Iterative Ramp Sharpening for Structure/Signature-Preserving Simplification of Images

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Abstract

In this paper, we present a simple and heuristic ramp sharpening algorithm that achieves local contrast enhancement of vector-valued images. The proposed algorithm performs pixelwise comparisons of intensity values, gradient strength and directional information in order to locate transition ramps around true edges in the image. The sharpening is then applied only for those pixels found on the ramps. This way, the contrast between objects and regions separated by a ramp is enhanced correspondingly, avoiding ringing artifacts. It is found that applying this technique in an iterative manner on blurred imagery produces sharpening preserving both structure and signature of the image. The final approach reaches a good compromise between complexity and effectiveness for image simplification, enhancing in an efficient manner the image details and maintaining the overall image appearance.

1. Introduction

An important issue in image processing is the enhancement of the subjective quality of digital images for human interpretation or machine application [7, 1, 9]. When dealing with images which suffer from poor contrast, are captured under nonuniform illumination conditions and/or evidence the presence of noise - *e.g.* satellite images [13], photographs [4] - there is ample room for improving their visual appearance [4]. But the goal of image enhancement also includes other tasks, such as simplifying the image, so that it is often employed as a preprocessing step to reduce the complexity in subsequent image analysis and interpretation [13].

In this context, various enhancement strategies and algorithms have been proposed [5, 9, 10]. Most of them are heuristic, as they usually do not require any information about how the image is degraded. However classical approaches often fail in applications where the basic spectral signature needs to be preserved, *e.g.* multispectral reflectance in satellite images [11]. The vector nature of multichannel images adds another degree of complexity to the enhancement problem, due to the inherent correlation between the different components [11]. Following [8], we introduce in this paper a new simple sharpening algorithm that is adequate for many applications where fast image enhancement preserving spatial structures and spectral signature is required. The proposed technique performs pixelwise comparison of intensity values, gradient strength and directional information derived from the gradient structure tensor. The sharpening is performed only for pixels found on the ramps around true edges, reducing their width, while homogeneous regions are preserved. Applying this technique iteratively enables to reach a good compromise between complexity and effectiveness for image simplification. The interest for such a simple algorithm, with little free parameters, is motivated by a preference for little computational complexity.

The rest of the paper is organised as follows. In Sec. 2, we introduce the ramp sharpening strategy for edge enhancement. Sec. 3 presents the heuristic algorithm used for image simplification. Sec. 4 discusses the approach and presents its foreseen developments.

2. Ramp sharpening strategy

In many practical situations, the (greylevel) intensity of pixels within an object vary slowly across the smooth, homogeneous interior of this object [3]. While the local contrast of such pixels should not be altered,

1051-4651 2010

DOI 10.1109/ICPR.2010.1120

the intensity of those pixels which are 'close' to the edges should be transformed. Indeed, the contrast of an image correlates highly with the gradient magnitude of its edges [3]. This suggests that improving the appearance of an image can be achieved by sharpening its edges [9]. A common strategy is edge detection followed by edge sharpening, which mainly consists in amplifying the magnitude of edge gradients, or equivalently the difference of pixel intensities on both sides of edges [1]. However, such algorithms often introduce over- and under-shoots, which causes questionable ringing or halo effects [4]. Besides, the width of the edges often remains unchanged, thus the sharpening effect is limited for edges that are wide and blurry [8].

Ramp functions can be used as a model of the basic structure of edges [3, 8, 4]. Indeed, the edge between two homogeneous regions usually spans over several pixels that form ramps [13]. In greylevel images, a ramp edge is usually represented as a slope going from dark to bright pixels at a constant rate. However, for most real images, the rate of change first increases, then peaks, and then drops back to zero [8]. In particular, the gradient value of a blurred edge becomes lower as the differences between the values of pixels close to it and belonging to different objects become smaller [3]. Therefore, it may be increased - and, hence, the edge be sharpened - by processing the ramp pixels so that they become closer to the object values [1]. Using this observation, a one-pass algorithm with linear complexity was developed in [8] to perform enhancement by local analysis of intensity and gradient. This approach is composed of three major steps: *(i)* decide whether a pixel belongs to a ramp edge or not, *(ii)* detect which part (low L, mid M or high H) of the ramp it lies on, *(iii)* in the case it lies on the L or H part, compute a sharpened value to assign to it. The sharpening algorithm is handled strictly locally, simply operating in 3×3 local windows. For each pixel in an image f, it estimates 3 intensity indices: f_L, f_M, f_H (*resp.* gradient: g_L, g_M, g_H) derived from a weighted averaging, depending on the gradient orientation, of its local intensity value (*resp.* gradient norm) with that of its 8 immediate neighbours [8]. These indices reflect both local intensity and gradient distributions along the gradient direction. The intensity slope is then used for checking

