, which is only a second for hard partitioning. Note that any analysis can be enriched if the datasets can be larger. Moreover, deep learning-based various segmentation approaches can be explored in the future to demonstrate the performances on larger datasets.

CONCLUSIONS

Left ventricular segmentation on cardiac cine-MRI data is a very important research area. Therefore, in this paper, six state-of-the-art segmentation algorithms are exploited to segment left ventricular from cardiac MRI data. Lack of information and overlapping of regions make this challenge even more difficult. Different segmentation schemes such as thresholding, clustering- and region-based, etc. are used to overcome the difficulties. Then another state-of-the-art evaluation scheme, the Dice similarity coefficient is used for the evaluation of segmentation. Global thresholding has provided a better result than the adaptive thresholding algorithm. The only adaptive thresholding algorithm used in this research shows a very poor result with 78.11% accuracy. But the global thresholding methods have used to provide excellent amount of information with the segmentation accuracy of more than 92%.

The best result is achieved from a clustering-based approach. By confining each pixel into one of the clusters, both Otsu and k-means algorithms have acquired 93% accuracy. However, by taking into account the overlapping of information among the clusters in fuzzy c-means clustering, segmentation accuracy has drastically increased to 96.04%. Except for adaptive thresholding, all other methods have successfully segmented the left ventricular with more than 92% accuracy. However, due to the presence of noise and the lack of information, all the challenges are not completely overcome. In this paper, we have chosen these six state-of-art methods due to their simplicity and less complexity.

In future, we intend to apply these segmentation methods into noisier images to test if these methods show the same level of competence. We also want to work on smart segmentation algorithms based on various deep learning-based methods on large datasets.

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DECLARATION OF COMPETING INTEREST

None

REFERENCES

Ahad, M. A. R., Kobashi, S., & Tavares, J. 2018. Advancements of image processing and vision in healthcare. *Journal of Healthcare Engineering, Hindawi*.

Abutaleb, A. 1989. Automatic Thresholding of gray level pictures using two-dimensional entropy. *Computer Vision, Graphics, and Image Processing* 47: 22-32.

Ahmad, W., Wan Zaki, Aini Hussain, & Ling Siong. 2018. Content-based image retrieval for medical application. *UKM Engineering Journal* 30(1): 111-121.

Ahmed, M., S. M. Yamany, N. Mohamed, A. A. Farag, & T. Moriarty. 2002. A modified fuzzy c-means algorithm for bias field estimation and segmentation of MRI data. *IEEE Transactions Med Imaging* 21: 193-199, 2002.

Alam, S. & Kobashi, S. 2016. Simple brain atrophy quantification method using MR images. 5th Int. Conf. on Informatics, Electronics and Vision, 743-746.

Anandh, K., C.M. Sujatha, S. Ramakrishnan, 2015. Analysis of ventricles in alzheimer MR images using coherence enhancing diffusion filter and level set method. 4th Int. Conf. on Informatics, Electronics and Vision.

Andrew, K., C. Wong, & P. K. Sahoo. 1989. A gray-level threshold method based on entropy principle. *IEEE Transactions on System Man and Cybernetics* 19(4): 886-871.

Boykov, Y. & O. Veksler. 2006. Graph Cuts in Vision and Graphics: Theories and Applications. Math. Models of C. Vision: The Handbook, *Springer*.

Bradely, D. & G. Roath. 2007. Adaptive thresholding using integral image. *Journal of Graphics Tool* 12(2): 13-21.

Chan, F., F. K. Lam, & H. Zhu. 1998. Adaptive thresholding by variational method. *IEEE Transactions on Image Processing* 7(3): 468-473.

Chan, T. & L. A. Vase. 2001. Active contour without edges. *IEEE Transactions on Image Processing* 10(2).

Christ, M. & R. M. S. Parvati. 2011. Fuzzy C-Means Algorithm for Medical Image Segmentation. 3rd International Conference on Electronic Computer Technology.

Dey, N., V. Bhateja, & A. Ella Hassanien. 2016. *Medical Imaging in Clinical Applications: Algorithmic and Computer-Based Approaches*. Springer.

Dhanachandra, N., K. Manglem, & Y. J. Chanu. 2015. Image segmentation using k-means clustering algorithm and subtractive clustering algorithm. *Procedia Computer Science* 54: 764-771.

