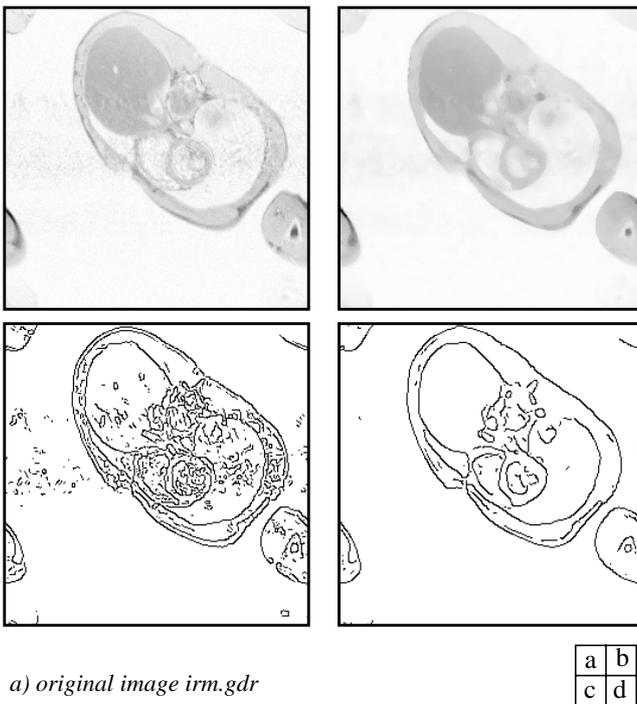


a) original image *angio.gdr*  
 b) filtered image, weighted  $d\alpha$  filter, size=11x11.  
 c) contours of a) Deriche operator,  $\alpha=1.5$   
 d) contours of b) Deriche operator,  $\alpha=1.5$

Fig. 6: Angiography



a) original image *irm.gdr*  
 b) filtered image, weighted  $d\alpha$  filter, size=11x11.  
 c) contours of a) Deriche operator,  $\alpha=1.5$   
 d) contours of b) Deriche operator,  $\alpha=1.5$

Fig. 7: MRI image

## 8. CONCLUSIONS

In this paper we introduce a new adaptive filter aiming at preserving thin structures, enhancing edges and smoothing noise. This filter takes into account both statistical and geometrical information that are locally estimated. The first leads to a better noise reduction, and the second allows the enhancement of details. This operator is well suited for processing natural complex images.

## 9. REFERENCES

- [1] P. Zamperoni, "Adaptive rank order filters for image processing based on local anisotropy measures", *Digital Signal Processing* vol. 2, pp. 174-182, 1992.
- [2] D. R. K. Brownrigg, "The weighted median filter", *Comm. of the ACM*, Vol.27, no.8, pp. 807-818, Aug. 1984.
- [3] J. L. Vila, Ph. Bolon, "Directional adaptive image filtering", *Proc. of ICIP 94*, pp. 382-386, Austin (Texas), Nov.1994.
- [4] J. Astola, Y. Neuvo, "Optimal median type filters for exponential noise distributions", *Signal Processing*, vol. 17, pp. 95-104, 1989.
- [5] O. Yli-Harja, J. Astola, Y. Neuvo, "Analysis of the properties of median and weighted median filters using threshold logic representation", *IEEE Trans. on Signal Processing*, vol. 39, pp. 395-410, Feb. 1991.
- [6] Ph. Bolon, "A family of NL-filters", *Proc. IEEE workshop on Nonlinear Digital Processing*, Tampere (Finland), Jan. 1993.
- [7] I. Issa, Ph. Bolon, "Filtrage adaptatif pour le prétraitement d'images naturelles", *15<sup>th</sup> GRETSI Conference 1995*, pp. 451-454, Juan-les-Pins (France), Sep. 1995.
- [8] A. Restrepo, A. C. Bovik, "Adaptive trimmed mean filters for image restoration", *IEEE Trans. ASSP* vol. 36, pp. 1326-1337, Aug. 1988.

