IMAGE ENHANCEMENT PROCESSING USING ANISOTROPIC DIFFUSION

QASIMA ABBAS KAZMI\textsuperscript{1}, KRISHNA KANT AGRAWAL\textsuperscript{2} & VIMAL UPADHYAY\textsuperscript{3}

\textsuperscript{1}Lecturer, BBS College of Engineering and Technology, Allahabad, Uttar Pradesh, India
\textsuperscript{2,3}Research Scholars, IIIT-Allahabad, Uttar Pradesh, India

ABSTRACT

A frequent problem we use to face during low-level vision consists of elimination of noise and small-scale details from an image at the similar time maintaining or even enhancing the structure of the edge. Anisotropic diffusion filtering using Non linear equations might be one of the adventitious solutions to acquire these goals. The given Approach is to generalize the diffusion process further into forward-and-backward process. Further the Forward - and Backward diffusion process could again be used in Enhancement of the resolution of the given image. A single image is being used for enhancement of resolution of that image by using interpolation and a forward-and-backward nonlinear diffusion post-processing provides suppression of ringing. Process is found to be very productive in distinguishing those medical images which gives similar images for two or more dangerous diseases. The process respects the boundaries between the edges.

KEYWORDS: Forward-and-Backward Process, Anisotropic Diffusion, Diffusion Coefficient, MRI Imaging, Perona-Malik Algorithm

INTRODUCTION

In the last decades, geometric partial differential equations (PDEs) had been used in image processing and computer vision for a numerous usance, including image restoration, smoothing, enhancement and segmentation. Between the following techniques, anisotropic diffusion has attained a lot of attention for image restoration and smoothing tasks. The first formulation of anisotropic diffusion was broached by Perona and Malik [1]. They developed an adaptable smoothing and edge detection scheme in which the linear heat diffusion equation is replaced by a selective diffusion that preserves the edges.

The conclusion derived from this innate analysis is that we basically need two strongly opposing forces of diffusion, which act simultaneously on the image value: one is backward force which works at medium gradients. And other one is forward one, used for suppressing Oscillations and reducing noise. To have advantage from both, we just combine them into one backward-and forward diffusion force with a diffusion Coefficient which is a hearty function of the gradient’s magnitude that ascertain both positive and negative values [2]. The Perona-Malik algorithm does blurring in the image with a criterion which is set to blur only in between homogeneous regions of an image, and stop blurring between regions, hence maintaining the edge details in an image. This method is implemented at the very pre-processing stage in order to diffuse the input image when compared to Gaussian blurring. This quality of the Perona-Malik algorithm helps to maintain the much needed edge information.

PREVIOUS TECHNIQUE AND ITS LIMITATIONS

This anisotropic diffusion methodology blurs regions in an image ground on the provided location data. In this algorithm, blurring is carried out within regions in an image, while blurring across regions within an image is restricted by the criteria.[1] This method hence helps us to preserve the boundary information of the output-blurred image. The final
blurred image is then used to get the aimed boundaries between different regions or shapes, after applying the edge detection. The Perona-Malik algorithm blurs the image that is ground on the algorithm of Anisotropic Diffusion which is further depends on a predefined criterion. This is advantageous as compared to Gaussian blurring, which uses isotropic diffusion that blurs in a similar way over the whole image.

**ANISOTROPIC DIFFUSION IMPLEMENTATION**

This section explains anisotropic diffusion on a square lattice; with brightness values are associated with the vertices. The equation 1-1 for anisotropic diffusion is discretized for a square lattice. In Figure 1.1, the brightness values are described by the vertices and the conduction coefficients are being shown along the arcs. Equations 1-1 and 1-2 are, respectively, general and discrete representations of anisotropic diffusion for the square lattice shown in Figure 1.1 represent an image subset as a square lattice [1].

\[
I_t = \text{div}(c(x, y, t)\nabla I) = c(x, y, t)\Delta I + \nabla c\nabla I
\]  
(1-1)

\[
I_t = I_{t,j}^{\ell} + \lambda [c_N \nabla^I + c_S \nabla^I + c_E \nabla^I + c_W \nabla^I]_{t,j}
\]  
(1-2)

The following figure describes the above equation:

![Figure 1: The Square Lattice](image)

The above figure explains the working of a Perona-Malik algorithm with the vertices delineates the image pixels and the lines shows the conductance.

