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# New anisotropic diffusion method to improve radiographic image quality

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## Abstract

Radiography imaging technique is popularly used for inspection of weld joints in many applications. The poor quality, the low contrast level and the presence of various kinds of noise make processing of radiographic images an intricate task. This paper presents a new anisotropic diffusion filtering method for radiography image sharpening and noise reduction. The novelty of our method is the integration of an adaptive diffusion flow vector ADF in the anisotropic diffusion formulation. This vector flow is used for active contours to reduce susceptibility to weak edges as well as deep and narrow concavity. The new anisotropic diffusion model permits to preserve perfectly weak image boundaries, while removing noise. Experimental results on different synthetic and real welding radiography images confirm the efficiency and robustness of our model in comparison with other diffusion methods.

**Keywords**: Adaptive diffusion flow; anisotropic diffusion; gradient vector flow; noise reduction; weld radiography.

## 1. Introduction

Radiography imaging is one of the most popular systems used in non destructive testing area. Particularly in welding inspection, it has an important role in the detection and the localization of defects that can occur in weld joints (Mery & Berti, 2003); (Carrasco & Mery, 2004). Weld defects may affect the smooth functioning of many systems, principally for serious applications, where failure can be catastrophic, such as welds of pressure vessels, aircraft, power plants etc. Radiography acquisition system is based on the transmission of X-rays or Gamma rays through an object to produce an image on radiographic film. Defects in weld are the cause of variations in film density. The regions of the film, which have received more radiation during exposure appear darker. Welding radiography image contains generally the base metal and the weld region placed horizontally in the middle of image. The quality of radiography images is evaluated by three factors; contrast, sharpness and the graininess. These factors are basic parameters that determine the radiographic image quality and have a great influence on the detection performance of defects in weld joints.

In this area, an automatic inspection system based on image processing and pattern recognition (Ambeth Kumar *et al.,* 2015); (Khairullah Khan *et al.,* 2016) is highly recommended to assist interpretation of weld radiographs. Weld radiography image analysis encounters many difficulties due to uneven illumination, the low contrast level where edges are very weak and the presence of a high level of noise generally with Gaussian and impulse nature. Therefore, a preprocessing step is highly recommended to decrease noise density and to sharpen image edges in order to facilitate in a further step the defect detection. Much effort has been spent to overcome this problem (Ben Mhamed *et al.,* 2012). In general proposed methods were proved to be effective on images with little noise and high contrast, while to those with large noise and poor quality, boundaries are usually destroyed.

Anisotropic diffusion methods were extensively employed for image filtering and enhancement in the past decade. This approach is based on partial differential equations (PDE) like the heat propagation equation. This technique produces high results compared to traditional low pass filters like Gaussian filter, Wiener filter or median filter. The first anisotropic diffusion model was proposed by Perona & Malik (1990). This method permits to carry out an iterative diffusion process controlled by a partial differential equation, where the image is selectively smoothed with well edge preserving. The main idea is to reduce the diffusion, as the image gradient raise and to increase it for low gradients. Since Perona and Malik work, many methods have been introduced based on PDE approach like the shock filter (Osher & Rudin, 1992). The principle of Shock filter is to perform locally either dilation or erosion process, depending on maximum or minimum pixel zone. This method is efficient to enhance image contrast but it is very sensitive to impulse noise. Hence, Alvarez & Mazorra (1994) 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. The same author has defined a new class of filter for noise reduction and edge enhancement by merging shock filter with a diffusion operator. The main idea is to add a term of smoothing diffusion with an adaptive weight between shock effect and diffusion process (Durikovic *et al.,* 1995). A new class of anisotropic diffusion model is proposed by Weikert (1999) in two categories, where the diffusion process is not controlled by a scalar function, but using a tensor based function which allows adjusting the smoothing effect according to edge direction. Known as coherence enhancing diffusion (CED), this method shows high performance in analyzing coherence structure. The used tensor function enables to measure gradient direction changes, which allow diffusion mainly along the structure direction and becomes stronger as the coherence increases. The disadvantage of CED method is developing false anisotropic structures and rounded corners. In oder to improve the numerical stability and higher order estimation of the second and fourth order derivatives in diffusion filter, Yu & Chua (2006) incorporated the gradient vector flow GVF (Xu & Prince,1998) into non linear diffusion models. This model achieves excellent robustness against noise with numerical stability. The limitation of this approach is the susceptibility to weak boundaries and principally when images are corrupted by impulse noise. Therefore, a modified version is proposed by Ghita & Wehlan (2010), which merge Yu Chua model with an adaptive median filter. Unfortunately, both Yu Chua and Ghita methods are based on the GVF vector field which is used to guide the diffusion process. GVF vector is not suitable for weak edges especially neighbored by strong ones, where usually these boundaries are destroyed and moved.