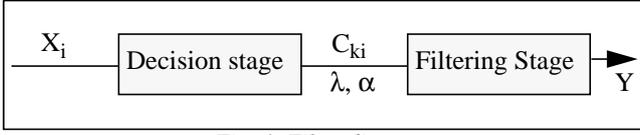


Fig. 4: Filter diagram.

To separate between stationary regions and non stationary ones (regions that contains edges or small structures) we need to define a threshold  $S_Q$  for edge detection (Eq. 5), in addition to a threshold value  $\lambda_0$  on the anisotropy coefficient. We decide that a filtering window contains edges or small structures if the two conditions  $\lambda \geq \lambda_0$  and  $Q(p) \geq S_Q$  are satisfied.

The adaptive filter operates as follows:

- Non stationary region:
  - We set  $\alpha = 0.5$  in order to achieve contrast enhancement in the vicinity of edges.
  - Coefficients  $C_{ki}$  are chosen according to (Eq. 9) (adaptivity with respect to the structure orientation.)
- Stationary regions:
  - $\alpha$  is chosen according to the local noise distribution, (adaptivity according to statistical information) in order to obtain the best noise reduction rate.
  - Equation (9) gives the values of coefficients  $C_{ki}$ . Since  $\lambda$  is small in this case, all pixels in the filtering windows have approximately the same weight.

## 7. EXPERIMENTAL RESULTS

In this section we present results obtained with synthetic and real images. We compare them with those obtained with classical filters such as adaptive trimmed mean [8], according to the Mean Square Error (M.S.E) or Mean Absolute Error (M.A.E) criteria.

Tables I and II display the results obtained with synthetic images (SAVOISE.gdr) altered by exponential (E), gaussian (G), triangular (T) or uniform (U) noises. The results indicate clearly that the new filter has improved the filtering operation.

Table III shows the results obtained with a conventional mean filter. In the latter case, the output variance corresponding to the four different noises are quite similar. The difference between the theoretical output variance ( $\sigma^2/M = 4$ ) and the actual output variance comes from the non-stationarities of the image.

Table I : Adaptive weighted  $\alpha$  filter.

filter size  $5 \times 5$ . input variance  $\sigma^2 = 100$

Noise	E.	G.	T.	U.
M.S.E	11.2	13.4	13.9	14.0
M.A.E	1.92	2.33	2.32	1.87

Table II : Adaptive trimmed mean [8] with  $\beta = 0.05$ .  
filter size  $5 \times 5$ . input variance  $\sigma^2 = 100$ .

noise	E.	G.	T.	U.
M.S.E	11.2	16.0	16.5	16.0
M.A.E	2.1	2.46	2.49	1.98

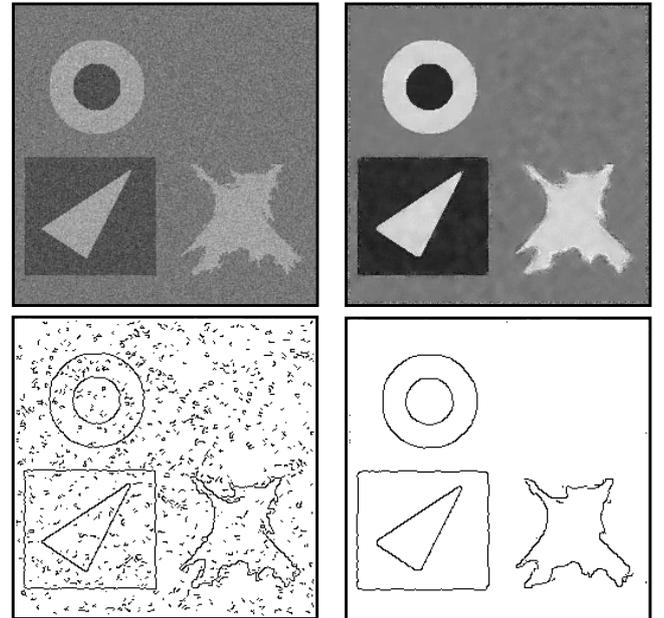
Table III : Conventional Mean Filter, filter size  $= 5 \times 5$ , input variance  $\sigma^2 = 100$ .

