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Improved Geometric Anisotropic Diffusion Filter for Radiography Image Enhancement

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ABSTRACT
In radiography imaging, contrast, sharpness and noise there are three fundamental factors that determine the image quality. Removing noise while preserving and sharpening image contours is a complicated task particularly for images with low contrast like radiography. This paper proposes a new anisotropic diffusion method for radiography image enhancement. The proposed method is based on the integration of geometric parameters derived from the local pixel intensity distribution in a nonlinear diffusion formulation that can concurrently perform the smoothing and the sharpening operations. The main novelty of the proposed anisotropic diffusion model is the ability to combine in one process noise reduction, edge preserving and sharpening. Experimental results using both synthetic and real welding radiography images prove the efficiency of the proposed method in comparison with other anisotropic diffusion methods.

KEYWORDS
Radiography; welding; anisotropic diffusion; edge preserving; image sharpening; noise reduction

1. Introduction

Radiography is one of the most popular techniques used in the nondestructive testing (NDT) area. In welding inspection, it has an essential role in the detection of defects that can occur in weld joints, which may affect the well functioning of many systems principally for serious applications where failure can be catastrophic, such as welds of pressure vessels, aircrafts, power plants etc.… The radiography acquisition system is based on the transmission of X-rays or Gamma rays through an object to produce an image on radiography film as shown in Figure 1(a), Zahran, Kasban, El-Kordy, and El-Samie (2013). Once the film is developed, the image is analyzed and measurements are made using a light box. Defects are evaluated as two dimensional from their shadows on the film. An example of a radiography welding images is shown in Figure 1(b), where some defects can be found in the middle of weld region. Weld radiography image contains two main parts: The base metal part and the weld seam part. The weld region is brighter than the metal area. Defects can be found randomly at the weld area with different small shapes; circular, and rectangular.

The quality of a radiography image can be evaluated by three factors: Contrast, graininess or noise and sharpness, Ge and Zhang (2011). The contrast and the graininess are highly related to the exposure time and the radiation dose. A low radiation dose produces a poor quality image with undesirable artifacts and noise. On the contrary, a high radiation dose permits to obtain a well contrasted image. However, operating with elevated radiation dose is not recommended due to its undesirable effects. Thus, minimizing radiation dose is much suggested and employing of image processing techniques for noise reduction and contrast enhancement becomes in this application highly needed. The third factor is the degree of sharpness of the radiography image, which is related essentially to geometric aspects of the radiography equipment and setup. Radiations do not originate from a single source, but rather over an area. As a result, obtained images suffer from geometric un-sharpness and to the loss of definition.

Anisotropic diffusion methods are popularly used for image noise reduction and edge sharpening in the past years. Based on partial differential Equations (PDE), this methodology produces high results compared to classic linear methods like Gaussian filter, Wiener filter or median filter. The first nonlinear anisotropic diffusion model was introduced by Perona and Malik (1990). This method is based on a diffusion process controlled by a partial differential equation where the image is selectively smoothed with well edge preserving. The main idea is to decrease the diffusion as the image gradient increase. Since "Perona and Malik" method, many works have been proposed, Guo, Sun, Zhang, and Wu (2012), Seddik, Tebbini, and Braiek (2014), based on the PDE approach such as the shock filter, Weickert, Romeny, and Viergever (1998), Rudin, Osher, and Fatemi (1992), which is based on the idea to apply locally either a dilation or an erosion process depending to pixel zone maximum or minimum. This method is efficient to enhance image contrast, but it is very sensitive particularly to impulse noise. Hence, Alvarez, Lions, and Morel (1992) replaced the edge detector in shock filter PDE by its convolution with a Gaussian function. The filter becomes more robust against noise, but usually it blurs and dislocates the important image features like edges, Ramos-Llorden, Vegas-Sanchez-Ferrero, Martin-Fernandez, Alberola-Lopez, and Aja-Fernandez (2015). To improve robustness of the last filter "Alvarez and Mazorra" have defined another class of filters for noise reduction and edge enhancement by merging shock filters with the diffusion operator, Xu, Jia, Shi, and Pang (2016). The main idea is to add a term of anisotropic diffusion with an adaptive weight between shock effect and diffusion process. Recently, Michel-González, Cho, and Lee (2011) proposed a new nonlinear diffusion filter, which permits reducing computation time greatly and achieving adaptive noise reduction. The main

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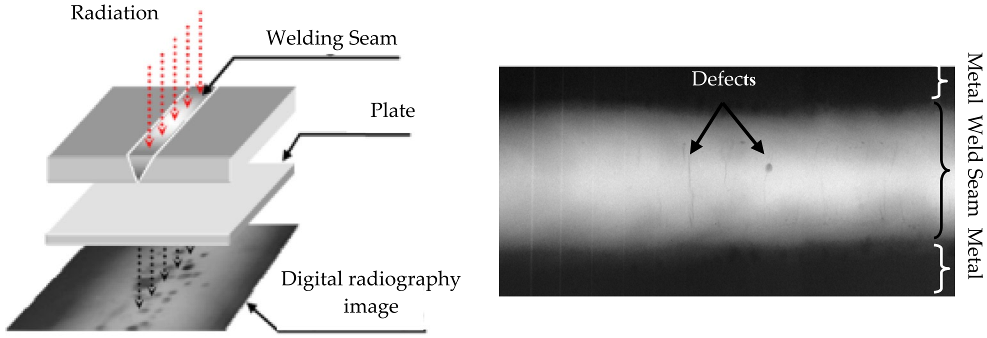

