Automated bolus tracker positioning for MRI liver scans

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TARGET AUDIENCE: Technologists and radiologists, particularly those working on MRI liver scans

PURPOSE: In MRI liver scans, dynamic study using contrast agent is currently widely used as it is effective for the detection and characterization of focal liver lesions. The bolus tracker is used to determine the arrival of the bolus and it must be put in place carefully with recognition of the 3D structure of the aorta. This is a complicated process for the operator, and placement accuracy is highly dependent on the skill of the operator. Accordingly, this process is one of the most important factors affecting the workflow of dynamic study. To improve the workflow, an additional 3D scout scan is not required when incorporating the automated feature. The present study showed that the bolus tracker can be automatically positioned with a certain degree of accuracy and practical computation time using a typical three-plane localizer (2D scout scan) dataset.

METHOD: Fig. 1 shows the flow chart of our algorithm. We analyzed SSFSE (Single Shot Fast Spin Echo) 2D scout scan images because of the good robustness to inhomogeneity of the magnetic field, which means that it has fewer artifacts and the aorta can be identified easily due to its dark signal. The 2D scout images consisted of five to fourteen axial slices, one sagittal slice, and five coronal slices. The scan parameters were given as TR/TE: 1100/80 ms, Scan matrix: 320 × 192, Slice thickness: 8 mm, Slice spacing: 5 mm, NEX: 0.54, FOV: 400 × 400 mm or 480 × 480 mm. The total scan time was 24 s (14 axial slices). No intensity correction was applied and subjects did not hold their breaths during the scan. A reconstruction matrix of 512 × 512 was scaled down to 256 × 256 following 2D median filtering. In SSFSE images, the aorta sometimes has a bright signal dependent on the timing of heart rate, which can cause miss detection as the aorta is assumed to have dark signal. To eliminate such bright signals of the aorta, we increased the area of the slice crusher gradients at the both sides of 180° pulses to 4 times greater than normal. In our method, we look at the aortic location that is normally seated around the spine. Therefore, the aorta can be searched by judging whether a rotating sub-window of varying size centered around the spine does or does not contain the aorta. As the cerebral spinal fluid (CSF), which is located in the center of the spine, shows the bright image intensity on the SSFSE, the detection of CSF enables rotation of the sub-window as shown in Fig. 1. The extraction of body region by morphology processing helps to detect the CSF because it allows narrowing of the search range (central region of the body) of CSF. The machine learning method AdaBoost[1] was used for this CSF search as it allows specified recognition from various image datasets from thoracic to abdominal regions. The position of the CSF was determined from the position of sub-window (21 × 21 pixels) showing the maximum confidence on AdaBoost (6 Haar-like features, 100 weak classifiers) output acquired with movement of the sub-window around the central region of the body. Subsequently, the justification of the aorta inside the sub-window is pursued from the position of the rotating sub-window (24 × 13) showing the maximum confidence on edge orientation histograms (EOH) AdaBoost[2] (44 orientation histogram features, 106 weak classifiers). In the final step, the location of the detected aorta becomes the starting point (seed point) to find the center of the aorta. Furthermore, mean shift is applied to identify the center of the aorta to avoid the effects of local maxima in the AdaBoost output. According to these steps, the center of the aorta is determined in all of the axial slices. Consequently, the bolus tracker can be placed at the position aligned to these detected points the starting point for which is close to the upper edge of the liver detected by our previously proposed method.[3] Following institutional review and approval, our method was tested in a total of 123 healthy volunteers.

RESULTS: In CSF detection, 265 positive samples and 1060 negative samples from 53 volunteers were used for the learning step of AdaBoost. Aside from these learning datasets, 377 axial images were used for testing from 62 volunteers. The success rate of CSF detection was 98.1%. In aorta detection, 272 positive samples and 6528 negative samples from 59 volunteers were used for the learning step of AdaBoost. Aside from these learning datasets, 234 axial images from 64 volunteers were tested for the detection of the aorta. Failure occurred in 4 images, and the success rate was 98.3%. Table 1 shows the accuracy of the detected center position of the aorta, which was calculated compared to the manual results (ground truth). Fig. 2 shows an example of detection results in successive slices. Computational time was around 20 s to obtain 10 aorta positions by a laptop with Core i5 processor and 2GB RAM.

DISCUSSION: The images on which CSF detection failed showed the effect of above average noise, and CSF contrast was insufficient (not bright). In aorta detection, the root causes of the failure were: 1) CSF detection failure; 2) the shape of the aorta was collapsed vertically in contrast to our expectation from the training data; 3) the esophagus located on the right side of the aorta was detected; and 4) the intensity of the aorta was not dark. Although Table 1 does not show distinct specifications of the errors, an error of 1 pixel is allowable considering the actual setting of the bolus tracker.

CONCLUSION: We proposed a new method for automated bolus tracker positioning, and demonstrated that our algorithm was able to detect the position of the bolus tracker with high success rate and with practical computational time. Automated adjustment of the tracker size is the next target to be addressed. Both the automated positioning and size adjustment will help the operator and will decrease the total study time required for MRI liver scan.

REFERENCES

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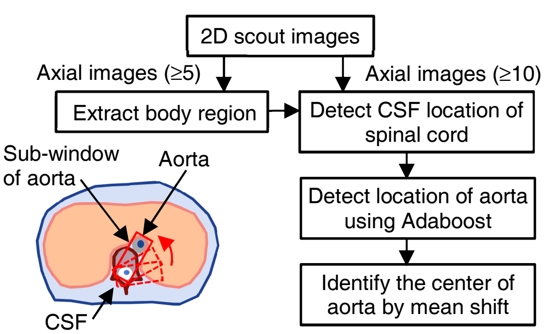

Fig. 1 Typical axial image illustration and flow chart of automated bolus tracker algorithm

Fig. 2 Results of aorta detection in successive slices

Table 1 Bolus tracker positioning error

Unit [pixel]

Location	Mean	SD	Absolute. Max.
R/L	–0.12	0.84	3.5
A/P	–0.13	0.93	4.0

R/L : Right and Left
A/P : Anterior and Posterior

1.875 [mm] / pixel in FOV 480 [mm]
1.563 [mm] / pixel in FOV 400 [mm]