# Adaptive Pre-Filtering Techniques for Colour Image Analysis

Dana Elena Ilea and Paul F. Whelan
*Vision Systems Group, School of Electronic Engineering*
*Dublin City University, Glasnevin, Dublin 9, Ireland*
*danailea@eeng.dcu.ie*

## Abstract

*One important step in the process of colour image segmentation is to reduce the errors caused by image noise and local colour inhomogeneities. This can be achieved by filtering the data with a smoothing operator that eliminates the noise and the weak textures. In this regard, the aim of this paper is to evaluate the performance of two image smoothing techniques designed for colour images, namely bilateral filtering for edge preserving smoothing and coupled forward and backward anisotropic diffusion scheme (FAB). Both techniques are non-linear and have the purpose of eliminating the image noise, reduce weak textures and artefacts and improve the coherence of colour information. A quantitative comparison between them will be evaluated and also the ability of such techniques to preserve the edge information will be investigated.*

## 1. Introduction

Data smoothing is a fundamental operation in the fields of image processing and computer vision that is carried out in order to pre-process an input image corrupted with noise and artefacts and prepare it for further analysis. In the context of colour image smoothing, the purpose of the filtering process is to eliminate or reduce the level of image noise and improve the local colour homogeneity. The literature on data smoothing is vast and the existing algorithms are divided into two major categories namely, linear and non-linear [1,2]. Some representative traditional linear smoothing techniques are the mean (average) filtering and Gaussian smoothing. Average-based filtering simply replaces each pixel value in an image with the mean (average) value of its neighbours. This approach reduces the noise level, but it is worth mentioning that this solution is ill suited since the data smoothing is achieved at the expense of severe edge attenuation that leads to poor feature preservation. Gaussian smoothing is similar to mean filtering but the main difference is that the weights assigned to all pixels situated in the neighbourhood of the central pixel are modulated by a Gaussian function and as a result the edge attenuation produced after the application of the local averaging operation is not as severe as that generated by the mean filtering smoothing strategy. To address the limitations associated with linear filtering schemes, a large number of non-linear smoothing techniques were proposed. The most popular non-linear filtering methods include median filters [2], statistical approaches based on non-parametric estimations [3,4] and the more recent developments based on non-linear diffusion. Among non-linear smoothing techniques the anisotropic diffusion received the greatest interest from the vision community [5,6,7,8,9] since this approach offers the optimal trade-off in smoothing efficiency, removal of weak texture and feature preservation. In this paper, two non-linear advanced filtering techniques are analysed from the context of adaptive data smoothing of colour images. The first technique evaluated in this study is the bilateral filtering while the second is the forward and backward (FAB) anisotropic diffusion. In this paper the main emphasis will be placed on the optimisation of the FAB anisotropic diffusion by the inclusion of a boost function that increases the values of medium gradients that are generated by the low colour contrast. While the goal of this paper is the development of optimal schemes for adaptive colour smoothing, our aim is to extend these filters to be able to deal with multi-dimensional data since the application of one-dimensional (1D) filters on all colour channels will generate spurious colours in the output data.

This paper is organized as follows. Section 2 introduces the bilateral filtering technique while Section 3 details the forward and backward anisotropic diffusion scheme together with the proposed improvements. In Section 4 experimental results are presented and evaluated, while Section 5 concludes the paper.

## 2. Bilateral Filtering for Colour Images

The bilateral filtering technique was proposed by Tomasi and Manduchi [10] and has the aim of smoothing colour data while preserving the most important edges present in the input image. The basic idea that lies behind this approach is the evaluation of the spatial and intensity information between the data points during the filtering process. As opposed to traditional linear smoothing strategies, the spatial averaging is reformulated in order to assign weights to the pixels situated in the neighbourhood that are calculated as a function of pixel similarity. While these weights decay with pixel intensity, the smoothing process is more pronounced in regions defined by noise and weak textures, while this process is halted where the image data shows intensity discontinuities. The bilateral filtering is applied to the entire data in a non-iterative manner as follows:

