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Signal–dependent Noise Characterization for Mammographic Images Denoising

Marcello Salmeri, Arianna Mencattini, Giulia Rabottino,
Alfredo Accattatis, Roberto Lojacono

Department of Electronic Engineering, University of Rome "Tor Vergata",
Viale del Politecnico, 1 – 00133 – Roma, Italy,
Phone: +39–0672597373, Email: {salmeri,mencattini,rabottino, accattatis,lojacono}@ing.uniroma2.it

Abstract – The paper deals with the noise characterization under the assumption of a heteroscedastic signal–dependent noise model in the context of medical imaging. In particular, in this kind of application, a sophisticated noise variance estimation algorithm is applied using robust estimators and nonlinear regressions. A direct relation between noise variance and pixel intensity values is obtained and used within a multiresolution denoising algorithm, performed by Wavelet Thresholding (WT). We will provide results of the noise estimation, by applying the proposed method to mammographic images.

I. Introduction

In the last decades Screen Film Mammography (SFM) have represented the leading technique for the early detection of breast cancer in women. Only in the last few years Digital Mammography (DM) have been applied to screening and diagnosis. The two methods have many differences both in technologies and in performance [1,2].
In SFM a phosphor screen in a light–tight cassette absorbs a fraction (typically 60 – 80%), called *quantum efficiency* of the incident X–rays. The phosphor transforms X–rays into light and a sheet of photographic film is directly impressed by it. Finally, by chemical processing the latent photographic film is converted into a pattern of optical density on the film which can be seen by transillumination. In order to produce a digitized version of the image a high resolution scanner device is used.
In DM the image is acquired by a detector, which converts X–rays into an electric signal and then it is digitized into 2^N intensity levels (typically N equals 12 or 16). The digital image has also a spatial resolution depending on the device.
Obviously, high quality images are needed in order to accurately detect subtle lesions (e.g., microcalcifications or low contrast massive lesions) in the breast. Image quality is evaluated in terms of *spatial resolution*, *contrast*, *absence of artifacts*, and *noise*.

- Spatial resolution is due to digitalization process. Typically, mammographic images with good quality have a spatial resolution in range [40–50] μm. This high resolution is needed to distinguish pathological structures such as microcalcifications (about 0.1 – 1 mm).
- Contrast is essentially due to relative differences in absorption characteristics among normal tissue and pathological lesions; obviously density and thickness of the structures of interest are crucial. Consequently, in order to assist radiologists in the detection of cancer signs contrast enhancement is always performed by a postprocessing procedure on the digitized image. Contrast and spatial resolution are also influenced by *motion blurring*, caused by physiological motions during the exposure (it takes about 4 s), *geometric and receptor blurring*, *breast compression*, etc. All these effects should be treated as systematic error contributions affecting the quality of mammographic images. Recently, we consider these effects in the uncertainty evaluation and propagation through the formation, acquisition and elaboration phases [3].
- Artifacts are unwanted effects that are unrelated to breast structures and that appear in the formation and digitalization process. They are typically due to dust, fingerprints, overexposure, x–ray sources, compression devices, breast support tables, darkrooms and are always corrected in any quality control program for mammography so that we can neglect them in this work.
- Noise is the leading effect that cannot be neglect since it impairs the detection of lesions especially when contrast improvement is needed in order to emphasize small cancer signs such as microcalcifications. Radiographic noise or *mottle* is any unwanted random variation of the optical density on a radiography. In SFM major sources of radiographic noise include *quantum noise*,

screen structure, *film grain*, *film processing artifacts*, *X–ray to light conversions*. In particular, radiation dose strongly influences noise contribution. When fewer X–rays are used, the fluctuation in the image increases and the image appears noisier. Other noise sources are *quantization noise* related to bins used in the digitalization process, *film granularity*, and the *statistical fluctuation of light* produced in the screen when an X–ray quantum is absorbed.

Noise characterization, in terms of noise variance, should be performed in order to reduce noise amount in mammographic images so as to optimize contrast enhancement performance. In particular, in the last ten years multiresolution analysis by wavelet transform has represented the leading approach for medical images denoising and enhancement. In fact, a multiscale approach allows us to separate and selectively process objects according to their size. In mammographic images, cancer signs are represented by microcalcifications (in a early stage) with mean diameter in [0.1–1] mm and massive lesions with a mean diameter in the range [0.5–40] mm. Other structures, related to pectoral muscle, glandular tissue, fatty tissue, or other parenchyma's structures, can be also visible.
In this paper we consider the following steps:

- noise modelling and characterization;
- denoising by wavelet thresholding.

