Cerebrovascular Segmentation Based on Edge Preserving Filters Technique in Magnetic Resonance Angiography Images: A Systematic Review

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Abstract

Magnetic resonance angiography (MRA) is an emerging magnetic resonance imaging method for the detection and diagnosis of cerebrovascular diseases including cerebral small vessel disease (CSVD). However, the challenges to extract cerebrovascular structures are recognised, especially from the time-of flight MRA (TOF-MRA) images due to the intricate vascular structures and inherent noise. This paper presents a comprehensive review on image processing pipeline which have been successfully applied on CSVD images such as Computed Tomography (CT) scan, Computed Tomography Angiography (CTA), Digital Subtraction Angiography (DSA), Magnetic Resonance Angiography (MRA), and Magnetic Resonance Imaging (MRI), review on various denoising filters in CSVD images such as Nonlocal Mean (NLM) filter, Multiscale filter, Anisotropic Diffusion filter (ADF), Bilateral filter (BF), Smoothing filter, 3D Steerable filter, Moving Average filter, Trilateral filter, Wiener filter, Blockmatching and 3D filtering (BM3D), Non-linear quasi-Newton method (L-BFGS), and Histogram Equalization (HE). This review also features edge preserving filter (EPF) techniques to reduce noises while preserving the edges from TOF-MRA images including ADF, BF, NMF, Mean Shift filter (MSF), and Sigma filter (SF).

Keywords: Cerebrovascular Segmentation, Time-of-flight Magnetic Resonance Angiography, Signal-to-noise Ratio, Vessel Enhancement, Cerebral Small Vessel Disease.

1. INTRODUCTION

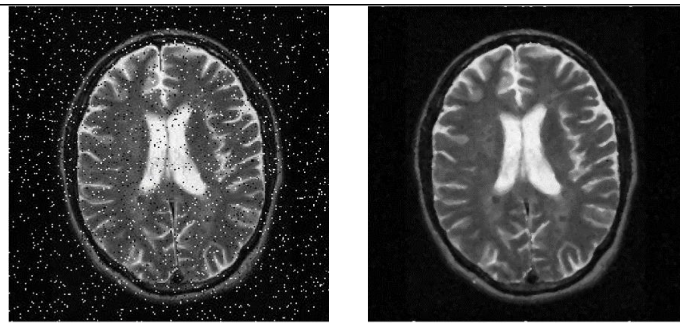
A sample of cerebral image as depicted in Figure 1 captured by using one of the imaging modalities, Magnetic Resonance Angiography (MRA), looks specifically at the blood vessels and help identify the abnormalities, if any. Abnormalities such as aneurysms, arteriovenous malformation (AVM) and atherosclerotic (plaque) disease are an example of Cerebral Small Vessel Disease (CSVD); pathological processes that affect the structure or function of small vessels on the surface and within the brain, including arteries, arterioles, capillaries, venules, and veins (Pantoni, 2010; Che Mohd Nassir et al., 2021). CSVD causes up to 45% of dementia and accounts for about 20% of all strokes worldwide, 25% of ischaemic (or lacunar strokes), of whom about 20% are left disabled (Pantoni & Gorelick, 2014). Cognitive impairment, depression and gait problems are also frequently seen in patients with CSVD (Shi & Wardlaw, 2016). Therefore, the diagnosis of these CSVD highly relies on the use of MRA which can demonstrate on vascular involvement of neurovascular imaging (Che Mohd Nassir et al., 2021). However, commonly in every clinical imaging, they have their downside visage that noise introduced attributable to the consequence of the coherent nature of the wave transmitted. Figure 1 shows the MRA image with blood vessels (in bright white colour), backdrop is the background while there are some small spots / dots (in white-to-grey colour) indicating noises inside this MRA image. Noise in MR images is uncorrelated, white colour (Aldroubi, 2017).

FIGURE 1: An example of cerebral MRA image and its component.

The MRA images are corrupted by the noise and lesions (Hibet-Allah et al., 2017). Noise is an inherent property of medical imaging, and it generally tends to reduce the image resolution and contrast. There are various types of noise models such as salt and pepper noise, speckle noise, Gaussian noise, Rician noise etc. Salt and pepper noise or also known as impulsive noise is the most frequently occurring noise in images (Fu et al., 2018; Liang et al., 2021). This noise in the image is shown by the white and black pixels and if the image is contaminated with impulsive noise, in the darker areas in the image will appear white pixels and on the lighter areas black pixels will be shown. Median filter has shown its robustness in supressing this type of noise (Zubair & Busari 2018). Speckle noise is a kind of a granular noise that degrades fine details such as edges and contrast resolution, resulting from constructive and destructive interference of the temporal coherent sound waves in the system (Jaybhay & Shastri, 2015, Ren et al., 2019). Speckle noise is one of noise commonly found in ultrasound images (Shruthi et al., 2015). Gaussian noise is a typical representative of the amplifier noise. This noise is independent on each pixel and each signal intensity. For example, the blue channels can contain larger amplitude than the red and green channels, which means that the blue channels can have more noises (MacDonald, 2006). Computed Tomography (CT) images are prone to Gaussian noise due to the electrical signals appear (Goyal et al., 2018). Rician noise refer to the error between the underlying image intensities and the observed data. Rician noise is not zero-mean, and the mean depends on the local intensity in the image (Tan, 2012). Rician noise is the dominant noises in MRI (Selvathi et al., 2012).

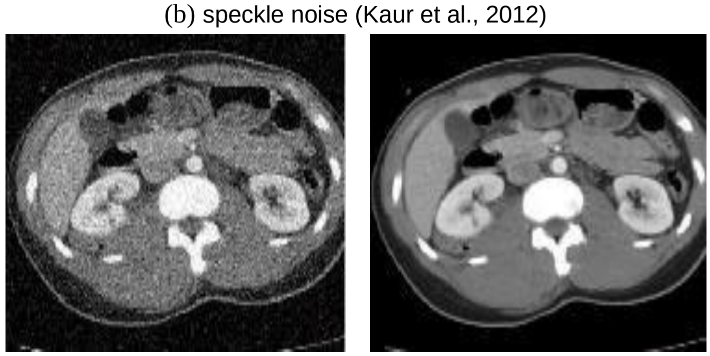
Figure 2 shows the sample of images before and after filtration on different type of noises. In MRA images, the type of noise varies, where most of them contain Rician noise (Chang et al., 2011; Jayabal & Damodaran, 2015; Ajam et al., 2016). While in practical MRA data noise is usually Gaussian (Sun & Parker, 1999; Zhang et al., 2020) because it is produced by the random motion of innumerable particles in electronic devices. Impulses noise also found in MRA images (Chen & Hale, 1995). Noises in MR images primarily are Rician noise, Gaussian Noise and Rayleigh noise (Goyal et al., 2018). However, Rician distribution tends to a Rayleigh distribution in low intensity (dark) regions of the magnitude image; while in high intensity (bright) regions, it converges to a Gaussian distribution (Nowak, 1999; Hartmann, 2005). Noises pose significant challenges to the extraction of blood vessels. High intensity noise may be classified as blood vessels. Some vessels especially the small vessels are quite nebulous to be observed, while some part of small vessels might be missing too. The MRA images have often low contrast that cause to barely detect the blood vessels especially the small ones and the noise which came from the acquisition process. Hence, pre-processing steps like noise reduction and vessel enhancement are necessary on handling such noises in MRA images to provide a better extraction of cerebral vessels (Liang et al., 2021).

(left) image with noise (right) filtered image

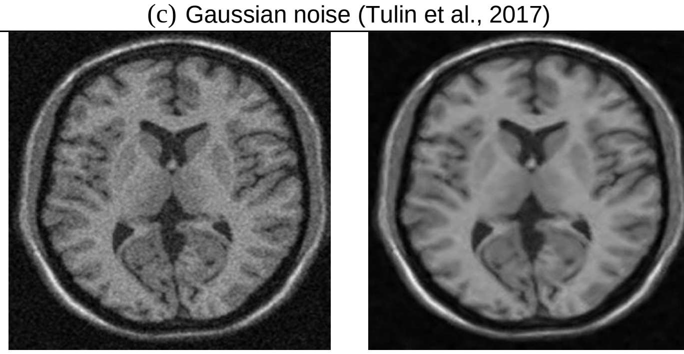


(a) salt and pepper noise (Flores, 2019)

(b) speckle noise (Kaur et al., 2012)



(c) Gaussian noise (Tulin et al., 2017)



(d) Rician noise (Hu et al., 2012)

FIGURE 2: Type of noises.