$$h(x) = k^{-1}(x) \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(\tau) c(\tau, x) s(f(\tau), f(x)) d\tau \quad (1)$$

and $$k(x) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} c(\tau, x) s(f(\tau), f(x)) d\tau \quad (2)$$

where *k(x)* represents the normalization term that enforces the sum of weights for all pixels to be one, $c(\tau, x)$ measures the spatial closeness between the centre pixel $x$ and the neighbouring pixel $\tau$, and $s(f(\tau), f(x))$ measures the similarity between the intensity values $f$ of pixels located at $x$ and $\tau$. While the similarity or closeness factor between two data points can be sampled using a large number of functions, in our implementation, the similarity is sampled by the Gaussian function that is used in conjunction with the Euclidian distance [10] as follows:

$$c(\tau, x) = e^{-\frac{\|\tau - x\|^2}{2\sigma_d^2}} \quad (3)$$

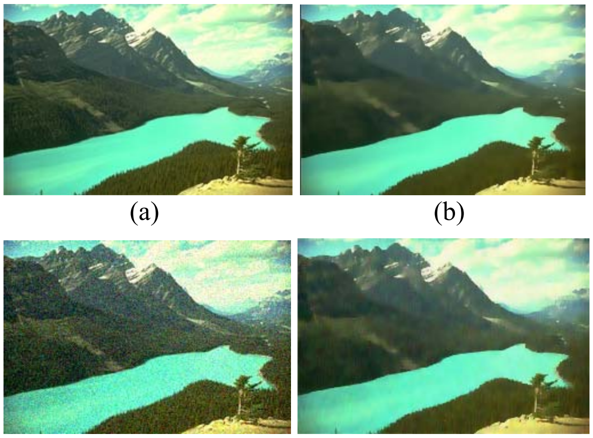
$$s(\tau, x) = e^{-\frac{\|f(\tau) - f(x)\|^2}{2\sigma_r^2}} \quad (4)$$

where $\sigma_d$ is the standard deviation that controls the smoothing in the spatial domain and $\sigma_r$ is the standard deviation that controls the smoothing in the intensity domain. In this regard, large values of $\sigma_d$ imply more spatial blurring (the decay of *c(τ, x)* is less pronounced) when the intensities of pixels from more distant image locations have a larger contribution in equation 1. In a similar fashion $\sigma_r$ controls the smoothing process with respect to intensity variations and the smoothing is more pronounced for larger values. These parameters control to what extent the spatial and intensity information is preserved during the smoothing process and the optimal set of parameters can be set in conjunction with the level of image noise present in the input image. For instance, if our objective is the preservation of very narrow details in the input image then it will be best to set the values of $\sigma_d$ to low values since the decay of *c(τ, x)* will be pronounced and only a small number of pixels will have a significant contribution in equation 1. Using a similar approach, if we want to preserve intensity discontinuities in intensity data, the value of $\sigma_r$ needs to be set to low values. Typical results obtained after the application of bilateral filtering are illustrated in Figures 1 and 2.

(a)

(b)

Figure 1. (a) Original natural image. (b) Filtered image resulting after the application of the bilateral filtering. The standard deviation values in the spatial and intensity domain are set to $\sigma_d$ =3 and $\sigma_r$ =20 respectively. (All images are also available at: http://www.vsg.dcu.ie/code.html).



(a) (b) (c) (d)

Figure 2. (a) Original image. (b) Filtered image using the bilateral filtering technique with the following parameters $\sigma_d$ =3 and $\sigma_r$ =20. (c) The original image corrupted with Gaussian noise (standard deviation 30 intensity levels on each colour channel). (d) Filtered image using the bilateral filtering technique with the following parameters $\sigma_d$=5 and $\sigma_r$=30. It can be noted the good feature presentation achieved even for images with low signal to noise ratio (SNR).

