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# X-ray Image Enhancement: A Technique Combination Approach

Afonso U. Fonseca*1, Fabrizzio Soares†*2, Leandro L. Oliveira*3, Mariana S. Ramada*4, Rogerio Salvini*5, Deborah S. A. Fernandes*6, Cristiane B. R. Ferreira *7 and Willian D. Ferreira*8
*Federal University of Goiás, *Pixelab Laboratory*. Goiânia - GO, Brazil
†Department of Computer Science, Southern Oregon University, Ashland/OR, USA
Email: {1afonso, 3leandroluis, 4mariana, 5rogeriosalvini, 6deborah, 7cristiane, 8william}@inf.ufg.br, 2soaresf@sou.edu

***Abstract*—Medical X-ray images are an important and valuable source of studies and diagnoses for diseases with low cost besides its high availability. However, radiological images are subject to degradations related to low contrast and presence of noise. Based on this finding, this article presents a simple but efficient enhancement method for these images with the objective of contrast gain and noise removal. The proposed method (MP) consists of a sequence of interactive steps. Start from the step of double precision conversion and end with removing impulsive noises. An evaluation with the PSNR, Entropy, AMBE, and IQR indicators was performed, besides gain check on the thresholding process and the histogram characterization. The evaluation was conducted on three different datasets in a total of 1409 images chest X-rays. The results compared to others known in the literature proved to be promising and put it as an interesting alternative in the process of enhancement medical X-ray images.**

***Index Terms*—X-ray image, image enhancement, medical images, contrast enhancement, enhancement techniques.**

## I. Introduction

Image enhancement process consists of a techniques collection that seeks to enhance the image visual appearance or transform it into a most suitable form for human or machine displaying and analysis [1]. The enhancement, however, is one of the most complex and important tasks in image processing. It is used in a variety of study fields such as face detection, remote sensing and medicine. Images are essential in the medicine routine, like disease diagnosis and monitoring. Most of the images like medical, remote sensing, aerial, and real-life photographs suffer from numerous interference in their acquisition process. This is because they are susceptible to different types of noise, and consequently quality loss.

Moreover, enhancement techniques are one of the most significant stages in the detection and analysis of medical images [2]. Another important characteristic is the huge information volume. Thus, any processing in which a medical image is submitted should ensure that there is no information loss that would impact on the diagnosis or therapy [3]. We emphasize that the goal of medical image enhancement is not to make them good or beautiful, but readable in terms of medical diagnosis, unlike other fields in which the output image of the enhancement process is better than the input image. Therefore, in the field of medical images, what really matters is the subjective information that the image presents to professionals and how it can contribute to improving their work. The objective characteristics (related to information theory) are in a secondary relevance level [4].

Medical images unlike other types of images have specific characteristics and are subject to several restrictions requiring special treatment. Their manipulation is more complex and represents a high risk or danger since the removal of useful information or the insertion of incorrect one, may result in diagnostic errors. It can be determinant in the treatment and life of patients [5]. In this context, the present paper proposes medical image enhancement methods to provide better conditions for more accurate diagnostics and better decision making for healthcare professionals, as well as for Computer Aided Diagnostic Systems (CAD) that use medical images as input.

The focus of our study is the enhancement of thoracic x-ray images due to the low cost of acquisition and high availability. X-ray images are available in large urban centers as well as in remote and very humble regions, qualifying them for epidemiological studies as recommended by the World Health Organization [6]. Although they contain confusing details and very low contrast, which can lead to adverse effects on physician judgment, X-ray images have been widely used in medicine, science and technology [7].

In this work, we propose a simple, but efficient enhancement technique to treat the main degrading factors in X-ray images, such as noise and low contrast features. To achieve this enhancement, a sequence of operations is performed in a new method based on the combination of homomorphic filtering and impulsive noise. As a way of evaluating the proposal, a comparison of traditional image enhancement methods is performed by analyzing the Absolute Average Brightness Error (AMBE), Noise Signal Peak (PSNR), Entropy and Interquartile Interval (IQR) indicators.