2. LITERATURE REVIEW

Several imaging modalities has been introduced, yet angiography is the most suitable method for the visualization of abnormalities in blood vessels, whether it is performed using X-ray, CT, or MRI. Angiography or arteriography is a medical imaging technique used to visualize the inside, or lumen, of blood vessels and organs of the body, with particular interest in the arteries, veins, and the heart chambers (Uemori et al., 2014). The images are captured after a contrast agent has been injected into the blood vessels. Each modality has its own characteristics as described in Table 1. It is important to choose a suitable modality, as otherwise the reconstruction or modelling process may be problematical owing to a lack of information.

Modalities/ Characteristics	**X-ray Angiography (XA)**	**Computed Tomography Angiography (CTA)**	**Magnetic Resonance Angiography (MRA)**
Spatial resolution	Highest	High	High
Contrast	Low	High	High
Acquisition time	Fast	Faster	Long acquisition time
Acquisition cost	Low cost	Intermediate cost	Intermediate cost
Application	Anatomical	Anatomical functional	Anatomical functional
Projection	2D	2D and 3D	2D and 3D
Advantage	Fast and easy method of imaging	Provides information about collateral circulation and improves contrast	Relies on magnetic properties of body moreover, blood in eternal magnetic field
Drawback	Superposition of structures creates difficulties for interpretation, it cannot pass through bone	High contrast agent dose per examination	Strong magnetic field may disturb implants

TABLE 1: Comparison between imaging modalities.

MR angiography is a type of MRI that looks specifically at the body blood vessels (Story, 2016). MRA has important attributes that make it valuable in assessing a wide spectrum of vascular diseases (Rosamond et al., 2007; Carr & Carroll, 2011). Compared to radiographic catheter-based angiography, it is non-invasive with no risk of neurologic deficit, circulatory compromise due to vascular injury or adverse effects of iodinated contrast material. With recent improvement in hardware and software techniques, MRA has undergone significant changes in technique and approach (Hartung et al., 2011). Recent advances in MR technology resulting from fast gradients and use of contrast agents have allowed MRA to make substantial advances in many arterial beds of clinical interest (Gupta, 2013). As a result, MRA has been successful in studying many arteries in the body including brain and other vessels in the neck (Bullitt et al., 2003; Chung et al., 2004; Hao et al., 2007; El-Baz et al., 2009; Liao et al., 2011; El-Baz et al., 2012; Kandil et al., 2018).

However, commonly in every clinical imaging, they have their downside visage that noise introduced attributable to the consequence of the coherent nature of the wave transmitted. The MRA images are corrupted by the noise and lesions (Hibet-Allah et al., 2017). Image noise is an unavoidable side-effect occurring because of image capture, more simply understood as inaudible, yet inevitable fluctuations. The quality of the images produced by imaging modalities is affected by local intensity abnormalities and background noise. These noises may corrupt the image and sometimes cause incorrect designation. Besides that, some vessels especially the small vessels are quite nebulous to be observed. Therefore, pre-processing steps like noise reduction and vessel enhancement are necessary on medical images. The next section describes the steps in blood vessels segmentation, types of filtering methods and elaboration in more details regarding the related work of denoising filters on CSVD images.

2.1 Application of Denoising Techniques on CSVD Images

Segmentation of blood vessels usually undergo several processes in pre-processing including noise reduction and vessels enhancement as described in Figure 3 below. Pre-processing is always known as desirable prerequisite to accurate cerebrovascular segmentation, thus makes it the most crucial steps to provide meaningful information about the geometry, position, and topological structure of vessels (Ajam et al., 2017). Noise reduction or also known as denoising filter is a process of removing noise in the image which involves several filtering techniques. Generally, there are two types of noise reduction approaches which are linear filtering, the classical filtering method and nonlinear filtering. Linear filters are used to remove certain types of noise. These filters remove noise by convolving the original image with a mask that represents a low-pass filter or smoothing operation. The output of a linear operation due to the sum of two inputs is the same as performing the operation on the inputs individually and then summing the results. However, these filters tend to blur the sharp edges, destroy the lines and other fine details of the image (Rani, 2013). Linear methods are fast, but they do not preserve the details of the image.

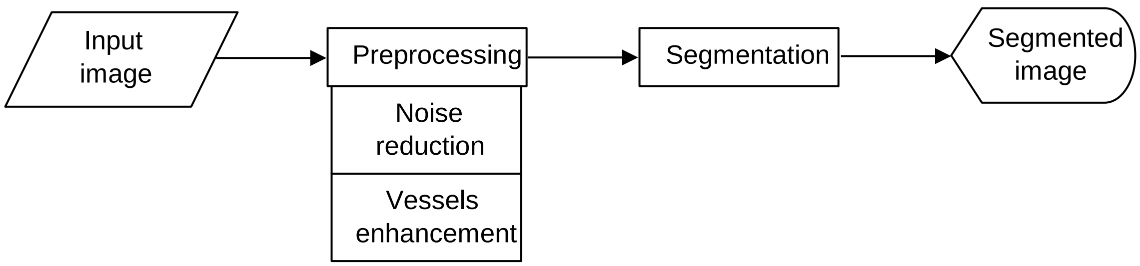


FIGURE 3: Basic steps in cerebrovascular segmentation.

Meanwhile, nonlinear filters are a filter whose output is not a linear function of its inputs. Nonlinear filters reduce noise while preserving edges and small structures of interest, such as vessels. Nonlinear filters have many applications, especially removal of certain types of noise that are not additive. Nonlinear filters are considerably harder to use and design than linear ones. Despite that, these filters have certain capabilities that makes them interesting for image filtering, such as being able to preserve edges while still suppressing noise (Johansen, 2011; Rajab, 2016). An example of edge preserving filters are such as the bilateral and anisotropic diffusion filter. Their equation exhibits high-order nonlinearity and tend to be highly powerful particularly for medical image segmentation including Magnetic Resonance Angiography (MRA) dataset.

Over the past decades, different algorithms have been proposed on medical images with varying denoising performances, yet the search for efficient image denoising methods is still a valid challenge (Vyas & Paik, 2018). In context of cerebrovascular denoising methods particularly, the nonlocal means (NLM) filter has become the most popular one for denoising cerebral images (Romdhane et al., 2014), based on a weighted average of voxels inside a search window. This filter has been shown to yield state-of-the-art denoising performance (Chen et al., 2015a). Nonlocal means filter has been introduced by Buades et al. (2005) addressing the preservation of structure in the image. The mathematical analysis is based on the analysis of the “method noise”, defined as the difference between the original image and its denoised version. The NL-means algorithm is proven to be asymptotically optimal under a generic statistical image model.

Coupé et al. (2008) proposed a 3D optimized block wise version of the NL-means filter that uses the redundancy of information in MRI data with multiple sclerosis (MS) lesions image to remove the noise. These different improvements allow to drastically divide the computational time while preserving the performances of the NL-means filter. Prima & Commowick (2013) using bilateral symmetry to improve nonlocal means denoising of MR brain images. Even in presence of strong Rician noise and strong misalignment, the results are successful on symmetrical images but not on more asymmetrical images. Experiments on real data show that there are voxels in the contralateral hemisphere providing patches with high weights, but the image had degraded using

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the BrainWeb simulator. A new method for MRI noise estimation has been presented (Borrelli et al., 2014a) to address the problem of biased estimation in case of spatially dependent noise distribution when background-based variance extraction is performed. The denoising performances are considerably improved using SVN-NLM in case of inhomogeneous noise. SVN-NLM behaves as well as standard NLM when homogeneous noise was added, proving to be a robust and powerful denoising algorithm for arbitrary MRI datasets.