In particular, we consider a noise model given by

$$I(n,m) = I_0(n,m) + \tilde{I}(n,m) = I_0(n,m) + \eta(n,m)\sigma(I_0(n,m))$$

where $I(n,m)$ is the noisy image, $I_0(n,m)$ is the noise–free image, $\eta(n,m)$ is a normal random process with zero mean and unitary variance, $\sigma(I_0(n,m))$ is the standard deviation of the noisy contribution $\tilde{I}(n,m)$. Note that we suppose an heteroscedastic noise model that consists in assuming an intensity–dependent noise standard deviation. So, in the following section we will describe an algorithm for the estimation of $\sigma\big(I_0(n,m)\big)$. Then, we will provide a method to embed this estimation into multiscale denoising.

II. Signal–dependent noise characterization

The main problem we address is noise estimation in order to provide its standard deviation. We expect that radiographic noise in this case includes very different noise contributions so that we do not expect a unified model for the standard deviation.

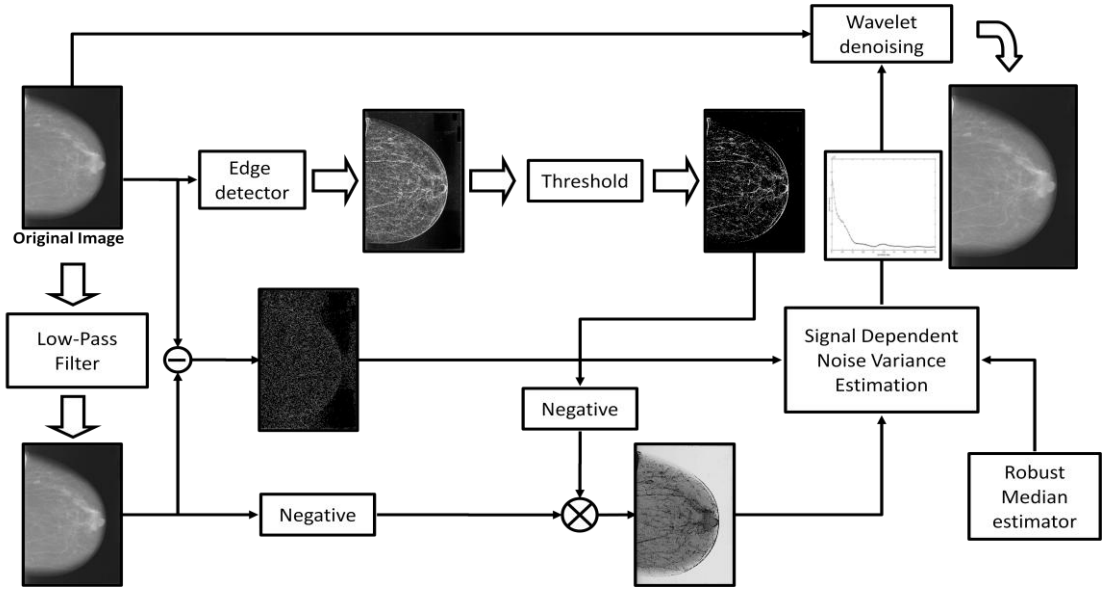

Figure 1. The noise variance estimation algorithm.

The main steps of the estimation algorithm can be summarized as follows.

(a) Extract low–frequency components from the image containing homogeneous regions. This step is performed by applying a low pass gaussian filter to the original noisy image obtaining a smoothed image that we denote with I_L.
(b) Evaluate the high frequency components of the image by the subtraction of the smoothed image to the original one. Obviously this image contains both small details, boundaries, and noise. We will denote this image with I_H
(c) Eliminate edges by applying a robust edge detector to the original image. This further step is needed in order to eliminate edges from the estimation procedure, that would decrease noise variance estimation accuracy. Then, by thresholding we obtain a binary mask of principal edges that we denote with I_E.
(d) Build an histogram of I_H relating each bin to the intensity of image $I_L \circ I_E$ considering pixels at the same position in the two images.
(e) Evaluate the standard deviation of each bin by a Median Absolute Deviation (MAD) estimator.
(f) Perform a robust regression analysis by Cubic Smoothing Spline in order to fit the data extracted at step (e).

