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Blood vessel segmentation in magnetic resonance angiography imagery

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ABSTRACT

Small blood vessels may be difficult to detect in magnetic resonance angiography due to the lack of blood flow caused by disease or injury. Our method, which uses a block-matching denoising approach to segment blood vessels, works well in the presence of noise. We examined extended regions of an image to determine whether they contained blood vessels by fitting a Gaussian mixture model to a region's histogram. Then, dissimilar regions were denoised separately. This approach was beneficial in low-contrast settings. It can be used to detect higher-order blood vessels that may be difficult to detect under normal conditions.

Keywords: block-matching, denoising, magnetic resonance angiography, region growing, segmentation, vascular

1 INTRODUCTION

Magnetic Resonance Angiography (MRA) is a non-invasive method that does not expose a patient to ionizing radiation. It is an imaging method based on Magnetic Resonance Imaging (MRI) and is frequently used to image blood vessels. Often, 3-D data representing a volume of the body is acquired and displayed in 2-D. Reduced flow in blood vessels due to blood clots or abnormal vascular anatomy can be detected and evaluated using MRA. These blood vessels can be thought of like branches of a tree where smaller blood vessels split off from larger ones. Consequently, the smaller size of these blood vessels reduces blood flow to them. If disease is present or an injury has occurred, blood flow can be further reduced. Identifying these small blood vessels is important for further treatment. Since the brightness of a blood vessel is proportional to blood flow, important regions of an MRA may be difficult to detect. A method is needed to reliably extract regions with impaired blood flow so treatment can be determined.

There have been many approaches to vascular segmentation including those based on skeletonization, multiscale analysis, and region growing to name a few.[1] For example, one technique uses an ordered region growing method that represents an image as an acyclic graph and is not heavily dependent on seed location.[2] At any given iteration, growth occurs from the point on the boundary of the growth region with the highest intensity. Eventually, the skeleton of a blood vessel can be produced by specifying endpoints or by a pruning process. Another approach is a fast level-set method that doesn't have some of the limitations of active contour and other methods.[3] In this approach, a level-set framework using a watershed algorithm was used to reduce the computational burden.

Advances in edge-detection have also contributed to vascular segmentation. For example, a weighted local variance method has been introduced that is robust against changes in intensity along edges and useful for low-contrast edges.[4] The approach quantifies intensity similarity on both sides of an edge. It returns edge strength and the edge normal direction which leads to the segmentation of blood vessels. To further address low-contrast edges and noise in vascular segmentation, the combination of spline wavelets and the local standard deviation was used in this approach.[5] It builds on wavelet edge-detection methods by smoothing out the intensity inhomogeneities that are present.

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Segmentation of low-contrast blood vessels is critical for diagnosis. When blood vessels are difficult to identify, then their boundaries may also be difficult to identify. Even in low-noise images, low-contrast edges may have noise present that inhibits reliable detection. Therefore, our approach to segment blood vessels is based on a denoising method. We examined extended regions of an image and determined whether they contained blood vessels by fitting a Gaussian mixture model to a region's histogram. Then, dissimilar regions were denoised separately. Finally, regions were combined and blood vessels extracted.

2 SEGMENTATION USING DENOISING

We used denoising as the primary method to segment blood vessels. When blood vessels have a large contrast from their background, a number of methods can be used for segmentation. When the contrast is small, segmentation is more challenging. Even when noise is not appreciable, the uncertainty of a vessel boundary can be thought of as corrupted by noise. Therefore, we considered a denoising method to enhance an image before segmentation.

A block-matching 3-D (BM3D) approach has been developed for additive white noise and is one of the best performing algorithms to date for denoising.[6] We used this approach in our work here by applying the method to different regions of an image. Although the noise is not typically Gaussian in MRA imagery, we grouped regions with similar contrasts and processed them separately. In effect, different regions were considered to contain white noise, but of a different variance for each region. The BM3D approach relies on both local and non-local characteristics of an image by initially grouping similar small blocks of an image. Then, the blocks are stacked to form a 3-D array. This process is repeated so that every portion of the image has been matched. Then, a 3-D transform, such as a wavelet or PCA, is performed on each block independently. Since the data is highly correlated in one dimension, the transform of the data is sparse and denoising methods provide an effective way to remove noise. After the data has been denoised in the transform domain, it is reconstructed, and the denoised image blocks are returned to their original locations. The most important parameter in the BM3D algorithm is the value of the noise variance because it affects the amount of denoising. Because the approach assumes white noise, a constant value of the variance for all arrays is typically used, independent of the data. Such an assumption cannot always be used for medical images because the noise is typically data dependent.