In this work GVF based anisotropic diffusion methods are improved to deal more robustly with weak boundaries. An adaptive diffusion flow vector ADF (Wu *et al.,* 2013) is integrated in a nonlinear diffusion equation in order to increase robustness against noise and to preserve weak edges while diffusion process. This new diffusion formulation is suggested to improve quality of welding radiography images. 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 anisotropic diffusion method. Experimental results and evaluation of the proposed method are shown in the third part. A conclusion and perspectives of this work are presented in the final part.

## 2. Related works

### 2.1. Anisotropic diffusion filter (P-M)

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

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

$div(.)$ and $\nabla$ 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 guiding the diffusion process. Two functions are proposed by Perona and Malik

$$\begin{aligned} g(|\nabla I|) &= 1 \Big/ (1 + \frac{|\nabla I|^2}{k^2}) \\ g(|\nabla I|) &= \exp(-\frac{|\nabla I|^2}{k^2}) \end{aligned} \tag{2}$$

$k$ is a parameter having a threshold role. If $|\nabla I| > K$ thus these pixels are regarded as edges and they will be less blurred. Whereas, if $|\nabla I| < K$ these points are considered as interior regions and will be highly smoothed.

### 2.2. GVF based anisotropic diffusion

Although the usefulness of P-M anisotropic diffusion equation its numerical stability still needs to be improved. One of the most important researches in this direction is Yu Chua's work. The gradient vector flow GVF is incorporated in P-M model to replace the second order derivatives to perform more stability during diffusion process.

P-M Equation (1) can be expanded as follow

$$\frac{\partial I}{\partial t} = g'|\nabla I| I_{\eta\eta} + g(|\nabla I|)\Delta I \tag{3}$$

$\eta$ is the direction of the gradient, $I_{\eta\eta} = \left\langle H^2 I, \frac{\nabla I}{|\nabla I|} \right\rangle$, $H^2$ is the hessian matrix and $\langle . \rangle$ is the scalar product.

$\Delta$ is the lapacian operator.

Yu & Chua (2006) demonstrate that the first term in P-M equation can be replaced as

$$g'|\nabla I| I_{\eta\eta} = -V_{GVF}.\nabla I \tag{4}$$

$V_{GVF}$ is the gradient vector flow GVF defined by C. Xu [11] as the vector field that minimizes the following functional

$$E(V_{GVF}) = \int_{\Omega} \mu |\nabla V_{GVF}|^2 + |\nabla f|^2 (V_{GVF} - \nabla f)^2 d\Omega \tag{5}$$

$f$ is an edge map, $V_{GVF} = [u, v]$ is the gradient vector field and $\Omega$ is the image domain.

The first term in GVF equation performs a diffusion of the edge information, the second term attract the GVF to the image gradient vectors near edges. The parameter $\mu$ controls the smoothness of the GVF vector field. Choosing a large value will create a strong diffusion which is suitable for noisy image but easily destroy weak edges. In contrast a small value of $\mu$ maintain poor boundaries but preserves excessive noise, this is a dilemma for GVF to suppress noise and preserve weak edge simultaneously.

The final Yu and Chua equation combined with GVF vector flow can be shown as follow

$$\frac{\partial I}{\partial t} = -(V_{GVF}.\nabla I)|\nabla I| + g(|\nabla I|)\Delta I \tag{6}$$

The integration of the GVF vector in non linear diffusion models has many advantages; the vector fields can be determined in advances so they are invariable during image diffusion. Moreover, it approximates the second order difference, which allows performing well on noise or spurious edges. As noted before, the gradient vector flow GVF is susceptible to weak edges especially to those very close to a strong one where poor boundaries are usually suppressed and not considered. This can be explained by the inherent competition of the diffusion process. Improving robustness of this model toward weak edges will be the main goal of the proposed model.

