Assessing the Effects of Vessel Segmentation Boundary Size on Flow Quantification Error and Comparing Multiple Automatic Segmentation Algorithms

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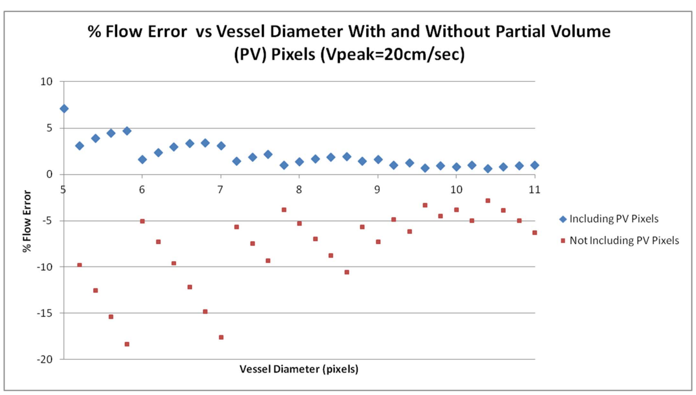
Purpose: To study the effects of vessel segmentation boundary size on flow quantification in PC-MRI through error analysis and compare the accuracy of multiple automatic segmentation algorithms developed within our in-house SPIN image processing software using simulated data.

Introduction: Segmentation of the vessel lumen is an important factor in obtaining an accurate measure of blood flow from velocity encoded PC-MRI data. Manual segmentation is time consuming and, being observer-dependent, can lead to significant variations of area measurement [1], which is used to calculate flow. Various image-processing algorithms for automatic or semi-automatic segmentation have been proposed and tested [2-4]; however, a theoretical analysis of the dependence of flow error on boundary size has yet to be used in determining how well an algorithm performed.

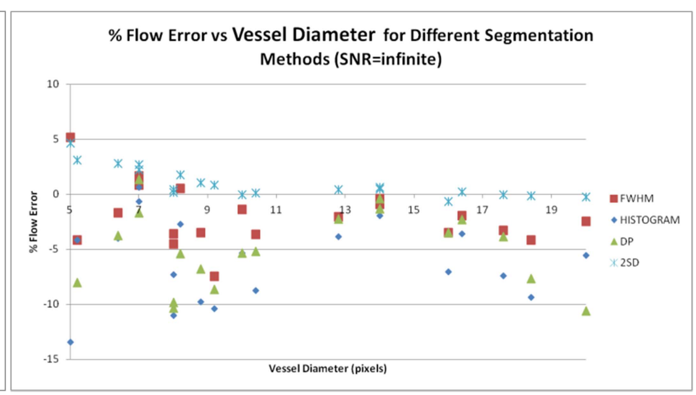
Theory: A vessel boundary created by any method can fall into three major categories: oversized, where the boundary includes at least every single pixel that contains any amount vessel; undersized, where the boundary would only include pixels that contain just vessel; and midsized, where the boundary will contain some, but not all, pixels that contain only part vessel. Taking into account theoretical flow error from partial volume effects, non-included vessel voxels, and noise [5], a mathematical analysis was performed which concluded that an oversized boundary, affected by partial volume error, will quantify flow more accurately than an undersized boundary, affected by missing vessel pixels (see Figure 1-Plot A). This will hold true as long as the oversized boundary is not so big that the noise within it from non-vessel pixels outweighs the information from the vessel pixels. This condition would require the boundary diameter to be roughly 65% larger than the vessel (assuming no additional background phase exists) which would be an obvious failure for any segmentation algorithm.

Methods: Magnitude and phase simulations were created that mimic human velocity encoded PC-MRI data as a function of the cardiac cycle for both arteries and veins. Ten vessels were included with varying sizes and blood velocity profiles, assuming laminar flow. Three different resolutions were used (256^2, 512^2, and 1024^2) which provided vessel sizes ranging from 2 to 33 pixels in diameter. Four different levels of noise were added to each of these which gave vessel SNR values of infinite, 20, 15, and 10:1 (giving a total of twelve simulations). The magnitude simulations took into account that the signal from blood will decrease as its velocity decreases below a certain threshold (6cm/sec). A venc value of 50cm/sec was used to calculate phase values from velocity. Four different segmentation algorithms were tested. Three of them use a threshold region growing technique, each one differing in how the threshold value was calculated (full width half maximum (FWHM), histogram [6], and 2-standard deviation (2SD)), and dynamic programming (DP) [7]. The 2SD threshold method is a variation of the histogram method that uses a 2SD cut-off rather than the use of a cost function. The algorithms were applied separately to the first time point of each simulation and copied to the rest of the time points. Since the total number of vessel pixels (including partial volume pixels), simulated vessel sizes, and velocity profiles are known, the percentage of vessel pixels captured by each method was calculated along with the flow quantification error.

Results: With no noise present, the 2SD threshold method never came out undersized and provided flow error less than 5% for all vessel diameters above 5 pixels, and less than 2% for vessel diameters above 7 pixels. The three other methods often resulted in undersized boundaries, creating errors up to almost 15% for vessel diameters of up to 20 pixels (see Figure 1-Plot B). At an SNR below 20:1, the 2SD method began to create undersized boundaries, though it still resulted in less than 10% error for a vessel diameter greater than 4 pixels. The performance of the other three methods continued to decline as more noise was added.



Plot A



Plot B

Figure 1: Plot A compares the flow error resulting from a boundary that includes every pixel that contains vessel (the smallest possible oversized boundary) with one that only includes pixels that contain just vessel (the largest possible undersized boundary). The jumps in error seen are caused by the sudden inclusion of pixels as the vessel diameter grows. Plot B shows the error resulting from the four different segmentation methods for the no noise simulations.

Conclusion: Automatic threshold region growing based vessel segmentation is a fast and accurate way to quantify the blood flow of arteries and veins. It was found that the 2SD region growing algorithm performed the best in both capturing a higher percentage of vessel pixels and achieving lower flow error in all simulations. This result supports the theory discussed earlier in this abstract. The theory also concluded that flow error from noise alone is inversely proportional to SNR and vessel diameter. Noise played a bigger role in increasing flow error by degrading the performance of the segmentation algorithms. Another important factor in how well these segmentation algorithms performed was the peak velocity of the blood at the time point they were applied. A high enough peak velocity would ensure that the velocities at the edge of the vessel are above the threshold velocity and thus will provide maximum signal. For a peak velocity under this threshold, it would be expected that these algorithms would perform worse. An additional general guideline that can be taken from this study is to avoid drawing an undersized boundary when using manual segmentation.

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