1. if $f_H > f_M > f_L$, the pixel is on a ramp.

The algorithm further processes ramp pixels only, over which it compares gradient indices. They indicate the location of a pixel relative to the *ramp centreline* [8]

2. if $g_H \geq g_M > g_L$, the pixel is situated on the low half L of the ramp as the intensity slope is increasing along its gradient direction,

3. if $g_H < g_M \leq g_L$, the pixel is situated on the high half H of the ramp as the intensity slope is decreasing along its gradient direction.

4. if $g_H < g_M \,\&\, g_M > g_L$, the pixel is on the centreline M of the ramp as its gradient is higher than that of its neighbours along its gradient direction.

Following, the intensity of a pixel is adjusted: if it is located on the H half, its intensity is increased; if it is located on the L half, it is reduced; if it is located on the M area, or if none of the above criteria 2-4 holds, its value is unchanged. In particular, the location of the centreline of an edge will not drift away from its original place. One difficulty of the approach is that it is not possible to ascertain the amount by which the intensity of a pixel L or H needs to be changed. In [8], an estimate of this value is given by interpolating from neighbours selected to be those pixels lying on the same side of the ramp. The interpolation is obtained for one unit away from the pixel in the direction opposite to the centreline. The new value f_1 of a pixel located on the H half with initial value f_0, for instance, is given by

$$f_1 = \begin{cases} f_0 + C \cdot (f_h - f_M) & \text{if } \frac{g_L - g_M}{g_M - g_h} \geq 0.5 \\ f_0 + 2 \cdot C \cdot (f_H - f_M) \cdot \frac{g_L - g_M}{g_M - g_h} & \text{else} \end{cases} \quad (1)$$

with C a factor compensating metrication error in the interpolation, and similarly for L pixels (see [8]).

3. Heuristic vector enhancement algorithm

We extend the unidirectional ramp sharpening technique of the previous section by involving certain heuristics in the different steps of this approach. The study so far has dealt with scalar images only, and its extension to the vector case is not straightforward. When it comes to the processing of multichannel images, a vectorial approach is usually preferred, in order to preserve the inherent correlation between the different channels. The main difficulties for extending [8] regard: *(i)* the extraction of the ramp pixels: criterion 1 is dependent on an ordering defined on the vector space, unfortunately it is not possible to define uniquely such ordering, *(ii)* the estimation of the gradient and its direction: it becomes a problem of detecting local changes in a vector field, and *(iii)* the estimation of the amounts by which the (vectorial) pixel values need to be changed. Therefore, adapting previous criteria 2-3 and Eq.(1) is necessary for processing vector-valued images.

