Real-Time Tracking of Contrast Bolus Propagation in Continuously Moving Table MR Angiography

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Abstract. The recent introduction of variable-velocity control for Continuously Moving Table Magnetic Resonance Imaging has introduced the ability for interactive examination across extended fields of view. A common application of this method is contrast-enhanced angiography, where propagation of an intravenously injected contrast agent is tracked throughout the peripheral vascular tree. Whereas current methods for performing contrast bolus tracking are entirely manual, we discuss the complete automation of this process through the use of real-time image processing. Specifically, we provide a coupled intensity-correction procedure and modified Fast Marching method for rapid segmentation of contrast enhanced vasculature in CE-MRA and discuss the incorporation of this process into a framework for fully automated and adaptive control of table motion for real-time tracking of contrast bolus propagation through the lower peripheral vasculature.

1 Introduction

Contrast-enhanced MR Angiography in its present form was first proposed by Prince et al. [1] in 1993 and has since become a dominant modality in the diagnosis of vascular disease. One common application of CE-MRA is in the diagnosis of lower peripheral vascular disease (PDV), a condition where atherosclerotic build-up leads to tissue ischemia in the extremities. As the spatial extent of the lower peripheral vasculature significantly exceeds the maximal field-of-view (FOV) that can be imaged in a single acquisition by contemporary MRI systems, it is inevitably necessary to move the patient table during the examination to analyze the entire region of interest. Movement of the patient bed to allow full coverage of the extended FOV may be performed either during the intermission between stationary imaging at fixed stations or continuously during the image acquisition process. The main challenge faced in extended FOV imaging is providing optimal arterial phase acquisition with minimal venous contamination at all imaged positions [2].

The current standard clinical protocol for this type of exam uses the fixed-station approach, with stationary images being acquired under steady-state contrast concentration conditions [3]. Patient-specific flow information is not taken into account to yield optimal arterial-phase images and, resultantly, there is a propensity for venous contamination to occur in images acquired at inferior stations. Furthermore, the steady-state nature of images acquired under this paradigm cannot provide information about contrast dynamics for use in flow-based diagnostics.

Fig. 1. Outline of Automated Bolus Tracking System

The use of a continuously moving table (CMT) during image acquisition overcomes several of the shortcomings of the fixed-station approach to extended FOV imaging [4,5]. Under this formulation, a single image depicting the entire extended FOV is acquired progressively and displayed in real-time through the use of fast reconstruction hardware [6]. Consequently, the velocity of the patient bed can be interactively controlled by the scanner operator in response to variation of contrast bolus dynamics at different regions of the body. This ability guarantees optimized arterial phase acquisition at all positions within the extended field-of-view. While bolus flow information is not assessed quantitatively when using this method, the ability to track the leading edge of the contrast bolus inherently provides a framework under which such information can be measured.

We propose a novel paradigm for fully-automated tracking of contrast bolus propagation via real-time segmentation of the contrast-filled vasculature and discuss how this process may be embedded within the CMT CE-MRA framework to provide an optimal arterial-phase, patient-specific, and autonomous image acquisition procedure. In addition to reducing operator burden and associated potential error, the progressive assessment of contrast flow resulting from the segmentation process can potentially be used for diagnostic analysis of flow-related diseases such as diabetes.

2 Methods

The procedure for tracking the propagation of the contrast bolus can be divided into a series of distinct processes, as shown in Figure 1. We first discuss the initialization of the tracking procedure using an automated triggering process and then develop an intensity remapping technique which enhances vascular signal prior to segmentation. A modification to the well-known Fast Marching method for curve evolution is then presented for optimized segmentation of the contrast-enhanced vasculature under the CMT framework, and we address the process utilizing the segmentation results for adaptive control of table motion dynamics.

2.1 Initialization Via Automated Triggering

Initialization of bolus-chase CE-MRA studies of the lower peripheral vasculature typically occurs following observation of contrast influx into the thoracic aorta. It has been previously shown that these studies may be automatically triggered using

real-time image processing techniques for sequential detection and analysis of key physiological events that occur prior to aortic filling [7]. We employ this recognition process for automatic placement of an initial seed point for Fast Marching-based segmentation.

2.2 Background Suppression and Enhancement of the Bolus Leading Edge

In CE-MRA, signal can generally be assessed as belonging to one of two classes: that arising from intraluminal contrast agent presence and that originating from within the background. The transient nature of intravascular contrast concentrations at different positions within the visible FOV, however, leads to strong intensity variation within both signal classes and thus a global intensity-based discriminant cannot be defined. For example, moderate soft-tissue enhancement from interstitial contrast diffusion tends to occur adjacent to vascular regions that have already reached steady-state contrast concentration levels. Despite the elevated background signal intensity, high contrast concentrations within the vasculature still provide adequate distinction between the two signal classes although the dividing threshold will be high. Conversely, tissues surrounding transient-state intravascular contrast signal will not be enhanced and thus signal arising from these regions will be minimal. Notwithstanding low intraluminal signal, adequate distinction between the signal classes is still present albeit the dividing threshold is significantly lower than in the steady-state case.