Another new denoising pipeline based on NLM algorithm to restore SWI MRI images is presented (Borrelli et al., 2014b). The images restored with the proposed algorithm fared consistently better than the other two schemes, showing that a proper handling of noise in the complex MRI dataset may lead to visible improvements of the overall SWI quality. Unfortunately, even the application of a robust denoising filter as NLM algorithm produces poor denoising results on SWI images, showing excessive blurring and loss of anatomical structure information. New method in the field of 3D image denoising based on combination between NL-means filters and the diffusion tensor presented (Romdhane et al., 2014) to normalize the weight factor of the NL-means filter. The results using MRI images are very promising and provide very good quality images in terms of noise reduction. Chen et al. (2015a) proposes to leverage common structures from multiple images to collaboratively denoise an image. Multiple MRI images from different individuals are spatially aligned to the image and NLM-like block matching is performed on these aligned images with the image as the reference. The proposed approach, collaborative NL-means (CNLM) outperforms the classic NLM and yields results with markedly improved structural details.

Hassani & Majda (2016) proposed an enhanced version of the NLM filter based on morphological reconstruction to separate the image into two regions-foreground and background. Results show that the proposed method perform better than the NLM filter and the UNLM under all tested noise levels. Phellan et al. (2017) describes a new automatic segmentation method for extracting vessels of the brain from 4D ASL MRA images that combines the reduced noise characteristics of an average intensity projection of a series of images with the finer details (small vessels). This method uses the NL-means filter for noise reduction and multiscale vesselness enhancement filter for enhancing the vessels. This method presents a fast and accurate assessment of cerebrovascular structures with dice coefficient of 0.931.

Besides from nonlocal means filter, there are also other filtering techniques that has been used towards segmentation of cerebral vasculature. Mou et al. (2015) presented a novel statistical cerebrovascular segmentation algorithm with particle swarm optimization to segment the cerebral vascular. The vascular structures are enhanced and segmented using a multiscale coronary response (MSCAR) method that combined 3D multiscale filtering. Experiments on CT data and MRI data verify the feasibility and validity of each model that has been proposed. Hibet-Allah et al. (2016) presents a new method which extracts the vascular structures. Hessian-based multiscale filtering used to remove noise and enhance vascular structures. The results on MRA images demonstrate the ability to extract most of the vascular structures successfully. However, the method unable to extract the thin vessels which have poor contrast.

A flexible segmentation method with a fixed mixture model has been proposed for vessel extraction (Lu et al., 2016) that uses the multiscale filtering algorithm on the MRA images to enhance vessels and suppress noises. The segmentation error ratios of the phantoms were less than 0.3% and the DSCs were above 94%. This method is accurate and robust for vessel segmentation from multi-modality angiographic images. Zhang et al. (2018) propose a method of precise segmentation of blood vessels based on DSA cerebrovascular sequence. Multiscale Hessian matrix used for enhancing the overall image and morphological methods used to eliminate the noise around the blood vessels. Proposed method can segment blood vessels more accurately and has a good visual diagnostic quality.

Weiping & Huazhong (2006) introduced a 3D steerable filter based on dyadic Bspline wavelets for noise reduction and enhancing the cerebral vessels in MRA. The method detects and segment these vessels from other tissues by employing the maximum of local oriented energy. The results are promising and shows a good behavior on small vessels and junctions. An adaptive smoothing filter aiming to improve the visibility and detectability of the obscuration of the lentiform nucleus in CT brain images presented (Tsai et al., 2006). The proposed method can enhance image data by removing noise without significantly blurring the structures in the images. Preliminary results demonstrate the superiority of the proposed method and its usefulness for detecting the obscuration of the lentiform nucleus.

Volkau et al. (2008) describe a process aiming to construct a 3D geometric model of the human normal intracranial venous system from MRA data. Filtering of noise is done by a moving average filter and applying the smoothing spline. The method can be used for geometric modelling of vasculature and for building vascular atlases. Chang et al. (2011) proposed a post-acquisition denoising algorithm to adequately and adaptively remove the random fluctuations and bias introduced by Rician noise. Adaptive trilateral filter eliminated a fair amount of noise while preserving edge boundaries and fine details with PSNR of 28.51 dB.

A novel MRI denoising technique based on neutrosophic set approach of wiener filtering has been proposed (Mohan et al., 2012). The wiener filter is applied to reduce the set's indetermination and remove the noise in the MR image. The visual and the diagnostic quality of the denoised image are well preserved. Elahi et al. (2014) proposed a new denoising approach for MRI based on a modified Block-matching and 3D filtering (BM3D) algorithm. The wavelet thresholding stage of BM3D was improved using Noise Invalidation Denoising (NIDe) technique. Combination of the new BM3D approach and variance stabilization transform (VST) provided an efficient MR image denoising approach.

Xu & Shi (2016) presents a novel method for Bayesian denoising of parallel MRI (pMRI) images. The priors of MR images have been learned via the FoE model. The noise is filtered by applying an efficient non-linear quasi-Newton method (L-BFGS) to explore an optimal solution for the MAP estimator. Compared with the ANLM, the proposed method increases slightly the objective evaluation of the denoised image on T1w BrainWeb phantom but cannot preserve the edges better than that of ANLM on T2w BrainWeb phantom. Hibet-Allah et al. (2017) proposed a novel method for segmenting the blood vessels from MRA images data. The proposed Contrast Limited Adaptative Histogram Equalization (CLAHE) method was applied to enhance, reduce noise the image. Vesselness filter then was used to detect both large and small vessels. The accuracy of the proposed method reaches 96.2%.

Besides that, few studies had applied the edge preserving filters as denoising method to the cerebral dataset (Manniesing et al., 2006; Zhao et al., 2010; Ajam et al., 2016). Anisotropic, Hessian based diffusion scheme on CTA cerebral data, steered by a vesselness filter has been applied to enhance vascular structures within the framework of scale space theory (Manniesing et al., 2006). It is shown that using Vessel enhancing diffusion (VED) as a preprocessing step improves level set based segmentation of the cerebral vasculature. However, the multiscale character of the vesselness filter and the non-linear character of the diffusion process puts a heavy burden on the computation resources. This speed up issues will have to be considered in order for the method to be used in practice.

A novel approach to MRA image segmentation that uses anisotropic diffusion for smoothing the images had been proposed (Zhao et al., 2010). The image enhancement and segmentation process by Frangi's vesselness measure while visualization based on ball BSpline method. Results on head MRA datasets demonstrate the availability of the method. However, although the shape of blood vessels looks like circle, in MRA images they always take on irregular shapes thus simple geometric shapes are unable to describe them. In addition, Ajam et al. (2016) adapt several techniques to enhance the MRA images. The method combines morphological opening and bilateral filter with Hessian-based vessel enhancement to provide better noise reduction. This method is capable of suppressing noise in the background and smoothing the vessels edges. However, there is a limitation such as small vessels are barely to be seen.

2.2 Application of Edge Preserving Filters on Other Medical Images

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Edge preserving filters such as bilateral filter and anisotropic diffusion filters are widespread used resource for medical image denoising (Russo, 2018) because they are designed to preserve the image details during noise removal. These are among popular image filters which effectively applicable for medical datasets including Computed Tomography (CT) scan, Computed Axial Tomography (CAT) scan, Magnetic Resonance Imaging (MRI) and Magnetic Resonance Angiography (MRA).

Numerous approaches which implemented the anisotropic diffusion filter in retinal images continued for the past few years (Abdallah et al., 2015; Siva & Vasuki, 2015; Abdallah et al., 2016; Soomro et al., 2017; Abdallah et al., 2018). Siva & Vasuki (2015) proposed a computer aided automatic detection and segmentation of blood vessels through the elimination of optic disc (OD) region in retina where the OD region is segmented using anisotropic diffusion filter. The proposed system achieved the average vessels segmentation accuracy of 98.08% in DRIVE dataset and 95.94% in STARE dataset respectively. A segmentation method for retinal blood vessels has been proposed by Soomro et al (2017) which uses the second order Laplacian of Gaussian along with an anisotropic diffusion filtering to make a coherent vessels network and initially analyze the vessels detection by especially concerning the tiny vessels. The proposed method obtained an average accuracy of 94% for both DRIVE and STARE dataset.

