FACTA UNIVERSITATIS (NIŠ)
SERIES: ELECTRONICS AND ENERGETICS VOL. 14, NO. 1 APRIL 2001, 109-117

A NEW OPERATOR FOR IMAGE ENHANCEMENT

Vasile Gui, Radu Vasiu and Zoran Bojković

Abstract: The main goal in image enhancement is to accentuate certain image features for subsequent analysis or for image display. In this paper, we describe a new nonlinear filter, called IEC (Iterative Extreme Clustering), intended to facilitate subsequent image segmentation. The objective is to enhance edges while keeping uniform regions as they are. At each iteration, the image is randomly partitioned in a number of fixed size rectangular blocks, which are classified according to their ranges as uniform or nonuniform ones. No changes are made in uniform blocks. Pixels in nonuniform blocks are clustered, with cluster centres obtained by gray level morphological dilation and erosion. Gray levels are then shifted towards corresponding cluster centres, according to a learning parameter. Results and algorithm complexity compare favorably with nonlinear diffusion and related approaches.

Key words: Image enhancement, nonlinear filter, iterative extreme clustering, image segmentation.

1. Introduction

Image enhancement refers to accentuation or sharpening of image features such as edges, boundaries, or contrast, to make a graphic display more useful for analysis. The enhancement process does not increase the inherent information content in the data, but it does increase the dynamic range of the chosen features, so that they can be easily detected. Image enhancement techniques, such as contrast, stretching, map each gray level into another

---

Manuscript received February 10, 2001.

V. Gui and R. Vasiu are with "Politehnica" University of Timisoara, Faculty of Electronics and Telecomunication Engineering, Department of Communication, Bul. Vasile Parvan, nr 2, 19000 Timisoara, Romania.(e-mails: gui@hermes.ee.utt.ro and rvasiu@ee.utt.ro).

Z. Bojković is with University of Belgrade, Faculty of Transport Engineering, Vojvode Stepe 305, 1100 Belgrade, Serbia, Yugoslavia (e-mail: bojkovic@net.yu).

gray level by a predetermined transformation. Other enhancement techniques perform local neighborhood operations as in convolution, transform operations, etc.

Edges play an important role in visual perception [6], as well as in many computer vision tasks, such as image segmentation. Therefore, edge enhancement techniques are often used as a preprocessing step for image segmentation. The simplest way of obtaining edge enhancement is to use a linear high-pass or a band-pass filter. Scale space filtering [9], can be used for example, allowing the control of the amount of details kept for segmentation through the scale parameter. However edge enhancement and image smoothing still remain conflicting demands that cannot be well addressed in the framework of linear filtering. Several nonlinear edge preserving smoothing techniques were proposed in the past, including adaptive filtering, morphological simplification [10], nonlinear diffusion [9], steerable filtering [4], offset filtering [8], or selected neighbourhood filtering [7]. Despite the impressive performances in several examples, these methods usually generate artificial boundaries in shaded image areas. Since many applications currently require object segmentation, considerable postprocessing may be needed to find real object borders. In order to alleviate this problem, we develop the IEC filter, which is able to treat differently blurred edges and shade regions.

A common characteristic of the image enhancement techniques mentioned above is that they use windows with constant size and most often with constant position. In the case of the selected neighbour filters, the processing window rotates around the currently processed pixel and always *contains* it. Notable exceptions are the recently introduced *nonlocal* offset filter [8] or the mean shift based technique proposed in [1], also used in our previous work on the subject [5].

In this paper, we use the strategy for improving the performances of gray level morphological dilation and erosion filters through an iterative and probabilistic approach. Each iteration, starts from a randomly displaced rectangular block partition. The blocks are classified as uniform or nonuniform blocks, according to a uniformity criterion, which is the range of their features, i.e. gray levels in the present work. Nonuniform image pixels are locally clustered and their features are successively attracted towards their cluster centres. Each nonuniform block has two clusters with centres obtained through gray level morphological dilation and erosion. Transition pixels from blurred edges have small chances to define cluster centres and therefore small chances to remain close to their initial states. This is not the case for pixels belonging to shade areas, belonging to uniform blocks.

2. Weighted Sums Versus Clustering

A cluster is a set of points in the feature space for which their local density is large compared to the density of the feature points in the surrounding region. Clustering techniques are useful for image segmentation and for classification of rowdata to establish classes and prototypes.