(a) **(b)**

Figure 1. Weld Radiography Imaging – (a) - Principle of the X-ray Weld Image Acquisition [2] – (b) - Sample or Weld Radiography Image.

idea is to incorporate in Perona Malik anisotropic diffusion model geometric parameters derived from the local pixel intensity distribution only in two directions rather than four directional gradients around the pixel of interest. Little works based on anisotropic diffusion methods are dedicated to non destructive testing (NDT) area to assist operator inspection and diagnosis. Chao and Tsai (2008) developed a new diffusion method for defect detection in glass substrates of TFT-LCD images. This method permits to carry out smoothing and sharpening simultaneously. Ben Mhamed, Abid, and Fnaiech (2012) modified Chao Tsai method using a sigmoid diffusion function, which allows improving noise reduction and edge sharpening for defect detection in radiography welding images. The main disadvantage of Tsai and Ben Mhamed methods is the high sensitivity to noise.

In this work we propose a new anisotropic diffusion method based on geometric local pixel parameters and combining adaptively smoothing and sharpening process at the same time. The remainder of this paper is organized as follows: In the first part a brief overview about related works, in the next part we present the new proposed anisotropic diffusion method. Tests and results evaluating the proposed method are shown in the third part. Conclusion and the perspectives of this work are presented in the final part.

2. Related Works

2.1. Anisotropic Diffusion Method (AD)

In order to preserve edges while removing noise, Perona and Malik (1990) proposed a nonlinear diffusion model that permits a selective image smoothing. The idea is to increase the diffusion in homogenous regions and decreasing it near strong gradient corresponding to edges. The proposed model is described by the following PDE.

$$\frac{\partial I(x,y)}{\partial t} = div(g(|\nabla I(x,y)|)\nabla I(x,y)) \tag{1}$$

$div(.)$ and ∇ are respectively the divergence and the gradient operators:

$g(z)$ is a decreasing function called the edge stopping function. It has an important role in controlling the diffusion process. Two decreasing functions are proposed by Perona and Malik

$$g'(|\nabla I(x,y)|) = \frac{1}{1+\frac{|\nabla I(x,y)|^2}{k^2}},$$
$$g''(|\nabla I(x,y)|) = \exp\left(-\frac{|\nabla I(x,y)|^2}{k^2}\right) \tag{2}$$

k is a parameter with a threshold role: if $|\nabla I| > k$ so these pixels are regarded as edges and they will be less blurred, in contrast $|\nabla I| \leq K$ these points are considered as interior regions and will be highly smoothed.

2.2. Geometric Anisotropic Diffusion Method (GAD)

Guo et al. (2012) defined two weighting functions to control the diffusion process in "Perona Malik" equation where there is no require to compute four directional gradient. Only in horizontal and vertical directions using geometric parameters derived from local pixel intensity distribution. These parameters are defined as follows:

$$D_x = \begin{cases} |I_E - I_W| - \delta & if\,|I_E - I_W| < \delta \\ 0 & else \end{cases} \tag{3}$$

D_x is the horizontal intensity difference in a neighborhood of 3×3.

I_E, I_W are the image intensities in the east and west neighbor's directions respectively.

δ is the standard deviation of the image noise, calculated adaptive to the local image intensity using the median absolute deviation (MAD) as in Mittal, Kumar, Saxena, Khandelwal, and Kalra (2010) and Yu (2002).

The average of the neighboring pixels A_x is computed with

$$A_x = (I_E + I_W)/2 \tag{4}$$

I_s is the image intensity of the pixel of interest. Gonzalez define $I'_{s,x}$ and P_x as follows:

$$I'_{s,x} = \begin{cases} I_s - D_x/2 & I_s < A_x \\ I_s + D_x & I_s < A_x \end{cases} \tag{6}$$

$$P_x = I'_{s,x} - A_x \tag{7}$$

Similarly, parameters in the vertical direction $D_y, A_y, I'_{s,y}$ and P_y can be defined by considering the north and south pixels directions. Two diffusivity functions are defined as:

$$c(D_x, P_x) = \frac{1}{1+\left(\frac{D_x}{P_x}\right)^2}, \qquad c(D_y, P_y) = \frac{1}{1+\left(\frac{D_y}{P_y}\right)^2} \tag{8}$$

The discrete implementation of the proposed filter can be written as:

