Improved color edge preserving smoothing

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Abstract

An edge preserving smoothing algorithm is presented. To prevent smoothing over edges, the algorithm requires that diffusion in a direction should not result in an increase in neighbouring gradients. Intuitively, we think that smoothing reduces gradients. This is, however, not true in the vicinity of strong edges where smoothing over the edge results in surface deformation. The possibility of reducing the calculation cost is explored by reducing the frequency of calculating the edge strength.

1 Introduction

The theory of image formation states that a scene recorded by a camera is noise free. Noise is added during acquisitions due to the limitations in the electronics, optics and the intensity of the light that can be focused on the surface of the sensor. Filtering noise from an image is, thus, a fundamental operation that is incorporated in all digital cameras and image processing software.

Real images are formally defined as the sum of two functions: one is camera noise, the other is an idealised noise free surface. Based on this definition, the challenge is to devise algorithms that filter the real image to remove noise without degrading the underlying original image.

Filtering is the process of replacing the value of an image at a certain location with the result of applying a function to the values in the same neighbourhood. Examples of noise reduction filters that comply to this definition are the mean, median, Gaussian and the Weiner filter [4, 6].

The introduction of partial differential equations to cast image noise filtering as an anisotropic diffusion process where flow from one location to another is allowed along edges but not across them, [7] led to a wealth of follow up methods with landmarks algorithms such as the use of level set methods [9] and total variation (TV) [8]. Although these methods are effective and mathematically elegant, they are criticised for being iterative, slow and inefficient.

The literature on image denoising is vast, including important methods such as bilateral filtering [10], method-guided filter [5] and non-local means [3]. The focus in this paper, however, is on iterative diffusion methods. Specifically, we wish to examine improving the efficiency an algorithm by Alsam and Rivertz [2]. We present a reformulation the method to reduce complexity, resolve color artefacts. Further we

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explore reducing the per-iteration calculation of the edge strength which is a prerequisite to the diffusion process.

The Alsam and Rivertz method [2], requires that blurring should always result in decreased gradients. Further, edge degradation is shown to be the result of increasing gradients in the vicinity of an edge. This observation that can readily be understood by applying an averaging filter to a block function where the result would be an increase as well as a decrease in gradients. To stop gradient increase, diffusion from a given pixel to its neighbour is permitted *if and only if* it does not result in increasing the neighbouring gradients. In other words, diffusion in the north direction is permitted if the result does not cause an increase in the south, east, west and diagonal gradients.

We start by presenting an efficient formulation of our previous work [2], we then run experiments on images to show results of the algorithm. Having done that, we limit the admissibility check to a limited number of iteration. Instead of checking the increase in the gradient in each iteration, we check at given intervals.

Not surprisingly, calculating the diffusion direction only once results in a very fast algorithm. Experiments show, however, that better noise reduction is achieved when the edge direction is calculated at a higher frequency. In search for deeper insight, we allowed the diffusion direction to change and tracked the number of directions that were removed or added from the first iteration. This investigation showed that the change drops fast with increased iteration number with more directions removed than added. We found that when the number of iterations is high, e.g. 100, the results of checking the gradient condition every second or fifth iteration resulted in clear noise reduction whilst the quality of the edges were not diminished.

2 Method

A color image is a rectangular array of RGB-values. The RGB-value at the point (x,y) is a vector $\mathbf{I}(x,y) = (R(x,y), G(x,y), B(x,y))$ consisting of the red, green and blue color components. At each point (x,y) we consider a 3-by-3-group of points centred around the point (x,y), which we will call the center point of that group. The remaining 8 points are called neighbours of (x,y). We denote the pixel values in the 3-by-3-group by

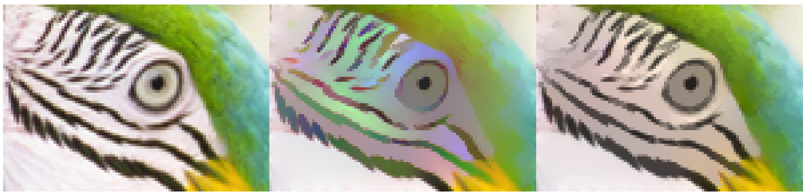
$$\begin{array}{lllllllll} \mathbf{I}_3 & = & \mathbf{I}(i-1,j-1) & \mathbf{I}_2 & = & \mathbf{I}(i,j-1) & \mathbf{I}_1 & = & \mathbf{I}(i+1,j-1) \\ \mathbf{I}_4 & = & \mathbf{I}(i-1,j) & \mathbf{I}_8 & = & \mathbf{I}(i,j) & \mathbf{I}_0 & = & \mathbf{I}(i+1,j) \\ \mathbf{I}_5 & = & \mathbf{I}(i-1,j+1) & \mathbf{I}_6 & = & \mathbf{I}(i,j+1) & \mathbf{I}_7 & = & \mathbf{I}(i+1,j+1) \end{array} . \tag{1}$$

The color differences between the eight neighbours and the center are $\mathbf{P}_j = \mathbf{I}_j - \mathbf{I}_8$, $j = 0,1,\ldots,7$.