Mean Square Error	Mean Absolute Error
21.7	2.62

Figure (5) shows the results obtained with a synthetic image from the CNRS database (SAVOISE.gdr). This image is altered by exponential, gaussian, triangular and uniform noises (a different type in each quadrant).

Figure (6) shows the results obtained with a real image from the CNRS database. It should be noticed that the filter preserves the thin structures (blood vessels) and smooths the noise.

Figure (7) shows the results obtained with another real image IRM (from the same data base). We can notice the performance of the filter for both noise removing and edge enhancement. Image details are preserved by the filtering operation, whereas image analysis is easier.



a) original image SAVOISE.gdr with 4 different noises (a different type in each quadrant)  $\sigma^2 = 100$ .

b) filtered image, weighted  $\alpha$  filter, size  $= 9 \times 9$ .

c) contours of a) Deriche operator,  $\alpha = 1.5$

d) contours of b) Deriche operator,  $\alpha = 1.5$

Fig. 5: Image SAVOISE.gdr

values in the current window. Small values of  $V(\beta)$  correspond to shallow tailed distributions, and large values to heavy tailed ones. Figure (2) shows  $V(\beta)$  variation versus  $\gamma$  value.

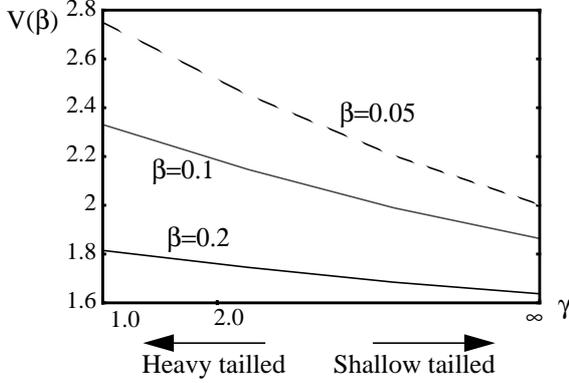


Fig. 1: Evolution of  $V(\beta)$  versus  $\gamma$  value eq. (2).

Four noise families are considered here: heavy tailed distribution (exponential), Gaussian like distribution, triangular like distribution and shallow tailed distribution (uniform).

The principle of the noise classification is similar to likelihood maximization with respect to the three  $\beta$  values and the four noise distribution values [7]. Once the noise distribution is locally classified, the  $\alpha$  value is set in order to maximize the noise reduction effect:

- Heavy tailed distribution (exponential)  $\rightarrow \alpha = 1.3$
- Gaussian like distribution  $\rightarrow \alpha = 2.0$
- Triangular like distribution  $\rightarrow \alpha = 3.5$
- Shallow tailed distribution (uniform)  $\rightarrow \alpha = 9.0$

In a nonstationary region, it is important to enhance discontinuities and smooth noise. Such an operation is possible if we set  $\alpha < 1$  (here we take  $\alpha = 0.5$ ).

#### 4. GEOMETRICAL CRITERION

In image processing we aim to avoid discontinuity smoothing and, if possible, to enhance contrasts. To achieve such an operation we need to localize discontinuities. Here we propose to use a geometrical parameter associated with an edge detector. This parameter is the local anisotropy coefficient  $\lambda$ . Filter coefficients will be chosen according to its value. As an edge detector we use the quasi-range operator defined by equation (5).

$$Q(p) = X_{(M-p)} - X_{(p)} \quad p = M/3 \quad (5)$$

Let  $N=2n+1$  be the filter size and  $M=N^2$  the total number of pixels inside the filtering window.

Let  $\{S_1, \dots, S_d, \dots, S_{4n}\}$  be a set of discrete line segments defining  $4n$  directions inside the filtering window (Fig. 2).