## 3. Forward and Backward Anisotropic Diffusion for Colour Images

The second technique evaluated in this paper is a further improvement of the anisotropic diffusion smoothing technique that was originally developed by Perona and Malik [5]. In their paper, data smoothing is formulated as a diffusive process that is performed within the image regions and suppressed at the regions boundaries. In order to achieve this behaviour, they developed a mathematical framework where the central part is played by a diffusion function that controls the level of smoothing. This translates in the implementation of a non-linear procedure where smoothing can be defined in terms of the divergence of the flux function as follows:

$$u_t = div(D(\nabla u)\nabla u) \tag{5}$$

where $u$ is the input data, $D$ represents the diffusion function (or conductivity function) and $t$ refers to time or iteration step. The smoothing strategy described in equation 5 can be implemented using an iterative discrete formulation as follows:

$$I_{x,y}^{t+1} = I_{x,y}^{t} + \lambda \sum_{j=1}^{4} [D(\nabla_j I)\nabla_j I]^{t} \tag{6}$$

where $I_{x,y}^{t+1}$ is the pixel intensity value at position *(x, y)* and iteration *(t+1)*, $I_{x,y}^{t}$ is the pixel intensity at the previous iteration $t$, $\nabla_j I$ is the two neighbour gradient operator and $\lambda$ is the contrast parameter that is set in the interval 0< $\lambda$< 0.3 (for this implementation $\lambda$=0.2). The diffusion function $D$ in equation 6 is bounded in the interval (0,1) and is defined as follows:

$$D(\nabla I) = e^{-\left(\frac{\nabla I}{k}\right)^2} \tag{7}$$

where $k$ is the parameter that controls the smoothing level. It can be noted that this function decays with the increase of the gradient value. Although anisotropic diffusion is an efficient smoothing procedure, it is useful to note that it has several drawbacks, namely problems with stability and the weak response of the diffusion function to medium gradients. The stability problems were caused by the fixed contrast parameter $\lambda$ that produces intensity offsets between the input and output data and to compensate for this, a number of implementations were proposed (for more details refer to [6,11]). The problems generated by the inability of the exponential diffusion function to model the diffusion process for low and medium gradients, received lower research interest from the vision community. This is surprising since the efficiency of the smoothing procedure is greatly influenced by the optimal use of gradient data. To address this problem Smolka and Platainiotis [12] proposed the forward and backward (FAB) anisotropic diffusion that also includes a time dependent cooling procedure in order to overcome stability problems. As opposed to the standard implementation proposed by Perona and Malik [5], the goal of the FAB anisotropic diffusion is to highlight the medium and large gradients that are noise independent. The strategy behind this smoothing procedure is conceptually simple and the process of emphasizing noise independent gradients would require reversing the diffusion process. In other words, to emphasize noise independent gradients the slope of the diffusion function needs to be inversed and this will move weight from the lower part to the upper part of the diffusion function. This can be implemented by applying two diffusions processes simultaneously: the first is applied forward while the second is applied backward. More precisely, the forward diffusion acts upon medium and large gradients that are noise independent while the backward diffusion is carried out in order to filter the gradients caused by noise that will not be eliminated during the forward diffusion process. The combination of these two methods results in a coupled forward and backward diffusion procedure where the diffusion function $D_{FAB}$ possesses both negative and positive values. The mathematical formulation of the diffusion (or conductivity) function is depicted in equation 8:

$$D_{FAB}(\nabla I) = 2e^{-\left(\frac{\nabla I}{k_1(t)}\right)^2} - e^{-\left(\frac{\nabla I}{k_2(t)}\right)^2}, \ |D| \leq 1 \qquad (8)$$

where $\nabla I$ represents the image gradient and $k_1$ and $k_2$ are the time dependent parameters that control the forward and backward diffusion. The advantage of the FAB anisotropic diffusion over the original Perona–Malik (PM) implementation is illustrated in Figure 3 where it can be observed that the sign of the $D_{FAB}$ becomes negative for medium gradients. Also, it can be clearly noticed the movement of weight from the backward diffusion towards the forward diffusion for medium and large gradients.

