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Estimated Radiation Dose Reduction Using Non-Linear Diffusion Method in Computed Radiography *

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Abstract— **In this paper we use a non-linear diffusion method to filter the inherent noise in a Computed Radiography (CR) for reducing the dose absorbed by the patients especially children in pediatric applications, related with the exposure mAs. The method is implemented in order to create a lower CR dose based on the selection of lower X-ray exposure and with a reduction of the noise using a non-linear diffusion method. The impact of several milliAmpere-seconds (mAs) setting on image quality has been studied using the RANDO phantom. The obtained results show good agreements between the filtered images and real images in terms of noise variance measurements. The new CR images allow medical researchers to analyze how a low dose affects the patient diagnosis.**

I. Introduction

The use of Computed Radiography (CR) into clinical practice has been followed by a high increase in the number of examinations performed and overdose cases in patients, especially children in pediatric applications.

In radiographic technique, the quality of radiation needed to produce an adequate image is specific to the Screen-Film system and chemical processing conditions. Otherwise, the acquisition process in CR is independent from the display process, and allows producing acceptable images over a wide range of exposures. Unfortunately, this fact introduces the risk of systematic overexposure.

According to the International Commission on Radiological Protection (ICRP), patient doses in CR, especially in case of children, should always be kept as as ALARA criterion: As Low As Reasonably Achievable.

The report shown in [1] is a support to the Commission's 2007 Recommendations with regard to the medical exposure of patients. This report makes emphasis on justification of the medical procedures and on the optimization of radiological protection. Those are the appropriate mechanisms to avoid unnecessary or unproductive radiation exposure.

In order to reduce the dose in radiography, some strategies have been proposed. In [2] it presents a new CT reconstruction algorithm, with adaptive statistical iterative reconstruction (ASIR) to reduce radiation dose at body CT. ASIR is also used to estimate radiation in coronary CT angiography [3]. In [4] dose reduction is presented with pediatric CT protocols tailored to clinical indications, patient weight, and number of prior studies. In [5] an analysis based on computer simulated noise reduction is presented.

However, there are few papers analyzing exposure (mAs) reduction in patient X-Ray imaging [6]. Nevertheless, reducing X-ray exposure has the inevitable consequence of increasing statistical noise degradations in image quality [7], [8]. Ball scale-based filtering [9] is a strategy for diffusion conductance to perform filtering.

We have investigated the techniques to obtain the image quality necessary to make a confident diagnosis for any given clinical application. This was done to show the possibility of reducing CR doses, especially in pediatric applications, while maintaining diagnostic integrity. Concretely, this paper investigates the feasibility of evaluating the diagnostic accuracy as a function of reducing dose, lowering the mAs, and applying a non-linear diffusive filter (NDF).

Since less radiation means more quantum noise in the image and since the acceptability of digital images depends on the noise content, we have studied the required techniques to guarantee the necessary image quality to make a confident diagnosis for any given clinical application. This was done to show the possibility of reducing CR doses. In particular, this paper investigates the feasibility of evaluating the diagnostic accuracy as a function of the reduction of dose.

The paper is organized as follows: Section II explains the algorithm and methodology used to remove the noise. The results of the experimental study are shown in Section III and finally, the conclusions are presented in Section IV.

The formatter will need to create these components, incorporating the applicable criteria that follow.

II. Remove noise

A. Non-linear diffusive filter (NDF)

As mentioned in the introduction, a class of image restoration methods is based on the use of non-linear

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diffusion equations [7], [8], [10], [11], [12], [13], [14], [15], [16], [17]), which usually appear associated to a variation problem and may be obtained from the minimization of the appropriate functional. The choice of a particular functional depends on the specific goal of interest. For example, several diffusive filters, suitable for medical imaging [14], have been obtained from the minimization of the appropriate functional.

Let us consider the functional [11][12],

$$J\left(u, \beta, \mu, \varepsilon\right) = \int_{\Omega} \left(\sqrt{\beta^2 + \left\|\vec{\nabla} u\right\|^2} + \frac{\mu}{2}\left(u - I_0\right)^2 + \frac{\varepsilon}{2}\left(\vec{\nabla} u\right)^2 \right) d\vec{x}, \quad (1)$$

where I_0 is the observed image (with noise), u is the filtered image, μ and ε are constant and Ω is a convex region of R^2 constituting the support space of the surface $u(x,y)$, representing the image. The first term in the functional for $\beta = 1$ represents the area of the surface which accounts for the image, [10], the second term gives account of the distance between the observed image and the desired solution u, and the third term controls the regularity of the solution.

