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자기공명 심장 영상의 좌심실 경계추출에서의 k 평균 군집화와 병합 알고리즘의 사용으로 인한 전처리 효과

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Preprocessing Effect by Using k-means Clustering and Merging Algorithms in MR Cardiac Left Ventricle Segmentation

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요 약 : 심장 질환의 정량적 분석을 위해서 자기공명 심장 영상에서 좌심실의 경계를 추출하는 것이 중요하다. Snake 또는 active contour 모델은 좌심실 경계 추출을 위해서 사용되어 왔다. 그러나 이 모델을 사용하는데 있어서 좌심실의 경계선이 좌심실 내부에 생긴 결절 때문에 경계선이 지역 최소값으로 빠져서 원하는 경계선에 수렴하지 못 할 수도 있다. 그러므로 본 논문에서는 active contour 모델의 성능을 향상시킬 수 있는 k 평균 군집화와 병합 알고리즘을 이용한 전처리 방법을 제안하였다. 제안된 방법으로 지역 최소값 수렴 문제를 해결함을 확인하였다.

Abstract : For quantitative analysis of the cardiac diseases, it is necessary to segment the left-ventricle (LV) in MR (Magnetic Resonance) cardiac images. Snake or active contour model has been used to segment LV boundary. However, the contour of the LV from these models may not converge to the desirable one because the contour may fall into local minimum value due to image artifact inside of the LV. Therefore, in this paper, we propose the preprocessing method using k-means clustering and merging algorithms that can improve the performance of the active contour model. We verified that our proposed algorithm overcomes local minimum convergence problem by experiment results.

Key words : Magnetic Resonance Imaging, Segmentation, K-means algorithm, Merging algorithm, Cardiac, Snake model

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INTRODUCTION

Cardiovascular disease is the leading cause of death in advanced countries such as the United States. Mortality of the cardiovascular disease has been rising although the life span of the human has been longer over the years. To decline it, one of the best techniques is magnetic resonance imaging (MRI) which provides time-varying three dimensional imagery of the heart. To help the diagnosis of diseagse, the physicians are interested in identifying the heart chambers, the endocardium and epicardium, and measuring the ventricular blood volume, the ventricular wall motion and wall thickening properties over various stages of the cardiac cycle. The left ventricle (LV) is of particular interest since it pumps oxygenated blood out to distant tissue in the entire body.

The segmentation problem is the first step in cardiac medical image analysis for diagnosis of disease [1],[2]. To reconstruct three dimensional images or to measure such as the ventricular blood volume and wall motion, it is necessary to segment LV endocardium and epicardium precisely [3]. A large amount of technique has been proposed and the segmentation problem has been particularly challenging.

Snake model, or active contour model, first proposed by Kass et al. is widely used to segment LV [4] and one of the best techniques in cardiac image segmentation. Snake model is defined as contour $u(s) = (x(s), y(s))$ attracted towards image features by constrained forces. There has been a large amount of active contour method used in segmentation.

The major problem in active contour model is a possibility of falling into local minimum. Initial contour is set and then it is attracted by internal and external forces by computing the energy minimization equation. But initial contour may be attracted toward undesirable position because it may fall into local minimum value. All points of the initial contour move to local minimum energy position in its surrounding region. Mostly all of MR cardiac images have artifacts inside LV which have an irregular shape and size. If image is distorted by artifacts, the contour may fall into local minimum position.

In this paper, we proposed the preprocessing method using k-means clustering and merging algorithms which removes artifacts inside of the LV. We used Gradient Vector Flow (GVF) snake model of Chenyang. Xu., which is one of the best snake models [10],[11].

MATERIAL AND METHODS

Snake model

Snake, or active contour, is curve defined within an image domain that can move under the influence of internal forces coming from within the curve itself and external forces computed from the image data. The internal and external forces are defined so that the snake will conform to an object boundary or other desired features within an image. Snakes are widely used in many applications, including edge detection, shape modeling, segmentation, and motion tracking.