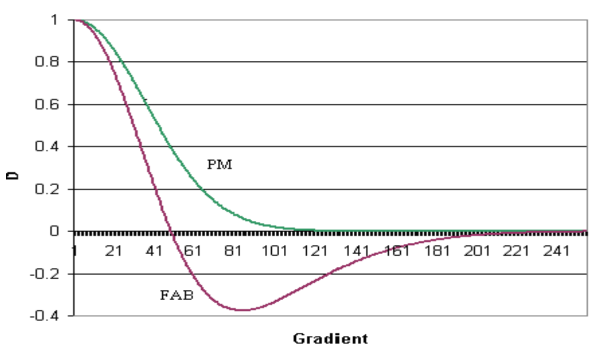



**Figure 3. Comparison between the FAB diffusion function and the standard PM diffusion function. Parameters $k$ = 40 (PM) and $k_1$=40 and $k_2$=80 (FAB).**

Nonetheless, since the $D_{FAB}$ function is defined by two parameters the problems associated with stability are more difficult to control. To address this problem Smolka and Platainiotis [12] proposed to apply a cooling procedure by progressively reducing the values of the diffusion parameters. This can be achieved by multiplying the diffusion parameters with a fixed parameter γ that takes values in the interval (0,1) as follows:

$$k_i(t+1) = k_i(t) * \gamma, \ i = 1,2,... \text{ and } k_i(t+1) < k_i(t) \qquad (9)$$

In equation 9 it can be observed that for γ =1 no cooling takes place (diffusion parameters have the same values at each iteration), and the cooling is faster for lower values of γ. The introduction of the cooling procedure was very appropriate since the noise removal is directly dependent upon the gradient value. Thus, the large value gradients cool faster than the low to medium gradients. In addition, since the diffusion parameters are lowered at each iteration, this will lower the effects of the smoothing process and for lower values of diffusion parameters this process can be halted. This is another advantage associated with this smoothing procedure. Since there is no requirement to specify the number of iterations, the smoothing process will cool itself naturally and it doesn't require the implementation of complex stopping rules or the use of a fixed parameter to specify the number of iterations, as is the case of the standard PM implementation. The cooling process is illustrated in Figure 4 where are depicted the $D_{FAB}$ curves for 5 iterations.

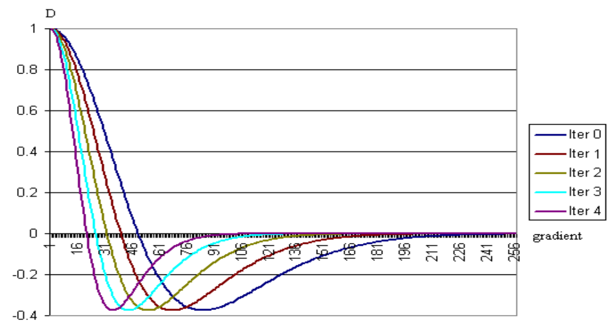



**Figure 4. The effect of the cooling process. Note that the position where the curve intersects the *x* axis is lowered at each iteration and this implies less smoothing.**

While the FAB anisotropic diffusion eliminates some of the problems associated with the standard PM anisotropic diffusion when applied to colour images, the results show that the smoothed data is still blurred especially around regions defined by medium gradients. To compensate for this problem in this paper we propose the inclusion of a boost function that has the aim of amplifying the medium gradients as follows:

$$\nabla I = \nabla I \left( 1 + 2 * \operatorname{sgn}(\nabla I) e^{-\frac{\|\nabla I - m\|}{k_1}} \right) \qquad (10)$$

where *sgn* defines the standard sign function and *m* is the median value of the gradient data. The boost function is illustrated in Figure 5 and typical results with and without boosting are depicted in Figure 6. It can be noted that the application of the gradient boosting procedure generated a smoothed image with crisper details (see the area around the cart's wheel in the right hand side of the image).

