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Motion-adaptive 3D nonlocal means filter based on stochastic distance for low-dose X-ray fluoroscopy

Min Seok Lee [a], Sang Wook Park [b], Sang Yoon Lee [a], Moon Gi Kang [a,*]

[a] School of Electrical and Electronics Engineering, Yonsei University, 50 Yonsei-Ro, Seodaemun-Gu, Seoul, South Korea
[b] Medical Device Development Center, Daegu-Gyeongbuk Medical Innovation Foundation, 80, Cheombok-Ro, Dong-gu, Daegu 41061, South Korea

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ABSTRACT

Low-dose X-ray fluoroscopy avoids radiation risks, but X-ray fluoroscopic image sequences are contaminated by quantum noise. In this paper, a 3D nonlocal means (NLM) filter based on stochastic distance that incorporates motion information is proposed, which can be applied to the denoising of X-ray fluoroscopic image sequences. First, the stochastic distance is obtained for use as the NLM filter similarity measure. This facilitates the removal of Poisson noise between the patches to be denoised within motion-compensated 3D volumes for spatio-temporal filtering. Second, motion state detection and motion-adaptive weights are proposed, which preserve the details of the motion that can occur during medical procedures. Experimental results obtained by applying the proposed method to real X-ray fluoroscopic image sequence images are shown in visual and numerical comparison with state-of-the-art denoising methods for spatio-temporal filtering techniques. The quantitative and qualitative results confirm that the proposed novel frameworks outperform other techniques in terms of objective criteria, as well as the subjective visual perception of the real X-ray fluoroscopic image sequences.

1. Introduction

X-ray fluoroscopy plays a crucial role in medical imaging, and this technique has been widely used in patient clinical examinations and interventional procedures (angiography). However, the radiation exposure experienced by patients and staff during clinical treatment has emerged as a major problem. Hence, the reduction of radiation exposure is an important challenge related to X-ray-based medical imaging. However, when the radiation dose is minimized, strong noise inevitably arises in the image. At a low signal-to-noise ratio (SNR), degradation of the image quality decreases the accuracy of the clinical diagnosis. Thus, an image denoising algorithm is necessary, not only to improve the image quality, but also to facilitate the use of low-dose X-ray fluoroscopy.

Currently, image-sequence denoising filters are being actively studied [1–6]; however, the processing of X-ray fluoroscopic image sequences remains a challenging problem. Because of the lower number of X-ray photons involved, low-dose X-ray fluoroscopic images are strongly dominated by quantum noise, which is statistically modeled as a signal-dependent Poisson distribution. Many denoising algorithms for signal-dependent noise have been presented in the literature [9–14]. In general, denoising methods can be divided into two categories based on the filtering domains, namely, spatial and temporal methods.

In the spatial domain, the use of patch-based approaches has become popular in recent years. For example, nonlocal means (NLM) filtering has been proposed in Ref. [15], while block-matching and a 3D filtering (BM3D) algorithm have been proposed in Ref. [8], all of which have been employed in denoising applications. With regard to Poisson noise removal, some patch-based methods specifically designed for signal-dependent noise have been presented [11,12]. The most common method involves use of a variance-stabilizing transform such as the Anscombe transform [9,10]. In the transformed domain, the Poisson noise behaves like Gaussian noise. Hence, denoising methods for signal-independent noise, such as the BM3D filtering developed in Ref. [8], can be adopted to remove the transformed Poisson noise. In addition, an NLM filter based on stochastic distances, which does not employ a variance-stabilizing transform, has been proposed [14]. For this NLM filter, the similarity in the Euclidean distance between the center patch and the neighboring patches is utilized for weight calculation [15]. In order to improve the weight calculation results for Poisson noise removal, however, the similarity measure is replaced by symmetric divergences, also known as stochastic distances [13].

In order to restore degraded image sequence data, denoising methods extended to the temporal domain have also been

* Corresponding author.
E-mail address: mkang@yonsei.ac.kr (M.G. Kang).

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presented in recent years [1–6]. Temporal filtering exhibits advantages in terms of preservation of fine details, because this filtering method does not average neighboring pixels, unlike spatial filtering. On the other hand, temporal filtering is likely to cause problems in cases involving moving regions, such as motion blurring and trailing artifacts. Motion representation plays a significant role in temporal filtering. In temporal filtering methods, corresponding motion information is categorized as explicit or implicit representation. In denoising, explicit motion representation refers to the detection of the true motion trajectories of a physical point via motion estimation and compensation. Many temporal filters, such as the locally adaptive linear minimum mean squared-error spatio-temporal filter (3D-LLMMSE) [1] and the multihypothesis motion-compensated filter (MHMCF) [2,3], adopt this approach. Such explicit motion representation is conceptually simple, but suffers from a fundamental weakness; that is, because of the difficulty in establishing correct correspondence for every pixel, uncertainty in the motion representation is inevitable. Thus, instead of explicit-motion-based filtering, implicit-motion-based filtering has been proposed, involving patch-based approaches extended to the temporal domain, for example. At present, patch-based approaches are also popular in 3D denoising methods. An NLM extended to the temporal domain [4], space-time adaptive filtering [5], and video block matching and 3-D filtering (VBM3D) [6] are some representative implicit-motion-based filtering methods. However, the methods that neglect motion estimation yield motion artifacts such as blurring and trailing. For images obtained using motion-compensated temporal filtering, the motion details are better preserved and the boundaries are less blurred than those obtained using implicit motion-based filtering. A patch-based denoising method and motion estimation algorithm inspired by the image fusion method have been proposed in Ref. [7].

