Lateral Inhibition based Holistic Approach to Adaptive Image Enhancement

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***Abstract*—We present a physiologically inspired adaptive algorithm for noise removal in an image while preserving significant amount of edge details. The algorithm is motivated by the classical lateral inhibition based receptive field in the visual system as well as the holistic approach of the well known bilateral filter. We propose an adaptive difference of Gaussian (DoG) filter with varying window size depending upon the edge strengths in the image. Our algorithm has advantages over similar other techniques such as simple Gaussian filter, DoG filter, and is comparable to the bilateral filter in terms of edge enhancement. Furthermore, time complexity of our algorithm is much less than the bilateral filter.**

Keywords— Lateral inhibition, edge enhancement, Gaussian blur, DoG, bilateral filter, Adaptive filter

I. Introduction

The human visual system has acquired in the course of evolution, such capabilities that still remain a distant dream to the image processing community. This is true not only with respect to high level tasks like object recognition, but also several low level tasks like edge detection. The way the visual system identifies crucial contrast edges eliminating the less important ones as noise while navigating in the visual world, as a very early vision task is itself a decisive step forward in the direction of object recognition and analysis. Several edge enhancement techniques have been proposed over the years based on different edge detection algorithms. An important group of these algorithms follow the track of different versions of Gaussian filtering that have been inspired by the Difference of Gaussian (DoG) based modeling of the center-surround visual receptive field [1]. Marr and Hildreth [2] for example, combined the Laplacian operator with Gaussian smoothing and tried to show the equivalence of such a derivative operator (popularly known as the Laplacian of Gaussian or LOG) to the DoG filter. Canny [3], suggested a different algorithm based on first order derivative of Gaussian and also tried to improve upon the issue of threshold selection as in the LOG or DoG based filtering. Another approach was proposed by Tomasi and Manduchi [4], which is a sort of adaptive Gaussian filtering called the bilateral filtering. But while the previous methods considered edges as a raw primal sketch of the external world and hence concentrated on edge detection, the bilateral filter approached the issue from a more holistic angle and tried to compute not the edge map, but an overall edge enhanced view of the raw image. The algorithm does not directly follow the lateral inhibition based DoG model that has been proposed by the neurobiologists, but yields good results. Our attempt in this work is to try and construct an adaptive DoG (A-DoG) based holistic model of the receptive field at low level that may yield similar interesting results in terms of image enhancement, particularly in presence of noise.

II. The Gaussian Filter and ItS Variants

As we know every realistic image is tainted by some noise and this small variation will lead to a significant change in the output. Some noise point has a likelihood of having an intensity difference with its neighbors, in edge analysis this may create spurious edge points. It is, therefore, desirable that before processing the image, the intensity of a noise point should be brought closer to the intensity of its neighborhood. The Gaussian filter is a widely used filter to smoothen the image before differentiation. A 2-D Gaussian function can be defined as

$$G(x,\sigma) = \frac{1}{\sqrt{2\pi}}\frac{1}{\sigma}e^{-\frac{r^2}{2\sigma^2}}, \text{ So that } \int G(x,\sigma) = 1$$

where $r^2 = x^2 + y^2$

It may easily be verified that the Fourier transform of a Gaussian function is also a Gaussian. So a Gaussian filter acts like a low pass filter. Therefore in addition to removing noise, the convolution of an image with the Gaussian function effectively wipes out all structures at scales smaller than the space constant σ of the Gaussian function.

A 2-D Gaussian function can be decomposed into two 1-D Gaussians i.e. $G(x,y) = G(x)G(y)$. So, for an image, Gaussian filter has an advantage from the computational view point. In fact Gaussian is the only rotationally symmetric function that is separable. As already mentioned in the Introduction, two types of filters, viz. the derivative operator and the smoothing operator, are both used extensively in digital image processing [2, 3]. In effect, initially the unwanted noises are to be removed (smoothened) from the image by convoluting it with a Gaussian function. Then a derivative filter is operated to detect the edge points.

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A. Difference of Gasussian Filter

The Difference of Gaussian filter is an enhancement technique that involves subtraction of a Gaussian blurred version of an image from another less blurred version. As already mentioned in the Introduction, it was proposed by the neurophysiologists to model the phenomenon of lateral inhibition in the visual receptive field. Mathematically,

$$DoG(\sigma_1, \sigma_2) = \frac{1}{\sqrt{2\pi}}\frac{1}{\sigma_1}e^{-\frac{r^2}{2\sigma_1^2}} - \frac{1}{\sqrt{2\pi}}\frac{1}{\sigma_2}e^{-\frac{r^2}{2\sigma_2^2}}$$

Where $r^2 = x^2 + y^2$

Also, as already mentioned above, the Gaussian filter is a low pass filter. That is, it allows low spatial frequencies to pass, while attenuating or eliminating high spatial frequencies. Accordingly, the subtraction of two Gaussians with different σ creates a band pass filter that attenuates all frequencies between the cut-off frequencies of the two Gaussians. Therefore when a DoG filtered image is subtracted from the original image the resulting image is able to retain more edge detail than just by a simple Gaussian filter.