The text is organized as follows: Section II introduces a brief review of related works, in Section III we describe the proposed method overview and the enhancement algorithm description for X-ray images, Section IV provides an experimental evaluation, Section V presents the results and discussions. Finally, the conclusion and future work are presented in Section VI.

## II. Related Work

Enhancement is one of the most common tasks in image preprocessing. It can be used for noise removal, contrast,

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sharpness or brightness increasing. It makes the image better to be used for identifying its characteristics [8].

Although the medical image enhancement study is not new in the scientific community, there is still much research on the subject. CAD systems are in constant evolution and of health care engineering industry is one of the worlds largest and fastest-growing industries. Fu et al. [9] described this scenario and explain various methods for medical processing. They emphasize the enhancement of noisy images of optical coherence tomography (OCT).

Recently, Rui & Guoyu [7] proposed a type of homomorphic filter. It uses a total variation model as transfer function aiming to enhance X-ray images balancing brightness and details. According to the authors, it showed a significant gain compared to CLAHE and Multi-scale Retinex (MSR) algorithms.

Medical imaging enhancement results were evaluated among six algorithms by Kaur, Randeep and Sandeep [2] to answer which technique produces the best contrast gain. The results show that the best algorithms were those of Neighborhood Operation and Sigmoid Function.

Enhancement of medical imaging was also addressed by Rana [10] in a review of techniques. They investigated and highlighted theirs limitations and disadvantages.

Tiwari & Gupta [11] proposed a method for increasing the contrast of medical images in two steps. The first one by increasing the overall contrast using gamma correction and weighted distribution of the luminance probability of pixel. The second by homomorphic filtering followed by normalization, in order to increase the sharpness of the image preserving its brightness. The authors compared the method with others recognized in the literature as HE, AHE, CLAHE, and US. They presented better rates AMBE and PSNR than comparison methods.

Philipse et al. [12] proposed a method for image normalization based on local energy standardization. It allows the isolation of different structures in different bands through the energy decomposition performance of the image in different bands. The energy located in each band is scaled according to a reference value so that a new image is reconstructed.

Alavijeh & Nasab [13] worked on the enhancement of images in multi-scale processing. They proposed a triangulation method, performing CLAHE and noise suppression simultaneously by means of morphological filtration. The decomposition of the image was performed by means of the discrete wavelet transform (DWT). The method, according to the authors, allows an adjustment of the image brightness and a significant enhancement of the contrast.

Vieira [14] worked on pre-processing techniques applied to digitized mammography images. First, he evaluated images by optical transfer functions and Wiener spectra of the noise, applying specific digital filters depending on the equipment used in the acquisition of the image. Later, adaptive filtering and noise variance stabilization transformations were used to remove quantum noise. His main objective was to reduce the radiation doses required for mammography exams.

In this short section, we have visited some studies on the enhancement of images with emphasis on medical images and more specifically on the X-ray, which does not exclude other techniques or methodologies not listed here.

## III. Proposed Approach

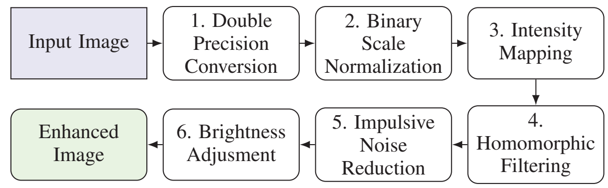



Fig. 1: The proposed method flowchart (MP).

Fig. 1 presents our proposal. An X-ray image is used as input and it is represented in a two-dimensional space with a dynamic low contrast gray range.

Based on this interpretation, each pixel in the image is represented as a grayscale value that corresponds to the amount of radiation that passes through the sensor. This intensity can also be defined as a range of gray levels. The value of these levels may, however, varies according to the scale, depending on the resolution of the image.

In our proposal, the first step is a change of gray levels of the image to double precision. In order to guarantee more accurate calculations and without rounding losses, the image class has been changed to double.