The purpose of image filtering is to exchange the intensity of a pixel as a function of pixel intensities obtained from its neighbourhood. A frequently used approach is to compute the new intensities as weighted sums of the intensities from neighbouring pixels. Weights can be optimally designed according to prior models of image content. Since the image content is variable, a commonly used method in adaptive filtering is to first estimate the type of data within the processing window and then select the weights corresponding to the model that best fits the observed data. Steerable filters belong to this category, the estimated parameter being local orientation. When the details that have to be enhanced come at different extents, the procedure has to be implemented using a multiscale approach, resulting in increased complexity. Offset filtering and mean shift filtering avoid multiscale processing by allowing the current window to move from the starting position, so that the processed pixel not necessarily belongs to the final window used to compute the output value. Instead of successively moving the processing window, we obtain a similar effect by iterating the estimation with a fixed size window several times, each iteration starting from new data.

One problem of the weighted sum approaches is that parametrizable image models are difficult to design for fitting complex image areas, such as corners or junctions of several edges. The risk of running into these kinds of difficulties increase with the window size. In IEC, the window size can be kept relatively small, typically 5×5 or 7×7 and the two class model is flexible enough to fit a wide range of local configurations. On the other hand, because of the iterative nature of the method and the randomized window displacements, model mismatches are not critical, unless they occure for most of the windows containing a certain pixel.

3. Iterative Extreme Clustering Filter

The information flow for the IEC filter is shown in Figure 1. Let $\boldsymbol{g}$ be the input image and $\boldsymbol{f}$ the output image, which is initially set as $\boldsymbol{g}$.

The role of the first stage is to divide the image field into a set of nonoverlapping blocks, $\boldsymbol{B}_{ij}$, of equal size, $W\times W$. Each time such a partition is defined, a displacement vector,

$$\boldsymbol{d} = [dx \ dy]^T, \tag{1}$$

is randomly generated

$$d_x = \frac{W}{2} - \text{random}(W), \tag{2}$$

$$d_y = \frac{W}{2} - \text{random}(W), \tag{3}$$

where random x returns a random integer which is uniformly distributed between 0 and $x - 1$. A block $\boldsymbol{B}_{ij}$ is defined as a rectangular region of $W \times W$ pixels, centred on the location

$$\boldsymbol{d}_{i,j} = [d_x + jW \ \ d_y + iW]^T, \tag{4}$$

with $i, j = 1, 2, \ldots$. Note that a number of n_p distinct tesselations are generated throughout the filtering process. The randomized way of generating the image blocks changes the relative position of a pixel in the block in each iteration, so that no pixel is favoured. This is necessary because all the pixels within the block are processed in each iteration, unlike in the usual way of carrying out filtering, with only one pixel processed at a time.The later paradigm is also motivated by the bootstrap, a resampling technique recently introduced in statistics [5].

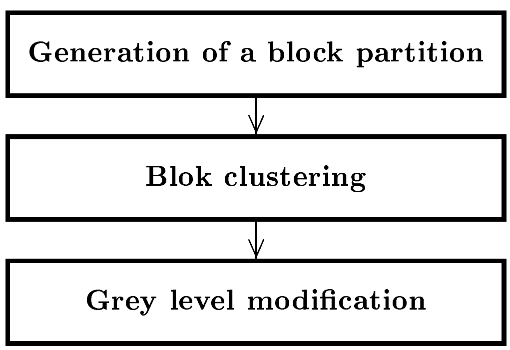


Fig. 1. Information flow of the IEC filter. These steps are repeated n_p times.

In the second stage, for each block, $\boldsymbol{B}_{ij}$, the median of absolute differences (MAD), which is a robust estimator of the local variance, is computed in order to estimate its uniformity. A block is classified as nonuniform if

$$MAD > r_{th}, \tag{5}$$

a range threshold parameter. For each nonuniform block, the extreme (minimum and maximum) gray levels are obtained and set as cluster centres. We denote the cluster centres by $c_{l_o}, l = 1, 2$.

