Compare image segmentation methods for evaluating aqueductal CSF hemodynamic

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Introduction

Inherently, there were spatial and temporal limitations in cerebrospinal fluid (CSF) flow study of aqueduct of Sylvius since its small structure is deeply located in a brain and to-and-fro motion gated with heart beat. According to our past studies [1], even sacrificed outside of aqueduct region with partially spatial overlapped, the total pixels in aqueduct imaging were merely 9~25 in normal volunteers. Therefore, post-processing in image segmentation played an important role in calculating aqueductal area, stroke volume and related flow parameters. To avoid errors from inter-observer and intra-observer in region of interest (ROI) selection, we adopted automated image segmentation, including adaptive threshold in magnitude image, pulsatility based segmentation (PUBS) [2] and independent component analysis (ICA) [3]. For accuracy and precision, both phantom and normal human study by using 2D cine magnetic resonance (MR) phase contrast (PC) imaging were compared.

Methods and Materials

All experiments underwent cine PC MRI, were performed on a 1.5 Tesla system (Siemens Vision+, Erlanger, Germany) in Department of Radiology at the Tri-Service General Hospital (TSGH). In phantom study, we adopted UHDC flow phantom and MR-compatible programmable pump provided by Shelley Medical Imaging Technologies (London, Ontario, Canada). The through-plane imaging parameters were VENC=20cm/s, 20 phases, FOV=20 cm, 256x256 matrix size. However, 9 healthy normal volunteers were imaging perpendicular to the proximal third of aqueduct of Sylvius with high temporal resolution (FOV=10cm with the same matrix size and VENC) via retrospective gating, 30 PC images from 64 phases.

Based on Bayesian discriminated function [4], we adopted adaptive threshold in magnitude image for boundary detection. Instead of spatial information, PUBS and ICA utilized temporal statistical information. With “seed” prior information, PUBS executed region growing algorithm according to correlate time curve of “seed”. However, ICA is a method for finding blindly those underlying factors or components from multivariate (multidimensional) statistical data. Here, we linked ICA program designed by Helsinki University of Technology.

Results

As Figure 1, an interactive GUI platform displayed image with size-known U-sharp pipe, were enclosed with 2 water bags for good filling factor, in oscillating flow. After ROI-segmented, as red color in Figure 1, with one of three methods, we could calculate velocity to time curve, as Figure 2, by corrected background data from static tissues. Note that we roughly selected a locally rectangular ROI to reduce time-computing. To extract the most significant component from ICA, we made a co-occurrence matrix of correlation coefficients to resolve. As Figure3, on the right side was temporal information from 30 slices and its unit is arbitrary; however, on the left side was segmented image with significant component.

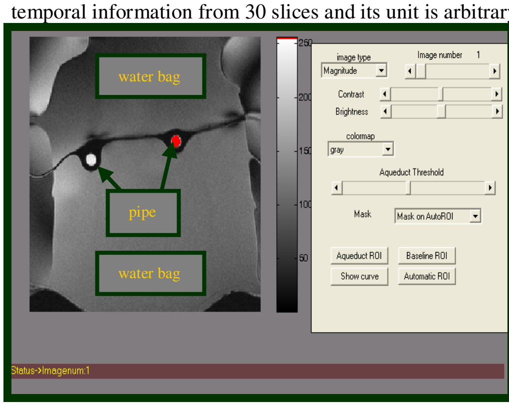

Figure 1. Interactive CSF GUI platform

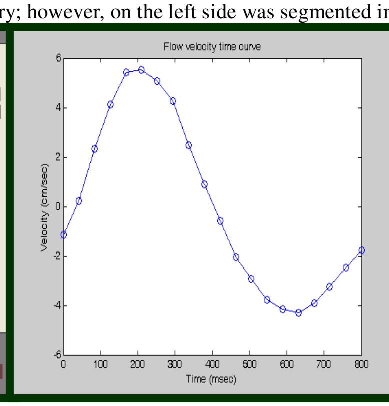

Figure 2. flow phantom velocity curve

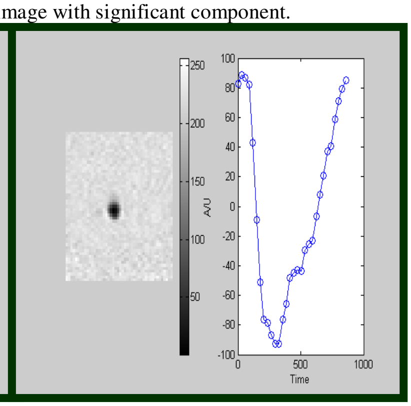

Figure 3. The most significant component was the 3rd component by using ICA. Left and right side represented spatial and temporal information, respectively.

Methods	threshold	PUBS	ICA
Estimated Area	97±4%	95±3%	89±7%
Estimated Stoke Volume	91±9%	92±4%	87±10%
Time Consuming	Good	Good	Poor

Table 1 Compare three image segmentation methods in phantom study. (Note: mean±SD)

Discussion

As for adaptive threshold method, partial volume effect dominated errors in magnitude images, which could make over-estimation in area. However, PUBS and ICA methods, based on temporal characteristics, might make under-estimation in such a noisy-like phase images. Thus, one could expect that errors might be apparent in some unobvious pulsatility cases, e.g. Lo-NPH patients. Again, although ICA method predominated over others in its blind test feature, yet ICA encountered both time-consuming and estimation-convergent problems particularly for higher component data. The larger in “roughly” ROI size was selected, the more statistical loading and worse performance were affected, especially in ICA. As Table 1, PUBS showed great accuracy and precision in such few pixels in both area and stoke volume estimation.

References

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