Biomedical Signal Processing and Control 40 (2018) 131–139

Contents lists available at ScienceDirect

Biomedical Signal Processing and Control

journal homepage: www.elsevier.com/locate/bspc

Spatially adaptive denoising for X-ray cardiovascular angiogram images

Zhenghua Huang [a,b,*], Yaozong Zhang [a,b], Qian Li [a], Tianxu Zhang [b], Nong Sang [b]

[a] Wuhan Institute of Technology, Wuhan, Hubei 430205, China
[b] Huazhong University of Science and Technology, Wuhan, Hubei 430074, China

ARTICLE INFO

Article history:
Received 30 November 2016
Received in revised form 19 August 2017
Accepted 16 September 2017

Keywords:
Spatially adaptive denoising
Wavelet shrinkage
Gradient factor
X-ray cardiovascular angiogram image

ABSTRACT

The X-ray angiogram image denoising is always one of the most popular research in the field of computer vision. While the methods removed the noise, the useful structure (such as peripheral vascular) had also been smoothed, the fundamental reason is that the denoising methods cannot efficiently distinguish structural areas from flat areas.

In this paper, we have proposed a spatially adaptive image denoising (SAID) method which contains two steps: spatially adaptive gradient descent (SAGD) image denoising and dual-domain filter (DDF). The SAGD denoising method contains the following parts: first of all, the wavelet shrinkage method is used to estimate redundant information which is composed of the noise and useful structures; secondly, according to the characteristic of second order matrix, a spatially adaptive gradient factor (SAGF) has been constructed to distinguish the structure from flat areas; finally, the SAGF replaces the original gradient factor and then the SAGD image denoising method is formed. To further improve the quality of the SAGD image, the SAGD image is re-denoised by a modified DDF which is guided with a rotationally invariant non-local filter (RINLF) in spatial domain and gets structural details by wavelet shrinkage in frequency domain. The results of simulation experiments verify that the proposed SAID method can get well quantitative and qualitative results which are even superior to those using the state-of-the-art denoising methods. Even more, the fluctuation of peak signal-to-noise ratio (PSNR) value is very small with a small disturbance of SAGF, which illustrates that our algorithm is more robust than the prior progressive image denoising (PID) method. Moreover, the comparison results of the extensive experiments on clinical X-ray cardiovascular angiogram images further illustrate that our method can yield clearer cardiovascular images which can provide more useful vascular information for clinicians to analyze and diagnose the cardiovascular diseases.

1. Introduction

Cardiovascular diseases (CVDs) has been the biggest culprit to human health. It is reported by the US Health Bureau that people who died in cardiovascular disease accounted for 57% among the number of deaths in each year [1]. Therefore, it is the problem for the world's researchers to effectively curb the continuous occurrence of CVDs. Now the main method for determining CVDs is that doctors utilize X-ray angiography technique to obtain an angiogram image (the main procedure to get angiogram images is shown in Fig. 1), and then make a diagnosis according to their clinical experience. However, due to the effect of imaging apparatus or image transmission, the obtained angiographic images, polluted by the additive Gaussian white noise (AGWN) [2], are not conducive for the doctors to diagnose the patient's condition. And it is also not convenient to extract cardiovascular from the noisy images for long-term study and research (such as three-dimensional cardiovascular reconstruction and cardiovascular motion analysis [3]). Therefore, it is imperative to restore the clear angiogram images with integral cardiovascular tree.

Image denoising has been one of the most important research topics in computer vision. In recent years, image donoising methods are coming out one after the other. Total variation (TV) based

* Corresponding author at: Wuhan Institute of Technology, Wuhan, Hubei 430074, China.

E-mail addresses: huangzhenghuahzh@163.com, d201277565@hust.edu.cn (Z. Huang).

http://dx.doi.org/10.1016/j.bspc.2017.09.019
1746-8094/

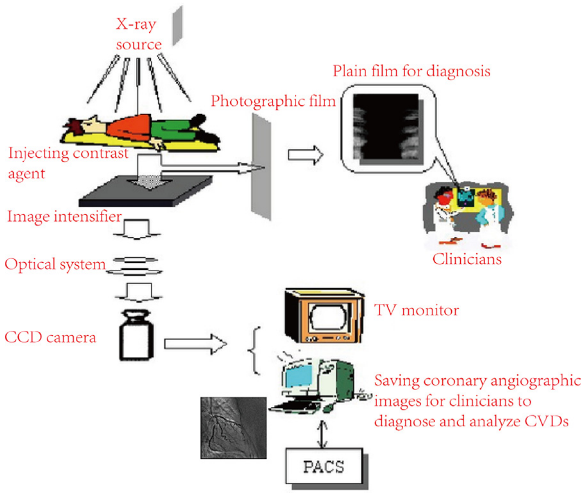

Fig. 1. The main procedure to get cardiovascular angiogram images.