In the third stage, for each nonuniform image block, the grey level of an output pixel with co-ordinates x, y and label l is adjusted at iteration step $n+1$, according to the equation

$$f_{x,y}^{(n+1)} = f_{x,y}^{(n)} + \alpha(c_l - f_{x,y}^{(n)}). \tag{6}$$

In the last equation, α is a parameter acting as a learning rate, which is varied according to the equation

$$\alpha = \begin{cases} \alpha_0(1 - \frac{n}{n_r}), & \text{if} \quad n < \frac{n_p}{2} \\ \frac{\alpha_0}{2}, & \text{otherwiese} \end{cases} \tag{7}$$

Whenever n is a multiple of a parameter n_r, an *output image reconstruction* stage is included in the gray level modification procedure. This step prevents gray level drifting towards the cluster prototype values in shaded regions, since such regions cannot be well represented by the constant facet image model. On the other hand, transition pixels usually do not survive n_r iteration steps and therefore are not reconstructed. This allows the filter to enhance the real edges. Reconstruction is carried out by iterating the equation

$$f_{x,y} = \arg\min_f |f_{x,y} - f_{x+j,y+i}|, \tag{8}$$

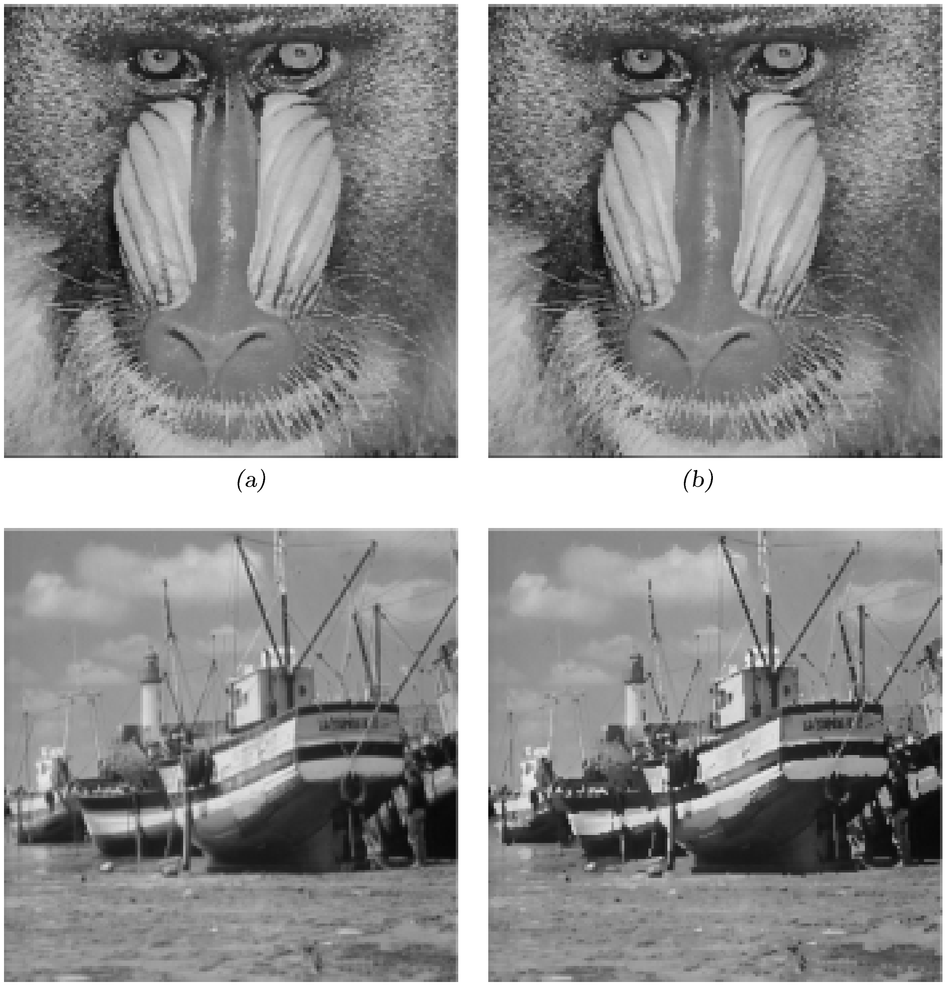
with $-1 \leq i, j \leq 1$, until no further change occurs.

4. Experimental Results and Disscussion

The proposed method has been applied to images with various degrees of complexity, ranging from relatively simple images to outdoor scenes. Some of the results are illustrated in Figure 2. The window size was set to 7×7, the range threshold to 16 and the number of iterations to 20. Notice the edge enhancement and the good preservation of conspicuous details. No false contours are generated in smooth image areas, like in morphological smoothing or offset filtering.

In order to test the effect of the IEC filter on a blured image, we applied a binomial smoothing to the original flower image before ehnancement.