There are two general types of active contour models in the literature today: parametric active contours[4] and geometric active contours [5]-[7]. Parametric active contours synthesize parametric curves within an image domain and allow them to move toward desired features, usually edges. Typically, the curves are drawn toward the edges by potential forces, which are defined to be the negative gradient of a potential function. There are also internal forces designed to hold the curve together (elasticity forces) and to keep it from bending too much (bending forces).

Classical snake model and GVF snake model

There are two key difficulties for parametric active contour algorithms. First, the initial contour must, in general, be close to the true boundary or else it will likely converge to the wrong one. Several methods have been proposed to address this problem including multiresolution methods [8], pressure forces [9], and distance potentials [10]. Their basic idea is to increase the capture range of the external force fields and to guide the contour toward the desired boundary. The second problem is that active contours have difficulties in progressing into boundary concavities. There is no satisfactory solution to this problem, although many methods have been proposed. However, most methods proposed to address these problems solve only one problem while creating new difficulties. For example, multiresolution methods have addressed the issue of capture range, but specifying how the snake should move across different resolutions remains problematic. Another example is that of pressure forces, which can push an active contour into boundary concavities, but cannot be too strong or weak edges will be overwhelmed. Pressure forces must also be initialized to push out or push in, a condition that mandates careful initialization.

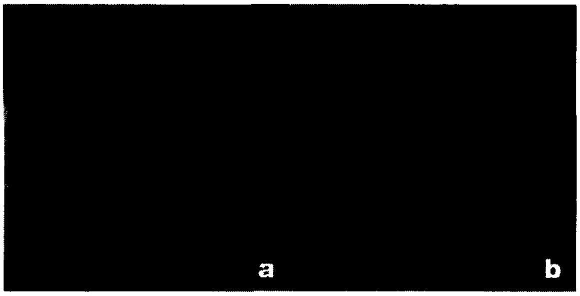

Fig. 1. Artifacts in (a) small blobs shape, (b) diffusible shape

The GVF snake model proposed by Chenyang. Xu. and Jerry Prince. has two major advantages respectively [10],[11]. First, its capture range is wider than any previous methods except distance potential methods. Second, it can progress into boundary concavities and then segment more precisely.

Artifacts in the original MR cardiac images

In this paper, MR cardiac data was acquired from five patients by using Simiens 1.5T MR machine, 16 phases, and eight slices. We used body array coil and FLASH2D sequence and TR = 900ms, TE=4.8ms, Flip angle=20, FOV=350mm, matrix=256×256, slice=8. Every image was scanned by breath-hold, cardiac gating, short-axis view and 16 images per slice through dynamic scan. Fig. 1(a) and Fig. 1(b) show the artifacts inside of the LV in MR cardiac images. In Fig. 1(a), the artifacts like small dark blobs which are created by blood flow or other reasons exist inside of the LV and Fig. 1(b) shows diffusible artifacts which make boundaries ambiguous. It is difficult to segment with them directly, therefore, some preprocessing methods are necessary. In this paper, we carried out simulation of only images which have small blobs type artifacts.

The proposed algorithms

Fig. 2 shows the overall proposed algorithms. For segmentation, region of interest (ROI) which includes the LV to segment is set. Then user sets initial points inside or outside of the LV near real wall boundaries roughly and initial contour is obtained by connecting them continuously. Segmentation is carried out by converging the initial contour into real wall boundaries using GVF snake model. In this paper, we proposed 3-steps preprocessing operation, composed of k-means clustering, labeling and merging, to remove artifacts. First, the original MR cardiac images are clustered by k-means

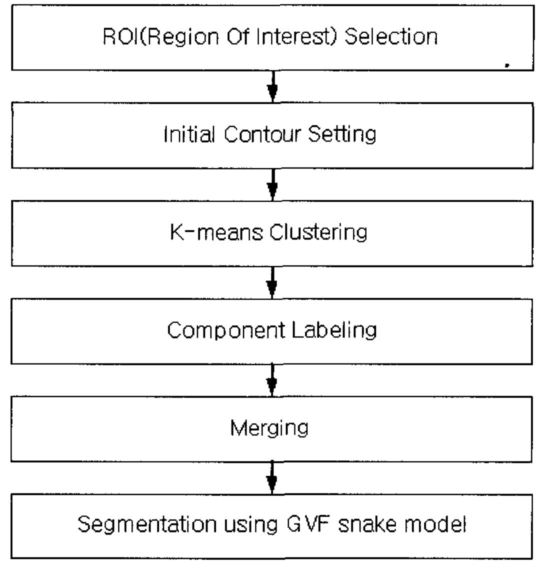

Fig. 2. The overall proposed algorithms

clustering by user defined numbers. Second, labeling is applied. Third, merging is applied. After preprocessing operation, original images are simplified and artifacts disappeared. Finally, preprocessed images are segmented by using GVF snake model.

