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A flexible patch based approach for combined denoising and contrast enhancement of digital X-ray images☆

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ABSTRACT

Denoising and contrast enhancement play key roles in optimizing the trade-off between image quality and X-ray dose. However, these tasks present multiple challenges raised by noise level, low visibility of fine anatomical structures, heterogeneous conditions due to different exposure parameters, and patient characteristics. This work proposes a new method to address these challenges. We first introduce a patch-based filter adapted to the properties of the noise corrupting X-ray images. The filtered images are then used as *oracles* to define non parametric noise containment maps that, when applied in a multiscale contrast enhancement framework, allow optimizing the trade-off between improvement of the visibility of anatomical structures and noise reduction. A significant amount of tests on both phantoms and clinical images has shown that the proposed method is better suited than others for visual inspection for diagnosis, even when compared to an algorithm used to process low dose images in clinical routine.

1. Introduction

Medical imaging based on X-rays is the main source of exposure to artificial radiation (Smith-Blindman et al., 2012), which, as highlighted in some recent studies, entails negative secondary effects for the patient health. Shuryak et al. (2010) have pointed out that all age groups run the risk of developing radio-induced cancers, and Ronckers et al. (2008) have shown that the patients affected by scoliosis have a higher probability of developing a cancer because they undergo more X-ray exams.

The way clinical image quality is perceived depends on how raw X-ray image quality is improved through the different steps of the image processing chain. In particular, the noise level on the outcome indirectly indicates if an image has been acquired in good conditions (Shepard et al., 2009). Therefore, it is important to define an algorithm robust to changes in the amount of signal at the detector, i.e. stable to changes in the amount of skin entrance dose and to inter-patient variability. The dose could be for instance reduced and still achieve the same diagnostic goal for a given study. Alternatively, the same amount of input signal could be used despite an increase in patient's size.

In this paper we consider X-ray images acquired with a low dose, and as a typical example we process images acquired with the stereo-radiographic imaging system EOS (Wybier and Bossard, 2013), that allows simultaneously acquiring full body frontal and lateral images of a patient in weight-bearing position. The density of the tissues significantly changes according to different anatomical regions (see Fig. 1a), which considerably affects signal values and noise levels. This intra-patient variability is another important factor that needs to be taken into account to optimally process the acquired data.

X-ray images present both components of noise and signal that cannot be clearly distinguished because the local contrast at the acquisition is low. Therefore, the image quality enhancement requires to both reduce the noise and increase the visibility of fine anatomical details. In some works (Sakata and Ogawa, 2009; Loza et al., 2014) the authors propose to restore the input image by using wavelet-based approaches and, then, to enhance it. Nevertheless, this type of approach can lead to a loss of spatial resolution that is not acceptable in clinical routine. The use of more advanced denoising filters that represent an image in a patch space could overcome the aforementioned issue. The patches are sub-images that capture local characteristics and, hence, the noise can be attenuated while preserving edges and texture. These filters have been also used in medical applications (Cerciello et al., 2012) showing promising results. Nevertheless, as pointed out by Lebrun et al. (2012) in a survey on this denoising technique, very fine texture, e.g. fine bone texture, may be flattened out. The use of highly performing noise reduction filters is then only a partial solution in radiography applications: the resulting

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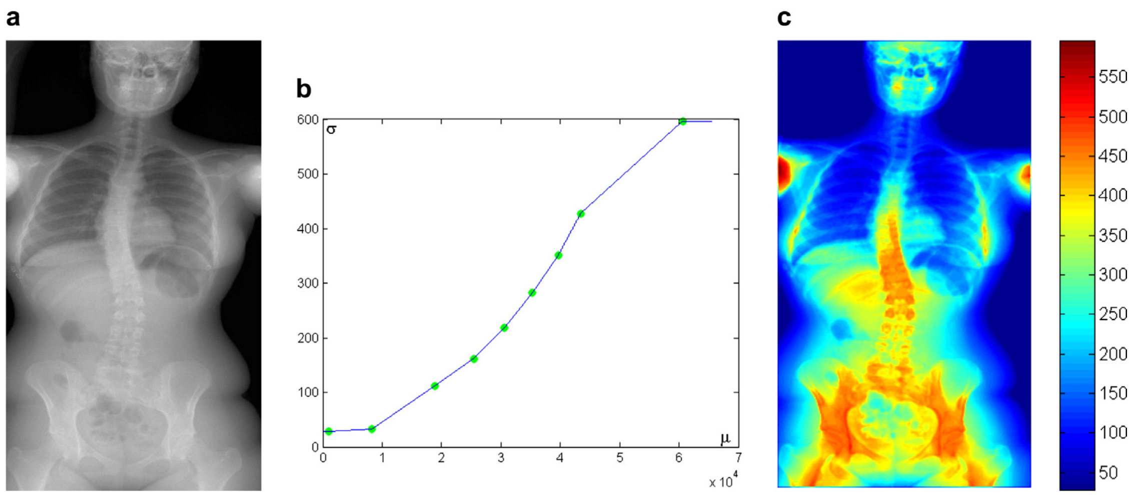