The algorithm has been applied on mammographic images taken from database DDSM [4] and below we show four different images as an example (Fig. 2). The results of the estimation applied to these images are shown in Fig. 3.

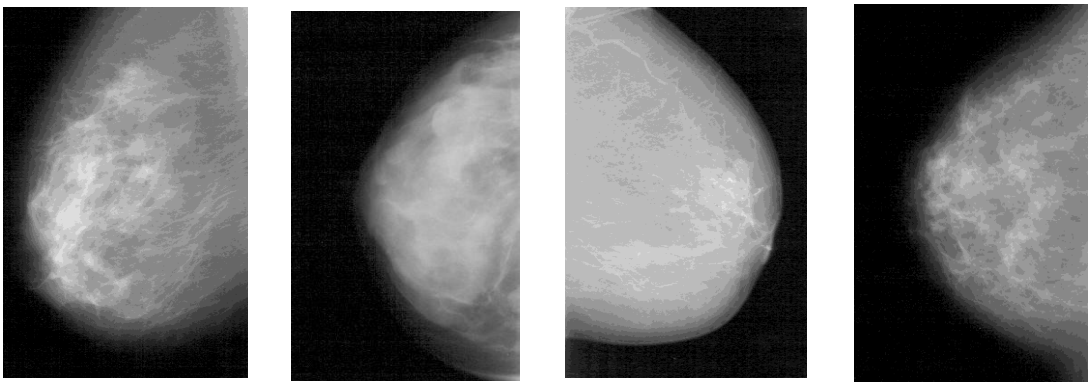

Figure 2. Four mammographic images taken from DDSM.

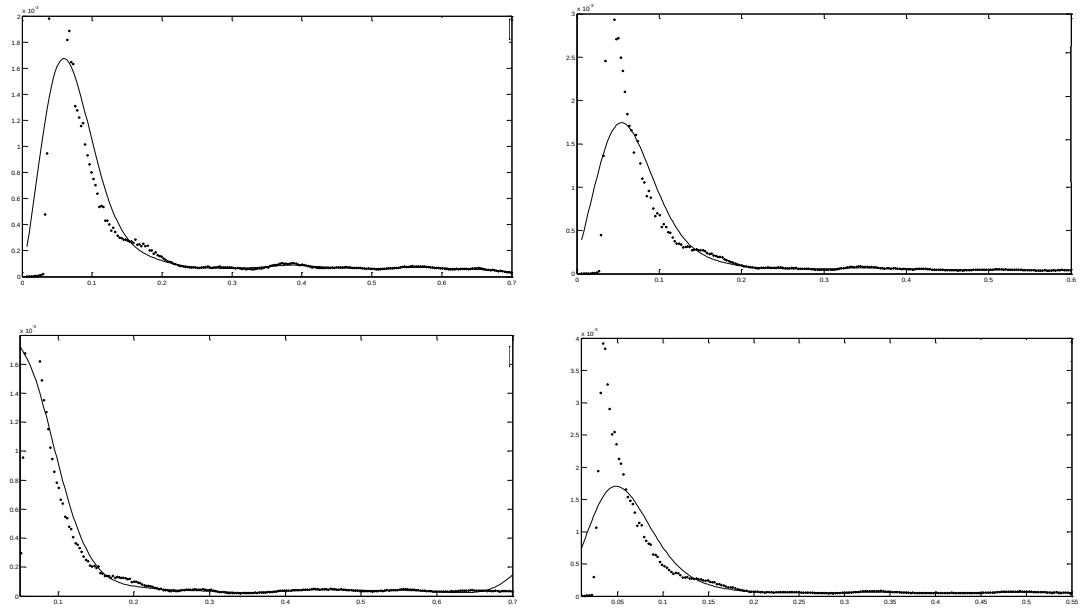

Figure 3. Estimated noise variance vs. pixel intensity for the above images: data and regression curves.