The step 2 resizes the image intensities using the Binary-Scale Normalization technique, inspired by the Decimal Scale [15]. This rescheduling ensures that all X-ray images have the intensity of their pixels in the same range of values. The normalization is obtained by applying equation 1.

$$z_i = \frac{x_i - min(x)}{max(x) - min(x)} \tag{1}$$

The rescheduling process guarantees image-fidelity normalization without loss or distortion, as double precision provides better numerical accuracy and enables more accurate calculations in image processing algorithms without the risk of numerical bursts [16].

In step 3, a mapping of intensities, with specific contrast limits, according to Equation 2 is performed. In this mapping, the image pixels that are below a lower bound ($low_{in}$ = 0.03) are set to '0', and those that are above the upper limit ($high_{in}$ = 0.97) are set to '1',

$$f(x_i) = \begin{cases} 0 & \text{if } x_i < 0.03, \\ 1 & \text{if } x_i > 0.97, \\ x_i & \text{otherwise} \end{cases} \tag{2}$$

This intensities mapping ensures image contrast enhancement with brightness preservation, which provides significant gains in Digital Image Processing tasks such as segmentation, as well as a visual enhancement in image detail [17].

Homomorphic filtering is performed in step 4. This filtering is a well-known frequency domain method used to enhancement / restore images with invariant degradations and with multiplicative noises such as illumination uniformity [11].

The homomorphic filtering model considers an image characterized by two primary components: the first, with the illumination amount of the incident source under the displayed scene *L(x,y)*; the second is the reflectance [1] of the object in the scene *(R(x,y)*. The image *I(x,y)* is then defined as:

$$I(x, y) = L(x, y) \cdot R(x, y), \tag{3}$$

In this model, an intensity of *L(x, y)* changes more slowly than *R(x,y)*. Therefore, *L(x,y)* is considered to have more low frequency components than *R(x,y)*. Using these facts, a homomorphic filtering technique aims to reduce the significance of an image texture element (L,x,y) - being made as low-frequency components of the image. It is achieved with the filtering process in the frequency domain. For frequency domain processing, an image may have been related to domain transformation at the frequency level. This can be done using transformation functions, such as the *Fourier Transform*. However, we first transform the components into additive components through a logarithm function [18].

$$\begin{aligned} ln(I(x, y)) &= ln(L(x, y)R(x, y)) \\ ln(I(x, y)) &= ln(L(x, y)) + ln(R(x, y)) \end{aligned} \tag{4}$$

Subsequently, to remove the low-frequency illumination component and preserve the high-frequency reflectance component, a high pass filter in the log domain is used. Fig. 2 shows the basic steps of homomorphic filtering.

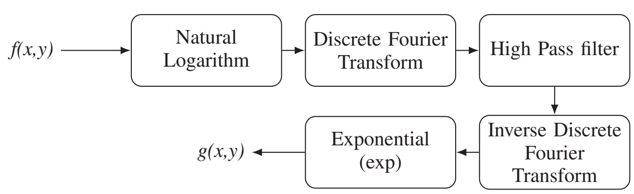



Fig. 2: Homomorphic filtering flow.

Once the homomorphic filtering is completed, the enhancement step is terminated with the impulsive noises removal by means of the filter developed by Frosio Borghese [19] plus a brightness adjustment. This filter is based on a switching scheme in which all the pulses are first detected and then corrected through a medium filter.

The pulse detector is based on the hypothesis that the major contribution to image noise is given by the photon-counting process, with some pixels corrupted by impulsive noise. Such statistics are described by a suitable mixing model. The filter is also reliably able to estimate the sensor gain.

[1]Reflectance is the ratio of the flux of electromagnetic radiation incident on a surface to the flux that is reflected. Often the reflectance is presented as a percentage.