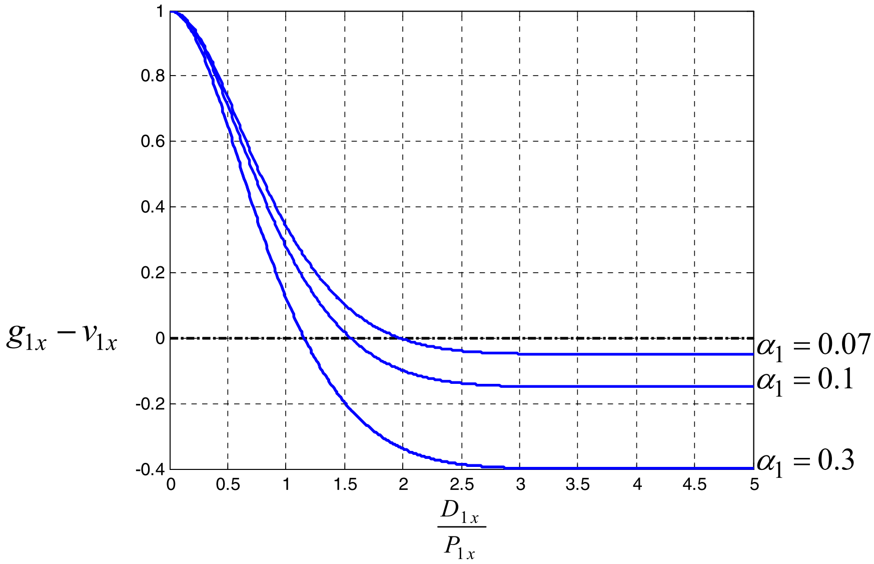

Figure 2. Plot of the Proposed Weighting Diffusion Function g_{1x} - v_{1x} for Different α Values.

$$I_{t+1}(x,y) = I_t(x,y) + \Delta t \cdot \left[c(D_x,P_x).(\nabla I_E + \nabla I_W) + c(D_y,P_y)(\nabla I_N + \nabla I_S)\right] \quad (9)$$

t, Δt are the index iteration and the step time respectively.

∇I_E, ∇I_W, ∇I_N, ∇I_S represents the difference between the central pixel and one of the east, west, north, and south pixels respectively.

2.3. Smoothing-sharpening Anisotropic Diffusion Method (SSAD)

This model is proposed first by Chao, et al. [13] and modified by Ben Mhamed, et al. [14] as an anisotropic diffusion that permits to fuse smoothing and sharpening simultaneously in one nonlinear differential equation defined as:

$$I_{t+1}(x,y) = I_t(x,y) + \frac{1}{4}\sum_{i=1}^{4}\left[g(\nabla I_t^i(x,y)) - v(\nabla I_t^i(x,y))\right] \cdot \nabla I_t^i(x,y) \quad (10)$$

$g(\cdot)$ is a non-negative monotonically decreasing function with $g(0) = 1$and $\lim_{|\nabla I|\to\infty} g(|\nabla I|) = 0$.

$v(\cdot)$ is the sharpening weighting function defined as $v(|\nabla I|) = \alpha[1 - g(|\nabla I|)]$.

α is the weighting factor that determines the sharpening strength.

The second term in the right side controls the diffusion process as in P-M diffusion equation, while the third term control the sharpening process.

3. Proposed Method

In the proposed method, the two previous anisotropic diffusion methods GAD and SSAD are combined in an one non linear diffusion model that we call Geometric smoothing-sharpening anisotropic diffusion (GSSAD) method. Geometric parameters derived from the local pixel intensity distribution are incorporated in a forward backward diffusion equation. As a result, the new anisotropic diffusion formulation allows concurrently a smoothing and sharpening process in a fast time and with a high robustness to noise. Moreover, a new diffusion weighting function is proposed to control smoothing and sharpening process. The proposed nonlinear diffusion equation can be defined in the discrete form as follows:

$$I_{t+1}(x,y) = I_t(x,y) + \Delta t \cdot \left[[g_{1x}(D_{1x},P_{1x}) - v_{1x}(D_{1x},P_{1x})](\nabla I_E + \nabla I_W) + [g_{1y}(D_{1y},P_{1y}) - v_{1y}(D_{1y},P_{1y})](\nabla I_N + \nabla I_S)\right] \quad (11)$$

D_{1x}, D_{1y}, P_{1x}, P_{1y} are calculated as in Equations (3), (7).

∇I_E, ∇I_W, ∇I_N, ∇I_S are the first difference derivatives in the four directions.

$\Delta t = 0.25$ is the time step size. For numerical stability it should be less than 1/2d where d is the number of directions along, which the gradients are calculated, Rudin et al. (1992). In our model d = 2 as the four gradient directions are merged in only horizontal and vertical directions.

The third term in this equation permits smoothing and sharpening in horizontal and vertical directions depending

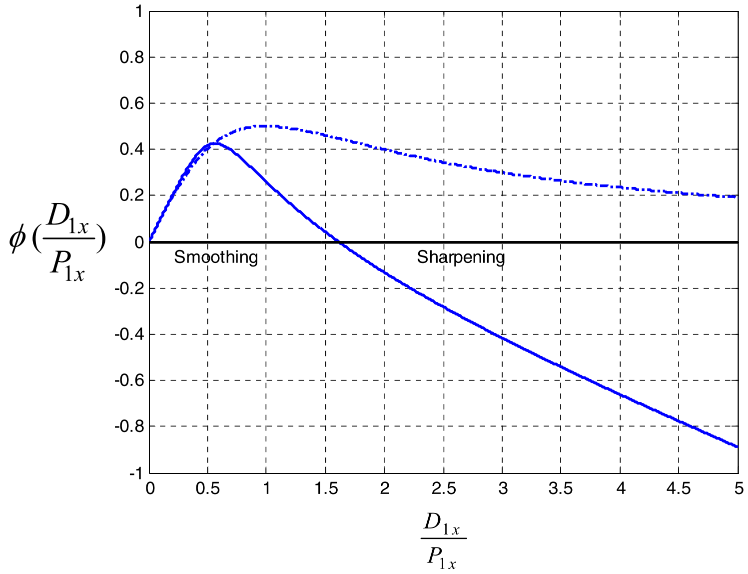

Figure 3. Plot of Diffusion Flux ϕ (.) for GAD (Dashed Line) and Proposed Method (Continuous Line).