Simulation results show that there is a strong dependence between the noise variance and pixel intensity values. Anyway, this dependency is far to be modeled by a known unified behavior. In particular, note that for very low intensity values (recall that dark regions correspond to high optical densities) noise variance is very high and evidently follows a very different signal–dependency. In contrast, at medium and high pixel intensity values noise variance exhibits a strong signal–dependence with very lower values. Preliminary remarks assume that there is an additional spatial correlation that noise keeps in dark regions probably depending on the digitalization process. This noise contribution however, is confined to dark regions and vanishes in the regions related to breast tissue. Consequently, our intent is to finely model noise variance for medium and high pixel intensity values, neglecting the behavior at low values. This result is used in a sophisticated denoising procedure performed by multiresolution analysis within a wavelet framework for medical image enhancement [7].

III. Denoising by wavelet thresholding

Since the presence of noise could disturb the processing in wavelet domain and corrupt the enhancement performance, a preliminary step is image denoising. Fig. 4 shows an example of contrast enhancement by Adaptive Contrast Equalization (ACE) without denoising. Note that noise is emphasized as well as microcalcifications and other structures so that image quality is worse.

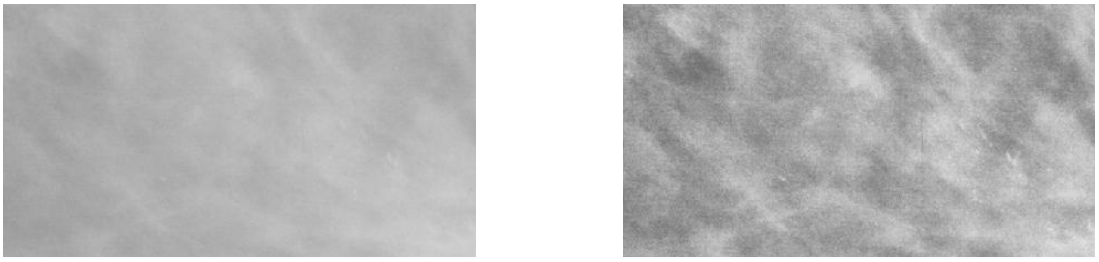

Figure 4. Effect of contrast enhancement by ACE without denoising.

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.
The key issue is the optimal selection of the threshold T_n. It is well known that T_n should be related to noise power for an optimal denoising but in our case the setting of T_n is difficult owing to the heteroscedasticity. Preliminary results for threshold selection under restrictive hypotheses can be found in [10]. The generalization under the heteroscedasticity assumption is under investigation by the authors.

In order to evaluate denoising performance we extract a portion with uniform luminance from the original ROI (Fig. 4 (left)) and from the denoised version. The two regions are shown in Fig. 5.

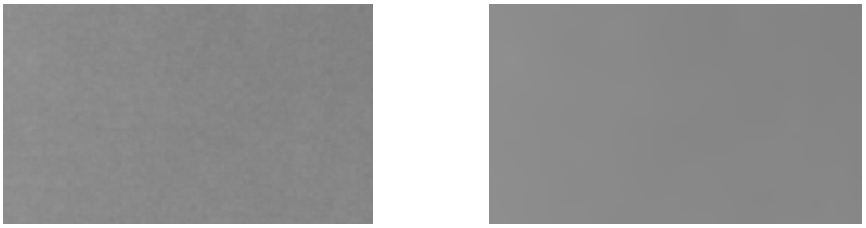

Figure 5. Uniform regions before (left) and after denoising (right).

Evaluating in each image the variance we obtain $\sigma_{BD}^2 = 1.82 \cdot 10^{-4}$ (before denoising) and $\sigma_{AD}^2 = 1.20 \cdot 10^{-4}$ (after denoising). Then, by subtracting these two values we obtain the noise variance in

that region $\sigma^2_{NOISE} = 6.15 \cdot 10^{-5}$. Comparing this value with that computed by the regression curve we obtain an estimated value $\hat{\sigma}^2_{NOISE} = 6.31 \cdot 10^{-5}$, thus proving the effectiveness of both noise estimation and denoising.

The whole denoising and contrast enhancement algorithm is represented by the block diagram shown in Fig. 6 only for two decomposition levels (three are actually used).

Our algorithm performs a very effective contrast enhancement specific for microcalcifications that is strongly influenced by the denoising step. As an example in Fig. 7 we also compare the final result of the algorithm shown in Fig. 6 with the same procedure inhibiting denoising. Note that, in this way noise contribution is emphasized as well as microcalcifications, thus altering the image and falsifying radiologist diagnosis capability.

