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HEART FAILURE DIAGNOSIS FOR TAGGED MAGNETIC RESONANCE IMAGES

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Abstract:

This paper proposes an automated method to track the tag intersections in the Tagged Magnetic Resonance Image (MRI) to diagnose Heart failure. Heart Failure brings about declining of a function to supply blood by contraction of myocardium. Physician always analyzes myocardial motion using the images. The proposed method employs Mean shift belief propagation (MSBP) that integrates all information about image to track tag intersections. This method enables us to extract tag intersections with disappearing tags over time. The experimental results show a clinical ability of tracking tag intersections.

Keywords:

Heart failure; Tagged MRI; Mean shift belief propagation; Voronoi diagram

1. Introduction

Heart failure is one of the heart diseases. It brings about declining of a function to supply blood by contraction of myocardium. Heart failure is caused by heart diseases such as Cardiomyopathy, high blood pressure and so on. Thus, these diseases are underlying diseases of the heart failure [1]. Physician always analyzes myocardial motion to diagnose the Heart failure. Physician often employs Tagged magnetic resonance imaging (MRI) images to analyze it. Tagged MRI is a non-invasive modality to analyze cardiac deformation. It generates tags within the heart by changing the state of spin of hydrogen nuclei. They watch the tags on the resultant MRI image. The tags deform as myocardial moves. Physician diagnoses myocardial motion by analyzing deformation of tags [2]. However, it requires much time and trouble to manually analyze Tagged MRI images. Therefore, an automated motion analysis method is needed. The automated method enables us to diagnosis of Heart failure in more detail and contributes to the prevention of it. Previous methods to segment tags were based on the knowledge that tag is periodic pattern. Osman et. al [3] proposed a method using isolated spectral peaks in the Fourier domain (HARP). Qian et. al [4] proposed a method using Gabor filter bank. This method was also based on the Fourier domain analysis. These methods enhanced tags and fitted active contours model on the enhanced tags. However, it is difficult to track tags using these methods as tags fade away over time.

This paper proposes a method to track tag intersections based on Mean shift belief propagation (MSBP) [5]. Belief propagation integrates various information about intensity, appearance and so on. Statistical machine learning method can track the tag intersections accurately even if tags fade away over time. Section 2 describes the proposed method based on MSBP. Section 3 shows experimental results on MRI images of a patient and a healthy person. Section 4 concludes our technical results.

2. Method

We show the 2D tagged MRI image on Figure 1. Periodic black lines are tags. The tags fade away as time goes. Tags generate local high intensity regions. We call these white regions as bright features. Bright feature is a primary feature to track the tag intersections, and it is useful to analyze myocardial motion. The main task is to track the tag intersections in the heart. In this step, we determine the heart region manually on the tagged MRI image to limit the region of processing. Figure 2 shows the region of interest of the heart. Yellow circle indicates the heart. Red circle indicates the left ventricle. We remove inside of red circle because the tags disappear in the left ventricle. Here, we describe our proposed method as follows.

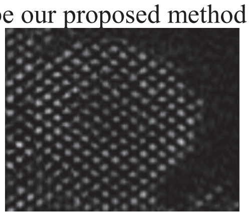

FIGURE 1. Tagged MRI image

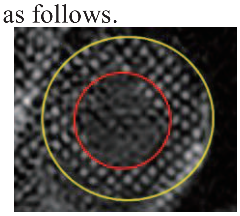

FIGURE 2. Region

2.1. Tracking of Tag Intersections

In this step we track the tag intersections. It is difficult to track the tag intersections in every frame because of the tags fade away as time goes. However bright features are comparatively clear in every frame. We use bright features as evidence that tag intersections exists near the points. The proposed method tracks bright features firstly using Mean shift belief propagation (MSBP). After that, this method tracks tag intersections using previous result of tracking step.

2.2. Mean Shift Belief Propagation (MSBP)

Discrete belief propagation [6] efficiently computed the marginal distribution in the graphical model. However, it did not compute the marginal distribution if hidden variable space was continuous. MSBP efficiently computes it because of MSBP regard entire hidden variable space as local regular grid of samples centered at the predicted state in each step. A message passing rule is performed to samples and weight (belief) is computed in each samples. After computation of weights, mean shift method is applied in regular grid of samples to predict expected values. MSBP performs these steps iteratively. We explain details of MSBP step by step.