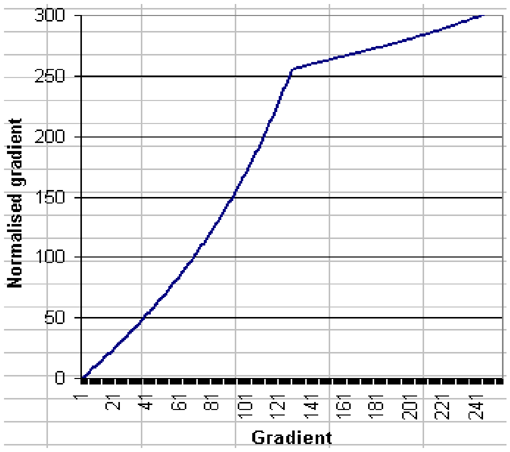



Figure 5. Gradient boosting function. Note the amplification of the gradients with medium values.

(a) (b)

(c)

(d) (e) (f)

Figure 6. Smoothing results when the anisotropic diffusion is applied to the original image depicted in Figure 7(a). (a) Standard PM algorithm ($k$=40, no iterations 5) (b) FAB - no gradient boosting ($k_1$=40, $k_2$=80). (c) FAB-gradient boosted ($k_1$=40, $k_2$=80). (d-f) Close-up details for the results depicted in (a), (b) and (c) respectively.

## 4. Experimental results

The smoothing strategies discussed in this paper have been applied to a large number of colour images including natural images, images that are corrupted artificially with noise and medical images. In order to evaluate the performance of the adaptive smoothing algorithms we need to asses their ability to reduce the image noise while preserving the important discontinuities present in the colour data (due to space constraints, the linear filtering techniques such as mean and Gaussian filtering mentioned in the introductory section are not evaluated in this study, since their performance when applied to colour images is very poor). In this regard we calculate the standard deviation from all colour channels to determine globally the efficiency of intra region smoothing while the feature preservation is evaluated by the edge strength (edge preservation). These measurements have been carried out on noiseless colour images and images that are artificially corrupted by noise. Some representative results are depicted in Figure 7 where it is illustrated the edge preservation offered by the analysed diffusion techniques. From the graphs shown in Figure 7 it can be concluded that the gradient boosted (GB) FAB anisotropic diffusion clearly outperforms the bilateral filtering and PM anisotropic diffusion. Additional results are shown in Figures 8, 9 and 10.

The next step is to globally analyse the performance of the smoothing strategies. As it has been indicated earlier the level of local smoothing is sampled by the standard deviation that is calculated in a 5×5 neighbourhood and experimental results are shown in Table 1. The results shown in Table 1 indicate that the bilateral and standard (PM) anisotropic filtering generate images with lowest RMS values of the standard deviation values. This indicates that these techniques generate smoother images but this is achieved especially at the expense of the attenuation of edges associated with medium gradients. The experimental results illustrated in Table 1 indicate that the gradient boosted GB-FAB data smoothing scheme offers the optimal trade-of between efficiency in smoothing and feature preservation. In these experiments the parameters for bilateral filtering are set as follows, $\sigma_d$=3 and $\sigma_r$=20. The parameter of the PM anisotropic diffusion algorithm is set to $k$=40. The parameters of the FAB anisotropic diffusion scheme are set to $k_1$=40 and $k_2$=80.