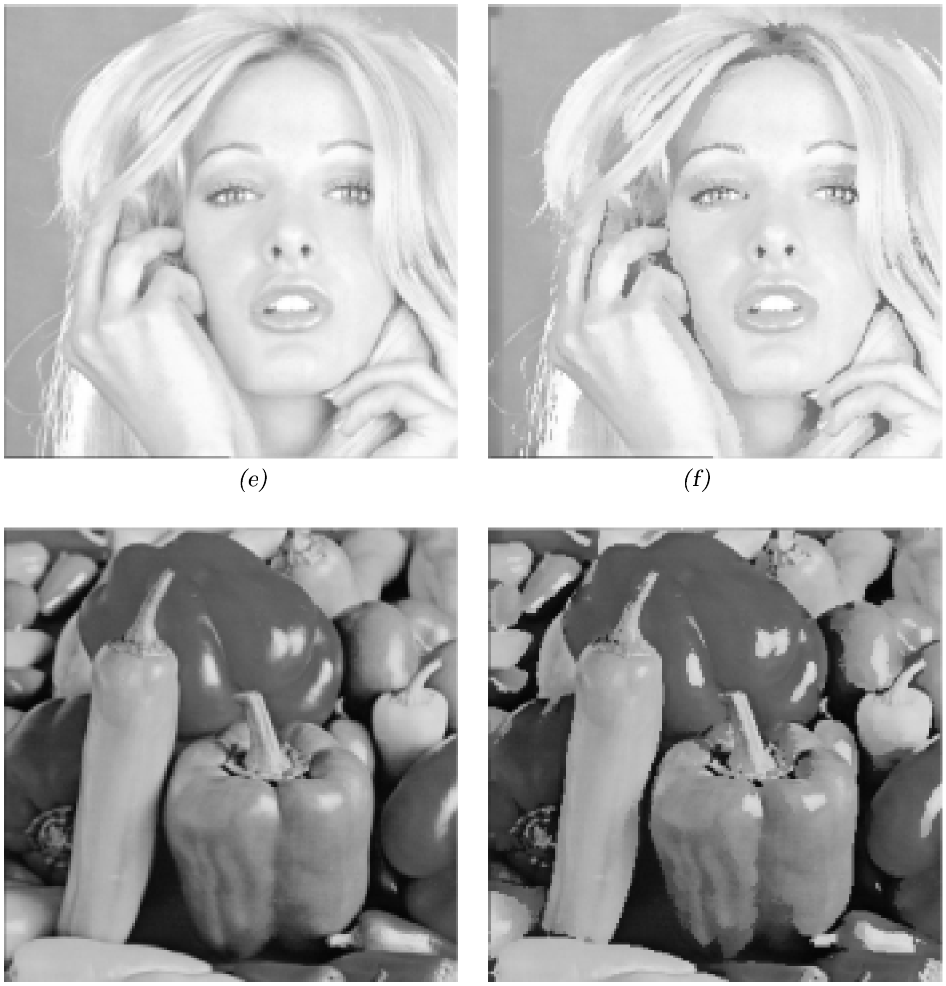
The results are given in Figure 3. For a better comparison, the same gradient type edge detector was applied to both blured and enhanced flower images. No postprocessing was performed, so that the difference in edge width and localization can be easily seen.



(a) *(b)*

(c) *(d)*

Fig. 2. *(a) baboon original;*
(b) IEC enhanced boboon;
(c) Boats image;
(d) IEC - enhanced Boats image.



(e) (f)

(g) (h)

Fig. 2. Continue. (e) Girl image;
(f) IEC - enhanced Girl image;
(g) Peppers image;
(d) IEC - enhanced Peppers image.

The algorithm complexity is only $kO(N)$, where N is the total number of image pixels. Notice that *all* pixels in a block are modifyed at each iteration. This feature compensates for the iterative nature of the method, since the number of iterations is tipically smaller than the block size.