## 3. Proposed method

In this section, the new anisotropic diffusion method is presented in two subsections. The first subsection presents a brief description of adaptive diffusion vector flow ADF and the second one depicts the new anisotropic diffusion formulation.

### 3.1. Adaptive diffusion flow (ADF) vector

The adaptive diffusion flow vector ADF (Wu *et al.,* 2013) is proposed as an improved version of the GVF vector to deal with active contours leakage problem in image segmentation. The smoothness term in GVF formulation is replaced by harmonic hyper-surface minimal function to alleviate the possible leakage problem. Moreover, an infinity Laplace function is added to ensure that the vector flow diffuses mainly along normal direction in homogenous regions of an image, more detail can be found in Wu work. As in GVF vector flow the ADF vector $V_{ADF}$ is obtained by minimizing this functional:

$$\begin{aligned} E(V_{ADF}) = \int_{\Omega} g[-m.\Theta_{L^\infty} + (1-m).\frac{1}{p(|\nabla f|)} \\ .(\sqrt{1+\Theta})^{p(|\nabla f|)}]d\Omega + h.|V_{ADF} - \nabla f|^2 d\Omega \end{aligned} \tag{7}$$

g, h, m are the weighting functions respectively, *p(.)* is a monotonic decreasing function and $\Theta = |G_\sigma \otimes \nabla V_{ADF}|^2$. Choosing appropriate weighting function is crucial to preserve weak edges and concavity convergence.

Using variational calculus, minimization of functional (6) is given by:

$$\begin{aligned} \frac{\partial V_{ADF}}{\partial t} = g[-m.(\frac{1}{|\nabla V_{ADF}|^2} \Delta_\infty V_{ADF}) + (1-m) \\ .div(\frac{\Phi'|\nabla V_{ADF}|}{|\nabla V \otimes G_\sigma|}.\nabla V \otimes G_\sigma)] + h.(V_{ADF} - \nabla f) \end{aligned} \tag{8}$$

$\Delta_\infty$ denotes the infinity laplacian equation defined with $\Delta_\infty = \sum_{i=1,j=1}^{2} V_{xi}.V_{xj}.V_{xixj}$.

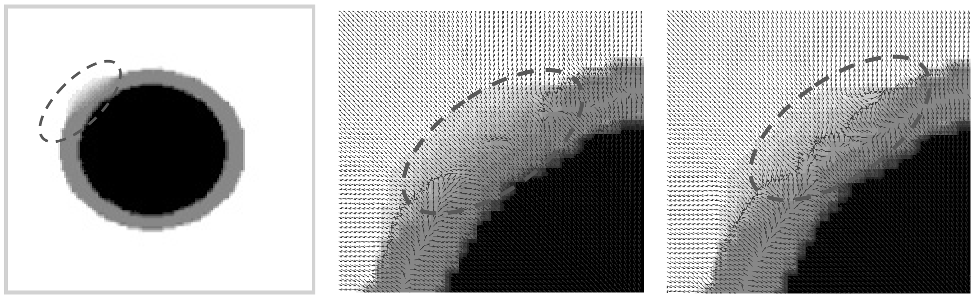
$\Phi(|\nabla V|)$ is the hypersurface minimal function, defined by Wu et al in their paper $\Phi(|\nabla V|) = 1/\sqrt{1+|\nabla V|^2}$. In this case, we can get $\Phi'(|\nabla V|)/|\nabla V| = 1/\sqrt{1+|\nabla V|^2}$.