We will consider the minimization problem [10]

$$\min_{u} J\left(u, \beta, \mu, \varepsilon\right) \quad subject \quad to \quad \frac{\int_{\Omega} \left(u - I_0\right)^2 d\vec{x}}{\int_{\Omega} d\vec{x}} = \sigma^2 \quad (2)$$

that is, we search for the image u that minimizes the functional $J(u,\beta,\mu,\varepsilon)$ and presents a variance σ^2 respect to the observed image. The noise standard deviation (SD) σ, of the image I_0 a priori is unknown, but it is important to know its value to minimize the equation (2). In our work we estimate σ by taking the median absolute deviation of the empirical wavelet coefficient of the finest scale and dividing by 0.6745 [18]. For all the studied images, the wavelet was a Daubechy of order 25. This process is the key stone of the NDF.

For the discretization time, we use a semi-implicit scheme and for solving the equations, we use the alternative additive operator splitting (AOS) [11],[15]. The stopping time selection in the diffusion equation was proposed by Mrázek and Navara, based on the decorrelation criterium[19].

B. Methodology

The used methodology is explained below. In order to reduce the doses, we take the image (*A*) with *A* mAs then, it is filtered using the NDF explained in the previous subsection and we obtain a new image (*A**). Also, we add Gaussian noise to the image with *B* mAs to obtain a new image (*B**), (*B*>*A*). Figure 1 shows this process. To test the reduction of dose, we then compare the SD noise corresponding to *A* mAs and B*, and also the corresponding ones to A* and *B* mAs, respectively.

In particular, in this paper we have selected *A* as 0.4mAs and *B* as 1mAs. The scheme is shown in figure 1.

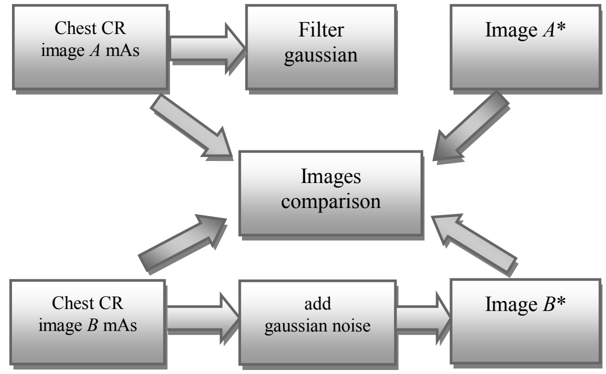


Figure 1. Process to dose reduce

III. EXPERIMENTAL RESULTS

Radiographic dose reduction techniques were first determined as a function of exposure variation using the chest of the RANDO® female Phantom (Alderson).

This phantom is marked with a real human skeleton which is cast inside soft tissue-simulating material. Tissues in the phantom are designed to have the same absorption as human tissue at the normal radiotherapy exposure levels. Figure 2 shows this phantom.

In this paper, we have applied the methodology to phantom thorax images. The images were acquired with an AGFA digital imaging device at 1, 0.8, 0.6, 0.5, 0.4mAs using 70kV and 80kV.

A single homogenous region of interest (ROI) at the centre of each CR image has been used to evaluate the SD of the pixel intensity number. The image noise, calculated as the SD of the pixel numbers from ROI in homogeneous areas, has been plotted versus mAs setting at Figure 3. This figure shows a quasi-linear dependence between image noise SD and exposure setting mAs.

To apply the methodology, we have studied five images (0.4, 0.5, 0.6, 0.8 and 1 mAs) with 70kV and 80kV. Figure 4 shows the chest CR of the phantom. For better appreciation of the image results, we analyze only a fragment of the image of size, 512x512 pixels.