In discrete anisotropic diffusion Equation 1-3, a four neighbor discretization of the Laplacian operator is used, where 0 <= λ <= ¼ and N, S, E and W are subscripts which are used for the vertex locations along each direction; the symbol \(\nabla\) represents the difference in the nearest neighbor lattice structure, and not the gradient:

\[
\nabla_N I_{y} = I_{i,j+1} - I_{i,j}
\]

\[
\nabla_S I_{y} = I_{i+1,j} - I_{i,j}
\]

\[
\nabla_E I_{y} = I_{i,j+1} - I_{i,j}
\]

\[
\nabla_W I_{y} = I_{i,j+1} - I_{i,j}
\]

(1-3)
The conduction coefficients or diffusion conductance updated with each iteration as a function of the brightness gradient (Equation 1-3), is offered in the list of conductance in (1-4):

\[
\begin{align*}
    c_{N_{i,j}}^t &= g(||(\nabla I)^t_{i+(1/2)j}||) \\
    c_{S_{i,j}}^t &= g(||(\nabla I)^t_{i-(1/2)j}||) \\
    c_{E_{i,j}}^t &= g(||(\nabla I)^t_{i+(1/2)j}||) \\
    c_{W_{i,j}}^t &= g(||(\nabla I)^t_{i-(1/2)j}||)
\end{align*}
\]

(1-4)

Perona and Malik,[1] in their paper on “Scale space edge detection adopting anisotropic diffusion” have established that image information at the next scale will lie between a maximum and minimum value in the environs of the pixel under consideration from the previous time step or scale. Hence, with \( \lambda \in [0,1/4] \) and \( c \in [0,1] \), the maximum and minimum of the neighbors of \( I_{i,j} \) at iteration \( t \) is \( (IM)_{i,j} = \max\{(I_{IN}, IS, IE, IW)_{i,j}\} \) and \( (IM)_{i,j} = \min\{(I_{IN}, IS, IE, IW)_{i,j}\} \).

Thus, the recent value at \( t+1 \) is \( I_{i,j}^{t+1} \) that lies between the maximum & minimum values in its vicinity, as illustrated in Equation 1-5.

\[
(I_{m})_{i,j}^{t} \leq I_{i,j}^{t+1} \leq (I_{M})_{i,j}^{t}
\]

(1-5)

Hence, it is not assertable for there to be local extrema or minimal values within the endogenous of the discreet scale space.

\[
I_{ij}^{t+1} = I_{i,j}^{t} + \lambda[c_{N}N_{i,j} + c_{S}S_{i,j} + c_{E}E_{i,j} + c_{W}W_{i,j}]
\]

\[
= I_{i,j}^{t} + \lambda(c_{N}N_{i,j} + c_{S}S_{i,j} + c_{E}E_{i,j} + c_{W}W_{i,j})
\]

\[
\leq I_{M_{i,j}}^{t} + \lambda(c_{N}N_{i,j} + c_{S}S_{i,j} + c_{E}E_{i,j} + c_{W}W_{i,j})
\]

\[
(1-6)
\]

Similarly,

\[
I_{ij}^{t+1} \geq I_{m_{i,j}}^{t} + \lambda(c_{N}N_{i,j} + c_{S}S_{i,j} + c_{E}E_{i,j} + c_{W}W_{i,j})
\]

(1-7)

The scale space mild edges can be acquired using either of the following functions for \( g(\cdot) \), as used by Perona and Malik in their act to blur images using anisotropic diffusion.

\[
g(\nabla I) = e^{-\left(\frac{||\nabla I||}{K}\right)^2}
\]

(1-8)
The scale space produced by these two functions is quite different, depending on the edges that they are used to discover. The first function (Equation 1-8) gives precedence to utmost contrast edges over low contrast edges, while the second function of $g(.)$ Equation 1-9 prioritizes wider ranges on smaller regions.

Perona and Malik [1] formulate the anisotropic diffusion filter as a process that encourages the intraregional smoothing approach while inhibiting the interregional denoising occurs. The Perona-Malik (P-M) nonlinear diffusion formulation is defined below:

$$I_t = \nabla \cdot (c(\|\nabla I\|)\nabla I),$$  
(1-10)

Where $c$ is a decreasing function of the slope, such as:

$$c(x) = \frac{1}{1 + \left(\frac{x}{f}\right)^2},$$  
(1-11)

Where, $K$ is a gradient threshold parameter.

The diffusion process is implemented in high-resolution images, rather than low resolution, as on blurring a low-resolution image the bright lines would disappear. The process of obtaining a coarse scale (blurred) image, from the original image, involves convolving the original image with a blurring kernel. In the case of an image, $I(x, y)$, at a coarse scale “t”, where t represents the variance, the output image is obtained by convolving the input image by a Gaussian kernel $K_\sigma$, as was illustrated in Equation:

$$I(x, y) = I_0(x, y) * K_\sigma(x, y, t)$$  
(1-12)

It is clearly found that a Dispersion in which the conduction coefficient is picked locally as a function of the gradient's magnitude of the luminosity function, i.e.

$$c(x, y, t) = g\left(\|\nabla I(x, y, t)\|\right)$$  
(1-13)

Will not exclusively preserve, but also sharpen, the resultant edges if the function $g(.)$ is chosen fitly. The impact is displayed in the image compression below in figure 1.2:

Figure 2: Comparison of MRI Images after Diffusion Technique
**THE DIFFUSION COEFFICIENT**

Consider the following formula of the diffusion coefficient [2] in the form of:

$$c_1(s) = \frac{1}{1 + (s/k_f)^n} - \frac{\alpha}{1 + ((s - k_b)/w)^{2m}}.$$  \hspace{1cm} (1.14)

Our original formulations are:

$$c_2(s) = \begin{cases} 
1 - (s/k_f)^n & , 0 \leq s \leq k_f \\
\alpha \left[ \left( (s - k_b)/w \right)^{2m} - 1 \right] & , k_b - w \leq s \leq k_b + w \\
0 & , \text{otherwise} ,
\end{cases}$$  \hspace{1cm} (1.15)

And its smoothed version

$$c_\sigma(s) = c_2(s) * g_\sigma(s),$$ \hspace{1cm} (1.16)

Where \( * \) denotes convolution and \( g_\sigma \) is a Gaussian of standard deviation \( \sigma \).

**RESULTS AND DISCUSSIONS**

Perona-Malik gave these two equations because somewhere we have to concentrate on the contrast of the images and at some places regions are being considered. We can work out this by just changing the option in our implementations i.e. option 1 is for implementing the first equation and option 2 is for second equation. By using this method we get an accuracy of approximately 95% which means this much noise has been removed.

This tool based on Anisotropic Diffusion method, developed by P. Perona and J. Malik [1] is used, that has determined to be very commodious in many ways. This is a dexterity aiming at reducing image noise without abolishing significant parts of the image content, customarily edges, lines or other trait that are substantial for the evaluation of the image. The conquest of many applications such as Robotics, Medical Imaging depends in many ways on the result of this process as example: figure 1.3.

![Figure 3: Comparison of MRI Images after Diffusion Technique](image)

In the above figures 1.3 we consider the first option in which we concentrate over the high contrast edges over low contrast. The Forward-and-Backward by Guy Gilboa[2] is highly persuasive in the enhancement of images.

This anisotropic diffusion approach blurs regions in an image based on location information, i.e. the blurring within an image is carried out depending on a predefined set of benchmark that specify the locations where blurring can be
performed. In this algorithm, blurring is carried out within regions in an image, while blurring across regions within an image is restricted.

After implementation, the final result of Forward – and - backward diffusion process applied on an MRI image shown in figures 1.4

![Figure 4: Comparison of MRI Images after Diffusion Technique](image)

In the above Result, we used an “Ultrasound Image” as Original Image and we used the parameters value like $K_b =5$, $K_f =25$, $w =20$, $\alpha =0.70$. After running the algorithm we see the Output Figure 1.4 to set these values manually.

Intuitively, the stability in the backward process afforded by its limitation for small areas containing very few pixels is surrounded by larger areas of many more pixels, where the forward diffusion provides a “safety belt” that avoids explosion. Indeed, since the majority of pixels in natural images are characterized by low gradients and mainly singular edges give distention to the reversal of the diffusion coefficient sign, stability is achieved. This argument does not hold any longer when the FAB diffusion process encounters a highly textured or extremely noisy image. Also the edges should be at their exact location because of which the actual images remain as it is. This is the extreme advantage of using this process, as the edges do not smudged away. This method respects the boundary as not changing the location of it. Hence Blurring is done by not moving their boundary position.

CONCLUSIONS

Ultrasonic imaging extends its application to many fields of medical diagnosis, with its natures of low cost, portability, non-invasion and real time image formation, compared with other imaging techniques. Because ultrasonic image not only can observe shapes of human viscera, but also can examine their functions and blood stream states, it has become an earnest part of medical imaging. We extended anisotropic diffusion to multitudinous directions to be used to reveal frail radial and angular constituents in ultrasound images. This nourishing feature set could be governed for contrast enhancement, image resolution, and segmentation. We engage anisotropic diffusion in eight directions, inaugurating four diffused images computed independently pertaining to four directional pairs.

Perona-Malik proposed a non-linear diffusion Process, where diffusion can take place with a variable diffusion in order to control the smoothing effect. The diffusion Coefficient in the P-M process was chosen to be a decreasing function of the slope of the signal. This operation selectively low-pass filters regions that do not contain large gradients (singularities such as step jumps or edge and thin lines in the case of images). Results obtained with the P-M process paved the way for a range of PDE-based methods that were applied to various problems in low-level vision. The conclusion derived from the intuitive analysis is that we basically need two opposing forces of diffusion, acting simultaneously on the
signal: one is backward force (at medium gradients, where singularities are expected). And other is forward one, used for suppressing Oscillations and reducing noise. To benefit from both, we combine them into one backward-and forward diffusion force with a diffusion Coefficient that imitate both positive and negative values.

REFERENCES