Fig. 1. Noise estimation using the percentile method: (a) Input image I. (b) Interpolated noise curve from the n points (μ_i, σ_i). (c) Resulting map of noise standard deviation ($\sigma(S)$).

images may risk to be perceived as unnatural by the clinicians due to a lack of information in the bone structures. The noise containment maps (Stahl et al., 1999) are an alternative approach that consists in defining, in a multiscale framework, whether a coefficient can be fully enhanced as associated with signal information, or not. Stahl et al. (1999) use density and activity measures to define the noise containment maps. However, the definition of these maps depends on global user-defined parameters, which is the main drawback of this method. Indeed, the capacity of containing the noise relies on these parameters. Finally, given the heterogeneity of digital X-ray data, parametric noise containment maps are sub-optimal.

Contributions. This work proposes a general framework for joint denoising and enhancement of X-ray full body images that addresses the aforementioned drawbacks of existing methods. The main contribution of this paper consists in showing how the output of a denoising filter applied to an X-ray image well approximates the ground truth image and can be then exploited to increase the visibility of anatomical details while containing the noise. We propose an extension of the Non Local Means (NLM) filter (Buades et al., 2005) that can be easily adapted to our noise model and is called X-ray Non Local Means (XNLM) filter. The result of this filter is exploited to define non-parametric noise containment maps that are used in a multiscale framework to robustly limit the presence of the noise in the final solution. Note that the independence from manually set parameters is a crucial element, which makes the method robust to the heterogeneity of the data to be processed. While the tests presented in this paper have specifically been carried out on EOS images, the approach could likely be applied to any image exhibiting similar characteristics.

The main scope of the validation consists in quantifying how much our work can help clinicians in their diagnosis. The provided outcomes are meant to be suitable for diagnosis without any further manual user interaction. Manual windowing can optimize contrast and brightness, however these adjustments can cause noise to raise and further slow down diagnosis process. For these reasons, the results that optimize the trade-off between contrast and amount of noise should be automatically obtained.

The quality of clinical images is not easy to objectively assess and this aspect is studied in this work. Therefore, two new validation approaches are proposed. In particular, classical measures of contrast (average local variance (Chang and Wu, 1998) and contrast improvement index (Laine et al., 1995)) are revisited by associating them with anatomically meaningful regions. Moreover, the image quality evaluation is completed with clinical assessments according to the feedbacks of a radiologist.

Some aspects introduced in this paper are partially related with two of our former works. The first one (Irrera et al., 2013) has allowed showing that the denoising filter parameters need to be tuned for different anatomical regions in order to efficiently restore a full body X-ray image. However, while in this previous work the parameters were set by manually adjusting the shape of a curve, this is not the case for the XNLM filter here introduced, that now exploits automatic estimates of the noise levels. In the second paper (Irrera et al., 2014) the denoising process has been combined with a multiscale decomposition with the aim of reducing the spatial resolution loss on EOS images used in follow-up examinations. This is very different from the noise containment approach proposed here, which has the advantage of not being limited to a specific clinical case as it is free from critical parameter setting.

The paper is organized as follows. Section 2 explains how to estimate a curve that gives the noise standard deviation as a function of the signal and, then, how to exploit it to formulate the XNLM filter. Section 3 outlines how to estimate the noise containment maps and to increase the visibility of anatomical details. Section 4 presents some results on both phantom and clinical images. Section 5 concludes the paper, and summarizes the achieved objectives and perspectives.

2. X-ray Non Local Means filter

2.1. Overview of the Non Local Means filter

The Non Local Means (NLM) filter estimates the intensity value of a pixel x_i by means of a weighted average that depends on the similarity between patches (Buades et al., 2005). The result of the filter is good as long as the information in the image is redundant, i.e. similar structures can be found at different spots. This hypothesis is valid for X-ray images. Given the input image I, the gray level of the filtered image $\hat{I}$ at a pixel x_i is formally defined as follows (Buades et al., 2005):

$$\hat{I}(x_i) = \frac{\sum_{j=1}^{|\Omega|} \varsigma(i,j) I(x_j)}{\sum_{j=1}^{|\Omega|} \varsigma(i,j)} \tag{1}$$

where $\varsigma(i, j)$ is the weight associated with $I(x_j)$ in the estimation of $\hat{I}(x_i)$. The domain Ω represents the search space for similar patches. In practice, this is a window of half-size w (i.e. $|\Omega| = (2w+1)^2$) centered at pixel x_i. The weight $\varsigma(i,j)$ quantifies the distance in the patch space between spatially near pixels. Formally, let P_i and P_j denote patches of half-size p (i.e. $|P| = (2p+1)^2$) centered, respectively, at