on geometric parameters derived from the neighborhood of pixel distribution. g_1 and v_1 are two new weighting functions to an adaptive control of the smoothing and sharpening degrees. g_{1x}, g_{1y} are two weighting smoothing functions defined as:

$$g_{1x}(D_x, P_x) = \frac{2}{1+\exp a\left|\frac{D_{1x}}{P_{1x}}\right|}, \qquad g_{1y}(D_y, P_y) = \frac{2}{1+\exp a\left|\frac{D_{1y}}{P_{1y}}\right|} \tag{12}$$

v_{1x}, v_{1y} are two weighting sharpening functions defined as:

$$v_{1x} = \alpha_1(1 - g_{1x}), \qquad v_{1y} = \alpha_1(1 - g_{1y}) \tag{13}$$

α_1 is a constant to control the sharpening strength.

At any noise pixels $P_{1x} \gg D_{1x}, g_{1x}$ becomes close to 1 allowing a strong diffusion permitting to eliminate noise pixels. Whereas v_{1x} will have lower values and thus the sharpening process is inhibited. At the edge pixels $P_{1x} \ll D_{1x}, g_{1x}$ becomes close to 0 allowing a small diffusion and an edge preserving, while v_{1x} should result to high values permitting to enhance and to sharpen edges. Figure 2 presents the weighting diffusion function $g_{1x}(\frac{D_{1x}}{P_{1x}}) - v_{1x}(\frac{D_{1x}}{P_{1x}})$ for our method with different values of α_1. The weighting diffusion function curves shows a positive decreasing, a zero-crossing, then a negative decreasing, which means that the smoothing process is stopped at high gradients corresponding to edges and turned to an inverse diffusion allowing edge sharpening. Moreover, we observe that increasing α_1 permits to reduce the zero-crossing level of the weighting diffusion function. The diffusion behavior of our method and its advantage comparing with GAD method is more explained in Figure 3, which depicts the diffusion flux functions calculated with $\phi_1 = c(\frac{D_{1x}}{P_{1x}}) \cdot \frac{D_{1x}}{P_{1x}}$ and with $\phi_2 = \left[g_{1x}(\frac{D_{1x}}{P_{1x}}) - v_{1x}(\frac{D_{1x}}{P_{1x}})\right] \cdot \frac{D_{1x}}{P_{1x}}$ [11] for a given $\alpha_1 = 0.1$.

Flux function's graph shows the advantage of new diffusion method comparing to anisotropic diffusion method AD and geometric anisotropic diffusion GAD filter where the flux function has just positive values permitting only a smoothing process. Thus, they can only preserve edges without any edge enhancement and sharpening. In other side, smoothing and sharpening using difference derivatives D_{1x}, D_{1y} depending on geometric local pixel topology allows to increase robustness to noise and particularly with impulse nature, which is in general the main limitation of diffusion based filters. Moreover, the proposed anisotropic diffusion formulation will have a fast computation time as the weighting diffusion functions are calculated only in horizontal and vertical direction unlike SSAD anisotropic diffusion algorithm, which uses four directions.

Proposed algorithm steps
• Step1: Read image
• Step 2: Select a region of interest ROI
• Step 3: Initialize parameters α_1, Δt, n
• Step 4: For n iterations
Compute the local median absolute deviation as in [15] [16].
Compute local geometric parameters D_{1x}, D_{1y}, P_{1x}, P_{1y}
Compute weighting smoothing and sharpening functions g_1, v_1
Compute $I_{t+1}(x, y)$ using differential discrete Equation (11)
• End

4. Experimental Results

In this section we evaluate the effectiveness of the proposed anisotropic diffusion method GSSAD. The performance of the proposed model (GSSAD) is compared respectively, with anisotropic diffusion (AD) filter, Geometric nonlinear diffusion (GAD) filter and SSAD anisotropic diffusion method. We carry out many experiments both on synthetic and real radiography images of welding. The proposed method is evaluated in terms of noise robustness, edge sharpening degree and defect detection accuracy. Figure 5 (a-b) shows a synthetic image filtered first with a circular averaging filter with radius r = 2 to create blurred edges and then affected with an additive Gaussian and impulse noise (SNR = 11.25). The radiography data are obtained from the federal institute of material research and testing (BAM) (http://www.bam.de/en/index.htm). The Number of iterations is fixed to 40 iterations and the step time Δt is set to 0.25.

