Automated Tracking of the Carotid Artery in Ultrasound Image Sequences Using a Self Organizing Neural Network

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Abstract

An automated method for the segmentation and tracking of moving vessel walls in 2D ultrasound image sequences is introduced. The method was tested on simulated and real ultrasound image sequences of the carotid artery. Tracking was achieved via a self organizing neural network known as Growing Neural Gas. This topology-preserving algorithm assigns a net of nodes connected by edges that distributes itself within the vessel walls and adapts to changes in topology with time. The movement of the nodes was analyzed to uncover the dynamics of the vessel wall. By this way, radial and longitudinal strain and strain rates have been estimated. Finally, wave intensity signals were computed from these measurements. The method proposed improves upon wave intensity wall analysis, WIWA, and opens up a possibility for easy and efficient analysis and diagnosis of vascular disease through noninvasive ultrasonic examination.

1. Introduction

Cardiovascular disease accounts for 30% of global deaths [1]. In particular, there is a need for early and accurate diagnosis of vascular disease. Such diagnosis had over the years relied upon invasive procedures. In 1990, Parker et al. [2] introduced the concept of wave intensity (WI) analysis for early diagnosis of cardiovascular disease. The wave intensity signal was defined as the product dP x dU, where dP and dU represent the change in pressure and flow (respectively) inside a given blood vessel. Both parameters of the wave intensity signal were measured invasively, and this limited clinical use. A theoretical WI signal is presented in Figure (1). The characteristics of this signal are two positive peaks, the first (W1) being higher than the second (W2), separated by a negative peak forming a negative area (NA). W1 occurs during early systole while W2 occurs at the end of ejection, and the intermediate NA is caused by reflected waves from the periphery [3].

Another technique, introduced recently [3], is known as Wave Intensity Wall Analysis (WIWA), where change in pressure (dP/dt) and flow (dU/dt) were approximated by the strain rate of the arterial wall in the radial and longitudinal direction, respectively. A block-matching algorithm (using the sum of absolute differences) was used for speckle tracking to estimate these strain rates. The results of this method were close to that of a commonly used and validated WI system (SSD-5500, Aloka Co., Japan).

While the WIWA method offers many advantages by being noninvasive and relying solely on acquired ultrasound images, its main limitation has been the accuracy-level of the speckle-tracking algorithm, which was originally designed with the intent of being utilized on myocardium tissue. Therefore, some important characteristics of the wave intensity signal were often not very evident because the tracking algorithm was not flexible enough to be able to adapt to various deformations in shape.

Therefore, in this paper, a novel algorithm based on Growing Neural Gas (GNG) [10] is employed for tracking the arterial vessel wall in an accurate and automated manner.

2. Image Segmentation

Extracting the vessel wall in ultrasound image
sequences poses a considerable challenge mainly due to the low signal-to-noise ratio, unclear boundaries, and varying intensities and shapes across different frames. Therefore the segmentation process should take advantage of both spatial and temporal information in the image sequences in order to segment the images accurately. Figure (2) shows a typical image of carotid artery stenosis (CAS), which occurs when some parts of this artery become thicker and narrower (as marked by the yellow circle).

At first, each single image was clustered using certain spatial/textural features, where every pixel became an object in an N-dimensional feature space. N was set to three in our case since the features chosen were: the mean, standard deviation, and entropy of a square neighborhood around each pixel. Based on these features, the k-means clustering algorithm was implemented to segment each image into three classes as shown in Figure (3).

In Fig. 3, it is not easy to differentiate vessel wall boundaries from other boundaries; since the features of these regions are very similar. Even a human operator cannot distinguish any characteristic differences by processing only a stationary image. However, when the images are set in sequence, motion allows us to identify the vessel walls, since it is mainly the vessel walls that move while other boundaries are relatively static. Therefore, temporal information needs to be integrated into the segmentation process. The feature utilized for this purpose was the standard deviation of pixel values across the frames in the image sequence.

At the end, this process ensures that the more prominent of the two walls will be selected; i.e. the one that is most dynamic (by virtue of the standard deviation feature) and the most visible (by virtue of the k-means algorithm). Figure (4) shows this vessel wall.

3. Motion Tracking

The ultimate aim of this work is to analyze the motion of the vessel wall in order to deduce the condition and function of the cardiovascular system. To that end, the movement of the vessel wall needs to be tracked from frame to frame in the image sequence. The algorithm that was implemented for that purpose is based on Fritzke’s GNG [10] method which is a topology-preserving self organizing neural network.

The GNG algorithm was at first applied upon the first image of the sequence. Then the resulting net was retained while node insertion was completely discarded when processing the 2nd image, and so on; the net resulted from processing each image was retained and used further with the next image.