The brightness adjustment was developed and added for the purpose of eliminating glare errors that are caused by filtering. This adjustment is achieved applying the Equation 5,

$$I_{out} = \frac{\bar{I}_{in}}{\bar{I}_{fb}} \cdot I_{fb} \tag{5}$$

where $I_{fb}$, $\bar{I}_{in}$, $\bar{I}_{fb}$ are, respectively, the image processed to the Frosio & Borghese filtering phase, the average brightness of the original image and the average brightness of $I_{fb}$. Finally, $I_{out}$ is a resulting image from the brightness adjustment and therefore of the proposed method.

## IV. Experimental Evaluation

A comparative evaluation was carried out between the proposed method and the methods HE, CLAHE, AGC_FIL [11] and US, taking into account the following indicators:

- Absolute Average Brightness Error (AMBE) used to calculate the difference between the average brightness of two images [11]. AMBE near zero is desirable and indicates brightness preservation.
- Peak Signal Ratio Noise (PSNR) is associated with information degradation and is commonly used to represent the degradation or quality loss of an image. It also widely used to measure the contrast enhancement, representing an approximation to the human perception of the reconstruction quality of an image. High PSNR usually indicates higher rebuild quality [20].
- Entropy statistical is a measure of randomness, which can characterize the texture of an image, being a quantifier number of the randomness of the image so the larger this number, more irregular, atypical, will be the analyzed image [21]. However high values of entropy indicate richer details and information of the image [20].
- Interquartile Interval (IQR) is often used to find *outliers* from a dataset. Here, it is used as reference to the distribution of gray levels, in order to quantify the overall radiograph contrast [22].

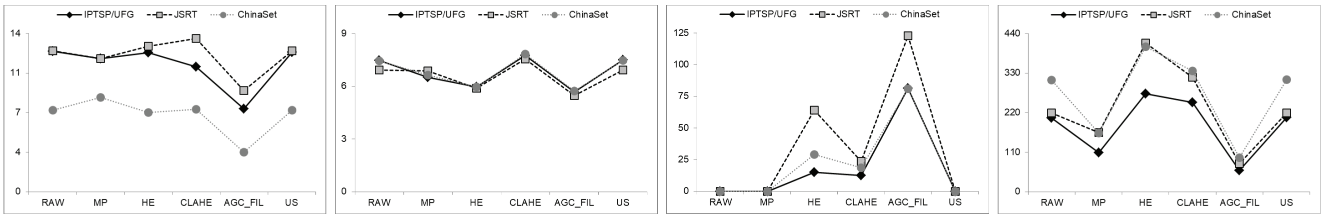
To conduct the experiments we used a desktop computer with a Core$^{TM}$ i5-2500 CPU @3.30Ghz processor, 8 GB RAM, Windows 7 - 64 bits, and Matlab software R2014a [21] and Image Processing and Computer Vision, Signal Processing and Communications, and Mathematics, Statistics and Optimization toolboxes.

## V. Results and Discussion

In this section, we present the results of the method performance and the organization of the experiments.

We used 1409 images of chest radiographs of 3 different public bases, described as:

- IPTSP base: 500 children images with clinical suspicion of pneumonia, which were selected and made available from Andrade [23]. They are in the RGB standard with 768 x 1024 pixels and stored in the JPEG format.
- JSRT base: 247 digital images with lung nodule locations of Japanese Society of Radiological Technology [24],




(a) PSNR Mean (b) Entropy Mean (c) AMBE Mean (d) IQR Mean

Fig. 3: Comparative PSNR, Entropy, AMBE and IQR values between bases.

dimensions 2K x 2K pixels, 4096 intensity levels, IMG format. They were convert to JPG format and were resized to 1024 x 1024 pixels.

- ChinaSet base: 662 digital chest X-ray images being 336 cases with tuberculosis manifestation and 326 normal cases from Candemir [25]. Their size varies for each X-ray, they were approximately 3K x 3K pixels PNG format and were resized to 1024 x 1024 pixels.

Tables Ia, Ib and Ic show the values found for each of the indicators, while Fig. 3 produces a comparison between them.