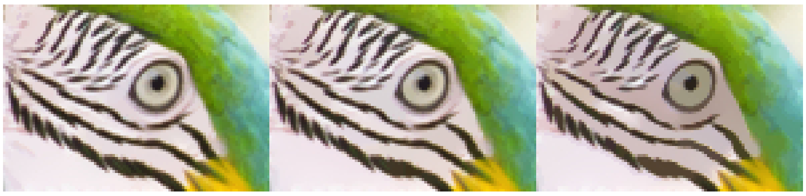
The proposed diffusion process is iterative, at each level, $\mathbf{I}_8$ is replaced by $\mathbf{I}_8' = \mathbf{I}_8 + \sum_{j=0}^{7} d_j \mathbf{P}_j$. The diffusion level d_j is non-zero only if the diffusion in j'th direction is admissible. Admissibility is determined by a test diffusion in a single direction. Let $\mathbf{I}_8^{(j)} = \mathbf{I}_8 + s\mathbf{P}_j$ be the test diffusion in the j'th direction. We let the size of the test diffusion level s be 0.2. The entire idea is that the test diffusion should not increase the differences $\mathbf{P}_i$ in any direction $i = 0,1,\ldots,7$. After a test diffusion, the differences are $\mathbf{P}_i^{(j)} = \mathbf{I}_i - \mathbf{I}_8^{(j)} = \mathbf{P}_i - s\mathbf{P}_j$. We require that diffusion in the j'th direction is admissible if and only if $|\mathbf{P}_i^{(j)}|^2 - |\mathbf{P}_i|^2 < s\alpha$ for all $i = 0,1,\ldots,7$. $|\mathbf{P}|$ is the 2-norm of $\mathbf{P}$ and α is a threshold.

Calculations gives the following equivalent condition for admissibility.

$$s|\mathbf{P}_j|^2 - 2\mathbf{P}_j \cdot \mathbf{P}_i < \alpha,$$



(a) Original image (b) Method from 2011 (c) Method from 2013



(d) New method $\alpha = 5$ (e) New method $\alpha = 10$ (f) New method $\alpha = 25$

Figure 1: The figure shows the results after 1000 iterations with different methods. The color artifacts with the method in [1] disappeared in the method from 2013 [2] and in the new method. The images (d-f) shows that the present method is very stable even after 1000 iterations. Higher value of α results in more smoothing. Edges are preserved in (d-f)

for all $i = 0, 1, \ldots, 7$. If diffusion is admissible in a vertical or horizontal direction, we let $d_j = d$ for the respective j. Otherwise, we let $d_j = d/\sqrt{2}$.

3 Results

We start the results section by a visual comparison between the current formulation and our previous work. In figure 1, we show the results based on one thousand iterations. Here we note that the method from 2011 had clear colour bleeding issues which were resolved in the later versions of the algorithm. In the 2013 work, the reduction of color smear was achieved by means of projections along the hue lines, i.e more calculation. As is evident from the previous section no projection is used in the current work.

In figures 2 and 3, we present the results of the algorithm on two images with 5, 10, 50 and 100. Here we observes that the images are smoothed, fine noise is removed and edges are preserved. These results vary with the chosen value of the threshold where more smoothing can be achieved with a higher value.

The dynamics of the iteration process

Experiments on the original photo in figure 4 shows that the number of obstructed diffusions differs throughout the diffusion process. Table 1 shows that the there are between 2 million and 2.5 million obstructions in each step. That is between 63% and 75% of all possible diffusions. We observe that there is a certain dynamics process where some obstructions are added in each step, but more are removed. Experiments were also done with 100 and 1000 iteration steps. There was a steady decrease of obstructions as well as the dynamics of the obstructions. An experiment where the obstructions from the first iteration were used throughout showed much less noise reduction. Figure 4 compare the results from the experiment with the dynamically changing constraints and static constraints. A visual inspection shows that the edges are equally preserved.

(a) Original image

(b) 3 iterations

(c) 5 iterations

(d) 10 iterations

(e) 50 iterations

(f) 100 iterations

Figure 2: The figures show the original picture (a) and several numbers of iterations in (b-f). The diffusion level in each step is 0.1 up and down and 0.0707 in the diagonal directions. The threshold is set to $\alpha = 25$.

(a) Original image

(b) 3 iterations

(c) 5 iterations

(d) 10 iterations

(e) 50 iterations

(f) 100 iterations

Figure 3: The figures show the original picture (a) and several numbers of iterations in (b-f). The diffusion level in each step is 0.1 up and down and 0.0707 in the diagonal directions. The threshold is set to $\alpha = 10$.

(a) Original image

(b) Static rule. 10 iterations

(c) Dynamic rule. 10 iterations

(d) Static rule. 100 iterations

(e) Dynamic rule. 1000 iterations

Figure 4: The above images show (a) the original picture of the parrots, (b) the result with a static constraint calculated in the first iteration, and (c) the result where the constraint is calculated in every iteration. The images (d) and (e) shows the results with 100 respectively 1000 iterations and with dynamic constraints. The diffusion level in each step is 0.1 up and down and 0.0707 in the diagonal directions. The threshold is set to $\alpha = 5$.

Iteration	Total	Added	Removed
1	2557435	2557435	0
2	2497360	194811	254886
3	2393305	97082	201137
4	2311478	59030	140857
5	2254723	41341	98096
6	2215126	31762	71359
7	2186976	26519	54669
8	2164778	22750	44948
9	2146259	20190	38709
10	2130197	18093	34155

Table 1: The table shows how many constraints that are added and removed in each step when processing the parrot picture. The value of α was five and the size of the image is 797×531.

4 Discussion

An algorithm to remove image noise without smearing the edges is presented. The core idea is a condition that allows diffusion in certain directions only if it does not cause and increase in the local gradients. Results after many iterations show clear edge color preservation. Experiments that need to be expanded show that it is possible to iteratively diffuse an image without having to calculate the edge strength at each step. This idea needs to be studied more with a larger set of images. Building upon those experiments, further exploration of the dynamics of admissibility as well as comparison with other diffusion methods are what is needed to be done in future work.

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