In our approach, we separated an image into regions with similar contrasts. That allowed blood vessels to be extracted more easily than when a wide range of contrasts were present. Because the contrast in an MRA image can change rapidly, the regions tended to stay small. However, by grouping larger regions the potential for noise reduction increases because of the increase in the size of the 3-D stacks in the BM3D approach. To determine if a region contained a blood vessel with a somewhat constant value of contrast, we first arbitrarily chose a region and denoised it. Then, we fit two Gaussian distributions to the histogram of the denosied region. Based on the mean and variance of the distributions, we decided if a blood vessel was present or if a region consisted mainly of the background of the image. If the difference of the means was relatively large and the variances were similar, then we concluded that a blood vessel was present. Otherwise, we said the region consisted only of the background.

After segmenting the image according to contrast, we combined regions in such a way as to make segmentation of blood vessels more favorable. For example, if two adjacent background regions were found, then the corresponding regions of the original images were combined. Then, this new region was denoised. If two adjacent regions of the original image were both determined to contain blood vessels and their contrasts were similar, then these region were combined. The new region was then denoised. If two adjacent regions were found to contain a blood vessel and only background, then they were also combined. In this way, small regions were grown to form larger regions with similar contrasts. This process was repeated until the regions did not change.

After the region growing process was complete, the regions were denoised separately. In the BM3D approach, the value of the noise variance has the largest impact on the results. The noise in the MRA data could be considered somewhat constant if the background region was much larger than the blood vessel region. However, because of the range of contrasts, important features could be eliminated when denoising high-contrast and low-contrast regions by the same amount. For example, the contrast of blood vessels with high-contrast would be increased if the noise was removed. The same is the case for low-contrast blood vessels; however, often low-contrast regions could be eliminated. Therefore, we adjusted the amount of denoising through the value of the noise variance. In short, the lower the contrast the smaller the value of the variance.

After growing regions and denoising them, we thresholded the resulting image to create a mask. Then, the product of the mask and the original image was formed to segment the blood vessels. The entire procedure is shown in Fig. 1. In addition, we modeled noise with a Rician distribution because it has been found that this type of noise is present in MRI imagery.[7] Rician noise can be modeled with two statistically independent normal random variables in the complex domain.[8] Two images are formed from $I_r(\mathbf{x}) = I_0(\mathbf{x}) + n_r(\mathbf{x})$, and $I_i(\mathbf{x}) = n_i(\mathbf{x})$, where $I_0(\mathbf{x})$ is the noise-free image and both $n_r(\mathbf{x})$ and $n_i(\mathbf{x})$ are Gaussian distributed with zero mean and standard deviation σ. The noisy image was formed from

$$I(\mathbf{x}) = \sqrt{I_r(\mathbf{x})^2 + I_i(\mathbf{x})^2}\ . \tag{1}$$

3 RESULTS

We compared our approach to that of the conventional BM3D approach using a 2-D MRA image corrupted with different values of Rician noise. Fig. 2(a) shows a section of an MRA image with a blood vessel present and Rician noise with $\sigma = 2$ according to Eq. 1. In the lower part of the image there are regions where the contrast of the blood vessel is low and there could be damage present. Fig. 2(b) shows the result of denoising the image in part (a) using the BM3D approach. The denoising does an excellent job of removing the noise, but when the blood vessel is segmented, errors result as shown in Fig. 2(c). Fig. 2(d) shows the result of segmentation using our approach with one iteration. Even though parameters have not been optimized, the results appear to be improved when compared to Fig. 2(c).

The image in Fig. 2(a) with increased noise $\sigma = 5$ is shown in Fig. 3(a). The BM3D approach simply cannot recover the blood vessel in the low-contrast regions as shown in Fig. 3(b). However, our method can extract almost the entire vessel as shown in Fig. 3(c). Fig. 4(a) shows appreciable noise of $\sigma = 10$. Although not fully segmented, our approach segments more of the blood vessel as shown in Fig. 4(c) when compared to using the BM3D approach in Fig. 4(b).

4 CONCLUSION

We described a segmentation method for blood vessels in MRA imagery that was based on denoising. By using a region growing method based on contrast and a BM3D approach, we were able to achieve improved results when compared to using the BM3D approach alone. In low contrast regions the amount of denoising was decreased so that important features were not eliminated. Parameters of our approach such as the region size and number of iterations had not been optimized. Therefore, we expect improved results with further work.