Clustering based on the k-means clustering algorithm is a widely used in region segmentation methods which, however, tend to produce unconnected regions [13]-[15]. They are due to the propensity of the classical k-means clustering algorithms to ignore spatial information about the intensity values in an image, since they only take into account the global intensity or color information. In order to alleviate these problems, Kompatsiaris proposed the use of an extended k-means clustering algorithm: the KMC algorithm [16]. In this algorithm, the spatial proximity of each region is also taken into account by defining a new center for the k-means algorithm. In this paper, k-means clustering and modified merging algorithms were used and the number of clusters K was set to be 4.

Based on the above subdivision, an eight connectivity labeling algorithm is applied. This algorithm finds all connected components and assigns a unique value to all pixels in the same component. Regions whose area remains below a predefined threshold are not labeled as separate ones. The labeling algorithm produces several connected regions. For these connected regions, he intensities I_ℓ, $\ell=1,2,\ldots,L$ are set to be different values respectively and the areas A_ℓ, $\ell=1,2,\ldots,L$ are calculated by counting the number of pixels in the each region.

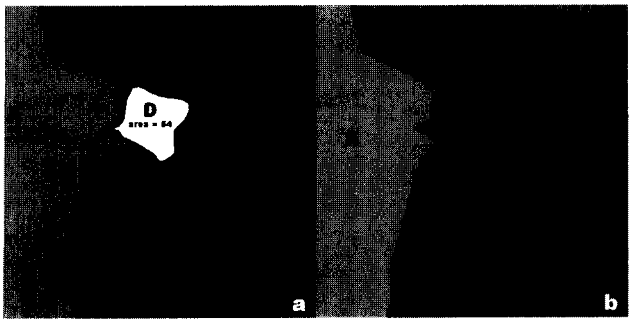

Fig. 3. Labeling and merging: (a) labeling, (b) merging.

In this paper, a merging algorithm, modified from KMC algorithms by Kompatsiaris, was proposed [16]. In KMC algorithms, regions made by k-means clustering are labeled if and only if they remain above the predefined threshold and if sum of differences between the new and old centers of intensity, spatial and motion of each region is above threshold, then it must repeat region assign process with intensity, spatial and motion center of each regions. However merging process used in this paper needs only area of each region and contact ratio among regions. In generally, contact ratio among regions is more important than such intensity and spatial location of region because most artifacts inner regions of LV after k-means clustering are surrounded by more large regions. Fig. 3 shows the example of the labeling and merging. In Fig. 3(a), the image is labeled by four labels A, B, C and D. If the number of labels is set to be 3 by user input parameter and then the threshold for merging is set to be area of label C since it is the third. Therefore label D becomes target label to be merged. Label D is merged into label which has the largest contact ratio of all neighbor labels. Fig. 3(b) shows label D is merged into label B since label B has the largest contact ratio.

In this paper, the number of labels was set to be 3. Final images were segmented by using GVF snake model. We evaluated the performance of active contour model as using K-means clustering and merging algorithms in comparison with using only active contour model.

RESULTS

In this paper, we focus on the preprocessing effects using k-means clustering and merging methods in MR cardiac LV segmentation. Thus we show the case of segmentation using GVF snake model on the original MR cardiac images and the case of segmentation using same model on the image preprocessed by the proposed k-means clustering and merging methods, and then we compare them each other.