It is important to note that for PSNR calculations we first verify the normality and homogeneity of images variances through the Lilliefors and Cochran test and, estimate the ANOVA that resulted in rejection of the null hypothesis with a significance level of 5% for any differences between the selected images for each one of the bases or labeled classes.

Then we selected from each base the one in which the product of the indicators of "Entropy" and "Interval Interquartile" presented the greatest product of these indicators. This criterion was used to guarantee the choice of an image with good overall contrast and, at the same time with a high level detail of information, characteristics considered desirable on a quality radiography [20].

Additionally, we performed an evaluation of the impact on the images histogram characteristic and on the task of thresholding by Otsu [26]. The results are presented in Fig.4.

In relation to the thresholding task: the PSNR indicator is among the three with no much difference in relation to the best AGC_FIL [11]. However, the proposed method does not present the highest mean value, which is desirable because it represents images with better contrast enhancement and reconstruction quality.

Regarding Entropy, the proposed method is well positioned with its value among the three largest compared to the original image, i.e. preserving the content and richness of detail.

About the AMBE indicator, it is necessary to clarify that, in the original image, the value is not applicable because there is still no other comparison image to perform the calculation. The proposed method shows its potential by being able to eliminate invariant degradations, to standardize illumination, to remove impulsive noises and, to present inexpressive AMBE value comparable to the US method.

TABLE I: Mean and SD of PSNR, Entropy, AMBE and IQR.

(a) IPSTP

| Method | Measures | | | |
|---|---|---|---|---|
| | **PSNR** | **Entropy** | **AMBE** | **IQR** |
| RAW | 12.41 ± 1.47 | 7.48 ± 0.22 | N/A | 205.20 ± 50.68 |
| MP | 11.78 ± 0.79 | 6.52 ± 0.23 | 0.00 | 108.09 ± 23.54 |
| HE | 12.32 ± 1.72 | 5.96 ± 0.04 | 15.09 ± 11.43 | 272.87 ± 44.82 |
| CLAHE | 11.06 ± 1.02 | 7.74 ± 0.13 | 12.41 ± 05.99 | 248.76 ± 38.80 |
| AGC_FIL | 7.32 ± 0.62 | 5.68 ± 0.26 | 81.54 ± 08.22 | 59.14 ± 15.45 |
| US | 12.36 ± 1.46 | 7.50 ± 0.21 | 0.00 | 205.91 ± 50.61 |

N/A - Non Applicable

(b) JSRT

| Method | Measures | | | |
|---|---|---|---|---|
| | **PSNR** | **Entropy** | **AMBE** | **IQR** |
| RAW | 12.47 ± 1.38 | 6.93 ± 0.25 | N/A | 219.16 ± 34.30 |
| MP | 11.79 ± 1.34 | 6.88 ± 0.14 | 0.00 | 164.91 ± 18.43 |
| HE | 12.85 ± 1.05 | 5.87 ± 0.10 | 63.89 ± 13.02 | 413.74 ± 48.78 |
| CLAHE | 13.54 ± 1.12 | 7.54 ± 0.16 | 23.81 ± 04.50 | 318.01 ± 29.23 |
| AGC_FIL | 8.93 ± 0.62 | 5.48 ± 0.20 | 122.90 ± 5.86 | 78.03 ± 11.40 |
| US | 12.46 ± 1.38 | 6.93 ± 0.25 | 0.00 | 219.26 ± 34.31 |