Dice, L. 1945. Measure of the amount of ecological association between species. *Ecology* 26(3): 297-302.

Elnakib, A., G. M. Beache, G. Gimelfarb, & A. El-Baz. 2014. Intramyocardial strain estimation from cardiac cine MRI. *International Journal of Computer Assisted Radiology and Surgery* 10(8).

Fan, J., F. Zhao, & X. F. Zhang. 2007. Recursive algorithm for three-dimensional otsu's thresholding segmentation method. *Acta Electronic Sinica* 35(7): 1398-1402.

Feng, D., S. Wenkang, C. Liangzhou, D. Yong, & Z. Zhenfu. 2005. Infrared image segmentation with 2-D maximum entropy method based on Particle Swarm Optimization (PSO). *Pattern Recognition Letters* 26(5): 597-603.

Gao, S. & J. Yang. 2012. Saliency-Seeded Localizing Region-based Active Contour for Automatic Natural Object Segmentation. 21st International Conference on Pattern Recognition.

Gong, J., L. Li, & W. Chen. 1998. Fast recursive algorithms for two-dimensional thresholding. *Pattern Recognition* 31(2): 295-300.

Gonzalez, R. & R. E. Woods. 2008. *Digital Image Processing*. 3rd edition. Pearson Education Inc.

Guo, C. & H. Li. 2007. Multilevel thresholding method for image segmentation based on an adaptive particle swarm optimization algorithm. *Lecture Notes in Computer Science, Springer* 4830: 1611- 3349.

H. Sliman, F. Khalifa, A. Elnakib, A. Soliman, A. El-Baz, G. M. Beache, A. Elmaghray, & G. Gimel'farb. 2013. Myocardial borders segmentation from cine MR images using bidirectional coupled parametric deformable models. *Medical Physics* 40(9).

Hossain, M. B., Manabu Nii & Syoji Kobashi. 2016. Construction of statistical shape model of femoral bone using MR images. 5th Int. Conf. on Informatics, Electronics and Vision. 658-662.

Irtija, N., Mahsius Sami, & M.A.R. Ahad. 2018. Fatigue Detection Using Facial Landmarks. 4th Int. Symposium on Affective Science and Engineering, and the 29th Modern Artificial Intelligence and Cognitive Science Conference.

Jeon, J. & R. Manmatha. 2004. Using Maximum Entropy for Automatic Image Annotation. *Lecture Notes in Computer Science, Springer*, 3115.

Jing, X., J. F. Li, & Y. L. Liu. 2003. Image segmentation based on 3-D maximum between-cluster variance. *Acta Electronic Sinica* 31(9): 1281-1285.

Kass, M., A. Wiitkin, & D. Trezopolous. 1988. Snakes: Active contour models. *International Journal of Computer Vision*: 321-331.

Khalifa, F., G. M. Beache, A. Elnaki, H. Sliman, G. Gimelfarb, K.C. Welch, & A. El-Baz. 2013. A New Shape-based Framework for the Left ventriclewall Segmentation from Cardiac First-pass Perfusion MRI. IEEE 10th International Symposium on Biomedical Imaging.

Kobashi, S., Ryosuke Nakano, Kei Kuramoto, Yuki Wakata, Kumiko Ando, Reiichi Ishikura, Tomomoto Ishikawa, Shozo Hirota, Yutaka Hata, & Naotake Kamiura. 2015. Neonatal brain segmentation using 4-D fuzzy object model. 4th Int. Conf. on Informatics, Electronics and Vision.

Kolliopoulos, S. & S. Rao. 1999. A Nearly Linear-Time Approximation Scheme for the Euclidean k-median Problem. *Proc. Seventh Ann. European Symp. Algorithms*: 362-371.

Liu, J. & W. Li. 1993. The automatic thresholding of gray-level pictures via two-dimensional Otsu method. *Acta Automatic Sinica* 19(1): 101-105.

MacKay, D. 2005. *Information Theory, Interference and Learning Algorithm*. Cambridge University Press.

Matousek, J. 2000. On approximate geometric k-clustering. *Discrete and Computational Geometry* 24: 61-84.

Morar, A., F. Molodoveanu, & E. Grller. 2012. Image Segmentation based on Active Contour without Edges. IEEE Intl. Conf. on International Computer Communication and Processing.