4.1. Influence of Parameter a

The parameter α must be fine-tuned. It has the role of a threshold between smoothing and sharpening process. Setting a small value (e.g. 0.03) limits the sharpening operation and defect

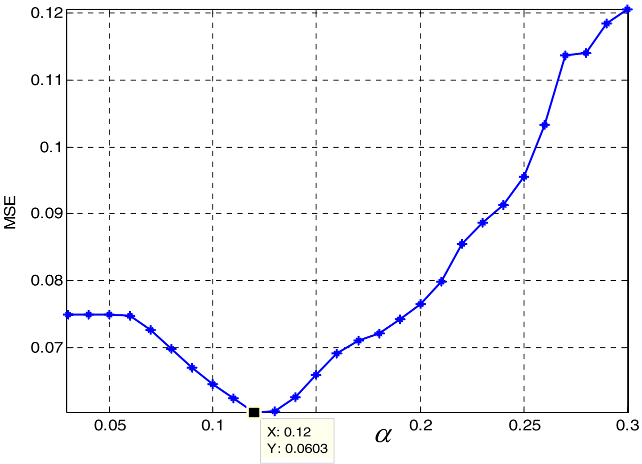

Figure 4. Influence of Parameter.

edges cannot be adequately enhanced. On the contrary, a high value (e.g. 0.5) carries out an over sharpening, which enhances undesirable artifacts and details in the image background. The optimal α value is roughly determined experimentally. Using the degraded synthetic image shown in Figure 5(b), we measure the mean square error (MSE) between the filtered and the original image for different α values of our algorithm varying between 0.03 and 0.3. The curve presented in Figure 4 shows that the smaller MSE value is achieved when $\alpha = 0.12$. This value is used in next experiments.

4.2. Evaluation on Synthetic Images

Radiography images are affected by a diverse kind of noise taking generally the Gaussian and impulse nature. The first experiment shows a synthetic image (88×85) corrupted with additive white Gaussian noise with a standard deviation with SNR = 11.25. Figure 5 (c)-(f) shows respectively anisotropic diffusion results with AD, GAD, SSAD and GSSAD method.

Results of AD method show a failure to remove impulse noise. Moreover, object boundaries are destroyed when smoothing the background due to the non-uniform illumination influence. Geometric anisotropic diffusion GAD filter allows de-noising the image well. However, we don't note any effect on blurred and unsharpened object edges. SSAD result confirms the ability to sharpen blurred image edges and to smooth small transitions related to Gaussian noise pixels. However, this method is unable to remove high discontinuities corresponding to impulse noise. The best result is obtained with the proposed method presented in Figure 5(f) . Our method permits to combine removing noise, smoothing background with sharpening image edges.

We present in Figure 6 a plot of the peak signal to noise ratio PSNR values. We use the same synthetic image used in the previous experiment affected by an additive impulse noise with density $d = 1\%$ and a white Gaussian noise with a standard deviation σ varies between 0.01 and 0.3. Peak signal to noise ratio PSNR is measured in decibels (dB) through the next formulation.

$$PSNR = 10 \log_{10} \left(\frac{255^2}{MSE} \right) (\mathrm{dB}) \tag{14}$$

$MSE = \frac{1}{r \times c} \sum_{i=1}^{r} \sum_{j=1}^{c} (I - I_f)^2$ is the mean square error, I is the original image and I_f is the filtered image while r, c are the number of image rows and columns respectively.

Obtained PSNR values of different methods proves the superiority of our method specifically comparing with Perona Malik filter AD and Chao Tsai method SSAD, which are highly sensitive to impulse noise. The results confirm that the proposed anisotropic diffusion method based on geometric parameters GSSAD is more robust to noise.

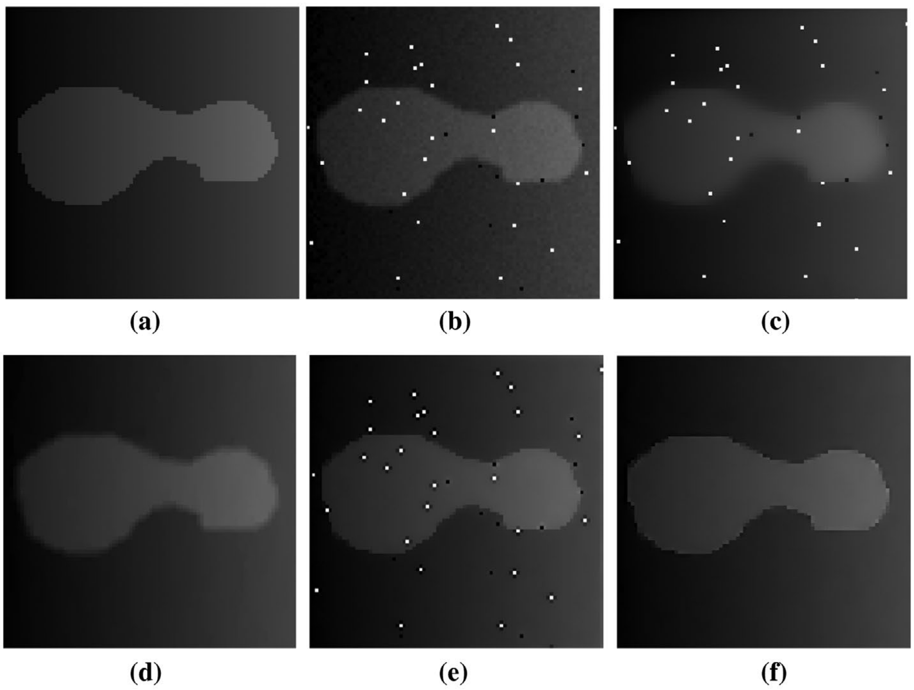

Figure 5. Evaluation of Noise Robustness (a) Original Synthetic Image, (b) Synthetic Image Affected with Additive Gaussian and Impulse Noise and Blurred with an Averaging Filter, (c) Result of AD Filter, (d) Result of GAD Filter, (e) Result of SSAD Filter, (f) Result of the Proposed Filter (GSSAD).