2.3. Computation of Weights

We consider a 2D continuous hidden variable space in our proposed method. Each node i have N samples $X_N^i = (x_N^i, y_N^i)$ of regular grid centered at current predicted state. Each node is connected to neighbor nodes j. We have to evaluate these samples by applying message passing rule. The messages are given by

$$m_{ij}(X^j) = \sum_{n=1}^{N} f_{ij}(x_n^i, X^j) g(x_n^i) \prod_{s \in N(i) \backslash j} m_{si}(x_n^i) \quad (1)$$

where X^j denotes sample of node j, f_{ij} (x_n^i, X^j) does the pairwise factor, $g(x_n^i)$ does the unary factor and s does neighbor nodes except node j. Pairwise factor is function based on the distance between node i and j. Unary factor is function based on the appearance of node. After computation of messages, the weights are given by

$$w_i(x_n^i) = Z g(x_n^i) \prod_{s \in N(i)} m_{si}(x_n^i) \quad (2)$$

where Z is the normalization constant.

2.4. Mean Shift

After computation of weights, mean shift is applied to samples of every node. Predicted value of next step m^{k+1} is given by

$$m^{k+1} = \frac{\sum_{n=1}^{N} K(x^{(n)} - m^k) w(x^{(n)}) x^{(n)}}{\sum_{n=1}^{N} K(x^{(n)} - m^k) w(x^{(n)})} \quad (3)$$

where m^k denotes the predicted value after the kth iteration and K is the kernel function. The bandwidth of kernel K depends on the bandwidth h_{MSBP}.

2.5. Tracking of Bright Features

We track the bright features using MSBP in every frame. The initial points are detected by searching local peaks of intensity. Figure 3 shows the detection of them. MSBP needs construction of unary factor and pairwise factor. We construct Hessian based unary factor. We know the local geometrical structures of image from Hessian [7]. We calculate Eigen vectors of Hessian $\lambda_{(\sigma,1)}$, $\lambda_{(\sigma,2)}$. Parameter σ is a standard deviation of Hessian. The Eigen vectors have positive high value on the bright features. A degree of bright feature is given by

$$V(x,\sigma) = \begin{cases} \sqrt{\lambda_{\sigma,1}^2 + \lambda_{\sigma,2}^2} & if \quad \lambda_1 > 0 and \lambda_2 > 0 \\ 0 & else \end{cases} \quad (4)$$

where $V(x,\sigma)$ denotes Eigen vector based degree in every pixels. After we compute them in every pixel, we normalize them. Figure 4 shows result of the computation from image of Figure 2. Using Equation (4), the unary factor is given by

$$g(x_n^i) = \exp(-\alpha(1 - V(x_n^i, \sigma))) \quad (5)$$

where α denotes a parameter to control influence of unary factor. We construct pairwise function, which is given by

$$f(X^i, X^j) = \exp(-\beta \times dist(X^i, X^j)) \quad (6)$$

where β is parameter to control connectivity between nodes and dist function means distance between nodes.

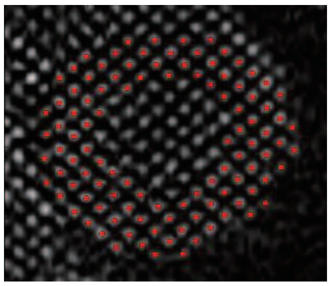

FIGURE 3. Detection of bright features

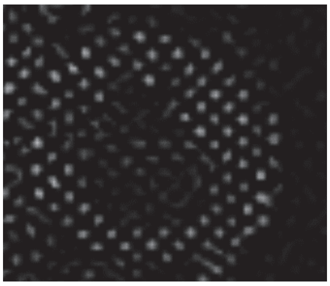

FIGURE 4. Likelihood of bright features

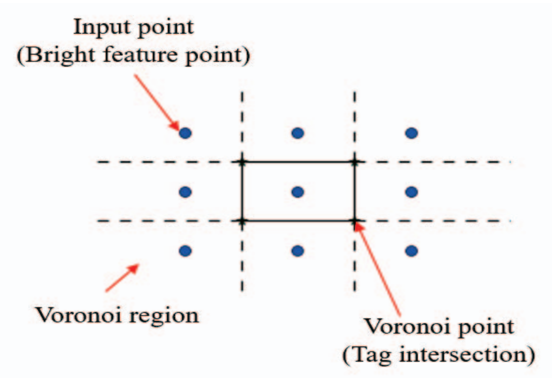

FIGURE 5. Mechanism of detection of tag intersections

2.6. Tracking of Tag Intersections

We track the tag intersections by applying MSBP mentioned above. The likelihood is made based on Voronoi diagram and bright features. Figure 5 shows this mechanism. We regard input points to Voronoi diagram [8] as bright features, and regard Voronoi points as tag intersections. The likelihood of intersections is computed by input approximate position to Kernel density estimation (KDE) [9]. The likelihood depends on the parameter h_{KDE} which controls the bandwidth of KDE. The unary factor is given by

$$g(x_n^i) = \exp(-\alpha(1 - P(x_n^i))) \tag{7}$$

where $P(x_n^i)$ denotes probability got from KDE. The pairwise factor is the same of Equation (6).