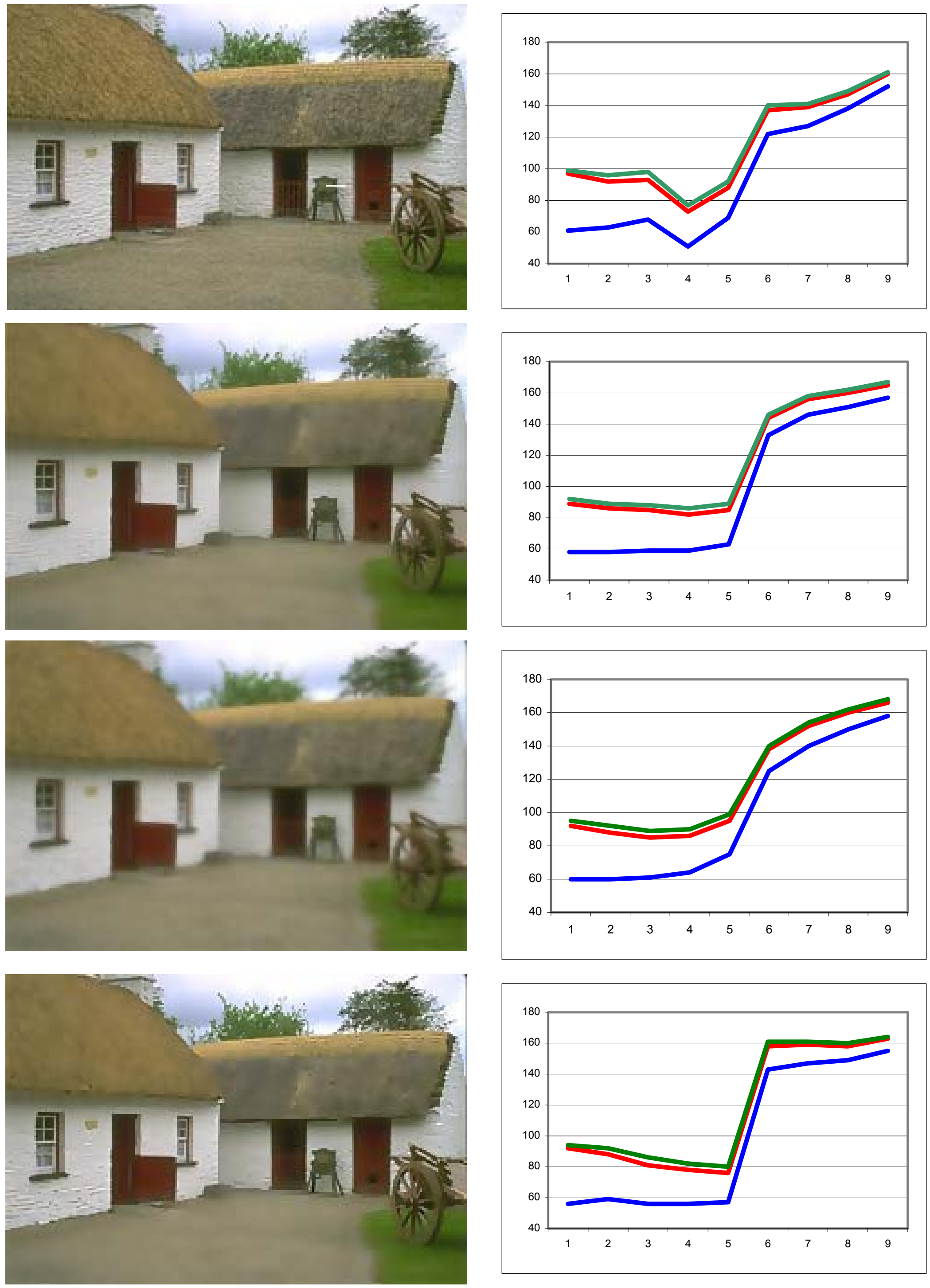
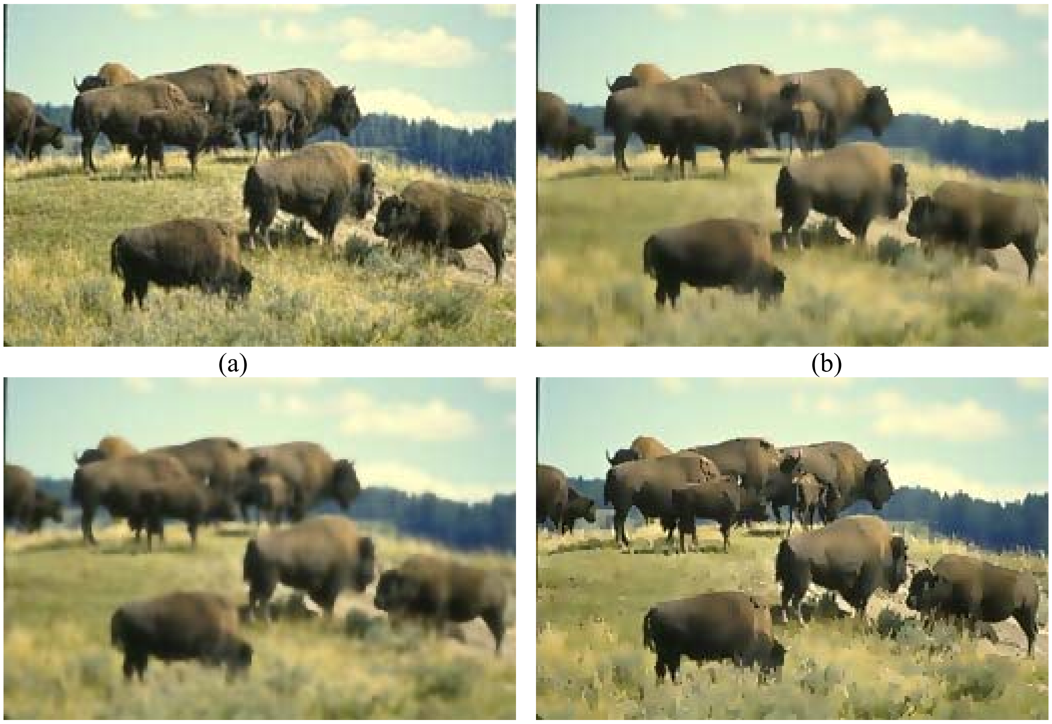