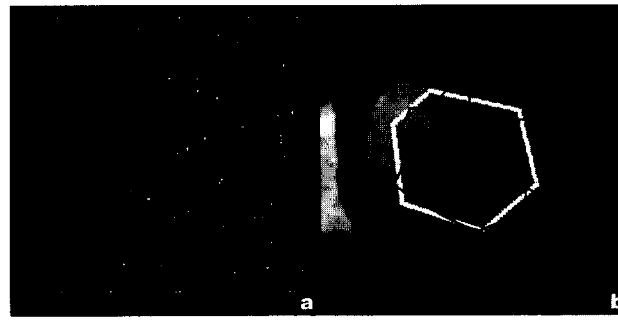

Fig. 4. (a) GVF field map of the original image(Fig. 1.(a)), (b)Segmentation result of the original image, where white solid line is an initial contour, black solid line is a final contour

There are several artifacts inside of the LV in the original 1.5T MR cardiac image(Fig. 1(a)). Fig. 4(a) shows the GVF field map of the original MR cardiac image with artifacts (Fig. 1(a)) and there are several undesirable points which a large amount of GVF field converge into. In generally, initial contour in the segmentation using GVF snake model is set inside of the LV. Because of the undesirable convergence points, the contour may converges into undesirable one. Fig. 4(b) shows the segmentation result of the original image using GVF snake model. As a result, the contour may not converge into the correct one because it locates closer to the undesirable convergence points, which are created by artifacts, than the real boundaries.

Fig. 5(a) shows the image processed by using k-means clustering with the number of clusters, 4. After k-means clustering processing, the original image become simpler, but there are still several artifacts inside of the LV. Fig. 5(b) shows that the artifacts in Fig. 5(a), the image after k-means clustering processing, disappear through the labeling and merging processing. Fig. 5(c) shows the GVF field of the preprocessed image by the proposed methods.

Fig. 5(d) shows the segmentation result of the image preprocessed by the proposed methods. Above two cases, the initial contours for the GVF snake model are just same. In case of using only the original MR cardiac images, the contour may not converge to the desirable one. In case of using the preprocessed image by the proposed methods, however, the contour can converge to the desirable one respectively.

In Fig. 6(a), it is found that there are two artifacts

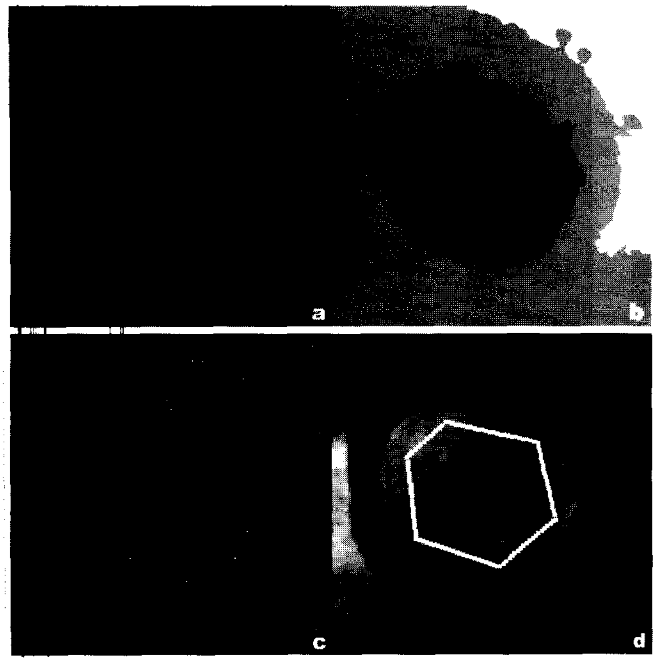

Fig. 5. (a) K-means clustering processing, (b) labeling and merging processing, (c) GVF field map of the merged image, (d) segmentation result using image processed by the proposed methods, where white solid line is an initial contour, black solid line is a final contour

inside of the LV close to the wall boundary and then it is difficult to discriminate the boundary and Fig. 6(b) shows its GVF field map. Fig. 6(a) shows the image after the k-means clustering processing and Fig. 7(b) shows the image simplified by labeling and merging. In Fig. 7(a), some artifacts close to the wall boundary inside of the LV are connected to the wall after the k-means clustering operation. At the results, in the merged image Fig. 7(b), the artifacts close to the wall boundary inside of LV are united to the wall. Fig. 7(c) shows the GVF field map of the final preprocessed image and Fig. 7(d) shows the segmentation result of Fig. 7(c). It is found that the contour cannot converge into the correct one because of the artifacts close to the wall boundary.