As a single threshold is requisite for termination of any Fast Marching scheme, we perform an intensity remapping across the image such that the local thresholds dividing the signal classes, as determined by intravascular contrast concentration, are all mapped to a constant and predetermined value. In continuously moving table CE-MRA, both the direction of contrast flow and the direction of table motion lie predominantly along the superior-inferior (SI) direction. It can be inferred that intravascular contrast concentration and ultimately the intensity threshold dividing the signal classes will also be a function of SI position. A uniform threshold can be achieved by scaling all points associated with a particular SI position such that the class discriminant is equal to the desired threshold.

As intravascular contrast signal is sparse within an image, it is statistically more powerful to estimate the termination threshold as an upper bound on the background signal class. The use of standard moments as estimators of the background class parameterization, however, will create a positively biased model resultant from the inclusion of high intensity intravascular contrast signals and the derived upper bound will lie significantly higher than that of the background class. Attempts to normalize the background across the image will result in equalization of contrast signal and background signal on lines containing no contrast presence. Resultantly, curve propagation will not be terminated prior to exiting the vascular region. The adverse effects associated with positive bias introduced from intravascular signal when using standard statistical moments can be avoided by means of robust estimators which are immune to outlier influence. A Gaussian model can be utilized as an asymptotic

Fig. 2. CE-MRA image before (a) and after (b) intensity correction

upper bound to the Rician density [8] that governs noise in magnitude MR images. The mean and variance of the background signal class for an image I , taken as a function of SI position, y , can be estimated as

$$\begin{aligned}\mu(y) &\approx \underset{\forall x, y' \in [y-\delta, y+\delta]}{\text{median}} (I(x, y')) \\ \sigma^2(y) &\approx \left[\frac{\underset{\forall x, y' \in [y-\delta, y+\delta]}{\text{MAD}} (I(x, y'))}{\Phi^{-1}\left(\frac{3}{4}\right)} \right]^2,\end{aligned}\quad (1)$$

where MAD is the median absolute deviation operator and Φ^{-1} is the quantile function. Non-zero parameterization of the variable δ allows the estimation process to be performed over a local window surrounding the SI position of interest, offering increased invariance to contrast-based signal and thus an improved measure of the background noise process. The value $\Phi^{-1}(3/4)$ arises as the expected value of $\text{median}(|Z|)$ for a random variable $Z \sim N(0,1)$, and its use as a scaling factor in (1) forces the MAD operator to be an unbiased estimator of the standard deviation [9]. Using the estimates in (1), an image can then be mapped via

$$I'(x, y) = \begin{cases} \frac{I(x, y) - \mu(y)}{\sigma(y)} & I(x, y) \geq \mu(y), \\ 0 & \text{else} \end{cases}, \quad (2)$$

and the uniform termination threshold for the Fast Marching scheme will be the z -score associated with the desired confidence of background signal containment, e.g. $z = 1.65$ will provide a bound which lies above 95% of the background signal class. As the upper bound on the background signal will always be above the mean of the class for a given SI position, any signal below that value can be neglected and set to zero with no effect on the curve evolution process. This action preserves the non-negativity property of the speed function when it is defined in terms of the intensity map. An example of the mapping results described in (2) can be seen in Figure 2.

2.3 Real-Time Vessel Segmentation Using a Modified Fast Marching Method

The Fast Marching method [10,11] is a non-iterative upwind technique for solving the Eikonal equation

$$|\nabla T|F = 1, \quad (3)$$

where T is the arrival time function and F is a strictly non-negative speed function. Whereas F is generally defined as a function of the image gradient and (3) is subsequently minimized, the dispersive nature of the contrast bolus at the leading edge does not provide an adequate boundary to restrict the evolution of the front to only within the vasculature and thus this approach is not valid for our particular application. Following the remapping procedure discussed in the previous section, we have a bimodal intensity distribution with a known discriminant threshold. We address the problem associated with gradient-based control of the Fast Marching curve evolution process by defining our speed function, F , to be a function of remapped image intensity, specifically

$$F = G * I', \quad (4)$$

where G is a smoothing kernel, and we instead maximize the relation in (3). Under this formulation, curve evolution will be driven towards image regions containing maximal contrast presence. The uniform termination threshold for I' will allow curve propagation into transient contrast concentration states such as the leading edge of the bolus but will restrict entrance into the non-vascular background despite elevated intensity due to soft-tissue enhancement. Following segmentation, determination of the leading edge of the bolus becomes a trivial task.