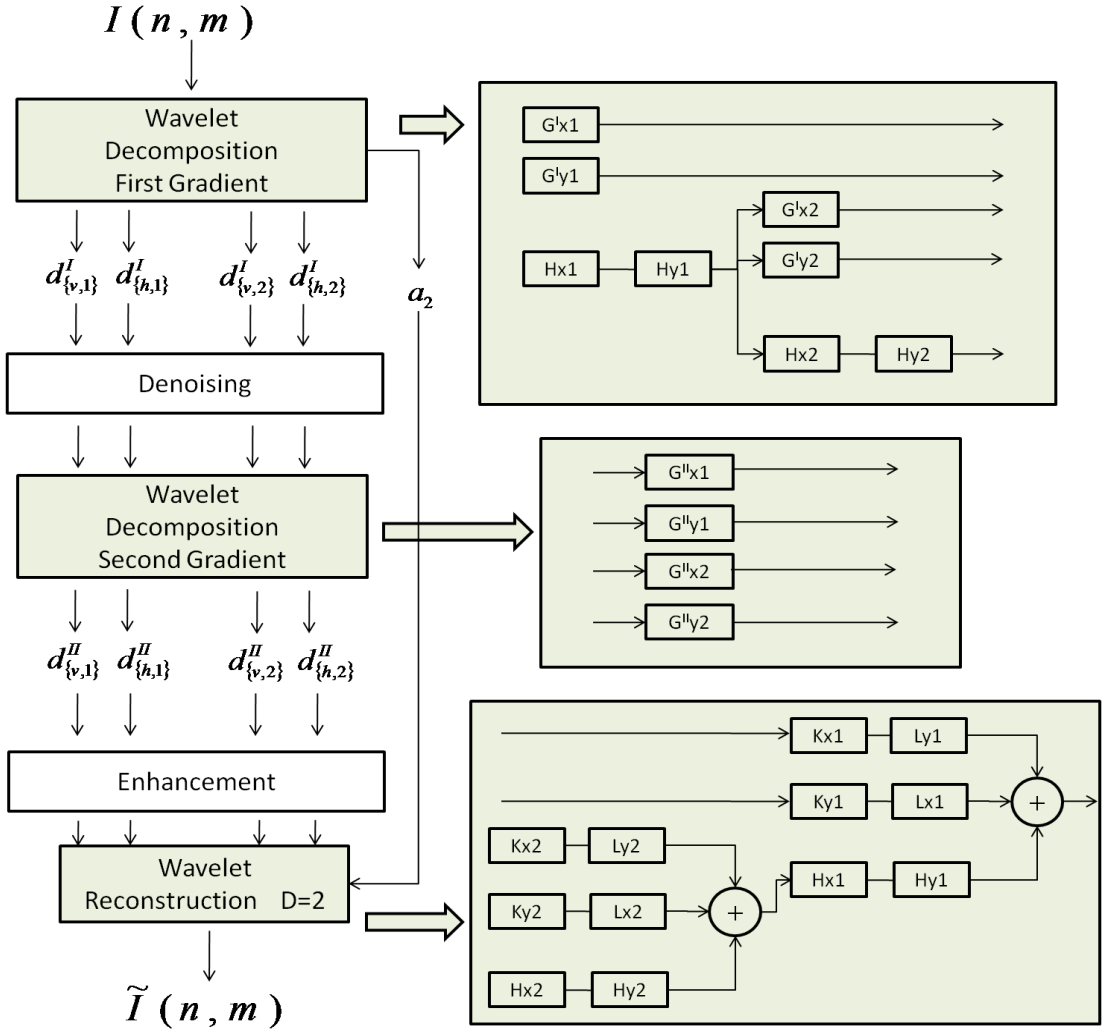

Figure 6. Effect of contrast enhancement by ACE without denoising.

Figure 7. Effect of contrast enhancement by ACE without denoising.

IV. Conclusions

The paper presents a novel method to estimate noise variance under the assumption of a heteroscedastic signal–dependent noise model. This procedure is used for denoising and contrast improvement of mammographic images in which breast cancer signs are very subtle due to low contrast and very small size.

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