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Arterial Hemodynamic Analysis on Non-enhanced Magnetic Resonance Angiogram Using Optical Flow

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Abstract: Peripheral arterial disease (PAD) is caused to the lower extremity atherosclerotic disease. Its diagnosis is needed to obtain much kind of the information of vascular morphology as well as the blood flow information based on hemodynamics. The diagnosis of the PAD using magnetic resonance imaging (MRI) equipment without contrast medium is available as a useful visual screening in clinical practice. In this paper, we propose a novel method for visualizing hemodynamics to arterial images obtained by a non-contrast enhanced magnetic resonance angiography (MRA) based on the Lucas-Kanade optical flow with the image pyramid processing, and satisfied experimental results are obtained.

Keywords: PAD, non-enhanced MRA, Lucas-Kanade optical flow, image pyramid processing

I. INTRODUCTION

Peripheral arterial disease (PAD), also called peripheral vascular disease, is atherosclerosis of the lower extremities causing ischemia. Severe PAD usually requires angioplasty or surgical bypass and may require amputation. Prognosis of this disease is generally good for treatment, although mortality rate is relatively high because coronary artery or cerebrovascular disease often coexists. In order to perform endovascular treatment or surgery, it is necessary to understand the vascular morphology and hemodynamic. In other words, by tracking the amount of blood flowing into the tissue, the treatment strategy is determined for the symptom. In diagnostic imaging for the PAD, computed tomography angiography (CTA) and magnetic resonance angiography (MRA) has seen widespread acceptance as noninvasive vascular diagnosis. When CTA and MRA are performed, however, it is necessary to consider the side effects when using contrast agent and these images are mainly used to diagnosis vascular morphology. On the other hand, non-contrast enhanced MRA is a very useful imaging technique which is obtained by magnetic resonance imaging (MRI). It has various advantages, for example, the ability to provide vascular morphology and hemodynamic without contrast agents. Especially, fresh blood imaging (FBI) method is useful for a non-enhanced MRA to detect a variety of vascular diseases causes of the PAD [1, 2].

The FBI is an electrocardiogram gated non-contrast enhanced MRA technique, which employs arterial signal difference between systole and diastole during a cardiac cycle, i.e. subtraction of the diastolic bright-blood arteries from the systolic black-blood arteries allowed visualization of the arteries by cancelling the veins. According to this experiment, the FBI has some density information corresponding to the cardiac cycle, which may be closely related to blood flow. In other word, the hemodynamic can be expressed by imaging the MRI signal information related to the pulse wave using the image density information during the cardiac cycle phase [3]. Nevertheless, it is difficult to express the direction and the velocity of blood flow on the FBI by using only image density information. In the medical image processing field and computer vision, it is important to develop hemodynamic analysis system. In particular, the vascular systems in human organs are distributed throughout the body, which generates a large number of image data in a single examination. In order to observe blood flow in a wide area may be also required some software for playing a supporting role in diagnosis such as the CAD systems [4]. Many CAD systems have been developed to analyze the internal organs based on CT, and MRI on the medical field [5]. Despite many researchers have developed various image processing techniques for blood flow, the related research papers concerning these techniques are very small, for which MRI imaging technique to acquire the original image are difficult. In addition, since the density information of the image rely on the subjects, determining between the normal region and the noise is also difficult.

A new development of CAD system to visualize hemodynamic using optical flow analysis is presented in this paper. The arterial images are obtained from non-enhanced MRA technique.

II. PROPOSED METHODS

In this section we will present our proposed image preprocessing method for detecting hemodynamic on MR images. Fig.1 shows the procedure of the subtraction for FBI images as an illustration. The FBI image is depicted as white blood in the early-systolic