A nice way of describing local multispectral information is given by the *gradient structure tensor* (GST) [6, 11]. The GST is a local measure of the directional signal variations based upon the gradient that allows accurate structure and geometry estimation [6], and is easily generalised for vector-valued images [2]. The estimation of the GST $\mathbf{S}$ of a mD image $\{f^i\}_{i\leq m}$ consists in computing locally the (2×2)-matrix: $\mathbf{S} = K_\rho \star \left(\sum_{i=1}^{m}(\nabla f_\sigma^i)(\nabla f_\sigma^i)^T\right)$, where $\star$ is the element-wise convolution operation, ∇f_σ^i is the gradient of the i-th component f^i pre-smoothed by a Gaussian with scale σ, and K_ρ is an analogous smoothing kernel of scale ρ. The pre-smoothing of the f^i is done to attenuate sensitivity to noise, while the Sobel operator used in [8] is highly noise sensitive. The subsequent averaging integrates information from a local neighbourhood without cancellation effects. For more accurate estimation, we follow two recommendations of [6]. First, the gradient ∇f_σ^i is up-sampled (factor 2) prior to the calculation of its outer product, which improves the estimation of $\mathbf{S}$ in the presence of corners. Second, we use a spatially-varying small-sized hourglass kernel K_ρ, with adaptive orientation. The estimated eigenvalues $\lambda_+ \geq \lambda_-$ of the derived nonlinear tensor $\mathbf{S}$ give the rates $\max$ and $\min$ of vectorial changes of f, while the corresponding eigenvectors e_+, e_- are the directions of changes $\max$ and $\min$. In particular, e_+ represents the direction of the multispectral gradient. The tensor representation also provides a reliable estimate of the gradient norm: $tr(\mathbf{S}) = \lambda_+ + \lambda_-$. However, it does not uniquely specify the sign of the eigenvectors. This undetermination in the orientation causes some difficulties in locating ramp pixels. A simple solution is proposed in [11], where the orientation of the tensor is approximated by the orientation of the gradient of the average $\bar{f}_m$ of the m channels of f. The scalar product of $\bar{f}_m$ with e_- determines the orientation: if it is negative, the direction of the eigenvector e_+ is flipped, otherwise it is unchanged. Following, we estimate the intensity indices f_L^i, f_M^i, f_H^i for the different channels f^i, and a set of gradient indices $\mathbf{g}_L, \mathbf{g}_M, \mathbf{g}_H$ derived from the tensor norm. Moreover, we refine the discretisation of the tensor orientation and perform the interpolation defining the indices using, again, the corresponding oriented hourglass function of [6].

We apply the ramp sharpening in an iterative manner. At each step, the indices are calculated (using constant $\sigma = 0.5$ and $\rho = 1$ along with the iterations for the GST) and the sharpening is applied. For that purpose, we first modify the criterion 1 for the vectorial context

1.’ if $\exists i \mid f_H^i > f_M^i > f_L^i \;\&\; \forall j \neq i, f_H^j \geq f_M^j \geq f_L^j$, the pixel is on a ramp.

We require moreover a ramp pixel to have a gradient magnitude $tr(\mathbf{S})$ that is larger than a threshold value defined locally as the median absolute deviation operator. Next, the criteria 2-3 are applied, unchanged, once for all channels, *e.g.*

2.’ if $\mathbf{g}_H \geq \mathbf{g}_M > \mathbf{g}_L$, the pixel is situated on the low half L of the ramp.

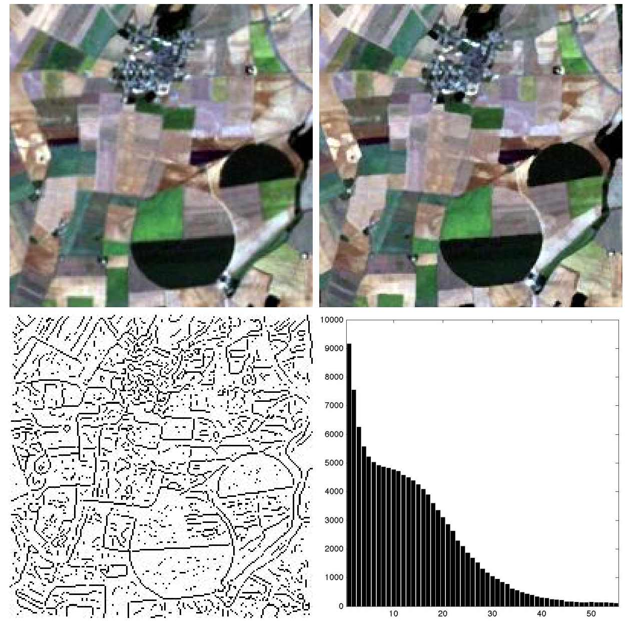

Figure 1. Iterative ramp sharpening of a satellite multichannel image. Original and sharpened (after 56 iterations) images (top), identified centreline pixels (in dark) and plot of the number of modified pixels through iterations (bottom).