Figure 7 shows curves of the signal to noise ratio SNR value against the number of iterations for the same synthetic image corrupted with additive white Gaussian noise with the standard deviation $\sigma = 0.2$ and impulse noise density $d = 0.5\%$. The change of the SNR with the number of iterations follows the same characteristics for other images. We note that we have used the same iteration step time $\Delta t = 0.25$ for all methods. The signal to noise ratio SNR is computed as follows:

$$SNR = 10 \log \frac{\sigma_f^2}{\sigma_n^2} \mathrm{dB} \tag{15}$$

σ_f^2 is the variance of noise free image and σ_n^2 is the variance of the noise.

We can see that our method achieves the better SNR results with the lower number of iterations comparing with other methods. Moreover, we can observe that the proposed algorithm has long steady state duration at optimal results than Perona and Chao filters where the stability period is limited to a little number of iterations.

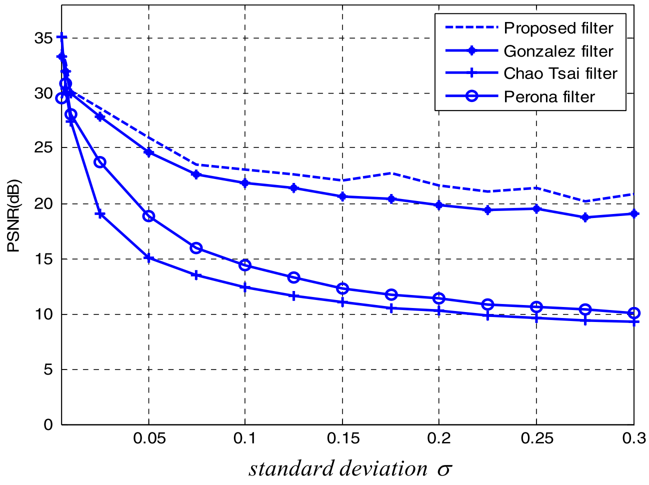

Figure 6. PSNR Plotted for Various Methods with an Additive Gaussian and Impulse Noise.

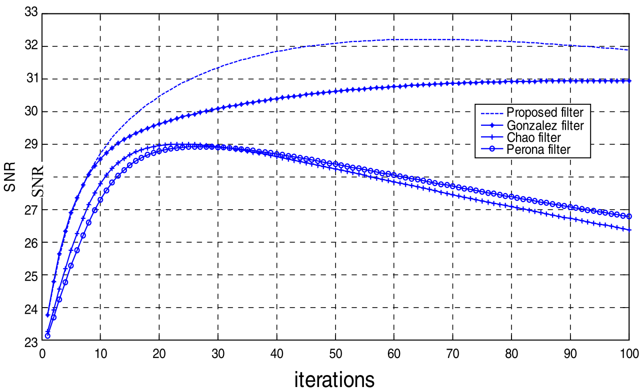

Figure 7. Signal to Noise Ratio (SNR) vs. Iterations Number.

4.3. Evaluation on Real Weld Radiography Images

The proposed method is applied and evaluated on weld radiography images containing different small defects as porosities and slags. In these images de-noising while preserving and sharpening defect edges is a complicated task due to the low contrast level and the small sizes of defects.

Figures 8, 9 and 10 (a)-(d) respectively shows the original image then results of geometric anisotropic diffusion GAD method, Chao Tsai anisotropic diffusion method SSAD and the proposed nonlinear diffusion method GSSAD. We note that we have added white Gaussian noise ($\sigma = 0.01$) to weld radiography image shown in Figure 10 to test robustness against the high level of noise.

It can be seen that geometric anisotropic diffusion (GAD) method allows to smooth and to remove noise while preserving image edges well. However, the ability to sharpen boundaries is very limited. SSAD method results show that edges are not only preserved but also sharpened. Nevertheless, this method is highly sensitive to the choice of the parameter α controlling the sharpening degree. Choosing high value permits to sharpen edges, but also to enhance noise pixels. This is can be clearly observed in Figure 10(c) of the weld radiography image affected by