Abdallah et al. (2015) proposed an algorithm for vessel extraction in retinal images which combines the anisotropic diffusion filter to reduce the image noise with a multiscale response based on the eigenvectors of the Hessian matrix and on the gradient information to extract vessels from retinal images. The experimental result shows a maximum accuracy average of around 91.55% and 94.02% for DRIVE and STARE dataset respectively. A new adaptive noise reducing anisotropic diffusion (ANRAD) method to improve the image quality, which can be considered as a modified version of a speckle-reducing anisotropic diffusion (SRAD) filter has been presented (Abdallah et al., 2016). The ANRAD filter able to reduce the noise while preserving image edges and fine details very well.

Abdallah et al. (2018) employed an algorithm for vessel detection in fundus images which combines a new version of an anisotropic diffusion method to remove noise with a multiscale vesselness response that is based on the Hessian matrix's eigenvectors and the gradient information image to detect all vessels from retinal images. This algorithm achieves a maximum average accuracy of around 93.89% and 93.88% for DRIVE and STARE dataset respectively. Krissian (2002) presented a new approach to anisotropic diffusion based on a multidirectional diffusion flux on CT data of the liver. The diffusion flux is decomposed in an orthogonal basis, effectively enabling enhancement of contours as well as diffusion along the contours.

Bilateral filter based on multiscale vesselness measurement to enhance the vessel structures in a retinal image has been proposed by Shi & Yang (2009). By substituting the intensity difference with vesselness difference, the modified bilateral filter performs well in the case of low contrast between vessel structures and background and can correctly reveal smaller thin vessels. A new method to measure retinal blood vessel with sub-pixel accuracy has been presented by Sun et al. (2010). The method is based on a modified canny edge detection method with a bilateral filter where bilateral filter is used to remove the vessel background noises and then the canny detector is used to detect all vessel edges. The method outputs the vessel positions and center lines in sub-pixel accuracy.

Anantrasirichai et al. (2014) presented an image enhancement algorithm for retinal optical coherence tomography (OCT). The enhancement process consists of intensity adjustment, wavelet-based despeckling, wavelet-based image registration and adaptive-weighted bilateral filtering which is a texture-preserving smoothing operation. Results show an improvement of image quality and improvement in accuracy of glaucoma detection. He et al. (2017) proposed an image filtering approach specialized for detecting vessels from retinal images. Different from existing techniques, the proposed approach leverages the special characteristics of vascular structures and determines a set of BLF spatial kernels that are oriented and scaled optimally. This approach provides a better performance than state-of-the-art techniques in detecting and preserving the thin vascular structures. Latest work on early detection of diabetic retinopathy was done by Sanya research group where an approach using morphological image processing was proposed (Sanya et al, 2021).

Bilateral filter has also been applied in coronary angiography images (Chen et al., 2015b) and histological images (Tsou et al., 2015). An improved bilateral filter based the MFFDOG filters and multi-scale Hessian matrix for coronary angiography image presented (Chen et al., 2015b). By improving two kernels of the bilateral filter, the proposed method can effectively remove the complicated noise and the achievement of image enhancement is much better than the original bilateral filter, but the effect to some tiny vessels is actually modest. Tsou et al. (2015) has proposed an algorithm to abstract the salient regions in blood vessel images and boost object identification in histological images. Bilateral filtering used to smooth the first component of the Gaussian color model and emphasize sharp features. Experimental results show that the proposed framework is capable of deriving vessel boundaries that are comparable to those demarcated manually, even for vessel regions with weak contrast between the object boundaries and background clutter.

Meanwhile, implementation of nonlocal means (NLM) filter specifically focusing on blood vessels is still progressing as such in recent studies, region growing segmentation method was proposed for accurate detection of Microaneurysms where NLM filter has been applied to reduce noises on the retinal fundus images (Badgujar & Deore, 2018). This method uses DIARETDB0 dataset and shows promising results with accuracy of 78%, positive predictive of 83.33%, specificity and sensitivity of 58.82% and 87.88% respectively. The detected MAs are represented as white areas on original retinal images. Selçuk et al. (2017) uses nonlocal means filter as a noise reduction method to emphasize coronary arteries on x-ray heart angiography images. The mean square error values obtained by the proposed method are more successful when compared other filters. China et al. (2015) introduced a hybrid wavelet based nonlocal means filter for despeckling of coronary artery intravascular ultrasound (IVUS) images. The proposed methodology is more efficient in despeckling for IVUS image denoising in comparison with other despeckling techniques.

New method for the segmentation of vessel cross-sections in contrast enhanced CT and MR images presented (Tek et al., 2001). The primary innovation of the technique is the boundary propagation by mean shift analysis combined with a smoothness constraint. The new algorithm allows real time segmentation of medical structures found in multimodality images. Rodríguez (2008) has proposed a new algorithm that applies recursively the mean shift filtering and uses entropy as the stopping criterion. With this new algorithm, the binarization was carried out after the image was segmented. This algorithm through recursive application of the mean shift found to be effective and more robust than the algorithm using graph. On the other hand, by using the retinal images and other standard images, Morales et al. (2012) has presented an iterative algorithm of the mean shift to conduct the image segmentation. As a result, the segmented images by using this iterative algorithm were less noisy than those obtained by means of other methods.

In addition, Lee (1983) has developed a simple, effective, and computationally efficient noise smoothing algorithm known as sigma filter. This filter is motivated by the sigma probability of the Gaussian distribution, and it smooths the image noise by averaging only those neighborhood pixels which have the intensities within a fixed sigma range of the center pixel. Consequently, image edges are preserved, and subtle details and thin tines such as roads are retained. Sigma filter found to be the most computationally efficient filter among other known filtering algorithms. Sigma filter then continued to be extended and improved (Lukin et al., 1996; Lee et al., 2008; Han & Sohn, 2009) that eliminates deficiencies of the original sigma filter and improves the algorithm efficiency.

3. RESULTS AND ANALYSIS

As shown in Table 2, numerus researchers had applied the nonlocal means filter on brain images as the noise reduction method (Coupé et al., 2008; Prima & Commowick, 2013; Borrelli et al., 2014a; Borrelli et al., 2014b; Romdhane et al., 2014; Chen et al., 2015a; Hassani & Majda, 2016; Phellan et al., 2017) as well as the multiscale filter where it has applied for various medical dataset including CT (Mou et al., 2015), MRI (Mou et al., 2015), MRA (Hibet-Allah et al., 2016; Lu et al., 2016) and also DSA images (Zhang et al., 2018). Meanwhile, the application on edge preserving filters such as anisotropic diffusion filter and bilateral filter aren't widely explored as much as the nonlocal means filters. While on the other hand, these edge preserving filters are well established on other medical images where numerous researchers has implemented them mostly on retinal images (Lee, 1983; Shi & Yang, 2009; Sun et al., 2010; Morales et al., 2012; Anantrasirichai et al., 2014; Siva & Vasuki, 2015; Abdallah et al., 2015; Abdallah et al., 2016; Dash & Bhoi, 2017; He et al., 2017; Soomro et al., 2017; Abdallah et al., 2018), liver images (Krissian, 2002), coronary images (Chen et al., 2015b) and histological images (Tsou et al., 2015). In regards, the next section will be discussed in more depth on various related works of edge preserving filters in other medical images.