B. Bilateral Filter

The bilateral filter is a nonlinear filter that does spatial averaging without smoothing edges through a different mechanism of combining Gaussians. It has shown to be an effective image denoising technique.

$$\mathrm{BF}[\mathrm{I}]_\mathrm{p} = \frac{1}{\mathrm{W_p}}\sum_{\mathrm{q} \epsilon \mathrm{S}} \mathrm{G}_{\sigma_s}(\|\mathrm{p}-\mathrm{q}\|)\mathrm{G}_{\sigma_r}(|\mathrm{I_p}-\mathrm{I_q}|)\mathrm{I_q}$$

This equation is a normalized weighted average where $G_{\sigma_s}(\|\mathrm{p}-\mathrm{q}\|)$ is a simple Gaussian weighting that reduces the influence of distant pixels. Here, $\mathrm{G}_{\sigma_r}(|\mathrm{I_p}-\mathrm{I_q}|)$ is the range Gaussian which decreases the influence of pixels q when their intensity values differ significantly from the targeted pixel.
The normalization factor ensures pixel weights sum to 1.0.

$$\mathrm{W_p} = \sum_{\mathrm{q} \epsilon \mathrm{S}} \mathrm{G}_{\sigma_s}(\|\mathrm{p}-\mathrm{q}\|)\mathrm{G}_{\sigma_r}(|\mathrm{I_p}-\mathrm{I_q}|)$$

The bilateral filter can also be defined as a weighted average of nearby pixels, in a manner very similar to Gaussian convolution, but with the difference that the bilateral filter takes into account the difference in RGB values with the neighbors to preserve edges while smoothing. The key idea of the bilateral filter is that for a pixel to influence another pixel, it should not only occupy a nearby location but also have a similar value. Parameter σ_s and σ_r determines the amount of filtering for the image.

From the above equation one can observe that the bilateral filter gives more weightage to pixels of similar intensity while giving less weightage to less similar pixels. Because of this a bilateral filter preserves strong edges very well. Instead of following the smoothing and differentiation combined approach, it rather follows a holistic approach to the problem of image enhancement. An important issue with the application of the bilateral filter is the selection of the filter parameters, which affect the results significantly. Despite producing impressive results the bilateral filter has two major drawbacks. One drawback is that along with smoothing the weak edges in the image also tend to get washed out. Another major problem with bilateral filter is its slow computation speed since, first of all, being a nonlinear filter it generally cannot be decomposed into two successive 1-D filters. Furthermore, the mask being adaptive has to be computed at each pixel. Therefore the convolution operation becomes really tedious. Because of this slowness the bilateral filter is completely impractical for application to video frames in real time.

III. The Proposed Adaptive DoG (A-DoG) Filter

The two problems, as mentioned above, associated with the bilateral filter can be overcome to some extent by our proposed Adaptive DoG (A-DoG). It first approximates the gradient at each image point using intensity values only in a 3×3 region around the image point using integer values only as in the well-known Sobel operator. We calculate the gradient in both directions (x and y). Then the overall gradient magnitude is calculated for each image pixel. Then we use two different DoG filters, one representing a larger receptive field that we apply for gradient values above a threshold and another, representing a smaller receptive field that we apply for gradient values below the threshold, where the threshold is the simple arithmetic mean of the approximated gradient values. In the real visual system of an organism there may be numerous such filter banks using the billions of neurons in the visual system representing different pathways. But for simplicity, we have tried to see the effect of a simple two pathway DoG switch which may be looked upon as a first step towards an Adaptive-DoG (A-DoG) model of the visual system. The intensity information of the above obtained image is combined with color information from the more blurred DoG image to produce the final image. This step has a physiological justification in terms of the density of rods and cones in the eye. The rods, which can detect only brightness, have an overall higher density in the retina than the cones, which can detect color. So it is justified to take color information from a more blurred image while intensity information has to be taken from less blurred image. Below we represent this algorithm:

A. Proposed Algorithm

- Step 1- Read the input image.
- Step 2- Calculate the gradient of the image.

- Step 3- A threshold gradient value by calculating the mean of all gradients.
- Step 4- Calculate two different DoG filtered images with two different radii. One image is sharper while the other is blurrier.
- Step 5- For each and every pixel in the image check the following-

  If gradient (pixel) > threshold value
  Replace it by the sharper DoG filtered pixel as computed in Step 4 above.
  Else
  Replace it by the less sharp DoG filtered pixel as computed in Step 4 above.