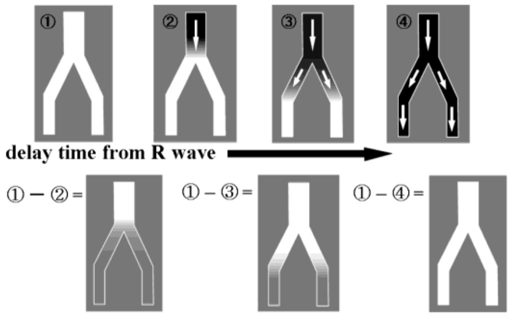


Fig. 1 A subtraction technique using successive MR images

Fig. 2 Examples of MIP images after subtraction

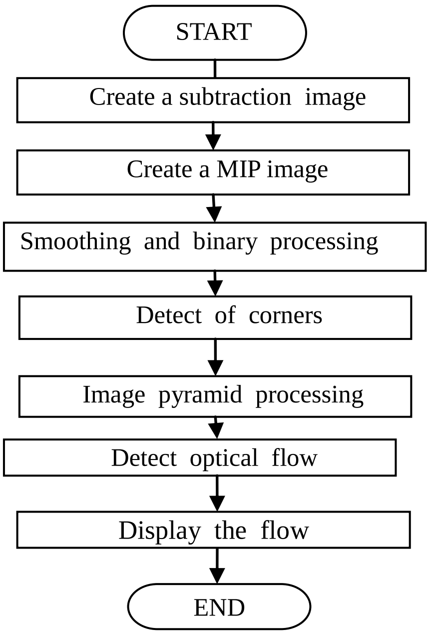


Fig. 3 Flow of procedure

phase, furthermore in the end-systolic phases; these images will become black blood as flows from the central to peripheral. From this result, these vessels are visualized such as angiogram by using subtraction technique as shown in Fig.1.

Fig. 2 gives examples of the maximum intensity projection (MIP) images obtained by the above method. A white area in Fig. 2 shows the blood vessel area. The outline of some image analyzing technique is shown below. Moreover, the overall scheme of the image processing techniques for tracking the region of blood vessels is illustrated in Fig. 3. The method consists of three main steps; detecting corners on the blood vessel region, feature tracking based on the Lucas-Kanade optical flow, and displaying the blood vessel. To acquire flow information on FBI images, some image processing techniques are introduced. In the first step, pre-processing technique such as smoothing and binarization are performed to reduce image noise, and then corners of features point are derived on these images. In the second step, using the Lucas-Kanade optical flow with an image pyramid processing to respond to rapid changes in the flow, velocity fields of the image are performed. In the third step, the estimated velocity vectors in the second step are depicted some arrows on the FBI images.

2.1 Detecting corners using Harris operator

Harris operator [6] is a method to derive feature points based on the correlation of image signal and the operator increase each correlation output value at the feature points of edges and corners. According to Schmid [7], this operator can be high repeatability to detect the points with the similar features. Even if the original image encounter these image transformations such as rotation and enlargement.

Given a point (x, y) and its shift $(\Delta x, \Delta y)$, the weighted auto-correlation function is defined as,

$$E(x,y)=\sum_{W}\left[I(x_i,y_i)-I(x_i+\Delta x,y_i+\Delta y)\right]^2 \cdot \tag{2.1}$$

Where W is the weighting function. Here we applied the Gaussian function. $I(\Delta x_i, \Delta y_i)$ denotes the image function and (x_i, y_i) are the points in the window W centered on (x, y).The shifted image is approximated by a Taylor expansion truncated to the first order terms,

$$I(x_i+\Delta x,y_i+\Delta y)\approx I(x_i,y_i)+\left[I_x(x_i,y_i)I_y(x_i,y_i)\right]\begin{bmatrix}\Delta x\\ \Delta y\end{bmatrix} \tag{2.2}$$

In this study, auto-correlation matrix; $\boldsymbol{M}$, can be expressed as follows:

$$M=\begin{pmatrix}\sum w\left(I_x(x_i,y_i)\right)^2 & \sum wI_x(x_i,y_i)I_y(x_i,y_i)\\ \sum wI_x(x_i,y_i)I_y(x_i,y_i) & \sum w\left(I_y(x_i,y_i)\right)^2\end{pmatrix} \tag{2.3}$$

This can be expressed as the following

$$E(x,y)=(\Delta x,\Delta y)M(\Delta x,\Delta y)^T . \tag{2.4}$$

Two eigenvalues of this matrix $\boldsymbol{M}$ ($\lambda 1$, $\lambda 2$) said that while the highest corner. We use the following formula R rating in order to reduce the computational cost.

$$R=\lambda 1\lambda 2-k(\lambda 1+\lambda 2)=Det(M)-k(TraceM)^2 \tag{2.5}$$

However, when the curvature is k=0.06, there is a feature point (R>0). Feature points of corners with these procedures are utilized for the following optical flow analysis.