In effect, the neural net covers the vessel wall of the first image; then no more nodes are allowed to be introduced into the net. Hence, the number of nodes remains fixed and these nodes adapt to the new vessel wall distribution in the following images of the sequence. In this manner every node’s movement from frame to frame is captured rendering the vessel wall movement in all its components within record.

The results of tracking the vessel wall for both simulated and real ultrasound image sequences are presented in the following two sections.

3.1. Application to Simulated Ultrasound Data

The GNG-based algorithm was applied to the same simulated image sequence used in [4]. The aim in [4] was to evaluate the estimation accuracy of both radial and longitudinal strain. Applying the segmentation process on this dataset was straight-forward. Analysis of the nodes’ motion is presented in section 4.1.
(5) provides a view of the resulting net distributed over the two vessel walls which are aligned vertically.

**Figure 5.** Net representing the two vessel walls in one frame of the simulated ultrasound video.

### 3.2. Application to Real Ultrasound Data

The method was also tested on real ultrasound image sequences of carotid arteries of healthy and pathological cases. As described earlier, the vessel wall was segmented in all images of each sequence. Figure (6) shows one such image, where the nodes’ locations are marked with (green) ‘+’ markers.

Any subset of nodes may be chosen by cropping a region of interest (ROI) in the first frame as shown in Fig. 6 by the (light blue) rectangle. Information about only the nodes located within the ROI is extracted.

**Figure 6.** Automated assignment of nodes marked with (green) ‘+’ markers onto the vessel wall.

### 4. Motion Analysis

After having modeled the vessel wall with a net of connected nodes, and after having kept record of the motion of each node from frame to frame, analyzing the motion of the vessel wall becomes an easy task. Any section of the vessel wall may be chosen by the user through cropping a selected ROI (or by selecting the entire vessel wall). Then, motion analysis is performed for only the nodes located within the ROI.

#### 4.1. Analysis of Simulated Data

The purpose of this section is to process these data using our method and compare the results with those obtained in [4]. Our results are presented in Figure (7). Radius variations and longitudinal displacements (shown in Fig. 7a and 7b respectively) were obtained directly using our automated method. Then, the corresponding radial and longitudinal strain curves (shown in Fig. 7c and 7d respectively) were derived.

The curves presented in Fig. 7 are very similar to the corresponding ones in [4], as well as the results of previous studies [5-9]. Repeating this experiment 10 times gives a maximal systolic radial and longitudinal strain estimations of -14.04±0.4% and 6.21±0.67% respectively (ground truth values: -13.89% and 5.3%). Ground truth values here refer to those of the signals that were used as input to the simulated model in [4], whereas the signals shown in Figure (7) were derived using our method from simply processing the image sequence of the simulated vessel walls in motion.

**Figure 7.** (a) Radial distention curve. (b) Longitudinal displacement curve. (c) Estimated radial strain. (d) Estimated longitudinal strain.

#### 4.2. Analysis of Real Data

Our automated WIWA method was tested on real ultrasound image sequences of carotid arteries. Twenty three cases were considered in total, thirteen of which were healthy and ten of which were pathological (CAS) cases. The resulted WI signatures were computed (using radial and longitudinal strain rates) and aligned with the corresponding electrocardiogram (ECG), as in Figure (8).

### 5. Utilization as a Diagnostic Tool

The WI signal may be used as a diagnostic tool [3], as it poses different features in healthy and pathological (CAS) cases. In healthy cases, W1 and W2 are usually higher in amplitude than for pathological cases; whereas NA is more dominant in sick individuals and in cases of hypertension.
In Figure (8), it can be easily noticed that W1 appears shortly after the R-wave of the ECG signal. It can also be observed that both W1 and W2 have lower amplitudes while the ratio (W1/W2) is increased in non-healthy cases. The NA is relatively small in all cases.

6. Conclusion

A novel WIWA algorithm was introduced and utilized to track and analyze the movement of the carotid artery. The algorithm improves upon the WIWA technique previously employed, and presents a completely automated procedure for diagnosing the cardiovascular system in a noninvasive way.

The tracking of the vessel wall is obtained through a self-organizing net of nodes. The node adaptation itself is robust to noise since noise attempts to move a given node in various opposing directions throughout the numerous iterations eventually resulting in a nearly-zero net movement.

The tracking algorithm implemented is not tailored to carotid arteries, but may be applied in the tracking and analysis of any image sequence with a high enough frame rate. Such an algorithm could prove very useful in gait analysis and in other medical imaging fields such as cardiovascular magnetic resonance imaging (MRI) where the image quality is better than in current ultrasound images.

References