While implementation of the Fast Marching segmentation process using a traditional gradient-based speed term is traditionally performed using a min-heap storage structure for minimization of (3), as we are instead maximizing the Eikonal equation in our implementation, optimal execution of our segmentation process can be achieved through use of a max-heap storage structure. Additionally, we can further optimize the segmentation process for real-time implementation by embedding the smoothing process directly into the curve evolution procedure. In applications involving evolutionary modeling of a growing object across a series of temporally-varying frames, the inter-frame variability in conformation of the front tends to be minimal and locally restricted relative to the preceding bounds. Despite these observations, subsequent frames are typically filtered globally and many of the smoothed points are never utilized. Prior to insertion of an image point onto the heap structure representing the segmentation curve, a single-element convolution can be executed. By restricting the domain of convolved pixels to consist of only points with which the front interacts during its evolution, the computational complexity of the smoothing process is inherently reduced from $O(N^2)$ to $O(1)$ while yielding the same effective results as if global smoothing had been performed.

2.4 Control of Table Motion Dynamics

As the velocity of blood and consequentially the contrast bolus varies significantly between different vascular regions, the speed of table motion must also vary if the

bolus leading edge is to be kept within the visible field of view at all times. Knowledge of the current and past bolus leading edge positions can be used as the basis for feedback control of table motion such that the predicted future position of the bolus leading edge will reside within the visible field of view. Implementation of such a control system is under way and will be discussed in a later work.

2.5 Inter-frame Curve Evolution

Between subsequent image frames, the magnitude of the positional change of the leading edge of the bolus will far exceed that due to local variations arising from pulsatility. Consequentially, contrast propagation will be monotonically outward and thus any prior segmentation boundary can be used as the initial segmentation boundary within a newly acquired frame. When using the boundary from the frame acquired immediately before the newly acquired image, expansion of the curve is limited to regions where contrast presence is new to the scene, as all steady-state regions will have been previously segmented. The effect of this inter-frame propagation approach is that, for any newly acquired image, segmentation of the vasculature can be achieved in the minimal possible number of operations for that particular frame.

Prior to allowance of a past segmentation boundary as the initial condition to the segmentation procedure for a newly acquired image frame, the boundary must first be updated to account for change of the visible field of view as well as changes in the intensity values associated with a particular spatial position. A shift in the visible field of view results from table motion that occurs during the bolus tracking procedure, and all boundary elements which have exited the scene must be removed as they are no longer valid for further evolution. The physical shift between sequential image frames can be obtained directly from the imaging system, and thus pruning becomes essentially trivial. Changes in image intensity between frames for a given spatial position arise from flow of the contrast into new vascular regions. All remaining boundary points visible within the new scene are placed onto a new heap structure and segmentation resumes. As the heap sort procedure is $O(M\log N)$, the boundary reformation process can be achieved quickly.

3 Experimentation and Results

All images used in experimentation were acquired on a General Electric Signal 1.5T MRI system using a time-resolved gradient echo (GRE) pulse sequence [12] and reconstructed using the continuously moving table methods described by Kruger et al. [4,5]. Images were typically acquired with the dimensions ($X = Y = 128$, $Z = 8$) and the prescribed visible fields of view were ($FOV_X = FOV_Y = 30\text{--}40\text{cm}$, $FOV_Z = 10\text{cm}$; under coronal orientation, X corresponds to the Superior/Inferior axis, Y corresponds to the Medial/Lateral axis, and Z corresponds to the Anterior/Posterior axis. The temporal resolution of image acquisition was 0.6s per frame. Following volume acquisition, a maximum intensity projection (MIP) was computed along the Z direction to produce the 2D images used in all processing methods described in this paper. Real-time processing of image data was performed using the Java programming platform on a 3GHz Pentium 4 PC containing 1GB RAM. The average processing time

Fig. 3. Tracking of contrast bolus propagation across the lower peripheral vasculature in a sample data set

per frame was approximately 25 ms and thus automatic table control is fully realizable within the real-time acquisition framework.

The automated bolus tracking method has been initially tested on six clinical extended field of view studies acquired under constant table motion (3-4 cm/s); extension to variable velocity testing will follow completion of the control system discussed in section 2.4. Figure 3 shows a sample series of images from one exam along with the associated segmentation produced by our algorithm. As is evident in the depicted example, the tracking results clearly correlate with the visible leading edge of the contrast bolus at all spatial positions within the extended field of view and the other five tested cases gave similar results.

4 Conclusion

We have presented a framework for autonomous tracking of contrast bolus propagation across and extended FOV using real-time CE-MRA. Through the incorporation

of real-time image processing techniques into the acquisition framework, optimal arterial phase images can be acquired, operator burden can be significantly alleviated, and both anatomical and physiological flow information are simultaneously measured. Potential future applications include the mapping of contrast bolus velocities onto the anatomical map of the vasculature tree produced by the segmentation process for use in detection of turbulent flow, the latter which has been linked to the formation of atherogenic plaques [13]. Other similar applications are also possible.

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