To improve ADF vector robustness to impulse noise, the edge map $f$ is computed using a median filter as follow

$$f = \frac{1}{1+|\nabla I_m|^2} \tag{9}$$

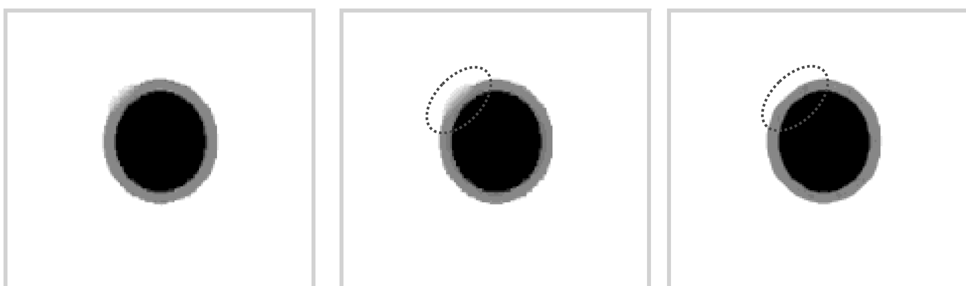
$I_m$ is the image filtered with a median filter $I_m = medfilt(I)$ with a size 3×3.

To illustrate the advantage of ADF in enhancing weak edges, Figure 1 shows field vectors of two flows ADF and GVF of a synthetic image containing a weak edge near a strong one. Only a part from the vector fields are zoomed around a destroyed edge circled with an interrupted red line to show behaviors of GVF and ADF vectors on this zone. It can be seen in this zone GVF vectors bypass weak edge and oriented to strong edge which can be explained by the flow opposition between two different neighbor edges. The weak edge is considered with ADF vectors as it can be seen at this zone in Figure 1 (c).



-a- -b- -c-

**Fig. 1.** Behavior of ADF and GVF vector fields on weak contours –a- synthetic image –b- GVF vector field –c- ADF vector flow



-a- -b- -c-

**Fig. 2.** Behaviors of diffusion methods on weak edges (for all methods $\Delta t = 0.1$, $30\,iterations$) –a- synthetic image -b- Yu and Chua result –c- proposed method result

## 3.2. Formulation of the anisotropic diffusion equation

In our model the adaptive diffusion flow vector $V_{ADF}$ substitute the GVF gradient vector flow in Yu Chua method, thus the new equation can be presented as

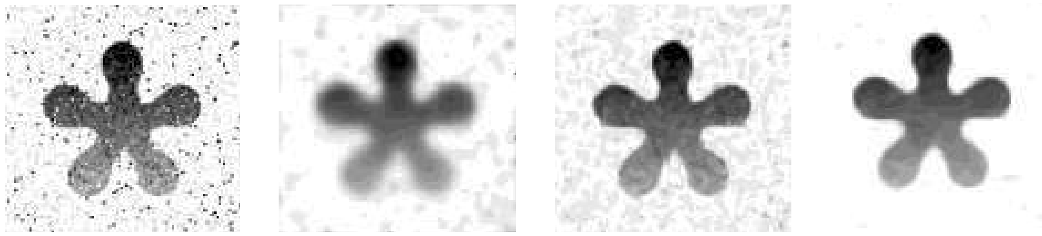
$$\frac{\partial I}{\partial t} = -(V_{ADF}.\nabla I)\left|\nabla I\right| + g(\left|\nabla I\right|)\Delta I \qquad (10)$$

g(.) is a decreasing function.

The first term in the proposed diffusion equation create an inverse diffusion in the direction of the gradient which allows edges sharpening whereas the second term permits a tangential diffusion along boundaries. Figure 2 shows the result of diffusion methods Perona Malik P-M, Yu Chua and our method. Yu Chua method based on GVF vector shows inability to sharpen and to improve damaged edge. Using proposed diffusion approach we can see clearly that destroyed edge is preserved and sharpened.

## 4. Experimental results

To evaluate the performance of the proposed method, we apply the proposed method to weld radiography images. In the first experiment we test its robustness against noise. Figure 3 shows a synthetic image corrupted with additive white Gaussian noise with standard deviation $\sigma = 0.1$ and an impulse noise with density d=0.05. Results of anisotropic diffusion method P-M and GVF based anisotropic diffusion of Yu Chua are compared with our method. Moreover, we show in Figure.4 a plot of SNR values against the number of iterations for the synthetic image. Visual interpretation of results shows the efficiency and robustness of our method in terms of noise reduction. P-M method fails to remove noise without blurring edges. Yu Chua method result shows high sensitivity particularly to impulse noise. The best result is obtained with our method, which permits to remove noise perfectly, while preserving object edges. The SNR versus iterations number plot shows that our method not only has the higher SNR values but also fast to reach the high SNR level and the steady state, after that just small improvements are observed.



