# Using Heuristics To Guide Anisotropic Diffusion Filtering

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***Abstract.*** *Anisotropic diffusion filtering is a well-established technique for image enhancement that works by means of diffusion functions. They are able to smooth images without destroying edge information. However, when many filtering iterations are applied or higher contrast parameter are used, edges gradually fade away and are ultimately smoothed by the process. We propose the adoption of a color gradient map and an adaptive contrast parameter to guide the smoothing in order to preserve the edges even after many iterations. Preliminary experiments show good results when compared with the traditional anisotropic diffusion filter.*

## 1. Introduction

The anisotropic diffusion filter discussed by Weickert (1998,2001) is a powerful image processing technique for noise removal and image enhancement. The filter works by performing smoothing on the image but at the same time preserving the boundaries between different regions. The process is controlled by a diffusion matrix that measures the color variation on the neighborhood of a hot spot and by a contrast parameter ($\lambda$) that defines where diffusion should be performed.

When the filter is applied over many iterations, the diffusion matrix slowly becomes adapted to the new local colors. When the original image contains tenuous edges, the smoothing process will gradually erase all edge information as iterations are sequentially applied. Other related problem is when higher $\lambda$ values are used, because the matrix-kernel or diffusion tensor acts like a simple convolution operation over tenuous edges.

In this work, we propose improvements to the anisotropic diffusion filter that introducing a color gradient, which behaves as static boundary evidence, and local adapting $\lambda$ contrast parameter. This heuristics enhances the response of the filter when applied several times to an image containing tenuous edges and/or higher $\lambda$ values.

## 2. Orienting the Anisotropic Diffusion Filter

The anisotropic diffusion filter used in our approach has been extensively discussed by Weickert (2001). We can be regarded as a convolution technique with an adaptive matrix-valued kernel that performs a special smoothing on images. The anisotropic diffusion inhibits the smoothing on edge pixels and stimulates it on internal regions. The basic diffusion equation (BROX, 2005) for an image $I(x, y)$ with $M$ channels and a signal initialized with $u(x, y, 0) = I(x, y)$ is

$$\partial_t u_i = \operatorname{div}\left( D\left( \sum_{k=1}^{M} \nabla u_k \nabla u_k^{\mathrm{T}} \right) \nabla u_i \right) \quad , (1)$$

where $D$ is a matrix-valued function or diffusion tensor, and $i = 1, \ldots, M$ are the individual channels. Each component of tensor $D$ can be computed by the follow diffusivity equation given by:

$$g(x) = e^{-\left[\frac{x^2}{\lambda}\right]} \quad , (2)$$

where $x^2$ denote variation in the region over the hot spot, and $\lambda$ determines how strong the diffusion must be into a region.

As the diffusion process is carried on through several iterations, the edges of the original image gradually fade away, because tensor $D$ takes into account only the results from the previous iteration. After a certain amount of iterations, even edges that were initially well defined may become blurred. In order to keep well-defined edges present in the original image, we propose the introduction of a static factor $G_i$ in equation (1) and an adaptive contrast parameter $\lambda$ in Equation (2). These properties depend on the original image only, avoiding the effects introduced by the repeated application of the diffusion filter.

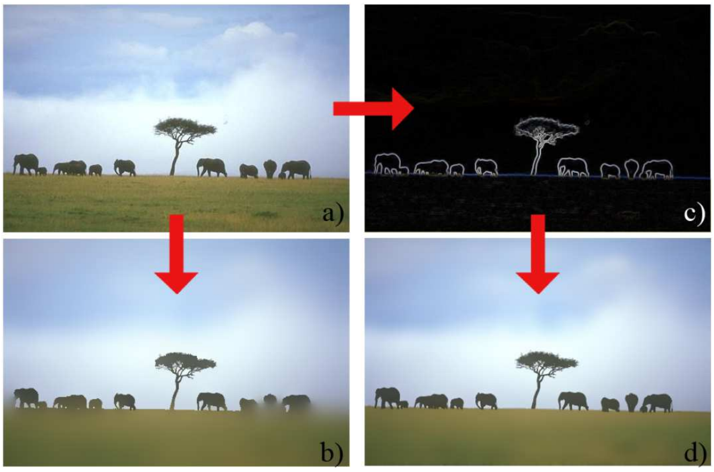


**Figure 1. Overview of traditional and gradient map-oriented filtering. a) the original image; b) the traditional filtering; c) the gradient map; and d) the filtering oriented by the gradient map and adaptive λ.**

An overview of this process is shown in Figure 1, where both versions of the filter are applied over 300 iterations. In a) is shown the original image used by the both approaches. In b) is demonstrated the result of traditional filtering algorithm and in d) the results of the proposed approach employing the color gradient map (in c) and the adaptive contrast parameter.

## 2.1. Color Gradient Map

The color gradient map $G$ is a static factor obtained from the original image and remains constant throughout all iterations. In order to accommodate $G_i$, Equation (2) can be rewritten as

$$\partial_t u_i = \mathrm{div}\left(D\left(G_i \sum_{k=1}^{M} \nabla u_k \nabla u_k^{\mathrm{T}}\right)\nabla u_i\right) \quad . (3)$$

The gradient map $G$ is calculated by a simple convolution operation using the following masks:

$$I_x = \frac{1}{4}\begin{pmatrix} -b & 0 & b \\ -a & 0 & a \\ -b & 0 & b \end{pmatrix} \text{ and } I_y = \frac{1}{4}\begin{pmatrix} -b & -a & -b \\ 0 & 0 & 0 \\ b & a & b \end{pmatrix} \quad . (4)$$

where $a = 2(\sqrt{2}-1)$ e $b = (2-\sqrt{2})$. The modulus of the vector $(I_x, I_y)$ is then used as an estimation of the gradient for each channel. In figure 1-c is shown an example the color gradient map produced for each color channel on the image. As we can observe in equation 3, the color gradient map locally inhibits the diffusion on high gradient responses, and smooths intra-regions of the objects, as demonstrated in figure 1-d.