- Step 6- Calculate λ for each pixel based on the following formula-

$$\lambda = \frac{R_i + G_i + B_i}{R_c + G_c + B_c}$$

Where R_i, G_i, B_i are the Red, Green, Blue value of the image resulted from step4 (Intensity information) and R_c, G_c, B_c are the Red, Green, Blue value of the less sharp DoG image (Color Information).

- Step 7- Calculate Red, Green, Blue value of each pixel for the final output image according to the following formula-

  R=λR_c, G= λG_c, B= λB_c

- Step 8- Stop

IV. RESULTS & ANALYSIS

Our proposed Adaptive Difference of Gaussian (A-DoG) filter provides encouraging results when compared to the previous filters. It is effective because of its preserving of contrast edges even while smoothing is significantly large and because the time complexity is much less than bilateral filter which otherwise provides good results. We demonstrate the results with the help of three images provided below each of which is filtered by Gaussian filter (at comparatively lower variance, since higher variances wipe out the edges), the classical lateral inhibition based DoG filter, and the bilateral filter and finally our proposed A-DoG filter.

Figure 1 (a) Original noisy image (Image1)

Figure 1 (b) Simple Gaussian filtered Image

Figure 1 (c) DoG filtered Output

Figure 1 (e) Proposed A-DoG Filtered Image

Figure 1 (d) Bilateral Filtered Image

Figure 2 (a) Original noisy image (Image2)

Figure 2 (b) Simple Gaussian filtered Image

Figure 2 (c) DoG filtered Output

Figure 2 (d) Bilateral Filtered Image

Figure 2 (e) Proposed A-DoG Filtered Image

Figure 3 (a) Original noisy image (Image3)

Figure 3 (b) Simple Gaussian filtered Image

Figure 3 (c) DoG filtered Output

Figure 3 (d) Bilateral Filtered Image

Figure 3 (e) Proposed A-DoG Filtered Image

A visual comparison of four different filtering techniques for three different images is shown in Figures 1(a) to 3(e). Although the bilateral filter gives impressive results, some creases, such as on the leaf in Figure 1(a), are better preserved in our proposed technique. A time comparison is given in Table 1.

TABLE I. TIME COMPARISON BETWEEN BILATERAL AND PROPOSED METHOD

Image Name	Bilateral Filter (seconds)	Proposed Method (seconds)
Image in Fig. 1(a) (500x500 pixels)	30.91	18.60
Image in Fig. 2(a) (500x331 pixels)	21.39	7.32
Image in Fig. 3(a) (481x321 pixels)	19.01	11.73

The experiments were performed on a 3.2GHz CPU with 1GB RAM using MATLAB 7.1.
It can be clearly seen that like the bilateral filter, our method is better than a simple Gaussian filter, because the Gaussian filter is unable to preserve significant details of an image. Similarly our algorithm also has an advantage over simple DoG filter because the DoG operator by itself is not capable of deciding which edges to preserve and which edges to omit because it lacks a mechanism to prioritize edges. It only globally enhances the edges and hence does not perform well for noisy images. In our algorithm we used the gradient value which is the indication of an edge and from the gradient we can easily distinguish the stronger edge from a weaker edge. So, for strong edges we suggest to use a DoG filter with larger radii which will less disturb the strong edges and for weak edges the filter with smaller radii which will preserve some of these details. So, automatically we are keeping strong edges as well as some weak edges intact. Moreover, we are taking color information from the less sharp DoG filtered image and intensity information from the A-DoG filtered image. Now, the threshold value will determine how much details we want to preserve. So, by changing the threshold value we can actually control the amount of details we need in the filtered image.

V. CONCLUSION

The proposed adaptive difference of Gaussian (A-DoG) algorithm is a physiologically inspired algorithm that attempts to reduce noise while preserving the strong edges of an image. It is simpler and faster compared to bilateral filtering, but gives output of comparable quality. It is utilizing an advantage of taking color information from more blurred image and intensity information from less blurred image of the same object. Moreover it is adaptive in nature as it is dependent on gradient of the edges. So our algorithm is capable of enhancing edges by taking into account gradient, intensity and color information. This algorithm is also capable of smoothing the image. So smoothing as well as edge enhancement can be achieved simultaneously by our algorithm. Being faster than the bilateral filter, it may be suitable for real life applications to image enhancement.

REFERENCES

[1] R W, Stone J: Analysis of receptive fields of cat retinal ganglion cells. Journal of Neurophysiology 28 833-849 (1965).
[2] Marr, D. and Hildreth, E.:Theory of edge detection. Proc. R. Soc. Lond. B, 207:187-217 (1980).
[3] J. Canny: A computational approach to edge detection. IEEE Trans. Pattern Analysis and Machine Intelligence, vol 8, pages 679-714 (1986).
[4] C. Tomasi and R. Manduchi: Bilateral filtering for gray and color images. Proc. Int. Conf. Computer Vision, 1998, pp.839–846.