2.2 Lucas-Kanade optical flow method for detecting the feature points

The optical flow is a method to detect the motion of the object by determining a flow vector which calculated the velocity of the image from a continuous image sequence in time. The gradient method, optical flow estimation, is calculated motion vectors based on the equation relating the temporal gradient of local characters on the image and a spatial gradient. A basic constraint equation in the gradient method is based on th e condition that the pixel value of any point is no changed when the subject has moved. The equation is calculated as follows. The initial hypothesis in measuring image motion is that the intensity structures of local time-varying image regions are approximately constant under motion for at least a short duration [8]. Formally, if $I(x,y,t)$ is the image intensity function,

$$I(x, y, t) = I(x + \Delta x, y + \Delta y, t + \Delta t) \qquad (2.6)$$

where (Δx, Δy) is the displacement of the local image region at $I(x,y,t)$ after time(Δt). Expanding the left-hand side of this equation in Taylor series yields

$$I(x + \Delta x, y + \Delta y, t + \Delta t) = I(x, y, t) + \Delta x \frac{\partial I}{\partial x} + \Delta y \frac{\partial I}{\partial y} + \Delta t \frac{\partial I}{\partial t} + \varepsilon \qquad (2.7)$$

where $I_x = \frac{\partial I}{\partial x}, I_y = \frac{\partial I}{\partial y}$ and $I_t = \frac{\partial I}{\partial t}$ are the 1st order partial derivatives of $I(x,y,t)$ and ε. The 2nd and higher order terms are assumed negligible. Subtracting I = (x, y,t) on both sides, ignoring ε and dividing by Δt yields

$$I_x u + I_y v + I_t = 0 \qquad (2.8)$$

Where I_x, I_y and I_t are spatio-temporal intensity derivatives and (u, v) is the image velocity. Equation (2.8) is known as the optical flow constraint equation and defines a single local constraint on image motion. However this constraint is not sufficient to compute both components of (u, v) as the optical flow constraint equation is ill-posed because of the reason such as the aperture problem. For this reason, the second constraint condition is added.

In Lucas and Kanade method the second constraint condition is that assume the neighborhood pixels in a small region have the same flow vectors. Under this assumption, the following equation for the k-th pixel is given by

$$I_{xk} u + I_{yk} u = -I_t k \cdot \qquad (2.9)$$

The simultaneous equation is solved at a ($n \times n$) pixel of this neighborhood region. A solution of this simultaneous equation is obtained by using weighted least-squares. In order to estimate the optical flow, the window function (5×5) is performed.

2.3 Optical flow analysis using image pyramid

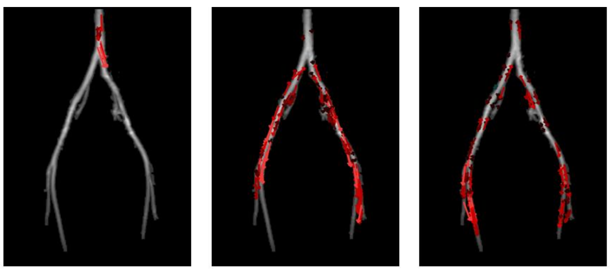
The blood flow in the human body often appears a small motion as well as a large motion in some vessel regions. The Lucas-Kanade optical flow is assumed to be as small and coherent motions; therefore, a large window will be required to detect large motions such as the blood flow. In the case of large and noncoherent motions, however, the large window would break the coherent motion assumption easily. We employed image pyramid to mitigate the problems caused by breaking the assumptions. When a pyramid-shaped a hierarchical structure is created by reducing the original image successively, the image moves accordingly decreases based on these image sizes. The feature points between images in a larger spatial scale with the optical flow are estimated initially, these feature points are then used as initial values between images at the following layer. Since these processes are iterated until the size of the original image, the reliability of the rapid changes in estimated flow is improved.