### 2.2. Adaptive Contrast Parameter

The adaptive contrast parameter λ is a heuristic used to control the diffusion at a region on the image. This is done by adapting the λ parameter according to the global and local neighborhood variation. The λ parameter is perceptually readjusted by increasing or decreasing its responses on diffusivity function (equation 2).

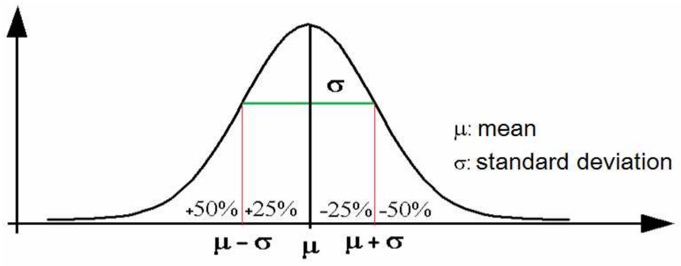


**Figure 2. Lambda inhibition or stimulation regarding of local variation and global mean.**

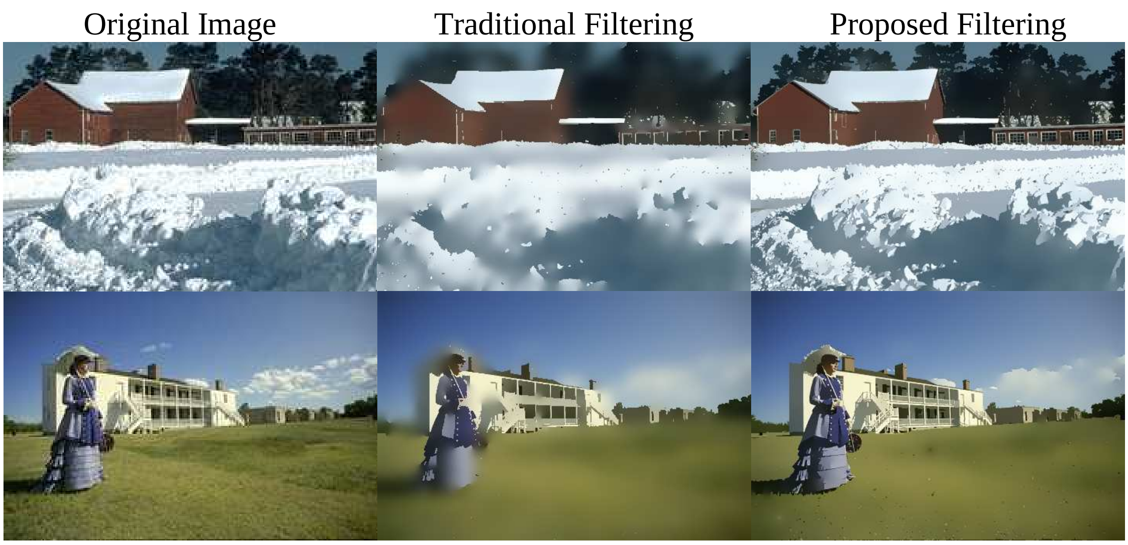


**Figure 3. From left; original images, traditional filtering and proposed filtering.**

In the figure 2 it is illustrated four ranges used to locally readjust the λ parameter according to the global arithmetic mean (μ) of RGB and the global standard deviation (σ) of RGB components. The inhibition is made decreasing the λ parameter by 25% if color components are above the average and up to one σ and by 50% if above the average and greater than σ. The stimulation is made by increasing the λ parameter by 25% if color components are bellow the average and up to one σ and by 50% if color components are bellow the average and greater than σ.

Finally, the λ is locally adapted allowing to perform strong smoothing for regions with low variation, and weak smooth for higher variations.

## 3. Conclusions and Discussions

The anisotropic diffusion filter is a powerful tool to improve the quality of images for its sophisticated border-preserving smoothing. We have shown how this filter can be further improved by using a color gradient map that remains the edge pixels unchanged over iterations and also by adaptive contrast parameter which controls the smoothing over gradient variation. These two heuristics preserve edges that are well defined in the original image.

In the figure 3 it is presented the filtering results of the both color gradient map and adaptive λ processed by the same parameters (iterations=120, λ=40). As it can be observed, pixels in the regions with high gradient levels are still preserved, while those in the regions with low gradient are smoothed. The internal regions are greatly smoothed, and the distinction between them remains clear. Other 40 images can be observed in http://150.162.202.1/m_adf/adf.html .

The traditional anisotropic diffusion filtering version has been explored in a parallel environment as described in (SOBIERANSKI, 2008). This new approach also could be easily extended to the environment.

In harmony with INRIA researches labs like WILLOW(Models of visual object recognition and scene understanding) and TEMICS(Digital image processing, modeling and communication) the improvements of anisotropic diffusion filter can be further explored with other applications context such as pre-processing in image segmentation for object recognition and video processing.

## 4. References

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