Figure 7. Analysis of the feature preservation. (a) Original image (the data plotted in these graphs is marked with a white line drawn in the chair area). (b) Bilateral filtering. (c) PM anisotropic diffusion. (d) Gradient boosted (GB) FAB-anisotropic diffusion. (For the graphs on the right hand side the *x*-axis depicts the pixel position on the white line, while on the y-axis are represented the pixel's RGB values).



(a) (b)

(c) (d)

Figure 8. Additional results – natural image. (a) Original image. (b) Bilateral Filtering. (c) PM anisotropic diffusion. (d) Gradient boosted FAB-anisotropic diffusion.

(a) (b) (c) (d)

Figure 9. Additional results – natural image. (a) Original image. (b) Bilateral Filtering. (c) PM anisotropic diffusion. (d) Gradient boosted (GB) FAB-anisotropic diffusion. (Results are best viewed when enlarged).

Table 1. Root Mean Square (RMS) of the standard deviation values.

| Figure No | Original | Bilateral | PM | FAB | GB-FAB |
|---|---|---|---|---|---|
| Figure 1(a) | 21.93 | 11.54 | 12.96 | 15.03 | 17.09 |
| Figure 2(a) | 17.25 | 7.96 | 9.28 | 10.90 | 12.17 |
| Figure 7(a) | 21.85 | 9.44 | 10.48 | 8.96 | 15.21 |
| Figure 8(a) | 31.45 | 17.01 | 18.30 | 20.51 | 26.55 |
| Figure 9(a) | 18.04 | 8.26 | 9.43 | 10.63 | 13.60 |
| Figure 10(a) | 8.66 | 2.29 | 2.86 | 4.44 | 5.94 |
| Figure 10(c) | 8.72 | 1.60 | 2.02 | 5.55 | 7.13 |

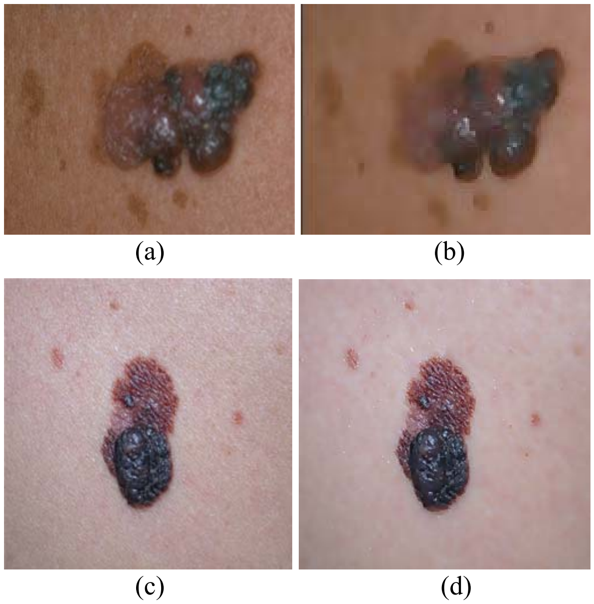



Figure 10. Additional results used in our evaluation. (a) and (c) represent original medical images. (b) and (d) are the images obtained after the gradient boosted (GB) FAB-anisotropic diffusion technique is applied.

