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A comparison of denoising methods for X-ray fluoroscopic images

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ABSTRACT

Fluoroscopic images exhibit severe signal-dependent quantum noise, due to the reduced X-ray dose involved in image formation, that is generally modelled as Poisson-distributed. However, image gray-level transformations, commonly applied by fluoroscopic device to enhance contrast, modify the noise statistics and the relationship between image noise variance and expected pixel intensity. Image denoising is essential to improve quality of fluoroscopic images and their clinical information content. Simple average filters are commonly employed in real-time processing, but they tend to blur edges and details. An extensive comparison of advanced denoising algorithms specifically designed for both signal-dependent noise (AAS, BM3Dc, HHM, TLS) and independent additive noise (AV, BM3D, K-SVD) was presented. Simulated test images degraded by various levels of Poisson quantum noise and real clinical fluoroscopic images were considered. Typical gray-level transformations (e.g. white compression) were also applied in order to evaluate their effect on the denoising algorithms. Performances of the algorithms were evaluated in terms of peak-signal-to-noise ratio (PSNR), signal-to-noise ratio (SNR), mean square error (MSE), structural similarity index (SSIM) and computational time. On average, the filters designed for signal-dependent noise provided better image restorations than those assuming additive white Gaussian noise (AWGN). Collaborative denoising strategy was found to be the most effective in denoising of both simulated and real data, also in the presence of image gray-level transformations. White compression, by inherently reducing the greater noise variance of brighter pixels, appeared to support denoising algorithms in performing more effectively.

1. Introduction

Fluoroscopy provides continuous-time X-ray images of a body part and is widely adopted as support in surgery procedures and diagnoses for the real-time displaying of surgical instrument (e.g. in orthopedic surgery), catheters or wire-guides (e.g. in angiography, angioplasty, pacemaker), structures highlighted by contrast agent (e.g. blood vessels, gastro intestinal tracts) and body moving parts (joint or implanted prosthesis). Since patients need to be exposed to radiation over a long period, very low X-ray doses are applied. As a result, fluoroscopic images result strongly corrupted by noise.

Noise reduction as well as contrast enhancement can be significantly improved by considering the specific nature of the fluoroscopic noise. Because of the limited X-ray photons involved, fluoroscopic images are dominated by signal-dependent Poisson noise, also known as "quantum noise". In general, at low exposure levels, pixel intensity (G) of a fluoroscopic image at the position $r=[x,y]^T$ can be modelled as Poisson-distributed:

$$P_G(G(r)) = \frac{[\lambda(r)]^{\alpha G(r)} e^{-\lambda(r)}}{\alpha G(r)!} \quad (1)$$

where $\lambda \gg 1$ is the expected photon count at that position in an interval of time (i.e. the reciprocal of the fluoroscope frame rate) and $c_d = 1/\alpha$ is a positive constant representing the detector gain [1–6]. According to the Poisson distribution model, variance of image noise is linearly dependent on the expected pixel intensity and results strongly signal-dependent [1–6]:

$$\mathrm{var}[H(r)] = c_d E[G(r)] \quad (2)$$

It is also worth to consider that over- and under-exposure of digital imaging sensors generate "clipping" effects at the extremes of the pixel intensity data range [6].

Gamma-correction is usually applied by fluoroscopic devices to improve contrast between tissues and to compensate for the X-ray exponential attenuation by determining an expansion of contrast for darker pixels and a compression for those brighter (i.e. white compression) [2,5–7]. This fundamentally changes the noise characteristics. After applying a gamma-correction transformation

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the pixel intensity of the fluoroscopic image can be expressed as [6,7]:

$$G_\gamma(r) = c_\gamma G(r)^\gamma \tag{3}$$

where c_γ is a positive constant and γ is typically ranged between 0.3 and 0.45 for commercial X-ray fluoroscopic equipment. By varying the γ-value it is possible to set an appropriate level of white compression. However, this also modifies the statistics of Poisson noise. As a consequence, noise level results a monotonically decreasing power function of mean pixel intensity of the gamma-corrected data [6]:

$$\mathrm{var}[G_\gamma(r)] \cong \gamma^2 \cdot c_\gamma^{1/\gamma} \cdot c_d \cdot E[G_\gamma(r)]^{2-(1/\gamma)}. \tag{4}$$