Morita, K., Syoji Kobashi, Kei Kuramoto, Yuki Wakata, Kumiko Ando, Reiichi Ishikura, Tomomoto Ishikawa, Shozo Hirota, & Yutaka Hata. 2015. Neonatal brain MRI normalization with 3-D cerebral sulci registration. 4th Int. Conf. on Informatics, Electronics and Vision.

Mumford, D. & J. Shah. 1989. Optimal approximation by piecewise smooth function and associated varriational problem. commun. *Pure Appl. Math* 42(5): 577-685.

Nazeer, K. & M. P. Sebastian. 2001. Improving the accuracy and efficiency of the k-means clustering algorithm. *Proc. of the World Congress on Engineering* 1.

Ngo, T. & G. Carneiro. 2014. Fully automated non-rigid segmentation with distance regularized level set evolution initialized and constrained by deep-structured inference. *IEEE Computer Vision and Pattern Recognition*.

Otsu, N. 1979. A threshold selection method from gray-level histogram. *IEEE Transactions on System Man Cybernetics* 9(1): 62-66.

Parker, J. 1991. Gray level thresholding in badly illuminated images. *IEEE Transactions Pattern Anal. Mach. Intell.* 13(8): 813-819.

Pedrycz, W. & J. Waletzky. 1997. Fuzzy clustering with partial supervision. *IEEE Transactions Syst Man Cybern Part B Cybern* 27: 787-795.

Petitjean, C. & J. N. Dacher. 2011. A review of segmentation methods in short axis cardiac MR images. *Medical Image Analysis* 15(2): 169-184.

Qi, C. 2014. Maximum entropy for image segmentation based on adaptive particle swarm optimization. *Natural Science Publishing Cor.*

Rangyaan, R. 2015. *Biomedical Signal Analysis*. 2nd edition. Wiley-IEEE Press.

Saha, S., M. S. Rahman, M. J. Rasna, A. K. M. M. Islam, & M.A.R. Ahad. Feature Extraction, Performance Analysis and System Design using the DU Mobility Dataset. *IEEE Access*.

Shannon, C. 1948. A mathematical theory of communication. *The Bell Syst. Tech.* 27: 379-423.

Shin, Y. 2008. Method for finding optimal threshold for image segmentation. *US Patent* 10817551.

Sliman, H., F. Khalifa, A. Elnakiib, A. Soliman, G. M. B. Beache, A. Elmaghraby & A. El-Baz. 2014. A New Segmentation-based Tracking Framework for Extracting the Left Ventricular Cavity from Cine Cardiac MRI. *Journal of Computer Science & System Biology.*

Suinesiaputra, A., Cowan, B., Al-Agamy, A., Elattar, M., Ayache, N., Fahmy, A., Khalifa, A., Medrano-Gracia, P., Jolly, M., Kadish, A., Lee, D., Margeta, J., Warfield, S., & Young, A. 2014. A collaborative resource to build consensus for automated left ventricular segmentation of cardiac MR images. *Medical Image Analysis, Elsevier*, 18(1): 50-62.

Syeda, U.H., Ziaul Zafar, Zishan Zahidul Islam, Syed Mahir Tazwar, Miftahul Jannat Rasna, Koichi Kise, & M.A.R. Ahad. 2017. Visual face scanning and emotion perception analysis between Autistic and Typically Developing children. *ACM UbiComp Workshop on Mental Health and Well-being: Sensing and Intervention*.

Taha, A. & A. Hanbury. 2015. Matrics for Evaluating 3D Medical Image Segmentation: Analysis, Selection and Tool. *BMC Medical Imaging*.

Yang, Y., & H. Yan. 2000. An adaptive logical method for binarization of degraded document images. *Pattern Recognition* 33(5): 787-807.

Yedla, M., S. R. Pathakota, & T. M. Srinivasa. 2010. Enhanced k-means clustering algorithm with improved initial center. *International Journal of Science and Information Technologies* 1(2): 121-125.

Yuan, Y. & C. He. 2012. Adaptive active contours without edges. *Mathematical and Computer Modeling* 55: 1705-1721.

Zhou, H., G. Schaefer, & C. Shi. 2009. Fuzzy c-means technique for medical image segmentation. *Fuzzy Systems in Bioinformatics and Computational Biology, Springer* 242: 257-271.