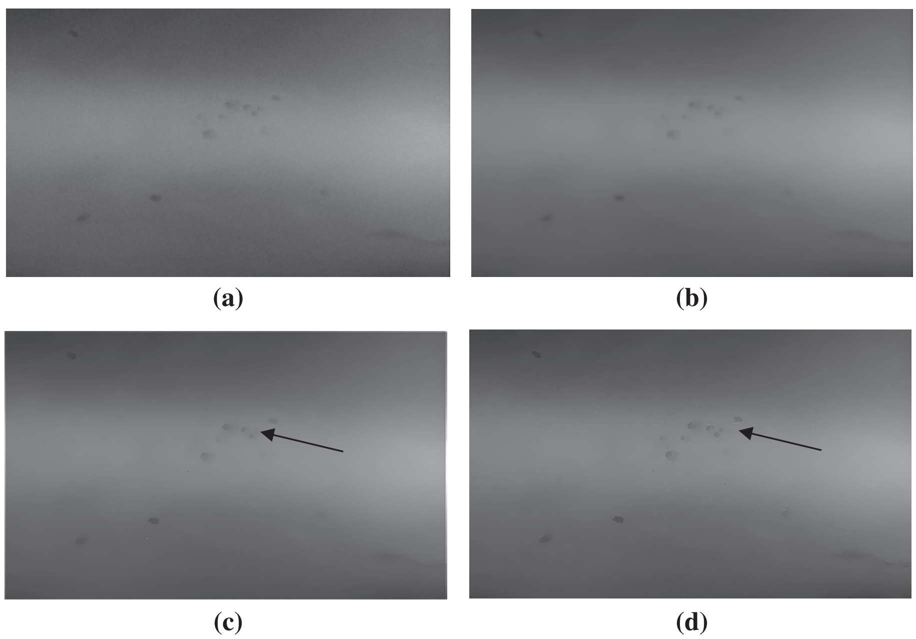

Figure 8. Anisotropic Diffusion Filters Result (a) Original Image with Additive Noise, (b) GAD Method Result, (c) SSAD Method Result, (d) Proposed Method (GSSAD) Result.

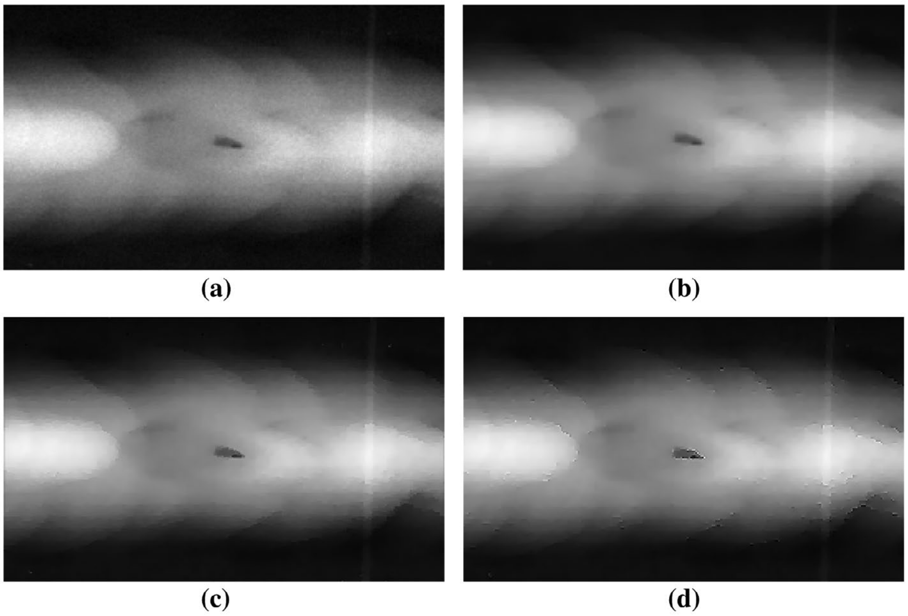

Figure 9. Anisotropic Diffusion Filters Result (a) Original Image with Additive Noise, (b) GAD Method Result, (c) SSAD Method Result, (d) Proposed Method (GSSAD) Result.

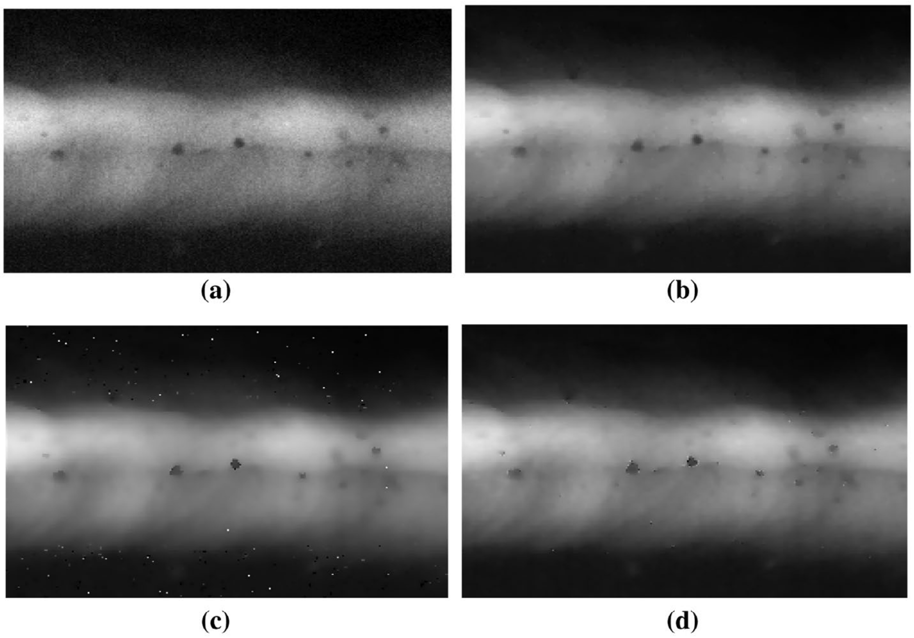

Figure 10. Anisotropic Diffusion Filters Result (a) Original Image with Additive Noise, (b) GAD Method Result, (c) SSAD Method Result, (d) Proposed Method (GSSAD) Result.

additive white Gaussian noise and impulse noise. The proposed anisotropic diffusion model shows the best results, it can be seen that noise is suppressed while defect edges are preserved and well sharpened. Results with additive noise in Figure 10(d) proves that our method can combine image denoising and edge sharpening not only with less noise, but also for images with high level of noise.