DISCUSSIONS AND CONCIUSIONS

We verified that our proposed algorithm overcomes local minimum convergence problem by experiment results. Further research must be concentrated on the case of small distance between artifacts and wall boundaries. The results from Fig. 6 to Fig. 7 show it typically. If the artifacts exist close to the wall boundary, they may connect the wall after k-means clustering

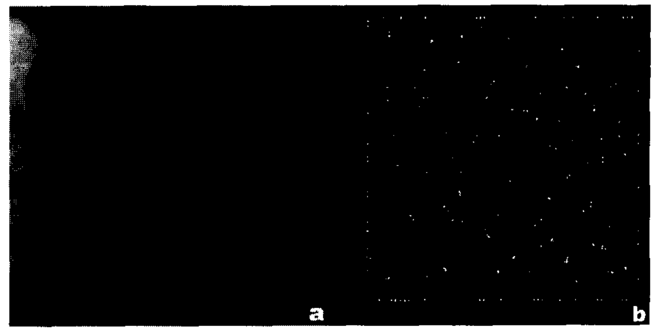

Fig. 6. (a) Original MR cardiac image, (b) GVF field map of the original MR cardiac image

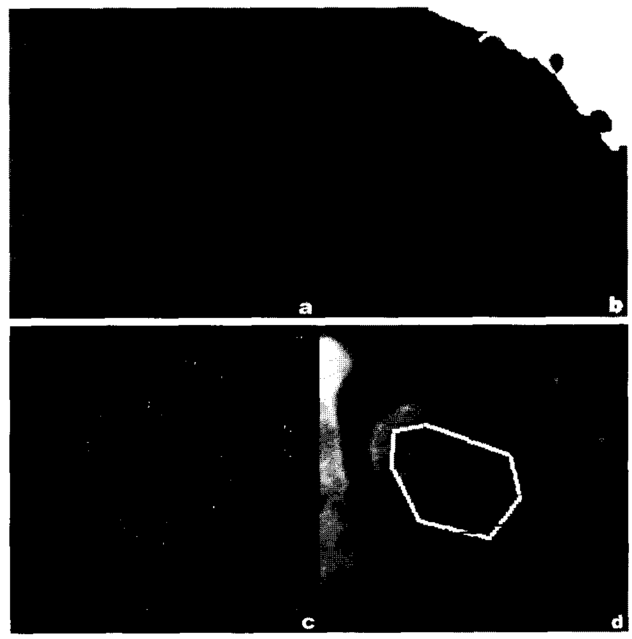

Fig. 7. (a) K-means clustering processing, (b) labeling and merging processing, (c) GVF field map of the merged image, (d) segmentation result of the merged image, where white solid line is an initial contour, black solid line is a final contour

processing (Fig. 7(a)). As a result, the artifacts and wall boundary may be united all together after merging processing (Fig. 7(b)).

The additional limit is the determination of the optimal parameters in k-means clustering and in merging process. In this paper the number of clusters and labels are set to be 4 and 3, which are obtained by choosing the best value after many operation with variable values. For the images acquired from different environment, however, each different parameters must be set for a good performance like our experiment results. For better performance, the algorithm to obtain the optimal parameters is necessary.

GVF snake model is used widely to segment the endocaridum of the LV and has shown a good performance for the simple and noiseless images. In the case that there are artifacts, however, it may not show a good performance respectively. In this paper, we proposed the preprocessing method using k-means clustering and merging algorithms for the correct segmentation.

The major advantage of the proposed method is to prevent the undesirable convergence of the contour. True external forces that attract a contour toward some features such as edges are acquired from the image itself. Artifacts may make the undesirable external forces and affect the convergence of the contour. Therefore it is important to remove artifacts and form correct external forces. Through the proposed method, artifacts inside of the LV are removed. Therefore regardless of the initialization, the contour can converge to the correct one. Through the proposed preprocessing methods, the performance of the GVF snake model can be improved.

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