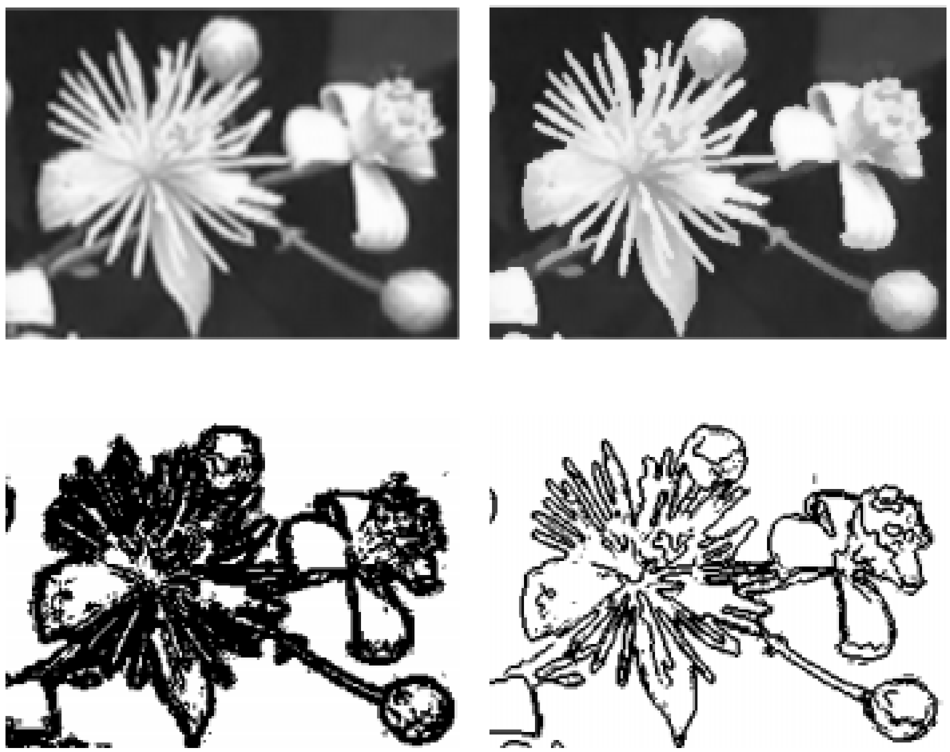


*Fig. 3. Up: blured Flowers image (left)
and IEC enhanced Flowers image (right);
Down: edges detected for the blured Flowers image (left)
and for the IEC enhanced Flowers image (right).*

5. Conclusions

A large number of image enhancement techniques are empirical and require interactive procedures to obtain satisfactory results.

Compared with scale space filtering [9], offset filtering [8], steerable filters [4], and men shift based filtering [1],[5], the IEC filter has a lower computational complexity. From the point of view of the results, our experiments show that the IEC filter is a useful preprocessing tool for image segmentation. The experiments with blured images suggest yet another possible application in image debluring. A visually appealing feature of the proposed filter is the lack of overshooths in its response. This kind of behaviour is also typical for morphological image processing, but the IEC filter enhances edge contrast much more effectively and does not produce false contours. Image enhancement remains a very important topic because of its usefulness in image processing information.

REFERENCES

1. D. Comanciu and P. Meer: *Mean shift analysis and applications.* In: Proc. 7th International Conference on Computer Vision, Kerkyra, Greece, Sept. 1999, pp 1197-1203.
2. B. Efron and R.J. Tibshirani: *An Introduction to the Bootstrap.*. Chapman & Hall, London, 1993.
3. B. Fischl and E. L. Schwartz: *Adaptive nonlocal filtering: a fast alternative to anisotropic diffusion for image enhancement.*. IEEE Trans. on Pattern Anal. Machine Intell., Vol. 21, No. 1, 1999, pp 42-48.
4. W. T. Freeman and E. H. Adelson: *The design and use of steerable filters.* IEEE Trans. on Pattern Anal. Machine Intell., Vol. 13, No. 9, Sept. 1991, pp 891-906.
5. V. Gui: *Edge preserving smoothing using adaptive-scale local Clustering.*. Submitted to Revue de l'Academie Roumaine.
6. D. Marr and E. Hildreth: *Theory of edge detection.*. Proc. of the Royal Society, B 207, 1980, pp 187-217.
7. M. Nagao and T. Matsuiama: *Edge preserving smoothing.*. Computer Graphics and Image Processing 9, 1979, pp 394-407.
8. M. Nitzberg, D. Mumford and T. Shiota: *Filtering, Segmentation and Depth.*. Springer Berlin, 1993.
9. P. Perona and J. Malik: *Scale-space and edge detection using anisotropic diffusion.*. IEEE Trans. on Pattern Analysis and Machine Intelligence, Vol. 12, No. 7, 1990, pp 629-639.
10. P. Salembier, L. Torres, F. Meyer and C. Gu: *Region-based video coding using mathematical morphology.* Proceeding of the IEEE, Vol. 83, 1995, pp 843-856.