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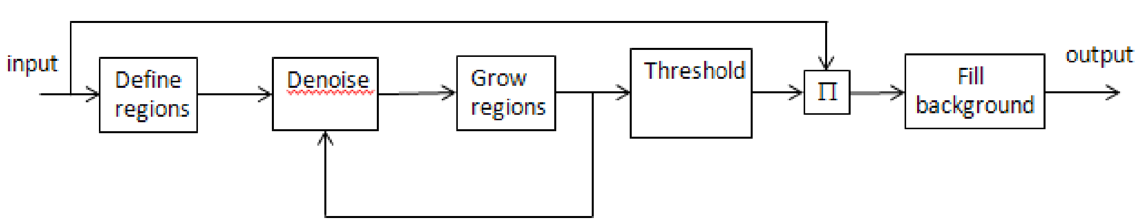
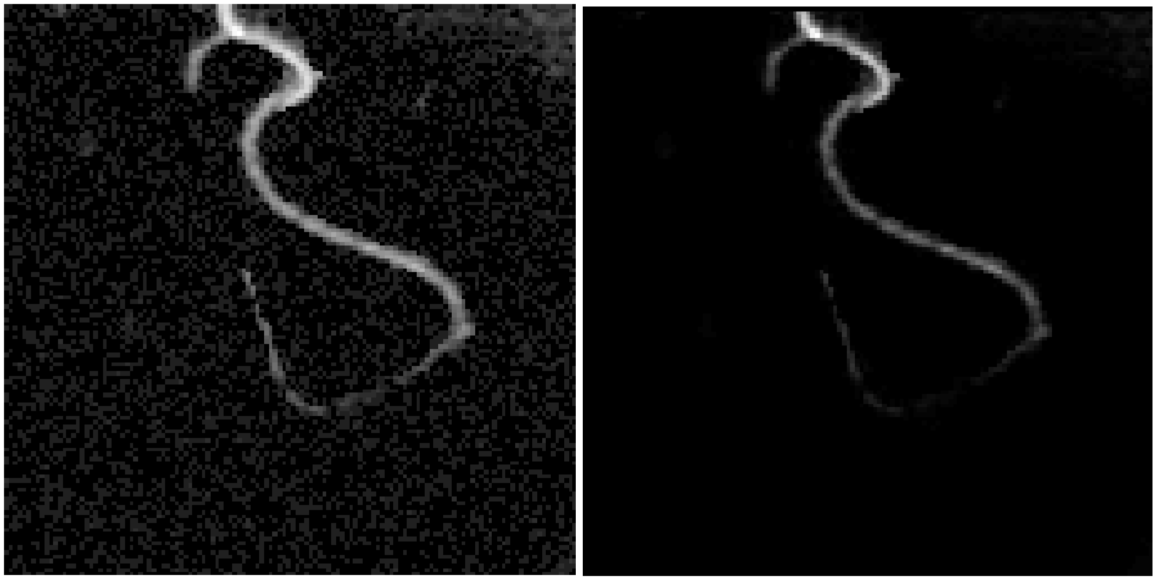
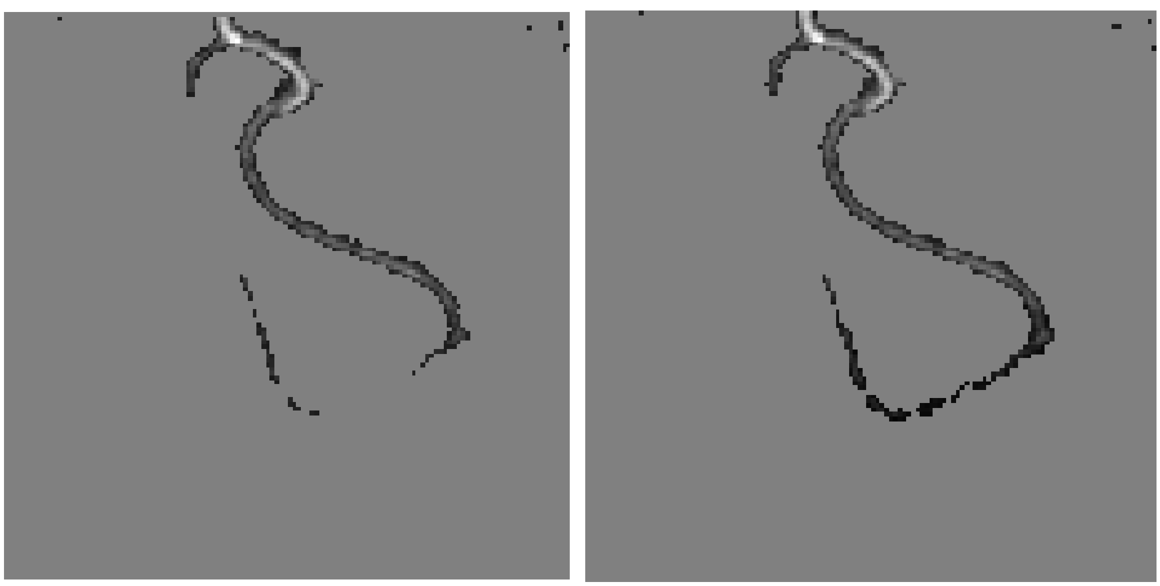


Figure 1 Block diagram of approach.