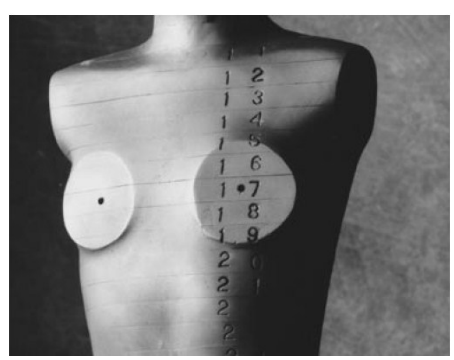


Figure 2. Chest Rando phantom

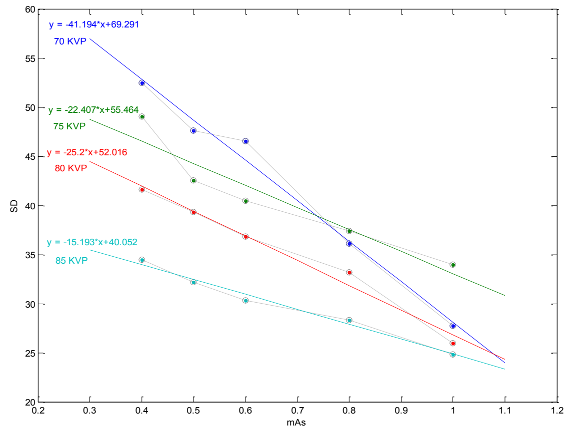
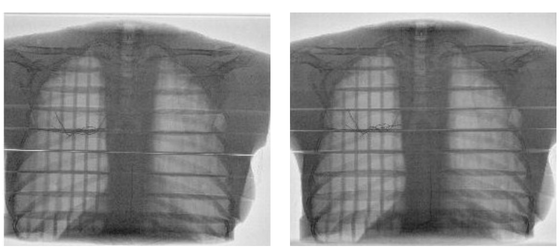


Figure 3. Relationship between image SD noise and exposure setting (mAs) at different kVp.

The results of SD noise for the fragment image, obtained as mentioned in the previous section, and depending on the mAs, are shown in figure 5. We can see that if the exposure increases, the SD noise of the image decreases. This behavior is similar to the relationship between ROI image SD noise and exposure presented in figure 3.

Applying the methodology, we take the real image with 0.4mAs and we apply the non-linear diffusion filter. In order to determine the amount of mAs has been reduced, we estimate the noise SD of the fragment of the resulting image. Table I shows the results. We can see that the image filtered corresponds to a real image between 0.8 and 1 mAs of exposure. Also for this case, the images with high kV present less noise. The figure 6 and 7 show the result after the process of Gaussian filter.



a b

Figure 4. Chest CR of RANDO phantom a)70V b)80V

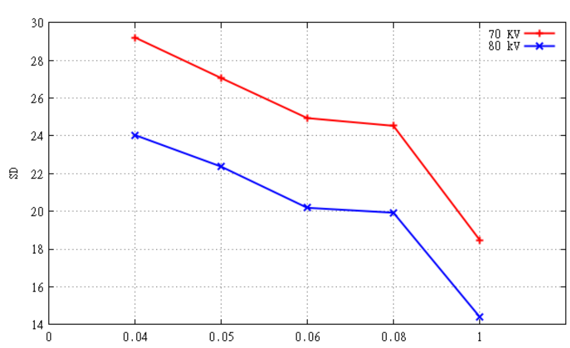


Figure 5. Results of SD noise of the total image of different mAs with 70V and 80V

TABLE I. COMPARISON SD NOISE RESULTS.

	0.4mAs	0.8mAs	1mAs	After of NDF with 0.4mAs
70V	29.2156	24.5312	18.4855	21.0745
80V	24.0432	19.9276	14.4075	17.2756