The literature is rich in denoising methods that assume additive white Gaussian noise (i.e. AWGN), while less attention has been paid to the design of denoising algorithms for Poisson noise. In addition, no observations about the effect of gray-level transformations applied to quantum-limited images on the performance of common denoising methods have been reported yet. In low-dose X-ray images noise reduction is generally achieved by means of simple linear averaging filters that can operate both in time and space. Linear filters usually assume noise to be additive, white and Gaussian (AWGN) and consider only a global estimation of noise content (i.e. noise is supposed not to be signal-dependent). Although these filters act very fast (allowing real-time applications), they exhibit the undesirable effect of degrading edges and tiny structures. This is not suitable for several applications, such as image segmentation, object recognition or image registration, that require an appropriate balance between noise reduction and signal preservation [8–11]. For instance, detection of boundaries is based on derivative operators which are particularly sensitive to noise and edge blurring [11]. The continue advance of computers allows to apply more complex digital processing methods and denoising strategies to overcome the limitations of linear filters. Edge-preserving adaptive filters [11,12], adaptive variational denoising [13], non local-means filtering [14,15], image denoising based on wavelet-domain hidden Markov models [16], sparse and redundant representations over learned dictionaries [17,18], total least square approaches [19] or partial differential equation techniques [20] are some example. Most of these algorithms assume noise to be signal-dependent and are based on the estimation of the local noise content; this generally permits to obtain a better trade-off between the amount of noise reduction and edge-preservation. In particular, by considering the specific nature of the fluoroscopic noise it is possible to more accurately set the denoising algorithm parameters to the noise characteristics.

The aim of this study is to compare the effectiveness of some popular denoising algorithms in restoring fluoroscopic images, i.e. in presence of Poisson noise and gray-level transformations. Denoising algorithms specifically designed for both signal-dependent noise [12,15,16,19] and independent additive noise (AWGN) [13,14,17,20] were compared by using known data corrupted by simulated Poisson noise and real fluoroscopic data.

2. Denoising algorithms

- An adaptive averaging spatial filter (AAS) specifically designed for signal-dependent noise was considered (similar to [11,12]). The filter performs the average of the only neighbouring pixels that differ less than a selected threshold from the gray level of the central pixel of the filter mask. The threshold is set to two times the estimated standard deviation of the noise associated with the local gray level. This intrinsically permits to preserve the edges with a gradient of gray greater than the local noise intensity.
- Denoising algorithms based on gradient dependent regularizers, such as nonlinear diffusion processes and total variation denoising, modify images towards piecewise constant functions. Although edge sharpness and location is well preserved, important image features (such as textures or specific details) are often compromised. The adaptive variational denoising (AV) is a mechanism that better preserves fine scale features in such denoising processes [13]. A basic pyramidal structure-texture decomposition of images is employed. A first level of this pyramid is used to isolate noise and relevant texture components in order to compute spatially varying constraints based on local variance measures. A variational formulation with a spatially varying fidelity term controls the extent of denoising over image regions. In other words, regions of the residual part with local variance higher than that of the noise are treated as textured regions where denoising is inhibited.
- The BM3D performs an image collaborative denoising strategy based on an enhanced sparse representation in transform domain [14]. The enhancement of the sparsity is achieved by grouping similar image regions (e.g. blocks) into 3-D data arrays which are called "groups." Collaborative filtering is realized using the three successive steps: 3-D transformation of 2-D image blocks into a group, shrinkage of the transform spectrum and inverse 3-D transformation. The result is a 3-D estimate that consists of the jointly filtered grouped image blocks. By attenuating the noise, the collaborative filtering reveals even the finest details shared by grouped blocks and, at the same time, it preserves the essential unique features of each individual block. The filtered blocks are then returned to their original positions. Because these blocks are overlapping, for each pixel, we obtain many different estimations that need to be combined. Aggregation is a particular averaging procedure which is exploited to take advantage of this redundancy. A significant improvement is obtained by a specially developed collaborative Wiener filtering. Although the BM3D algorithm is designed for AWGN, it has been also widely used for non-Gaussian noise.
- A denoising algorithm for signal-dependent "clipped" noisy observations (BM3Dc) was performed [15]. The approach involves a BM3D filter designed for AWGN and derives specific homomorphic transformations to stabilize the variance of the clipped observations (i.e. to adapt the estimated noise variance to the actual signal-dependent noise model), to compensate the bias due to the clipped distribution in the variance-stabilized domain and to compensate the estimation bias between the denoised clipped variables and the non-clipped true variables.
- Wavelet-domain denoising is generally based on the assumption that the wavelet coefficients are statistically independent or jointly Gaussian. However, in several cases (e.g. image compression) non-Gaussian models for individual wavelet coefficients are required. Moreover, statistical dependencies between coefficients should be characterized in order to derive optimal signal processing algorithms. A framework for statistical signal processing based on wavelet-domain hidden Markov models (HMM) that concisely models the statistical dependencies and non-Gaussian statistics encountered in real signals was assumed [16]. The method involves an efficient expectation maximization algorithm for fitting the HMM to observational signal data. This approach can be very useful for reconstructing image affected by non-Gaussian noise.
- The K-SVD is an image denoising algorithm for AWGN based on sparse and redundant representations over trained dictionaries [17]. Using the K-SVD algorithm, a dictionary that describes the image content effectively can be obtained. Two training options are considered: using the corrupted image itself or training on a corpus of high-quality image database. Since the K-SVD is limited in handling small image patches, its deployment is extended to