In Figure 11 (a)-(f) we present the defect segmentation results using a local threshold method proposed by Sauvola and Pietikäinen (2000) applied respectively to the outputs GAD method, SSAD method and our proposed method. Defect segmentation accuracy is related to the preprocessing step. The favorable one is the method who achieves accurate defect extraction. The detection is achieved after selecting the region of interest ROI, this step used by many researchers is highly recommended not only to reduce computation time, but also to avoid false detections.

It can be proven from a visual evaluation that the best defect region extraction result is obtained using our anisotropic diffusion method GSSAD, which performs the most accurate defect segmentation result with the lowest false detections.

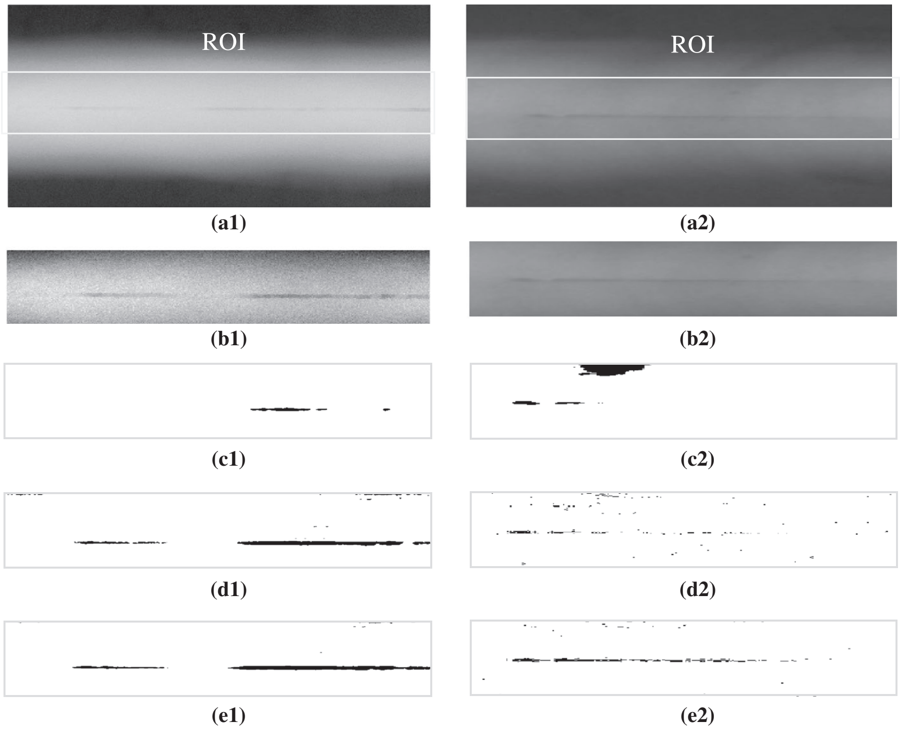

Figure 11. Defect Segmentation with Different Anisotropic Diffusion Filters (a1, a2) Original Images (b1, b2) Selected ROI Image (c1, c2) Defect Detection with GAD Method (d1, d2) Defect Detection with SSAD Method (e1, e2) Defect Detection with the Proposed Method.

5. Conclusion

Weld defect inspection based on radiography imaging is a difficult task due to the low contrast, noise and the blurred defect edges. Therefore, a pre-processing step for radiography image enhancement is extremely needed to facilitate weld supervision. In this work we have proposed an anisotropic diffusion method based on local geometric derivative parameters with a process fusing smoothing and sharpening. Moreover, a new weighting function is proposed to improve the control of the diffusion process. Many comparative tests on synthetic images and real weld radiography images are achieved to evaluate the performance of the proposed anisotropic diffusion method. A comparison is realized with classical anisotropic diffusion model (AD), geometric diffusion model (GAD) and smoothing-sharpening anisotropic diffusion (SSAD). The results prove the effectiveness of the proposed method comparing with other models in terms of noise reduction, edge preserving and sharpening. Moreover, results show that the proposed anisotropic diffusion scheme can effectively improve defect segmentation. In future work we plan to extend this work for some applications in the medical imaging area.

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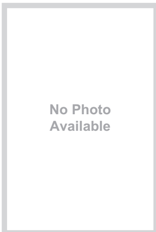
Disclosure statement

No potential conflict of interest was reported by the authors.

Notes on contributors



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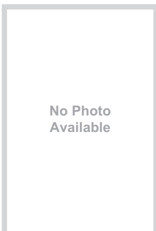

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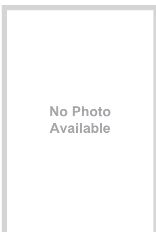

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