(a) noisy image (b) denoised with BM3D method



(c) segmented using BM3D denoising (d) segmented using our approach

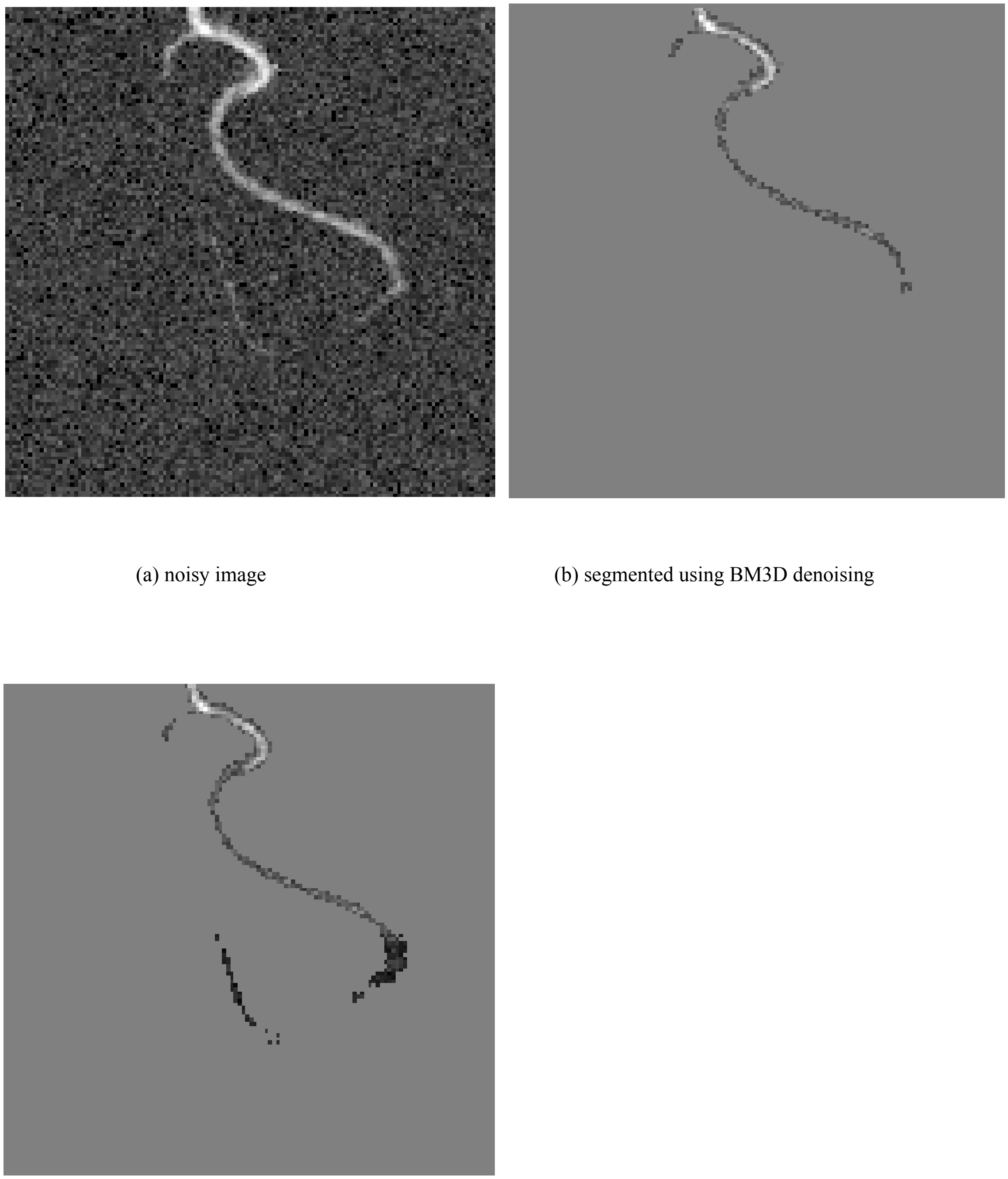
Figure 2 Image of blood vessel with Rican noise with $\sigma = 2$.

(a) noisy image

(b) segmented using BM3D denoising

(c) segmented using our approach

Figure 3 Image of blood vessel with Rican noise with $\sigma = 5$.



(a) noisy image

(b) segmented using BM3D denoising

(c) segmented using our approach

Figure 4 Image of blood vessel with Rican noise with $\sigma = 10$.