A new switching median filter for digital radiography

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Abstract—Localized hardware failures on sensor and communication channel often introduce in digital radiographies a characteristic impulsive noise, known as “salt & pepper”. Eliminating these failures, which generate the corrupted pixels, is a very costly or even impossible task; therefore, image processing techniques have been developed to correct the gray level values of these pixels. We propose here a new switching median filter for digital radiography, which has been inspired by the properties of the human visual system: a pulse is detected on the radiography by measuring its visibility in terms of local contrast and signal to noise ratio. The local background value is estimated applying a 3x3 median filter to the image, and noise distribution is evaluated by means of a simple and reliable model, which describes the properties of the digital sensor and incorporates the statistical characteristic of the noise. Since the filter requires no iteration and, it can work in real time also on large images (less than 0.7s for 12 bit, 4.8MPixel images). The presence of edges does not affect the pulse detection and correction, thus resulting in a more efficient approach with regards to more traditional methods. Some residual pulse may remain visible only in the darkest zones of the radiography, which are usually poor of diagnostic information.

I. INTRODUCTION

Localized hardware failures on sensor and communication channel often introduce in digital radiographies a characteristic impulsive noise, known as “salt & pepper”. This kind of noise can badly affect image processing or lead to poor visualization results, [1], [2], especially when algorithms such as unsharp masking are applied to the image to improve the visibility of small details. Eliminating the hardware failures, which generate the corrupted pixels, is often a very costly or even impossible task; therefore, image processing techniques have been developed to correct the gray level value of these pixels.

Median filtering is known for its capability to remove local outliers from images. Nevertheless its application to all the pixels of an image produces an unacceptable distortion in the form of low-pass filtering [1], [3]. To avoid unnecessary pixel modification, the switching median filtering schema has been proposed: first a pulse detector localizes all the corrupted pixels; only these are subsequently filtered, whereas all the other pixels are left unaltered, [1] - [6].

The pulse detector is the critical component of this solution. Morphological operators and rank conditioned filters have been introduced to implement fast local strategies for pulse localization; however, when high gradients or edges are present, these pulse detectors can fail, [4] - [6]. Different methods, based on iterative processing and analysis of the image, [1] - [3], are more reliable, but computationally intensive to run in real-time.

To the best of our knowledge, all the existent approaches do not take into account the properties of the human visual system, HVS, in the pulse detection stage. Incorporating the HVS characteristics and a sensor model in the pulse detector, we have developed a reliable switching median filter for digital radiographies, which can operate in real time.

II. PROPERTIES OF THE HVS

Our pulse detector is based on two main properties of the HVS. First of all, given a background luminance, b, and an object of luminance \( b+\Delta b \), the Just Noticeable Difference, JND, is defined as the minimum \( \Delta b \) required to a human observer to clearly distinguish the object from the background. JND is a linear function of \( b \), as expressed by the Weber’s law, [7]:

\[
JND = b - C_T,
\]

where \( C_T \) is a threshold contrast; experimentally, the best performance of a human observer corresponds to a threshold contrast \( C_T = 0.02 \). A pulse can therefore be detected if its contrast with the background, \( C(x,y) = |\Delta b/b| > C_T \), is larger than \( C_T \).

Object visibility is also limited by the presence of noise, as expressed by the Rose’s criterion. This states that an object can be distinguished by a human observer only if \( K > K_T = 2-5 \) [7], where \( K = \Delta b/\sigma_b \) is known as the Rose number, \( \sigma_b \) is the background noise standard deviation and \( K_T \) is the detectability threshold. This criterion can be regarded as a condition on the signal-to-noise ratio and it can be rewritten in terms of Just Notable Difference as: 

\[
JND = K_T \sigma_b,
\]

(Fig. 1).

III. PROPERTIES OF THE IMAGING SYSTEM

In absence of noise, the transformation between the number of photons, \( p(x,y) \), which reach the sensor in position \( X(x,y) \), and the resulting gray level value, \( b(x,y) \), is given by:
between the pixel and the background, noise standard deviation, local background around the pixel, radiography and lower in the brighter ones.

obtained by subtracting radiography, of local contrast, greater than the is computed: a pixel is classified as pulse if this difference is luminance of each pixel and that of the surrounding background distinguished by a human observer, the difference between the restricting value determines the visibility of a pulse: the Rose’s criterion for computing JND as a function of the background gray level. The most local contrast for the pixel can be derived as:

\[ \sigma_s = G \cdot \sqrt{p_s} \]  
(2).

As a consequence, noise is higher in the darker zones of the radiography and lower in the brighter ones.