-a- -b- -c- -d-

**Fig. 3.** Robustness against noise (for all methods $\Delta t = 0.1$, $30\,iterations$)–a-synthetic noisy image –b- result of P-M method k=0.25 –c- Result of Yu Chua method $\mu$=0.2 –d- result of proposed method

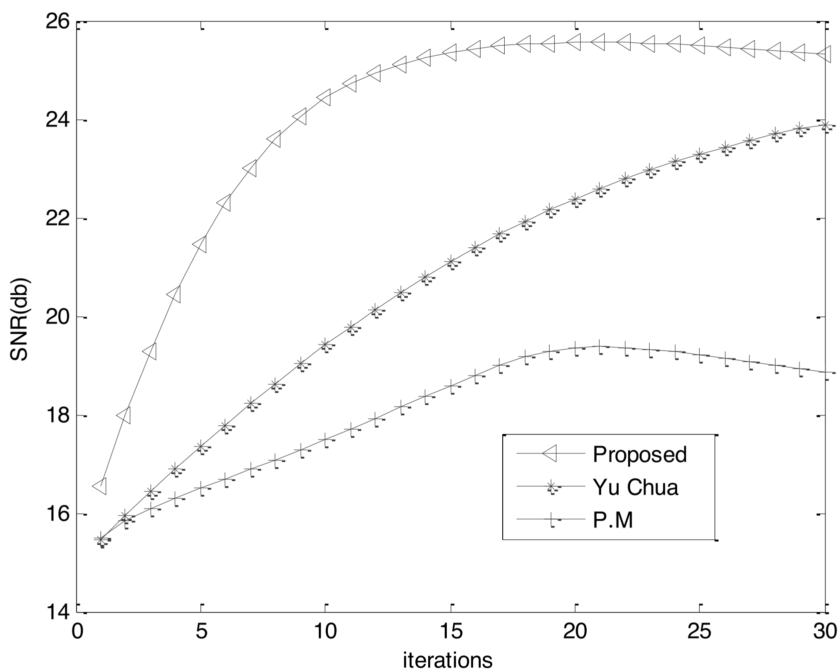
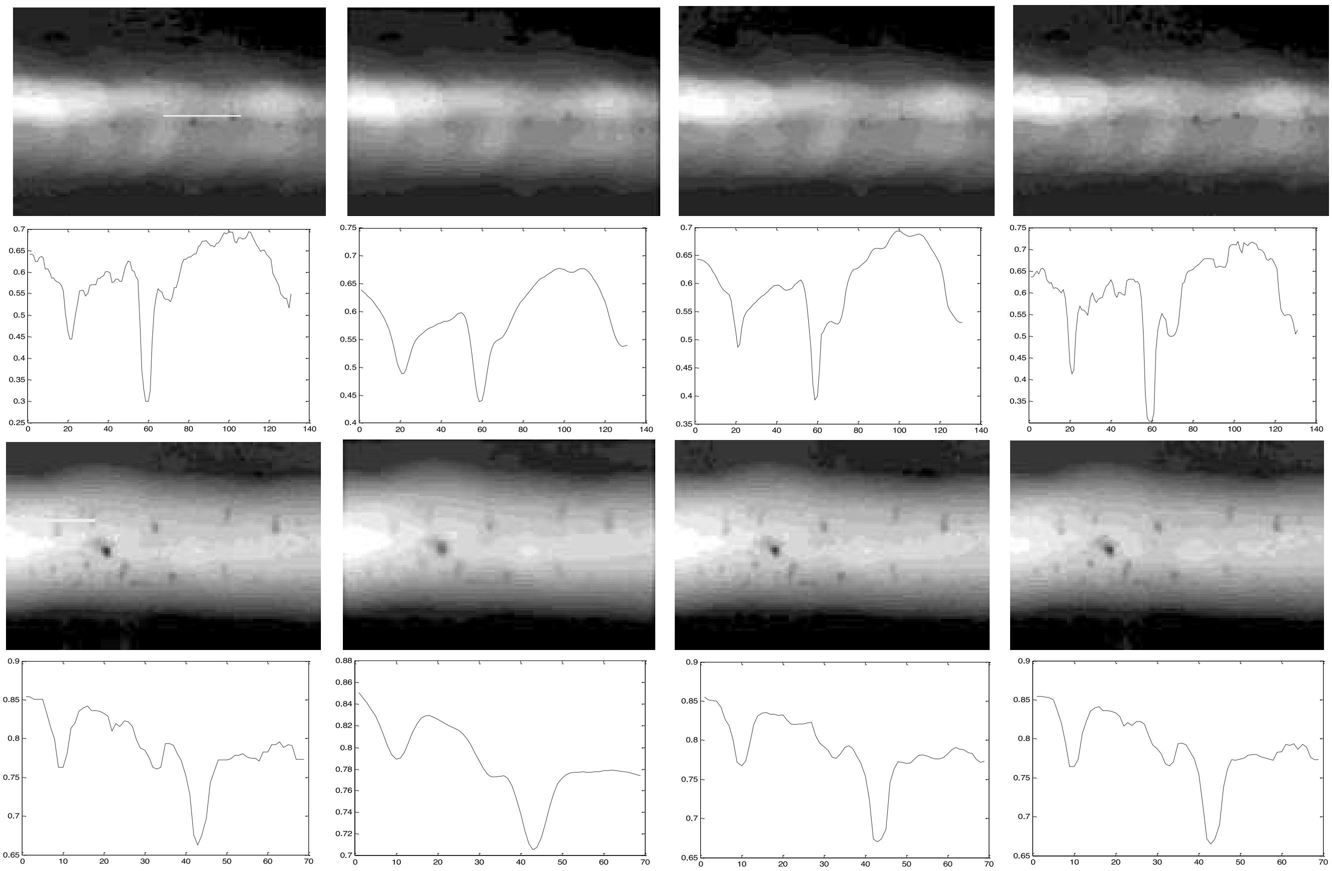



