Noise estimation in mammographic images for adaptive denoising

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I. INTRODUCTION

Contrast, detail, and noise are the primary factors in image quality, and they play a major role in screen film radiography (SF) and digital Radiography (DR). Subject contrast is the relative difference in X-ray exposure on the exit side of the patient and is the result of the attenuating properties of the tissues under study. Noise can be defined as any fluctuations in the image that do not correspond to variations in the X-ray attenuation of the object being imaged. Finally, details carry tumoral markers, such as mass contours, microcalcifications etc. In recent years, several computer-assisted diagnosis (CAD) schemes for breast cancer signs detection and enhancement have been developed. All these methods have to simultaneously improve contrast, preserve details, and reduce noise. To do this, wavelet analysis is the leading approach for contrast enhancement and image denoising, owing to the multiscale nature of different cancer signs (masses are space-occupying lesions, described by their shapes, margins, and denseness properties, while microcalcifications are tiny deposits of calcium that appear as small bright spots in the mammogram). In fact, using wavelet transform, it is possible to detect details that appear at different scales and selectively enhance them within different resolution levels [1], reducing noise that appears only at higher levels.

Ideally, in this context noise is dominated by the X-ray quantum noise which has a Poisson distribution. However, all image receptors contain some internal sources of noise. Examples of other sources of noise are film granularity noise in SF, electronic noise in DR, quantization noise, scatter radiation [2]. In particular the primary effect of scatter is a reduction of subject contrast and of SNR because it contains no signal but does contain Poisson quantum noise.

II. THE PROPOSED DENOISING METHOD

Since the presence of noise could disturb the processing in wavelet domain and corrupt the enhancement performance, it is firstly necessary to denoise the data.

However, conventional filtering techniques cannot be applied in the context of medical imaging because they produce edge blurring and loss of details. In order to achieve edge preserving filtering we apply the well known wavelet shrinkage denoising [3] on the wavelet coefficients at each level. Firstly, the original image is decomposed by suitable filters (see [4]) so that details and low frequency information are mapped into different domains. Then, a suitable thresholding operator is applied only on detail coefficients, since low frequency coefficients are noise-free. Moreover, in order to avoid orientation distortions, the two oriented wavelet coefficients corresponding to horizontal and vertical details should be simultaneously processed, so the magnitude M of these coefficients must be considered. The following shrinking operator is used $C(M) = |M| - T_n$, for $|M| \geq T_n$, 0 otherwise. Note that this operator is a monotonically non decreasing function in order to avoid the introduction of artifacts. The key issue is the optimal selection of the threshold T_n. A threshold too large produces blurring of small edges, while a low one does not remove enough noise. In [4], [5] we perform noise variance estimation through a fuzzy logic system [6] under the assumption of white gaussian additive noise. Really, noise in X-ray images have different sources, as noted above. In particular, some commonly assumed hypotheses should be relaxed such that: additivity, signal independency, and normal distribution. The main problems arises from signal dependency of Poisson noise from luminance values, so in this paper we mainly address this topic, still assuming additivity (as a first order approximation).

To do so, we implement a noise variance estimator following algorithm described in [7]. Briefly, the method builds a non-linear model $\sigma_n^2 = f(I, \alpha_1, \alpha_2, \ldots)$ that depends on local intensity I, and a set of parameters $\alpha_1, \alpha_2, \ldots$ that are determined by the image acquisition protocol. If multiple repeated images can be acquired then, by statistical

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The work is within "TELESAL" project, developed with ASI, Min. della Salute, Eur. Onc. Inst., Kell s.r.l.

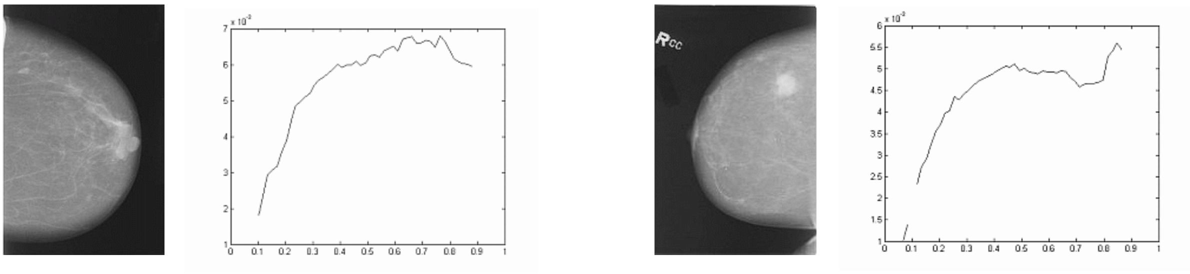
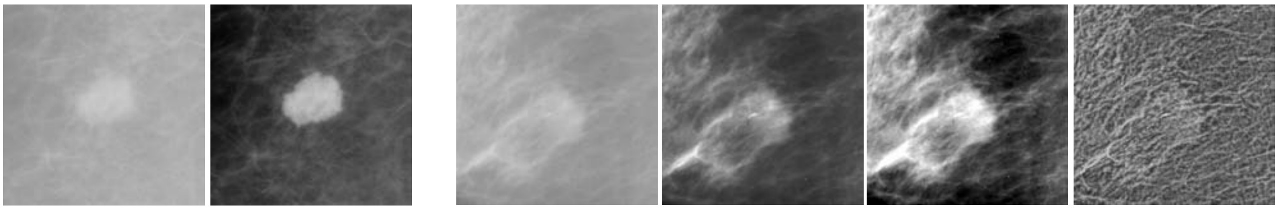


Fig. 1. Map of noise variance versus image intensity for two mammographic images.



(a) (b)

Fig. 2. (a) Enhancement of a tumoral mass. (b) Enhancement of a cluster of microcalcifications. Original image (first). Enhanced image (second). Standard enhancement method (third). Enhancement without denoising (fourth).

analysis, the model can be easily estimated. Conversely, when only a single image is available, as commonly in medical imaging, a further analysis has to be performed in order to estimate the model. In particular, owing to a very low noise level, homogeneous regions can be found by applying a low pass gaussian filter and then by evaluating the noise image, by subtraction of the smoothed image to the original one. A further step is needed in order to eliminate edges from the noise images, that would decrease noise variance estimation accuracy.

Now a histogram is built in order to classify noise according to local intensity extracted by the original X-ray image. Finally, the standard deviation of each interval is evaluated by a Robust Median Estimator (RME). Fig. 1 shows two mammographic images, from DDSM [8] and the corresponding noise variance map versus image intensity. By performing the same estimation on many images taken from the same database, we observe the same logarithmic regression, so that a direct model can be built, suitable for a wide class of mammographic images. In this way, noise variance estimation could be a one-step procedure, thus allowing a very fast denoising.

In Fig. 2(a)-(b) we provide two examples of mammographic images enhancement with denoising performed by the described method. Case in (a) shows enhancement of a tumoral mass, while case (b) shows enhancement of a linear distributed cluster of microcalcifications inside a tumoral mass. In particular Fig. 2(b) shows a comparison with standard denoising approaches (Wiener filter) and contrast enhancement (histogram stretching) (third figure) and with enhancement performed on wavelet coefficients without denoising (fourth figure), thus proving the effectiveness of our approach.

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