3. Experimental Results

3.1. Datasets

The proposed method has been applied to two Tagged MRI images. They consist of healthy person and patient who have heart failure. The number of frames are 45 and 21. The imaging was done by 3T MRI scanner (Achieva, Philips Healthcare, Best, and the Netherlands). The size of multiples short axis view images are 176 ×176. The parameters are like this. Repetition time 9.3 msec, echo time 4.7msec, flip angle 10 degrees, slice thickness 8.0mm, frames per heart cycle 21, number of positions 3 (25, 50, and 75% of the entire heart), and tag spacing 6mm.

3.2. Results

We determined region of interest (ROI) of the heart manually. The parameters of MSBP to track the bright features were (σ=1.0, α=7.0, β=1.0, h_{MSBP}=1.0). The grid size of MSBP is 10×10. The parameters to track the tag intersections were (α=7.0, β=1.0, h_{MSBP}=1.0, h_{KDE}=0.05). The size of grid of MSBP is 10×10. Figures 6 and 7 show the result of tracking intersections of a patient and a healthy person. We checked that the method correctly tracked the tag intersections in every frame. However the method depending on the parameters of MSBP. We checked that if we adjust the parameters incorrectly, the method failed to tracking of tag intersections in some images. To make comparison between our proposed method and HARP, we tracked the tag intersections by HARP. Figure 8 and 9 shows result of tracking by HARP. As shown in figure 8 and 9, our proposed method more accurately tracked them than HARP.

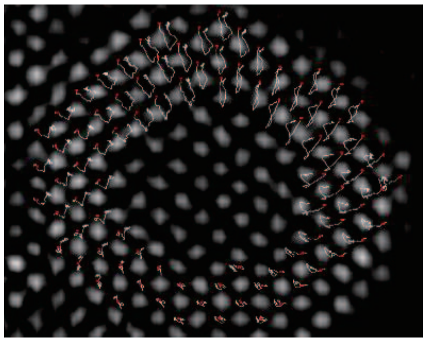

FIGURE 6. Tracking result of patient

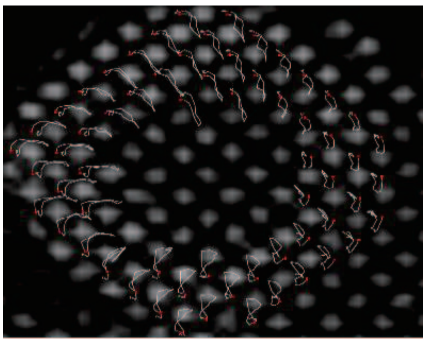

FIGURE 7. Tracking result of healthy person

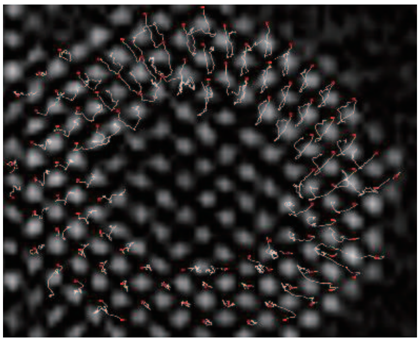

FIGURE 8. Tracking of patient by HARP

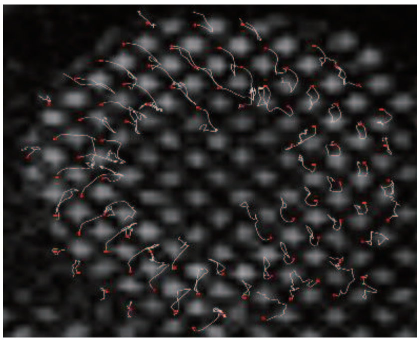

FIGURE 9. Tracking of healthy person by HARP

4. Conclusions

We have proposed a method to track tag intersections based on MSBP and Voronoi diagram. We first extracted the bright features using MSBP based on Hessian based likelihood model proposed here. We second tracked the tag intersections using the MSBP based on bright features and Voronoi diagram. Tagged MRI image has poor quality in some frames. Statistical machine learning method like MSBP was very effective to treat it. The experimental results showed successful tracking of tag intersections. The future work is analyzing the myocardium motion using the tag intersections to predict Heart failure.

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