Thus, a method based on motion-compensated 3D spatio-temporal volumes along with motion trajectories is proposed in this study. These motion-compensated 3D volumes are used to provide 3D filtering support for spatio-temporal filtering of X-ray fluoroscopic image sequences. Previously, a motion-compensated spatio-temporal filter operating in a multi-scale space has been proposed [24]. Further, several denoising algorithms based on spatio-temporal filtering techniques have been developed and used for medical imaging [16–25].

The contribution of this work is twofold. First, we propose a framework for a 3D NLM filter based on stochastic distance in order to reduce the quantum noise, which is modeled as a Poisson distribution. The developed 3D NLM filter is based on 3D motion-compensated support composed of sequences of support volumes stacked along the motion trajectories. Second, we consider the motion states of an X-ray fluoroscopic image sequence and the spatio-temporal similarity in order to obtain a motion-adaptive weight for the 3D NLM filter. This motion-adaptive weight contains a motion detection value between neighboring frames within the motion-compensated 3D filtering support. The proposed motion-adaptive 3D NLM filter based on stochastic distance is designed to suppress quantum noise in X-ray fluoroscopic image sequences while preserving image features such as edges, textures, and details, even if complex motion occurs.

The remainder of this paper is organized as follows. Beginning with the spatio-temporal filter structure of the static 3D NLM, we define the proposed 3D NLM structure based on stochastic distance for X-ray fluoroscopy, and proceed to explain the novelty and motivation behind the proposed method. In the experimental results section, we demonstrate the performance of the algorithm using real X-ray fluoroscopic image sequences obtained at different low-dose levels. The evaluation is performed on a set of six fluoroscopic image sequences including 50 frames, using a chest phantom with two different motion types and two different X-ray dose levels. Finally, we conclude the paper.

2. Static 3D NLM filter for Gaussian noise

The NLM filter [15] is one of the most popular denoising methods, and has been studied extensively. As an averaging-based filter that directly smoothens the pixel values in the spatial domain, the NLM filter is an effective denoising method. In the NLM filter, the similarity between the Euclidean distance between the center patch and the neighboring patches is utilized for weight calculation. Further, the NLM-based spatio-temporal filter is obtained by extending the 2D spatial filter support to a 3D time–space support [4]. This static 3D NLM filter is defined as

$$\hat{f}_{3DNLM}(\mathbf{x},t)=\frac{1}{N(\mathbf{x},t)}\int_{\Omega_{S(\mathbf{x},t)}}\int_{\Omega_{T(\mathbf{x},t)}} e^{\frac{(G|g(\mathbf{x}+.,t)g(\mathbf{y}+.,s)|^2)(0)}{h^2}} g(\mathbf{y},s)d\mathbf{y}ds, \tag{1}$$

where $g(\mathbf{x}, t)$ is an observed value at a 2D pixel index $\mathbf{x}$ in frame t, $g(\mathbf{y}, s)$ is an observed value at a 2D pixel index $\mathbf{y}$ in frame s, h is the smoothing parameter, G is a 2D Gauss kernel, and $N(\mathbf{x}, t)$ is the normalizing factor, as given by

$$N(\mathbf{x},t)=\int_{\Omega_{S(\mathbf{x},t)}}\int_{\Omega_{T(\mathbf{x},t)}} e^{\frac{(G|g(\mathbf{x}+.,t)g(\mathbf{y}+.,s)|^2)(0)}{h^2}} d\mathbf{y}ds. \tag{2}$$

The filter is 2D but integral in both the time and space dimensions in a 3D search window (Ω_S, Ω_T), where Ω_S is a 2D spatial search window around $\mathbf{x}$ and Ω_T is a 1D temporal search window around t. This means that (Ω_S, Ω_T) constitutes a 3D temporal-spatial block around ($\mathbf{x}$, t). In addition,

$$(G*|g(\mathbf{x}+.,t)-g(\mathbf{y}+.,s)|^2)(0) = \int_{\Omega_C} G(\mathbf{z})|g(\mathbf{x}+\mathbf{z},t)-g(\mathbf{y}+\mathbf{z},s)|^2 d\mathbf{z}, \tag{3}$$

defines a similarity function between $g(\mathbf{x}, t)$ and $g(\mathbf{y}, s)$, based on the similarity of their neighborhoods (Ω_C is a 2D neighborhood domain defining the comparison window, the so-called "image patch"). The similarity represents a Euclidean distance weighted by a Gaussian kernel with standard deviation. Note that the static 3D NLM filter is ineffective in a low-dose X-ray fluoroscopic image sequence. Further, low-dose X-ray fluoroscopic images are strongly dominated by quantum noise, which is modeled as Poisson noise. In order to remove the Poisson noise from the X-ray fluoroscopic image sequences, we propose the use of a 3D NLM filter based on stochastic distance. The proposed filter is described in the next section.

3. Proposed 3D NLM filter based on stochastic distance

In this section, we define the model for a noisy X-ray fluoroscopic image sequence, and recall the definition of 3D NLM filters given in Section 2. We present the framework and basic facts concerning the 3D NLM filter based on stochastic distance for X-ray fluoroscopic image sequence denoising.

3.1. Framework of proposed method

As noted above, the noise model considered in this work is Poisson noise, and X-ray images are known to have signal-dependent Poisson noise. At low exposure levels, the photons emerging from a