**Fig. 4.** Signal to noise ratio SNR against iteration number computed with the synthetic image

The signal to noise ratio SNR is computed using this formulation $SNR = 10\log(\frac{\sigma_f^2}{\sigma_n^2})(dB)$. Where $\sigma_f^2$ the variance of noise free image and $\sigma_n^2$ is the variance of noise.

Experiments in Figure 5 correspond to real weld radiography images containing small defects as porosities and slags. These images are obtained from federal institute for material research and testing (BAM). In these images, noise reduction while edge preserving and sharpening is too difficult. Confusion between edge pixels and noise can happen easily due the low image contrast level. We show diffusion result with P-M method in the second column, GVF based anisotropic diffusion result is shown in the third column, while the result of the proposed method is presented in the right side. We show also result images profiles shown with a white line on the original image. It seems that our method has the best results in terms edge sharpening quality and boundaries preserving; image profiles permits also to validate superiority of our method.



-a- -b- -c- -d-

**Fig. 5.** Filtering result comparison for weld radiography image (for all methods $\Delta t = 0.1$, $30\,iterations$) –rows 1 and 3: -a- original image –b- P-M result k=0.25 –c- Yu Chua result $\mu$=0.2 –d- our method result – rows 2 and 4: corresponding results image profiles.

Efficiency and performance of a preprocessing method is related to the future step corresponding to defect segmentation. The favorable one is the method that achieves the most accurate defect isolation. In Figure 6 we present defect detection results using local threshold method (Sauvola & Pietikainen, 2000) applied on the outputs of respectively P-M, Yu Chua and our method. The detection is achieved after selecting a 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. Defects found in these weld radiography images are lack of penetration defect, which is a dark line centered horizontally at the middle and porosities defect with circular shapes. It can be seen in images at left row that P-M and Yu Chua methods are unable to extract almost all defect regions, where line defect region is not segmented. In the right images, P-M method does not permit to isolate the whole defect region; Yu Yu Chua method shows much false undesirable detections. The proposed method shown in the last line achieves the best defect segmentation results.