Instead of Eq. 1, the new expression for the value f_{k+1}^i of a ramp pixel located on the H half at step $k+1$ is derived from step k as:

$$f_{k+1}^i = \min\left(f_k^i + C\cdot(f_H^i - f_M^i)\cdot\frac{g_h^i - g_M^i}{1+2\cdot g_M^i}, f_H^i\right)$$

with g^i interpolated from the gradient norm $|\nabla f_\sigma^i|$ of the i-th component, and similarly for L ramp pixels. Finally, we further ensure the convergence of the sharpening by constraining the absolute value of the adjustment on each pixel to decrease with the iterations.

4. Discussion

In Fig. 1, we show the results of the iterative sharpening of a satellite image together with the evolving number of modified pixels. The proposed approach is particularly appropriate when sharpening such image as it preserves the spectral signature, without introducing new artificial spectral signatures. Indeed, it increases

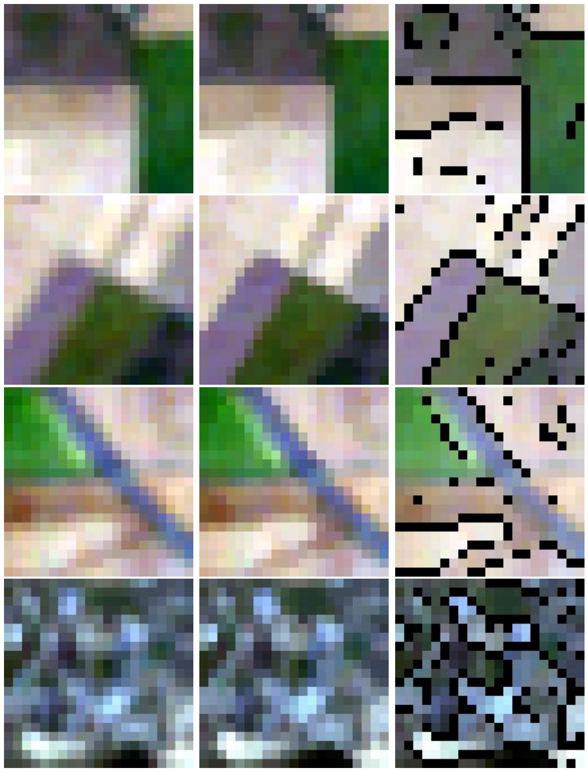

Figure 2. Sharpening of typical features. Details of the input image of Fig 1 (left), corresponding sharpened outputs (middle), with the detected centreline pixels displayed on it (right).

the slope of edges without producing artifacts, which renders clean, crisp edges, thereby improving the overall appearance of the image (see Fig. 2). This has the effect of retaining the homogeneity of intensities within a given region while enhancing the contrast between the different regions. Similar to [3], our approach assumes a ramp model for edges, however there is no need for estimating the local scale as the iterative process enables ramp sharpening at several scales. Moreover, it does not use any information about the nature of the blurring function and it is almost parameter-free. Typically, a 2D linear ramp reduces to one-pixel width area after few iterations and can be identified as the thin multiscale edges of the image. Finally, this approach is related to the morphological filter of [7], that switches between dilation and erosion depending on the local convexity or concavity of the image. Compared to *shock filters* [10, 12], which provide piecewise constant results and do not achieve true deblurring, it improves the visibility and the perceptibility of the various regions into which an image can be partitioned.

5 Conclusion

The approach described in this paper can be used prior to segmentation or edge detection for making these operations easier: simpler and more relevant information can usually be obtained from the enhanced [13] image. Indeed, it reaches a good compromise between simplicity and effectiveness. Moreover, since the algorithm uses at each pixel a very small neighbourhood and few iterations are needed, it can be applied in a reasonable computational time and it is straightforward to implement on a massively parallel computer. However, an aspect of the problem we will need to address is noise removal. Indeed, a critical issue in the enhancement of images is the noise increase that is produced by the sharpening process [5, 4].

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