Denoising filter	Input image	Method	Result	Reference
NL-means filter	MRI	A 3D optimized blockwise version of the NL-means filter that uses the redundancy of information in MRI image to remove the noise.	Divide the computational time while preserving the performances.	Coupé et al. (2008)
	MRI	Use bilateral symmetry to improve nonlocal means denoising of MRI images.	On real data shows that there are voxels in the contralateral hemisphere providing patches with high weights, but the image had degraded using the BrainWeb simulator.	Prima & Commowick (2013)
	MRI	New method for MRI noise estimation.	Denoising performances are considerably improved using SVNNLM, robust and powerful denoising algorithm for arbitrary MRI datasets.	Borrelli et al. (2014a)
	MRI	New denoising pipeline based on NLM algorithm to restore SWI MRI images is presented.	Images restored with the proposed algorithm fared consistently better than the other schemes but produces poor denoising results on SWI images, showing excessive blurring and loss of anatomical structure information.	Borrelli et al. (2014b)
	MRI	New method in the field of 3D image denoising based on combination between NL-means filters and the diffusion tensor.	The results using MRI images are very promising and provide very good quality images in terms of noise reduction.	Romdhane et al. (2014)

	MRI	Leverage common structures from multiple images to collaboratively denoise an image.	CNLM outperforms the classic NLM, and yields results with markedly improved structural details.	Chen et al. (2015a)
	MRI	An enhanced version of the NLM filter based on morphological reconstruction.	Proposed method performs better than the NLM filter and the UNLM under all tested noise levels.	Hassani & Majda (2016)
	MRA	Uses the NL-means filter for noise reduction, multiscale vesselness enhancement filter for enhancing the vessels.	Fast and accurate assessment of cerebrovascular structures with dice coefficient of 0.931.	Phellan et al. (2017)
Multiscale filter	CT and MRI	A novel statistical cerebrovascular segmentation algorithm with particle swarm optimization where the vascular are enhanced and segmented using MSCAR method, 3D multiscale filtering, Hessian matrices and EM estimation.	The proposed system able to do the diagnosis in different ways; volume rendering, 2D and 3D measurement, virtual endoscopic etc.	Mou et al. (2015)
	MRA	New method to extracts the vascular structures. Hessian-based multiscale filtering used to remove noise and enhance vascular structures.	Able to extract most of the vascular structures but unable to extract the thin vessels which have poor contrast.	Hibet-Allah et al. (2016)
	MRA	A flexible segmentation method where uses multiscale filter to enhance vessels and suppress noises.	Segmentation error ratios less than 0.3% and the DSCs were above 94%.	Lu et al. (2016)
	DSA	Method of precise segmentation of blood vessels based on DSA cerebrovascular sequence where multiscale hessian matrix used for enhancing the image and morphological methods used to eliminate the noise.	Proposed method can segment blood vessels more accurately and has a good visual diagnostic quality.	Zhang et al. (2018)
Anisotropic diffusion filter	CTA	Anisotropic, Hessian based diffusion scheme on CTA cerebral data, steered by a vesselness filter to enhance vascular structures.	VED improves level set based segmentation of the cerebral vasculature. However, VED puts a heavy burden on the computation resources.	Manniesing et al. (2006)
	MRA	A novel approach to MRA image segmentation that uses anisotropic diffusion for smoothing the images. The image enhancement and segmentation process by Frangi's vesselness measure.	Results on head MRA datasets demonstrate the availability of the method. However, due to irregular shapes in MRA images, simple geometric shapes are unable to describe them.	Zhao et al. (2010)
Bilateral filter	MRA	The method combines morphological opening and bilateral filter with Hessianbased vessel enhancement to provide better noise reduction.	Capable of suppressing noise in the background and smoothing the vessels edges. However, there is a limitation such as small vessels are barely to be seen.	Ajam et al. (2016)

Smoothing filter	CT	An adaptive smoothing filter aiming to improve the visibility and detectability of the obscuration of the lentiform nucleus.	Preliminary results demonstrate the superiority of the proposed method and its usefulness for detecting the obscuration of the lentiform nucleus.	Tsai et al. (2006)
3D steerable filter	MRA	Introduced a 3D steerable filter based on dyadic B-spline wavelets for noise reduction and enhancing the cerebral vessels in MRA.	Shows good behavior on small vessels and junctions and suitable for other types of curvilinear structures such as cardiovascular vessels, bronchial tree.	Weiping & Huazhong (2006)
Moving average filter	MRA	Filtering of noise is done by a moving average filter and applying the smoothing spline.	The method can be used for geometric modeling of vasculature and for building vascular atlases.	Volkau et al. (2008)
Trilateral filter	MRI	Post-acquisition denoising algorithm to adequately and adaptively remove the random fluctuations and bias introduced by Rician noise.	Adaptive trilateral filter eliminated a fair amount of noise while preserving edge boundaries and fine details with PSNR of 28.51dB.	Chang et al. (2011)
Wiener filter	MRI	A novel MRI denoising technique based on neutrosophic set approach of wiener filtering which uses to remove the noise.	Visual and the diagnostic quality of the denoised image are well preserved.	Mohan et al. (2012).
Blockmatching and 3D filtering (BM3D)	MRI	New denoising approach based on a modified BM3D algorithm. The wavelet thresholding stage of BM3D was improved using Noise NIDe technique.	Combination of the new BM3D and VST provided an efficient image denoising approach.	Elahi et al. (2014)
Non-linear quasi-Newton method (L-BFGS)	pMRI	A novel method for Bayesian denoising. Noise is filtered by applying an efficient non-linear quasi-Newton method (L-BFGS) to explore an optimal solution for the MAP estimator.	The proposed method increases slightly the objective evaluation of the denoised image on T1w BrainWeb phantom but cannot preserve the edges better than that of ANLM on T2w BrainWeb phantom.	Xu & Shi (2016)
Histogram Equalization (HE)	MRA	A novel method for segmenting the blood vessels. CLAHE was applied to enhance, reduce noise the image.	Accuracy: 96.2%	Hibet-Allah et al. (2017)

TABLE 2: Comparison between various denoising filters in CSVD images.

Based on Table 3 below, there are quite comprehensive studies for several edge preserving filtering techniques used in image processing for blood vessels segmentation. The results shows a great number from bilateral, nonlocal means and anisotropic diffusion filters (Abdallah et al., 2015; Siva & Vasuki, 2015; Dash & Bhoi, 2017; Soomro et al., 2017; Abdallah et al., 2018; Badgujar & Deore, 2018). Meanwhile, the implementation of mean shift and sigma filter in medical images are quite occasional compared to the other three filters where sigma filter mostly use in natural images. Yet, as both are edge preserving (Lee, 1983; Solomon et al., 2014), their results are also quite significant (Lukin et al., 1996; Lee et al., 2008; Rodríguez, 2008; Han & Sohn, 2009; Morales et al., 2012). In a nutshell, this paper attempts to implement five edge preserving filters; (i) anisotropic diffusion filter, (ii) bilateral filter, (iii) mean shift filter, (iv) nonlocal means filter and (v) sigma filter for cerebrovascular segmentation on MRA dataset. The next section will be explained about the edge enhancement and segmentation techniques that will be implemented in this study.

No.	Filtering Technique	Description
1	Anisotropic diffusion filter	• Used to enhance vascular structures and eliminate noisy lines • Extend and improve the anisotropic diffusion filter to improve the image quality • (Krissian, 2002; Abdallah et al., 2016) • Used on retinal images (Abdallah et al., 2015; Siva & Vasuki, 2015; Abdallah et al., 2016; Soomro et al., 2017; Abdallah et al., 2018) and CT scan - liver images (Krissian, 2002) • 91.55% accuracy for DRIVE, 94.02% for STARE dataset (Abdallah et al., 2015) • 93.89% accuracy for DRIVE, 93.88% for STARE dataset (Abdallah et al., 2018) • 94% accuracy for DRIVE and STARE dataset (Soomro et al., 2017) • DRIVE: 98.08 accuracy, 93.99% sensitivity, 98.37% specificity while STARE: 95.94% accuracy, 93.6% sensitivity, 98.96% specificity (Siva & Vasuki, 2015)
2	Bilateral filter	• Used to preserve the details of vessels while effectively eliminating image noise Improve bilateral filter to enhance the images (Anantrasirichai et al., 2014; Chen et al., 2015b) • Used on retinal images (Shi & Yang, 2009; Sun et al., 2010; Anantrasirichai et al., • 2014; He et al., 2017), coronary images (Chen et al., 2015b) and histological images • (Tsou et al., 2015)
3	Mean shift filter	• Used to remove noise and image segmentation • The filter applied recursively (Rodríguez, 2008; Morales et al., 2012) • Used on medical images such as retinal images and other standard images (Morales et al., 2012)
4	Nonlocal means filter	• Used as noise reduction method to despeckling and emphasize the images • Introduce a hybrid wavelet based nonlocal means filter (China et al., 2015) • Used on retinal fundus images (Badgujar & Deore, 2018), coronary arteries on x-ray heart angiography images (Selçuk et al., 2017) and coronary artery intravascular ultrasound images (China et al., 2015) • DIARETDB0 dataset: 78% accuracy, 83.33% positive predictive, 58.82% specificity and 87.88% sensitivity (Badgujar & Deore, 2018)
5	Sigma filter	• Used as noise removal • Extend and improve the sigma filter to eliminate the deficiencies of the original Lee sigma filter (Lee et al., 2008) • Used on medical images (Lee, 1983) but so far mostly on non-medical images (Lukin et al., 1996; Lee et al., 2008; Han & Sohn, 2009)

TABLE 3: Edge preserving techniques with description.