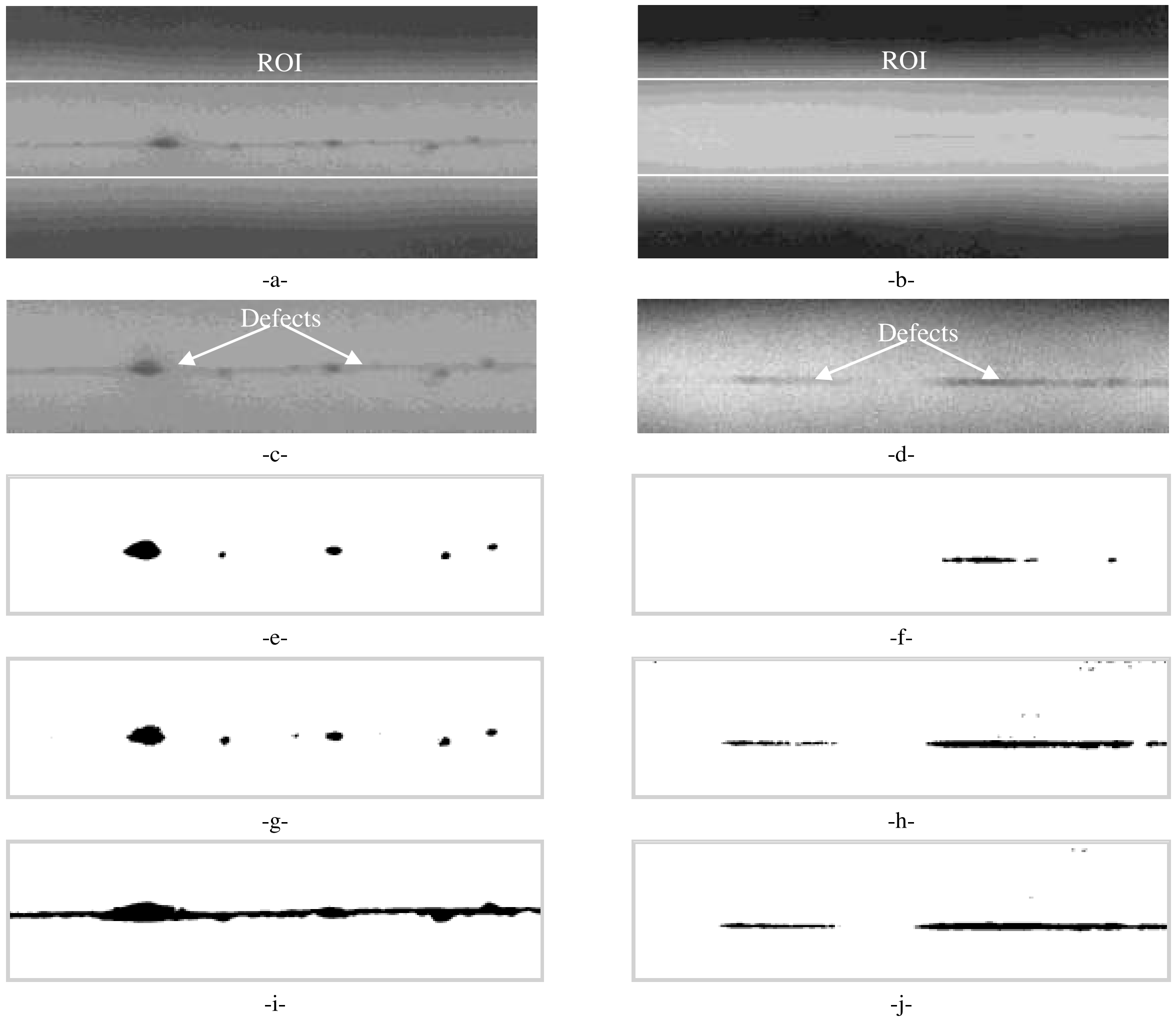



**Fig. 6.** Defect segmentation ( $\Delta t = 0.1,\ 30\,iterations$ )–a-b- original image –c-d- selected ROI image –e-f- defect detection with P-M method k=0.25 –g-h- defect detection with Yu and Chua method $\mu$=0.2 –i-j- defect detection with proposed method

## 5. Conclusion

The aim of presented method in this paper is to improve usefulness of the gradient vector flow GVF in image enhancement with non linear diffusion schemes, particularly when weak edge and poor boundaries are present. Thus, we have proposed the use of the adaptive diffusion flow (ADF) vector to guide the diffusion process. The new method is tested and evaluated on welding radiography images in terms of noise robustness, edge preserving, edge sharpening and defect detection accuracy. Results shows effectiveness of our method comparing to GVF based diffusion method. The proposed method can be useful for other vital image applications and computer vision to resolve problems related to noise and weak boundaries like in medical area, microscopical imaging, remote sensing, this will be our future work.