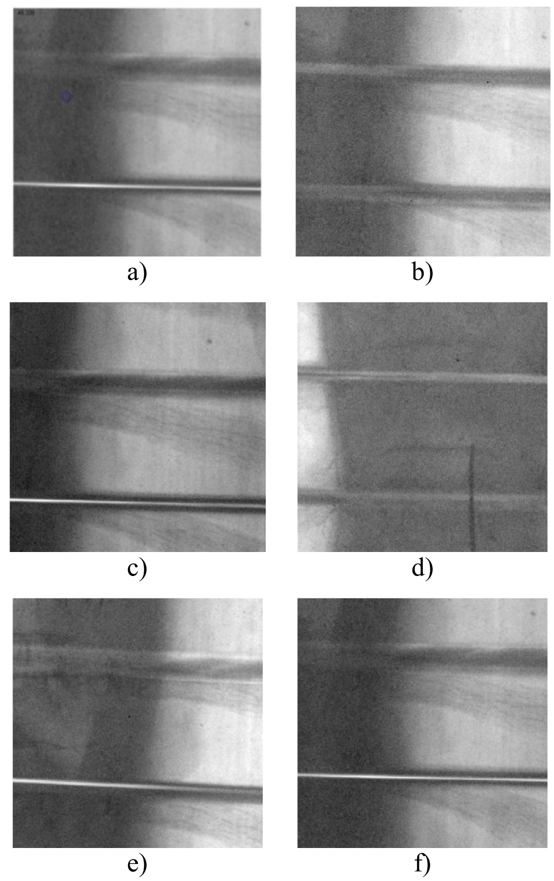


Figure 6. Image fragment of chest CR of RANDO phantom with 70KV. a)0.4 mAs b)0.5 mAs c)0.6 mAs d)0.8 mAs e)1 mAs f) Filtered image after Difussion method.

Now, in order to check the consistency of the method, we take the image with 1mAs and we add Additive Gaussian noise (σ=0.0481). The results are shown in table II. We can see that the SD noise of the image obtained is similar to the SD noise corresponding to a real image with 0.4mAs.

Also, after applying the non-linear diffusion filter to this contaminated image, we obtain similar results to the ones presented in table I. We mention that the doses given to the patients, is a quasi linear function depending on the exposure.

We can see that the SD noise of the image filtered is similar to the SD noise corresponding to a real image with 0.9 mAs approximately.

TABLE II. COMPARISON SD NOISE RESULTS.

	0.4mAs	0.8mAs	1mAs	After of Gaussian noise to 1mA
70V	29.2156	24.5312	18.4855	29.8719
80V	24.0432	19.9276	14.4075	24.5901

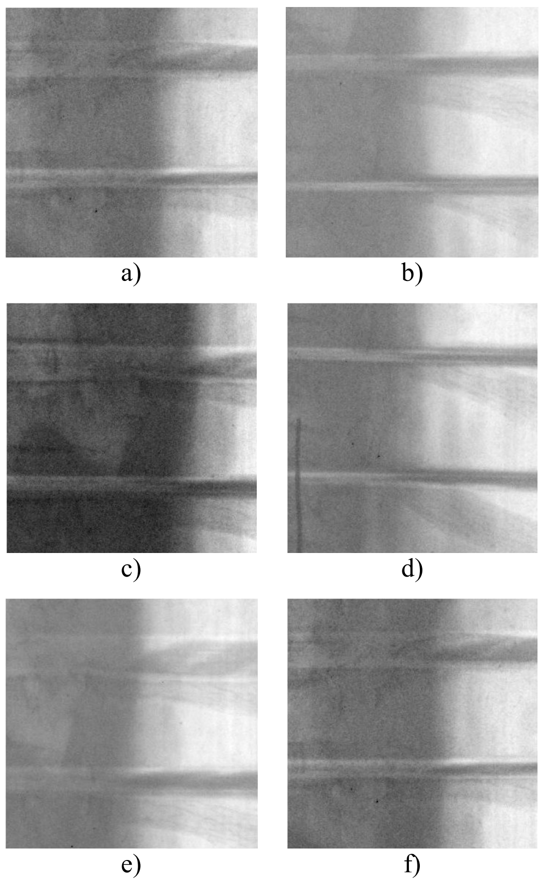


Figure 7. Image fragment of chest CR of RANDO phantom with 80KV. a)0.4 mAs b)0.5 mAs c)0.6 mAs d)0.8 mAs e)1 mAs f) Filtered image after Difussion method.

IV. CONCLUSIONS

This paper presents a methodology to reduce doses in images taken from X-ray CR through a non-linear Gaussian filter. We have checked that a good solution to reduce the dose to patients, especially children in pediatric applications in X-Ray computed radiography, is to decrease the exposure (mAs) and then, to filter to image with the non-linear diffusion method presented in the paper. The comparison has been made using the SD noise of the total image, estimated by taking the median absolute derivation of the wavelet Daubechy of order 25.

It is interesting to complete this work in the near future, radiologist evaluation of the image quality for diagnostic acceptance level. For future works, we will analyze the use of an anisotropic or ball-scale filtering, in order to smooth the image.

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