4. CONCLUSION AND FUTURE WORK

There are in-depth related works in regards of the blood vessels segmentation process on medical images. No single segmentation approach is suitable for all the different anatomical region or imaging modalities (Moccia et al., 2018), thus the primary goal of this project is to provide source of information about the state of the art of image denoising algorithms for edge preservation so that the most suitable noise reduction and enhancement techniques can be chosen. In future, the work on the MRA image filtration would highly consider these five filters for edge preserving; (i) anisotropic diffusion filter, (ii) bilateral filter, (iii) mean shift filter, (iv) nonlocal means filter and (v) sigma filter, with the help of other post-processing techniques for image segmentation enhancement.

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6. REFERENCES

Abdallah, M. B., Azar, A. T., Guedri, H., Malek, J., & Belmabrouk, H. (2018). NoiseEstimation-Based Anisotropic Diffusion Approach for Retinal Blood Vessel Segmentation. *Neural Computing and Applications,* 29(8), 159-180.

Abdallah, M. B., Malek, J., Azar, A. T., Belmabrouk, H., Monreal, J. E., & Krissian, K. (2016). Adaptive Noise-Reducing Anisotropic Diffusion Filter. *Neural Computing and Applications,* 27(5), 1273-1300.

Abdallah, M. B., Malek, J., Azar, A. T., Montesinos, P., Belmabrouk, H., Esclarín Monreal, J., & Krissian, K. (2015). Automatic Extraction of Blood Vessels in the Retinal Vascular Tree Using Multiscale Medialness. *International Journal of Biomedical Imaging*, 519024. https://doi.org/10.1155/2015/519024

Ajam, A., Aziz, A. A., Asirvadam, V. S., Izhar, L. I., & Muda, S. (2016). Cerebral Vessel Enhancement Using Bilateral and Hessian-Based Filter. In *2016 6th International Conference on Intelligent and Advanced Systems (ICIAS),* 1-6.

Ajam, A., Aziz, A. A., Asirvadam, V. S., Muda, A. S., Faye, I., & Gardezi, S. J. S. (2017). A Review on Segmentation and Modeling of Cerebral Vasculature for Surgical Planning. *IEEE Access, 5,* 15222-15240.

Aldroubi, A. (2017). *Wavelets in Medicine and Biology.* Routledge.

Anantrasirichai, N., Nicholson, L., Morgan, J. E., Erchova, I., Mortlock, K., North, R. V., & Achim, A. (2014). Adaptive-Weighted Bilateral Filtering and Other Pre-Processing Techniques for Optical Coherence Tomography. *Computerized Medical Imaging and Graphics, 38*(6), 526-539.

Badgujar, R. D., & Deore, P. J. (2018). Region Growing Based Segmentation Using Forstner Corner Detection Theory for Accurate Microaneurysms Detection in Retinal Fundus Images. In *2018 Fourth International Conference on Computing Communication Control and Automation (ICCUBEA),* 1-5.

Borrelli, P., Palma, G., Comerci, M., & Alfano, B. (2014a). Unbiased Noise Estimation and Denoising in Parallel Magnetic Resonance Imaging. In *2014 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP),* 1230-1234.

Borrelli, P., Tedeschi, E., Cocozza, S., Russo, C., Salvatore, M., Palma, G., & Haacke, E. M. (2014b). Improving SNR in Susceptibility Weighted Imaging by a NLM-Based Denoising Scheme. In *2014 IEEE International Conference on Imaging Systems and Techniques (IST) Proceedings,* 346-350.

Buades, A., Coll, B., & Morel, J. M. (2005). A Review of Image Denoising Algorithms, with a New One. *Multiscale Modeling and Simulation, 4*(2), 490-530.

Bullitt E., Gerig, G., Pizer, S. M., Lin, W., & Aylward, S. R. (2003). Measuring Tortuosity of the Intracerebral Vasculature from MRA Images. *IEEE Transactions on Medical Imaging, 22*(9), 1163-1171.

Carr, J. C., & Carroll, T. J. (Eds.). (2011). Magnetic Resonance Angiography: Principles and Applications. Springer Science & Business Media.

Chang, H. H., Hsieh, T. J., Ting, Y. N., & Chu, W. C. (2011). Rician Noise Removal in MR Images Using an Adaptive Trilateral Filter. In *2011 4th International Conference on Biomedical Engineering and Informatics (BMEI), 1,* 467-471.

Che Mohd Nasir, C. M. N., Damodaran, T.,Yusof, S. R., Norazit, A., Chilla, G., Huen, I., K. N. B. P., Mohamed Ibrahim, N., Mustapha, M. (2021). Aberrant Neurogliovascular Unit Dynamics in Cerebral Small Vessel Disease: A Rheological Clue to Vascular Parkinsonism. *Pharmaceutics*, *13*(8):1207, 1999-4923.

Chen, G., Zhang, P., Wu, Y., Shen, D., & Yap, P. T. (2015a). Collaborative Non-Local Means Denoising of Magnetic Resonance Images. In *2015 IEEE 12th International Symposium on Biomedical Imaging (ISBI),* 564-567.

Chen, H., & Hale, J. (1995). An Algorithm for MR Angiography Image Enhancement. *Magnetic Resonance in Medicine, 33*(4), 534-540.

Chen, K., Yin, Q., Jia, X., & Lu, M. (2015b). Vessel Enhancement Based an Improved Bilateral Filter for Coronary Angiography. In *2015 8th International Congress on Image and Signal Processing (CISP),* 308-312.

China, D., Mitra, P., Chakraborty, C., & Mandana, K. M. (2015). Wavelet Based Non-Local Means Filter for Despeckling of Intravascular Ultrasound Image. In *2015 International Conference on Advances in Computing, Communications, and Informatics (ICACCI),* 1361-1365.

Chung A. C., Noble, J. A., & Summers, P. (2004). Vascular Segmentation of Phase Contrast Magnetic Resonance Angiograms Based on Statistical Mixture Modeling and Local Phase Coherence. *IEEE Transactions on Medical Imaging, 23*(12), 1490-1507.

Coupé, P., Yger, P., Prima, S., Hellier, P., Kervrann, C., & Barillot, C. (2008). An Optimized Blockwise Nonlocal Means Denoising Filter for 3-D Magnetic Resonance Images. *IEEE Transactions on Medical Imaging, 27*(4), 425-441.

Dash, J., & Bhoi, N. (2017). A Thresholding Based Technique to Extract Retinal Blood Vessels from Fundus Images. *Future Computing and Informatics Journal, 2*(2), 103-109.

Elahi, P., Beheshti, S., & Hashemi, M. (2014). BM3D MRI denoising Equipped with Noise Invalidation Technique. In *2014 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP),* 6612-6616.

El-Baz, A., Elnakib, A., Khalifa, F., El-Ghar, M. A., Mcclure, P., Soliman, A., & Gimelrfarb, G. (2012). Precise Segmentation of 3-D Magnetic Resonance Angiography. *IEEE Transactions on Biomedical Engineering, 59*(7), 2019-2029.