III. EXPERIMENTAL RESULTS

To acquire blood flow information, we applied automatically proposed method to MRA images obtained by FBI method. Image size is 256 x 256 [pixels] and the image set consists of 60 to 80 slices images per case. Visualizing hemodynamics for the blood flow is performed by utilizing L-K optical flow with the image pyramid processing in order to respond to rapid changes of blood flow. 8 cases experimental results on flow processing, displaying the flow vectors, are shown that the proposed method performed well. The results of the optical flow vectors processing in cardiac cycle are shown in Fig. 4(a), 4(b), and 4(c), respectively.

The flow vectors are generated from the abdominal artery near the heart, and these vectors are viewed as a movement from the external artery to the femoral artery over time. It was possible to display the flow vectors comparable to some antegrade arterial blood flow from the abdominal aorta to the femoral vessels in all cases.

Overall the performance for these flow detection results are evaluated by tested a statistically significant differences between each cardiac cycle times that are detected first moment at the femoral artery and are most often detected flow vectors. An example of a graph measured the velocity of the cardiac cycle in the femoral artery with a velocity measurement method by using MRA technique called the phase shift (PS) is shown in Fig. 5. The results of the cardiac cycle time obtained from the respective first moment obtained by the results of Fig. 5 are shown in Table 1. The result counted the number of vectors at the first moment in the ROI set in the femoral artery. The analysis results of cardiac cycle time obtained from the respective first moment and the cardiac cycle time of the maximum count number are shown in Table 2, respectively.



(a) (b) (c)

Fig. 4 Results of optical flow

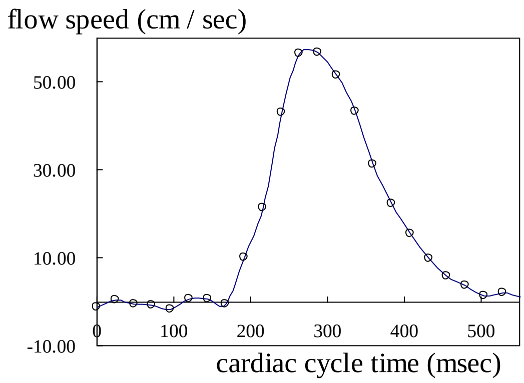


Fig. 5 An example of flow speed measurement using PS

Table 1 Result of calculated times at the first moment to each subject of 8 cases

Subject	First moment (msec)
A	170
B	170
C	155
D	165
E	165
F	160
G	155
H	155

Table 2 Results of cardiac cycle time of 8cases

Subject	maximum count (msec)	first moment (msec)
A	150	170
B	180	170
C	180	155
D	150	165
E	180	165
F	150	160
G	150	155
H	180	155

Based on these results, a significant difference test was performed by Mann-Whitney U test. The results of the analysis of the eight samples are $p = 0.39$ ($p > 0.05$), and there were no statistically significant differences between two groups.

IV. DISCUSSION AND CONCLUSIONS

In this paper, we developed a CAD system to visualize the hemodynamic using arterial images which are obtained from a non-enhanced MRA technique. Due to employ the ideas of subtraction technique between images, after pre-processing such as smoothing and Binarization, a good performance was obtained by using corner detection and analysis of optical flow. From the Table 2, since there were no statistically significant differences between the times of cardiac cycle detected the maximum number of the flow vectors and the time at each first moment of the blood flow, it may be considered that the flow vectors are able to show blood flow in the human body. Therefore, this correlation is considered that the flow vectors indicate a first motion of blood flow in the cardiac cycle. Although, the flow vectors do not necessarily indicate reflection for the speed of blood flow and blood volume. The first motion of blood flow reflects a pulse wave of the blood ejected from the heart. It is predictable from these discussions that the flow vectors obtained by optical flow analysis on the non-enhanced MR angiography images are able to estimate blood flow indirectly.

In order to set the threshold value based on the experience for binarization processing to process image noise, however, it should always be considered a risk that the detection rate of flow depend on the quality of original image. For these reasons, it is necessary to develop a flow detection algorithm without depending on the quality of the original image.

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