## 5. Conclusions

The aim of this paper is to describe the implementation of feature preserving smoothing schemes where the main emphasis was placed on evaluating their performances when applied to colour images. In this paper we investigated the performance of bilateral filtering and the performances offered by a number of smoothing schemes based on anisotropic diffusion filtering. The experimental data indicates that the coupled forward and backward (FAB) anisotropic diffusion smoothing schemes outperform the standard (PM) anisotropic diffusion algorithm and bilateral filtering with respect to feature preservation. Since the standard smoothing techniques offer poor feature preservation around medium gradients, in this paper we have proposed a new approach to boost the medium gradient data and the experimental data indicate that the inclusion of gradient boosting in the implementation of FAB anisotropic diffusion generates crisper images where the contrast in the colour data is preserved. The implemented FAB anisotropic diffusion schemes have been included in the development of an adaptive colour segmentation algorithm and their addition proved to be an important factor in reducing the level of over-segmentation caused by image noise, shadows and weak textures.

## 6. References

[1] V. Hong, H. Palus, and D. Paulus, “Edge Preserving Filters on Colour Images”, *Lecture Notes in Computer Science*, Springer Berlin / Heidelberg, 2004, Volume 3039, pp. 34-30.

[2] M. Sonka, V. Hlavac, and R. Boyle, *Image processing, analysis and machine vision,* 2nd edition, PWS Boston, 1998.

[3] B. Smolka, R. Lukac, A. Chydzinski, K.N. Plataniotis and K. Wojciechovski, “Fast adaptive similarity based impulse noise reduction filter”, *Real Time Imaging*, Academic Press Ltd. London, 2003, 9(4), pp. 261–76.

[4] K. Tang, J. Astola, and Y. Neuovo, “Nonlinear multivariate image filtering techniques”, *IEEE Trans. Image Processing*, Institute of Electrical and Electronics Engineers, New York, 1995, 4(6), pp. 788–97.

[5] P. Perona and J. Malik, “Scale-space and edge detection using anisotropic diffusion”, *IEEE Trans. on Pattern Analysis and Machine Intelligence,* IEEE Computer Society Washington, 12(7), July 1990, pp. 629-639.

[6] N. Nordstrom, “Biased anisotropic diffusion. A unified regularization and diffusion approach to edge detection”, *Image and Vision Computing*, Springer-Verlag, New York, 1990, 8(4), pp. 18-27.

[7] J. Weickert, B.M. ter Haar Romeny, and M.A. Viergever, “Efficient and reliable schemes for nonlinear diffusion filtering”, *IEEE Trans. on Image Processing*, 1998, 7(3), pp. 398-410.

[8] M.J. Black, G. Sapiro, D.H. Marimont, and D. Heeger, ”Robust Anisotropic Diffusion”, *IEEE Trans. on Image Processing*, 1998, 7(3), pp. 421-432.

[9] O. Ghita, K. Robinson, M. Lynch and P. Whelan**, “**MRI diffusion-based filtering: a note on performance characterization”, *Computerized Medical Imaging and Graphics*, 29(4), 2005, pp. 267-277.

[10] C. Tomasi and R. Manduchi, "Bilateral Filtering for Gray and Colour Images", *Proceedings of the 1998 IEEE International Conference on Computer Vision*, Bombay India, January 1998, pp. 839-846.

[11] J. Weickert, *Anisotropic diffusion in image processing*, Teubner Verlag, Stuttgart, 1998.

[12] B. Smolka and K.N. Plataniotis, “On the Coupled Forward and Backward Anisotropic Diffusion Scheme for Colour Image Enhancement”, *CIVR*, Springer, London, 2002, pp. 70-80.