El-Baz, A., Gimel'farb, G., Kumar, V., Falk, R., & El-Ghar, M. A. (2009). 3D Joint MarkovGibbs Model for Segmenting the Blood Vessels from MRA. In *2009 IEEE International Symposium on Biomedical Imaging: from Nano to Macro,* 1366-1369.

Fu, B., Zhao, X. Y., Ren, Y. G., Li, X. M., & Wang, X. H. (2018). A Salt and Pepper Noise Image Denoising Method Based on the Generative Classification. arXiv preprint arXiv:1807.05478.

Goyal, B., Agrawal, S., & Sohi, B. S. (2018). Noise Issues Prevailing in Various Types of Medical Images. *Biomedical & Pharmacology Journal, 11*(3), 1227.

Gupta, T. K. (2013). *Radiation, Ionization, and Detection in Nuclear Medicine.* Heidelberg: Springer.

Han, H., & Sohn, K. (2009). Automatic Illumination and Color Compensation Using Mean Shift and Sigma Filter. *IEEE Transactions on Consumer Electronics, 55*(3), 978-986.

Hao, J., Shen, Y., & Wang, Q. (2007). Segmentation for MRA Image: An Improved Level-Set Approach. *IEEE Transactions on Instrumentation and Measurement, 56*(4), 1316-1321.

Hartmann, U. (Ed.). (2005). Aktuelle Methoden Der Laser-Und Medizinphysik: Tagungsband Der 2.

Hibet-Allah, O., Hajer, J., & Kamel, H. (2016). Vascular Tree Segmentation in MRA Images Using Hessian-Based Multiscale Filtering and Local Entropy Thresholding. *In 2016 2nd International Conference on Advanced Technologies for Signal and Image Processing (ATSIP)*, 325-329.

Hibet-Allah, O., Hejer, J., & Kamel, H. (2017). 3D MRA Segmentation Using the Vesselness Filter*. In 2017 40th International Conference on Telecommunications and Signal Processing (TSP)*, 615-620.

Hartung, M. P., Grist, T. M., & François, C. J. (2011). Magnetic Resonance Angiography: Current Status and Future Directions. *Journal of Cardiovascular Magnetic Resonance, 13*(1), 19.

Hassani, A. E., & Majda, A. (2016). Efficient Image Denoising Method Based on Mathematical Morphology Reconstruction and the Non-Local Means Filter for the MRI of the Head. In *2016 4th IEEE International Colloquium on Information Science and Technology (CIST),* 422-427.

He, Y., Zheng, Y., Zhao, Y., Ren, Y., Lian, J., & Gee, J. (2017). Retinal Image Denoising via Bilateral Filter with a Spatial Kernel of Optimally Oriented Line Spread Function. *Computational and Mathematical Methods in Medicine.*

Hu, J., Pu, Y., Wu, X., Zhang, Y., & Zhou, J. (2012). Improved DCT-Based Nonlocal Means Filter for MR Images Denoising. *Computational and Mathematical Methods in Medicine*.

Jayabal, P., & Damodaran, N. (2015). Rician Noise Removal and Straightening of Blood Vessel in MR Images. *Journal of Biomedical Engineering and Medical Imaging, 2*(6), 28-28.

Jaybhay, J., & Shastri, R. (2015). A Study of Speckle Noise Reduction Filters. *Signal & Image Processing: An International Journal (SIPIJ), 6*(3), 71-80.

Johansen, M. (2011). *Nonlinear Filtering in Digital Image Processing.* Master's Thesis, Institute for Electronics and Telecommunications 2011.

Kandil, H., Soliman, A., Fraiwan, L., Shalaby, A., Mahmoud, A., Eltanboly, A., & El-Baz, A. (2018). A Novel MRA Framework Based on Integrated Global and Local Analysis for Accurate Segmentation of the Cerebral Vascular System. In *2018 IEEE 15th International Symposium on Biomedical Imaging (ISBI 2018),* 1365-1368.

Kaur, K., Singh, B., & Kaur, M. (2012). Speckle Noise Reduction Using 2-D FFT in Ultrasound Images. *International Journal of Advances in Engineering & Technology, 4*(2), 79.

Krissian, K. (2002). Flux-Based Anisotropic Diffusion Applied to Enhancement of 3-D Angiogram. *IEEE Transactions on Medical Imaging, 21*(11), 1440-1442.

Lee, J. S. (1983). Digital Image Smoothing and the Sigma Filter. *Computer Vision, Graphics, and Image Processing, 24*(2), 255-269.

Lee, J. S., Wen, J. H., Ainsworth, T. L., Chen, K. S., & Chen, A. J. (2008). Improved Sigma Filter for Speckle Filtering of SAR Imagery. *IEEE Transactions on Geoscience and Remote Sensing, 47*(1), 202-213.

Liang, H.; Li, N.; Zhao, S. (2021) Salt and Pepper Noise Removal Method Based on a Detail-Aware Filter. *Symmetry*, *13*(3):515, 2073-8994.

Liao, W., Rohr, K., Kang, C. K., Cho, Z. H., & Wörz, S. (2011). A Generative MRF Approach for Automatic 3D Segmentation of Cerebral Vasculature from 7 Tesla MRA Images. In *2011 IEEE International Symposium on Biomedical Imaging: From Nano to Macro,* 2041-2044.

Lu, P., Xia, J., Li, Z., Xiong, J., Yang, J., Zhou, S., & Wang, C. (2016). A Vessel Segmentation Method for Multi-Modality Angiographic Images Based on Multi-Scale Filtering and Statistical Models. *Biomedical Engineering Online, 15*(1), 120.

Lukin, V. V., Ponomarenko, N. N., Kuosmanen, P. S., & Astola, J. T. (1996). Modified Sigma Filter for Processing Images Corrupted by Multiplicative and Impulsive Noise. In *1996 8th European Signal Processing Conference (EUSIPCO 1996),* 1-4.
Macdonald, L. (2006). *Digital Heritage.* Routledge.

Manniesing, R., Viergever, M. A., & Niessen, W. J. (2006). Vessel Enhancing Diffusion: A Scale Space Representation of Vessel Structures. *Medical Image Analysis, 10*(6), 815-825.

Moccia, S., De Momi, E., El Hadji, S., & Mattos, L. S. (2018). Blood Vessel Segmentation Algorithms—Review of Methods, Datasets and Evaluation Metrics. *Computer Methods and Programs in Biomedicine, 158*, 71-91.

Mohan, J., Guo, Y., Krishnaveni, V., & Jeganathan, K. (2012). MRI Denoising Based on Neutrosophic Wiener Filtering. In *2012 IEEE International Conference on Imaging Systems and Techniques Proceedings,* 327-331.

Morales, R. R., Domínguez, D., Torres, E., & Sossa, J. H. (2012). Image Segmentation through an Iterative Algorithm of the Mean Shift. In *Advances in Image Segmentation.* Intechopen.

Mou, X., Wang, X., Wu, Z., Wang, X., & Zhou, M. (2015). An Automatic Ehealth Platform for Cardiovascular and Cerebrovascular Disease Detection. In *2015 International Symposium on Bioelectronics and Bioinformatics (ISBB),* 63-66.

Nowak, R. D. (1999). Wavelet-Based Rician Noise Removal for Magnetic Resonance Imaging. *IEEE Transactions on Image Processing, 8*(10), 1408-1419.

Pantoni, L. (2010). Cerebral Small Vessel Disease: From Pathogenesis and Clinical Characteristics to Therapeutic Challenges. *The Lancet Neurology, 9*(7), 689-701.

Pantoni, L., & Gorelick, P. B. (Eds.). (2014). Cerebral Small Vessel Disease. *Cambridge University Press.*

Phellan, R., Lindner, T., Helle, M., Falcão, A. X., & Forkert, N. D. (2017). Automatic Temporal Segmentation of Vessels of the Brain Using 4D ASL MRA Images. *IEEE Transactions on Biomedical Engineering, 65*(7), 1486-1494.