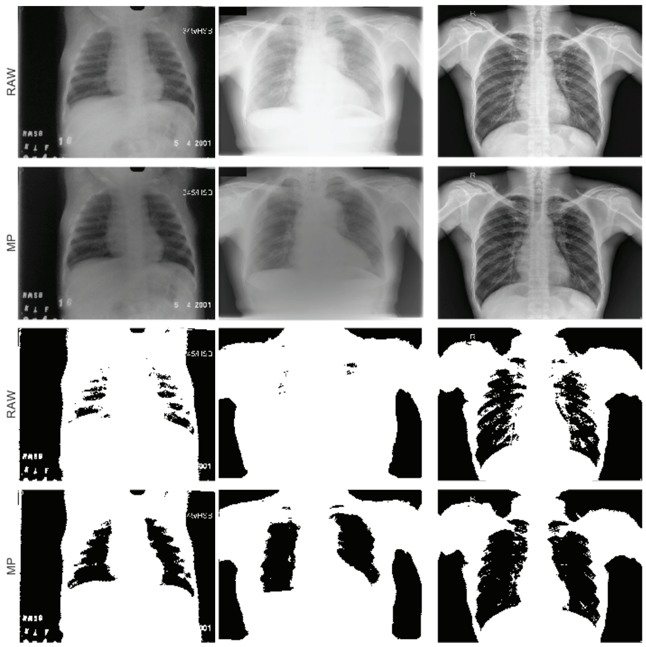
(c) ChinaSet

| Method | Measures | | | |
|---|---|---|---|---|
| | **PSNR** | **Entropy** | **AMBE** | **IQR** |
| RAW | 7.22 ± 2.31 | 7.44 ± 0.14 | N/A | 310.70 ± 49.73 |
| MP | 8.34 ± 2.46 | 6.65 ± 0.42 | 0.00 | 162.97 ± 46.39 |
| HE | 6.99 ± 0.88 | 5.96 ± 0.03 | 29.14 ± 13.71 | 403.43 ± 40.00 |
| CLAHE | 7.31 ± 1.26 | 7.83 ± 0.07 | 18.70 ± 07.29 | 335.45 ± 23.90 |
| AGC_FIL | 3.49 ± 0.67 | 5.73 ± 0.25 | 80.96 ± 18.37 | 95.24 ± 20.32 |
| US | 7.20 ± 2.31 | 7.46 ± 0.15 | 0.00 | 311.26 ± 49.64 |

The IQR presented a significant decrease in global image contrast. It is inferior only to that presented by the US method, though its loss is compensated by a higher value of Entropy. The same goes for HE, which shows a great contrast increase but at the cost of a great loss of information [22].

We emphasize that although quality indicators represent an important performance measure of a method, they alone are not enough to indicate enhancement in the medical evaluation or tasks of CAD systems. It is necessary that the image enhancement brings to the observer a real perception of visual quality gain. Additionally, it is required that this enhancement represents a gain in tasks to which they are submitted. To verify the impact of the proposed method (real gain), we did a comparison of this one with the others evaluating the performance in the thresholding process. This is quite common in tasks of CAD systems, such as the lungs segmentation.

In Fig. 4, we can see a small sample of the threshold for some database images. An expressive gain in the definition of the lung region is noted in all images (line 4 in relation to line




(a) IPTSP database (b) JSRT database (c) ChinaSet database

Fig. 4: Evaluation of the proposed method in the thresholding process.

3). Also a better delineation between the lungs and the soft tissues is observed in upper and lower pulmonary apices and costophrenic angles.

## VI. Conclusion and Future Work

In this paper we presented a new method for enhancement medical X-ray images. It is composed of an interactive sequence of steps. Starts from an image conversion for double precision to an impulsive noise removal filtering based on the work of Frosio & Borghese [19] (details for brightness adjustment has been added to it).

The method was evaluated and compared with others methods of literature enhancement based on the AMBE, PSNR, Entropy and IQR indicators. These are indicators commonly used to measure the quality of a resulting image. Based on the three datasets considered, the proposed method showed robustness, decreasing only the IQR value. It maintained PSNR, Entropy, and AMBE, among the desired values.

The proposed method was also evaluated with respect to the performance in the thresholding process. The analyses of results pointed out that the method is promising in the task of enhancement bringing gain in the definition of the lung region and provides a better delineation between the lungs and the soft tissues. In the future, we plan to test it with other X-ray image bases such as mammograms, skull X-ray and others.

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