![Fig 1. Rose’s criterion and Weber’s law in digital radiography allow computing JND as a function of the background gray level. The most restricting value determines the visibility of a pulse: the Rose’s criterion for the dark pixels, and the Weber’s law for the bright ones.](image)

IV. METHOD

In order to localize all the pulses that can be clearly distinguished by a human observer, the difference between the luminance of each pixel and that of the surrounding background is computed: a pixel is classified as pulse if this difference is greater than the JND. This condition can be described in terms of local contrast, \( C(x,y) \), or local Rose number, \( R(x,y) \). To compute \( C(\cdot) \) and \( K(\cdot) \), the following estimates are needed: the local background around the pixel, \( b(x,y) \); the difference between the pixel and the background, \( \Delta b(x,y) \); and the local noise standard deviation, \( \sigma_s(x,y) \).

Local background is estimated by filtering the digital radiography, \( i(x,y) \), with a 3x3 median filter. \( \Delta b(x,y) \) can then be obtained by subtracting \( b(x,y) \) from \( i(x,y) \). As a consequence, local contrast for the pixel \( (x,y) \) can be written as:

\[ C(x,y) = \frac{\Delta b(x,y)}{b(x,y)} \]  
(3).

A rough estimation of noise is performed for each pixel of the image, by considering the background value \( b(x,y) \) as the “true value” of the pixel in position \( X(x,y) \), and defining the noise, \( n(x,y) \), as the difference between \( i(x,y) \) and \( b(x,y) \). By pooling together all the pixels characterized by the same “true” luminance, \( b \), the standard deviation of the noise, \( \sigma_n \), can be estimated. Combining (1) with (2) we can then obtain:

\[ b = (\frac{1}{G}) \cdot \sigma_n^2 + B \]  
(4),

and subsequently:

\[ b \cdot G - B \cdot G = \sigma_n^2 \]  
(5),

where \( \sigma_n \) has been substituted by its rough estimation, \( \sigma_n^\prime \).

Equation (5), written for each gray level \( b \), is a linear system in the unknown \( B \) and \( GB \); it can be solved using a traditional least squares approach, where \( b \) and \( \sigma_n^\prime \) play the role of the coefficients of the system. Once \( G \) and \( B \) have been computed, the number of photons associated to each gray level is estimated through (1); then, noise standard deviation, \( \sigma_s \), is determined for each level \( b \), inverting (2), as shown in Fig. 2.

![Fig 2. Rough (\( \sigma_n^\prime \), dots) and modeled (\( \sigma_n \), continuous line) estimate of noise standard deviation as a function of gray level. Outliers of \( \sigma_n \) are clearly visible.](image)

Once \( \sigma_n \) has been estimated, also the local Rose number, \( R(x,y) \), can be computed on the entire image.

At this point, all the pixels that contemporary satisfy the two conditions \( C(x,y) > C_T = 0.02 \) and \( K(x,y) > K_T = 2 \), are recognized as pulses and their value corrected from \( i(x,y) \) to \( b(x,y) \), as required by the switching median filter schema.

V. RESULTS AND DISCUSSION

Fig. 3 shows the de-noising effect obtained with the proposed algorithm, for a portion of cephalometric radiography; the algorithm efficiently removes all the corrupted pixels from the image. The most expensive computational step, the median filter, is performed only once and this, thanks to an optimized implementation of the filter [8], leads to a computational time of 0.67s for images of 4.8 Mpixels on 12 bits.
When a few pixels assume a certain luminance value, \( b^* \), a critical condition takes place for the computation of the noise standard deviation: if one or more pulses are associated to \( b^* \), \( \sigma_p \) may be overestimated, as shown in Fig. 2, and behaves as an outlier in the least squares system associated to (5). This could be eliminated from the computation of \( \sigma_p \) by using robust statistics; on the other hand, this would require a significant amount of time, which contrasts with real time operation. However, the adoption of the global noise model described by (2), allows minimizing the impact of the outliers; the only observable effect is a slight overestimation of \( \sigma_p \), as demonstrated by Fig. 2. Highly corrupted images could be problematic in this sense; however, this case should be avoided in modern digital radiography.

Other real time pulse detectors, as those proposed in [4], [5] or [6], can be badly influenced by the presence of locally high gradients or edges, and residual pulses can be observed after the de-noising treatment. Instead our algorithm uses a global approach to measure \( \sigma_p \), thus resulting in a more reliable method. Moreover, the 3x3 window used here for median filtering is small enough, to guarantee that locally high gradients or edges do not critically influence the performance of the pulse detector. Few residual pixels remain visible only in the darkest zones of the radiography, which are usually poor of diagnostic information.

At present, our approach is limited to digital radiographies; adaptation to other digital images is currently under investigation.

![Image 1](image1.jpg)

![Image 2](image2.jpg)

**Fig 3.** A portion of a typical cephalometric image, sized 1836x2605, on 12 bits (upper panel). A zoom of the same image, treated with unsharp masking filter (mask 13x13, gain 2) is shown in the intermediate panel; the lowest panel demonstrated that our algorithm efficiently removes salt & pepper noise: no pulse is visible after the application of unsharp masking filter. The percentage of pixels corrected on the entire image is 0.7%.

**VI. REFERENCES**