Prima, S., & Commowick, O. (2013). Using Bilateral Symmetry to Improve Non-Local Means Denoising of MR Brain Images. In *2013 IEEE 10th International Symposium on Biomedical Imaging,* 1231-1234.

Rani, V. (2013). A Brief Study of Various Noise Model and Filtering Techniques. *Journal of Global Research in Computer Science, 4*(4), 166-171.

Rajab, M. I. (2016). Performance Evaluation of Image Edge Detection Techniques. *International Journal of Computer Science and Security, 10*(5), 170-185.

Ren, R., Guo, Z., Jia, Z., Yang, J., Kasabov, N. K., Li, C. (2019). Speckle Noise Removal in Image-based Detection of Refractive Index Changes in Porous Silicon Microarrays. *Scientific Reports, 9*, 15001.

Rodríguez, R. (2008). Binarization of Medical Images Based on the Recursive Application of Mean Shift Filtering: Another Algorithm. *Advances and Applications in Bioinformatics and Chemistry (AABC), 1*, 1–12.

Romdhane, F., Benzarti, F., & Amiri, H. (2014). 3D Medical Images Denoising. In International Image Processing, *Applications and Systems Conference,* 1-5.

Rosamond, W., Flegal, K., Friday, G., Furie, K., Go, A., & Greenlund, K. (2007). Heart Disease and Stroke Statistics--2007 Update: A Report from the American Heart Association Statistics Committee and Stroke Statistics Subcommittee. *Circulation, 115*(5), E69–E171.

Russo, F. (2018). On the Accuracy of Denoising Algorithms in Medical Imaging: A Case Study. In *2018 IEEE International Symposium on Medical Measurements and Applications (Memea),* 1-6.

Sanya, W., Bajpai, G., Amour, M., Alawi, M., & Adnan, A. (2021). A Novel Advanced Approach Using Morphological Image Processing Technique for Early Detection of Diabetes Retinopathy. *International Journal of Image Processing, 15*(3), 22-36.

Selçuk, T., Tuncer, S. A., Tekinalp, M., & Alkan, A. (2017). Non-Local Means Based Image Enhancement on Coronary Angiography Images. In *2017 International Artificial Intelligence and Data Processing Symposium (IDAP),* 1-4.

Selvathi, D., Selvi, S. T., & Malar, C. L. S. (2012). The SURE-LET Approach for MR Brain Image Denoising Using Different Shrinkage Rules. In *Advancing Technologies and Intelligence in Healthcare and Clinical Environments Breakthroughs,* 227-235.

Shi, F., & Yang, J. (2009). Multiscale Vesselness Based Bilateral Filter for Blood Vessel Enhancement. *Electronics Letters, 45*(23), 1152-1154.

Shi, Y., & Wardlaw, J. M. (2016). Update on Cerebral Small Vessel Disease: A Dynamic WholeBrain Disease. *Stroke and Vascular Neurology, 1*(3), 83-92.

Shruthi, B., Renukalatha, S., & Siddappa, D. M. (2015). Speckle Noise Reduction in Ultrasound Images-A Review. *International Journal of Engineering Research and Technology, 4*(02).

Siva Sundhara Raja, D., & Vasuki, S. (2015). Automatic Detection of Blood Vessels in Retinal Images for Diabetic Retinopathy Diagnosis. *Computational and Mathematical Methods in Medicine.*

Solomon, J., Crane, K., Butscher, A., & Wojtan, C. (2014). *A General Framework for Bilateral and Mean Shift Filtering, 1*(2), 3.

Soomro, T. A., Paul, M., Gao, J., & Zheng, L. (2017). Retinal Blood Vessel Extraction Method Based on Basic Filtering Schemes. In *2017 IEEE International Conference on Image Processing (ICIP),* 4422-4426.

Story, C. M. (2016). *Magnetic Resonance Angiography (MRA).* Healthline. Retrieved from https://www.healthline.com/health/magnetic-resonance-angiography.

Sun, X., Chai, Z., Miao, C., Jiang, Y., Duan, Z. Y., Wang, L. G., & Chang, S. H. (2010). Retinal Vessel Tracking Using Bilateral Filter Based on Canny Method. In *2010 International Conference on Audio, Language, and Image Processing,* 1678-1682.

Sun, Y., & Parker, D. L. (1999). Performance Analysis of Maximum Intensity Projection Algorithm for Display of MRA Images. *IEEE Transactions on Medical Imaging, 18*(12), 1154-1169.

Tan, J. (Ed.). (2012). *Advancing Technologies and Intelligence in Healthcare and Clinical Environments Breakthroughs.* IGI Global.

Tek, H., Comaniciu, D., & Williams, J. P. (2001). Vessel Detection by Mean Shift Based Ray Propagation. In *Proceedings IEEE Workshop on Mathematical Methods in Biomedical Image Analysis (MMBIA 2001),* 228-235.

Tsai, D. Y., Lee, Y., & Takahashi, N. (2006). An Adaptive Enhancement Algorithm for CT Brain Images. In *2005 IEEE Engineering in Medicine and Biology 27th Annual Conference,* 3398-3401.

Tsou, C. H., Lu, Y. C., Yuan, A., Chang, Y. C., & Chen, C. M. (2015). A Heuristic Framework for Image Filtering and Segmentation: Application to Blood Vessel Immunohistochemistry. *Analytical Cellular Pathology.* doi: 10.1155/2015/589158.

Tulin, I. J., Imam, M. Z., & Das, P. P. (2017). Computer-Aided Kidney Segmentation on Abdominal CT Images Using Fuzzy Based Denoising for Gaussian Noise. *International Journal of Neurosciece and Behavioral Science, 5*(4): 59-65.

Uemori, N., Sugitani, Y., Tamada, H., Ohi, Y., & Ishikawa, C. (2014). Incidence and Clinical Predictors of Stent Restenosis and Early Stent Occlusion in Patients with Acute Myocardial Infarction Treated by Bare Metal Stents: Importance of Infarct Location and Serum Creatinine Level. *Angiol, 2*(136), 2.

Volkau, I., Ng, T. T., Marchenko, Y., & Nowinski, W. L. (2008). On Geometric Modeling of the Human Intracranial Venous System. *IEEE Transactions on Medical Imaging, 27*(6), 745751.

Vyas, A., & Paik, J. (2018). Applications of Multiscale Transforms to Image Denoising: Survey. In *2018 International Conference on Electronics, Information, and Communication (ICEIC),* 1-3.

Weiping, Z., & Huazhong, S. (2006). Detection of Cerebral Vessels in MRA Using 3D Steerable Filters. In *2005 IEEE Engineering in Medicine and Biology 27th Annual Conference,* 3249-3252.

Xu, Z., & Shi, Q. (2016). Denoising Model for Parallel Magnetic Resonance Imaging Images Using Higher-Order Markov Random Fields. *IET Image Processing, 10*(12), 962-970.

Zhang, B., Liu, S., & Zhou, S. (2020). Cerebrovascular Segmentation from TOF-MRA using Model- and Data-driven Method via Sparse Labels. Neurocomputing, 380, 162-179.

Zhang, M., & Gunturk, B. K. (2008). Multiresolution Bilateral Filtering for Image Denoising. *IEEE Transactions on Image Processing, 17*(12), 2324-2333.

Zhang, Y., Jiang, H., & Ma, L. (2018). Blood Vessel Segmentation Based on Digital Subtraction Angiography Sequence. In *2018 IEEE International Conference on Systems, Man, and Cybernetics (SMC),* 2049-2054.

Zhao, S., Wu, Z., & Zhou, M. (2010). A Multi-Scale Method for Extraction of Cerebral Blood Vessels. In *2010 IEEE International Conference on Progress in Informatics and Computing,* 2, 1280-1283.

Zubair, A. R., & Busari, H. O. (2018). Robustness of Median Filter for Suppression of Salt and Pepper Noise (SPN) and Random Valued Impulse Noise (RVIN). *International Journal of Image Processing, 12*(1), 12-27.