is always one of the most popular methods for image denoising. Many latest denoising methods are still TV-based. TV-based image denoising was first proposed by Rudin et al. in 1992 [4]. However, original TV-based image denoising methods would produce "staircase effects" in flat areas, smooth useful details (such as edges) while removing noise, and even be very dependent on the regularization parameter. Therefore, to solve the above problems, a series of TV-based image denoising methods were proposed. Chan et al. [5–7] proposed L^1-regularization, wavelet operator and stochastic method in TV model. A iterative method for regularization was proposed by Osher et al. [8]. Non-local regularization [9] methods had improved much image denoising performance over conventional TV-based methods. Zuo et al. [10] proposed gradient histogram preservation (GHP) algorithm according to image prior knowledge including gradient information, sparse representation, and non-local self-similarity; Dong et al. [11] proposed spatially adaptive iterative singular-value thresholding (SAIST) by assuming that the matrix of non-local similar patches has a low rank structure. The SAIST method which gave less artifacts than most of the TV-based methods estimated signal variances by solving singular value decomposition (SVD) of similar packed patches, and preserve details very well.

Another very popular image denoising methods are block-based approaches. Block-based method clusters similar patches within neighborhood window and denoises them simultaneously. Dabov et al. [12] proposed block matching with 3D filtering (BM3D) method by the use of 3D-wavelet shrinkage. The BM3D method, obtaining high-quality images, has been a benchmark in image denoising. Dabov et al. [13] proposed BM3D image denoising with shape-adaptive principal component analysis (BM3D-SAPCA), which utilized PCA to find sparse representation of blocks, and until now, it remains unchallenged in its numerical performance. According to the sparseness and self-similarity of the images, Manjón proposed a oracle-based discrete cosine transform 3D (ODCT3D) filter in Ref. [14], then proposed a local PCA (LPCA) denoising method to reduce random noise in multi-component diffusion weighted image (DWI) [15], and in Ref. [16], the denoising method first obtained denoised image by the use of non-local PCA (NLPCA) thresholding strategy to automatically estimate the local noise level and then viewed it as a guide image within a rotationally invariant non-local means filter. Xu et al. [17] proposed a patch group (PG) based image nonlocal self-similarity (NSS) prior learning scheme to learn explicit NSS models from natural images for high performance denoising, called patch group prior based denoising (PGPD) method. Other block-based image denoising methods were also shown in Refs. [18–21]. Not only are there higher signal to noise ratio (SNR) in these methods, but the qualitative denoising results are also well in finer details and less artifacts. However, the computational complexity of these methods limits their further expansion and application.

Other image denoising methods including diffusion based methods [22,23], wavelet/curvelet based filters [24–27], sparse representation based methods [28,29], and deep learning based methods [30,31] especially denoising convolutional neural network with known specific noise level (DnCNN-S) in Ref. [32], had also been great success in obtaining high-quality images.

Recently, a patch-less dual-domain image denoising (DDID) method, which was proposed by Knàus and Zwicker [33], is guided with bilateral filter (high-contrast component) [34] in spatial domain and extracted structural details (low-contrast component) with wavelet shrinkage [35] in the frequency domain. The DDID is much simpler than the BM3D, and results of which can be comparable to those of the BM3D. The image restored by the DDID method is combined with the high-contrast image and the low-contrast image. Although the simple method had achieved good results, the empirical parameters in the bilateral filter and the wavelet shrinkage factor are always different in the three iterative steps, even artifacts are exposed in the restored images.

Then, Knàus and Zwicker [36] proposed a progressive image denoising (PID) method which was derived from the DDID method but different from it. The PID method estimated noise by the wavelet shrinkage method in frequency domain and incorporated the noise into the gradient descent to obtain the estimated image. Compared to DDID method, the parameters in bilateral filter and the wavelet shrinkage in the PID method are both adaptive, and the restored results are robust with a disturbance of these parameters (even within the range of 0.1), and the artifacts of the restored image are free. Although the results of the PID method is impressive, it still has its drawbacks. On the one hand, the gradient factor λ is not adaptive, which has a very big impact on the quantitative PSNR value. So the restored image is very dependent on the gradient factor λ. On the other hand, the bilateral filter can get high-contrast image but lose too much structural information which leads to appear ringing artifacts or the loss of structure. To solve the above problem, a spatially adaptive gradient factor (SAGF) λ_{SAGF}, which can distinguish structural areas from flat areas, is proposed according to the eigenvalues of the second order Hessian matrix. As λ_{SAGF} is spatially adaptive, the restored results are robust with a disturbance of gradient factor λ. Moreover, to further improve the image quality, the modified DDF method, which is guided with rotationally invariant non-local filter (RINLF) in spatial domain, can preserve more details and "heal" ringing artifacts caused by the wavelet shrinkage in the frequency domain. Not only can the proposed method called spatially adaptive image denoising (SAID) solve the instability of the PID algorithm with the small disturbance of the gradient factor, but more details have been also preserved and the estimated images are artifact-free, which illustrates that the results restored by the SAID method are much closer to the real images.

In the following paper, the proposed spatially adaptive image denoising method is first detailed introduced in Section 2. Then, several experimental results, including the stable analysis of the PID method and the SAID method with a disturbance of gradient factor, the comparison of both qualitative and quantitative results using the advanced methods for simulated images, and the comparison of applicable results using the advanced methods for clinical X-ray cardiovascular angiogram images are presented in Section 3. Finally, the work of this paper are concluded and discussed in Section 4.