## References

**Alvarez, L. & Mazora, L. (1994).** Signal and image restoration using shock filters and anisotropic diffusion. SIAM Journal of Numerical Analysis, **31**(2):590-605.

**Ambeth, K., Visam, D., Ramakrishnan, M., Malathi, S. & Ashok, K. (2015).** Performance improvement using an automation system for recognition of multiple parametric features based on human footprint. Kuwait Journal of Science, **42**(1):109-132.

**Ben Mhamed, I., Abid, S. & Fnaiech, F. (2012).** Weld defect detection using a modified anisotropic diffusion model. Journal on Advances in Signal Processing, **46**, DOI: 10.1186/1687-6180-2012-46.

**Carrasco, M. & Mery, D. (2004).** Segmentation of welding defects using a robust algorithm. Materials Evaluation, **62**(11):1142-1147.

**Mery, D. & Berti, M. (2003).** Automatic detection of welding defects using texture features. Insight X-Ray Image Processing, **45**:676-681.

**Ghita, O. & Whelan, F. (2010).** A new GVF-based image enhancement formulation for use in the presence of mixed noise. Pattern Recognition, **43**:2646-2658.

**Sauvola, J. & Pietikainen, M. (2000).** Adaptive document image binarization. Pattern Recognition, **33**:225–236.

**Weickert, J. (1999).** Coherence-enhancing diffusion of colour images, Image and Vision Computing, **17**(3–4):199–210.

**Khairullah, K., Ashraf, U. & Baharum, B. (2016).** Pattern and semantic analysis to improve unsupervised techniques for opinion target identification. Kuwait Journal of Science, **43**(1):129-149.

**Perona, A. & Malik, J. (1990).** Scale-space and edge detection using anisotropic diffusion. IEEE Transactions on Pattern Analysis and Machine Intelligence, **12**(7):629–639.

**Ďurikovič, R., Kaneda, K. & Yamashita, H. (1995).** Dynamic contour: a texture approach and contour operations. The Visual Computer, **11**(6):277-289.

**Rudin, I., Osher, S. & Fatemi, E. (1992).** Nonlinear total variation based noise removal algorithms. Physical D, **60**:259–268.

**Xu, C. & Prince, J. (1998).** Snakes, shapes, and gradient vector flow. IEEE Transactions On Image Processing, **7**(3):359-69.

**Yu, H. & Chua, C. (2006).** GVF-based anisotropic diffusion models. IEEE Transactions on Image Processing, **15**(6):1517–1524.

**Wu, Y., Wang, Y. & Jia, Y. (2013).** Adaptive diffusion flow active contours for image segmentation. Computer Vision and Image Understanding, **117**:1421–1435.

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# طريقة جديدة لانتشار متباين الخواص لتحسين صورة التصوير الإشعاعي

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## ملخص

تُستخدم تقنية التصوير الإشعاعي على نطاق واسع للكشف عن وصلات اللحام في العديد من التطبيقات. إن النوعية الرديئة، وانخفاض مستوى التباين ووجود أنواع مختلفة من الضوضاء هي عوامل تجعل معالجة الصور الإشعاعية عملية معقدة. ويقدم هذا البحث طريقة فلترة جديدة لانتشار متباين الخواص لجعل التصوير الإشعاعي أكثر وضوحاً وأقل ضوضاء. والجديد في طريقتنا هو دمج متجه تدفق انتشار تكيفي (ADF) في صيغة الانتشار متباينة الخواص. وتم استخدام هذا التدفق المتجه للخطوط الكنتورية النشطة للحد من التعرض للحدود الضعيفة وكذلك التقعر العميق والضيق. يسمح نموذج الانتشار متباين الخواص الجديد بالحفاظ تماماً على حدود الصورة الضعيفة، في حين يتم التخلص من الضوضاء. وتؤكد النتائج التجريبية على مختلف صور التصوير الإشعاعي للحام الصناعي والحقيقي كفاءة ومتانة نموذجنا بالمقارنة مع طرق النشر الأخرى.