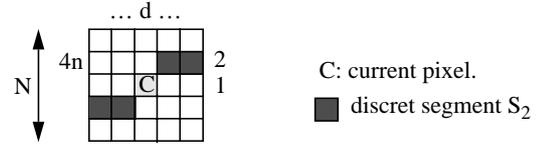


Fig. 2: Discrete line segments in the filter window.

Let  $A_d$  (resp.  $R_d$ ) be the average (resp. the range) of pixel values in segment  $S_d$ .

$$\text{Let } A_m = \min \{A_i\} \text{ for } i \in [1, 4n], \quad (6)$$

$$A_M = \text{Max} \{A_i\} \text{ for } i \in [1, 4n], \quad (7)$$

and  $d_0 = \text{argmin } R_d$

The anisotropy parameter  $\lambda$  is defined by [1]:

$$\lambda = \frac{A_M - A_m}{A_M + A_m + \epsilon} \quad (0 < \epsilon \ll 1) \quad (8)$$

Parameter  $\lambda$  ranges from 0 to 1. As mentioned in [1] large values are associated with thin lines (such as roads in aerial views or blood vessels in medical images), intermediate values correspond to edges, and small values correspond to stationary regions.

#### 5. COEFFICIENTS DISTRIBUTION

We propose to emphasize the effect of pixels located on the most homogeneous segment ( $S_{d_0}$ ), with respect to those located outside  $S_{d_0}$ . Let us define the discrete segments  $S_\Delta$  parallel to  $S_{d_0}$  (Fig. 3) where  $\Delta$  is the distance between  $S_\Delta$  and  $S_{d_0}$ .

Coefficients  $C_{ki}$  are defined as follows:

$$C_{k,i} = \begin{cases} 1 & \text{if } i \in S_{d_0} \\ (1 - \lambda)^\Delta & \text{if } i \in S_\Delta \end{cases} \quad (9)$$

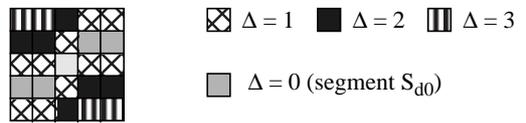


Fig. 3: Segment  $S_{d_0}$  and parallel segments  $S_\Delta$ .

#### 6. FILTER STRUCTURE

The filter is composed of two stages: the decision stage and the filtering stage.

- The decision stage is composed of an edge detector, a noise classifier and a geometrical analyser.
- The filtering stage integrates the information of the decision stage to calculate the optimal output of the filter.

# ADAPTIVE WEIGHTED $d\alpha$ FILTER

*I. ISSA, Ph. BOLON*

Laboratoire d'Automatique et de MicroInformatique Industrielle  
LAMII/CESALP - Université de Savoie - B.P 806 - F.74016 Annecy Cedex (France)  
(CNRS G1047 - Information-Signal-Image)  
e-mail: issa@esia.univ-savoie.fr bolon@univ-savoie.fr

## ABSTRACT

In this paper we propose a new adaptive weighted  $d\alpha$  filter. The filter is adaptive regarding noise amplitude distribution, orientation of structures and anisotropy measures. The filter coefficient are chosen according to structure orientation and anisotropy measures.  $\alpha$  value is chosen according to the result of local noise distribution and anisotropy coefficient estimations. Some experimental results on synthetic and natural images are presented. Results are compared with those of adaptive filters such as the adaptive trimmed mean.

*Key words:* Order statistics, adaptive filtering, noise distribution, image processing, anisotropy coefficient.

## 1. INTRODUCTION

In the domain of image processing, the segmentation stage is often essential. The success of this stage depends upon the preprocessing stage and requires an overenhancement of all the image features that are perceived as discontinuities (texture transitions, edges, lines, or detail), and a smoothing of all that is perceived as homogeneous. Most of proposed filters use either statistical or geometrical information, but not both together. In this paper we propose a preprocessing operator which uses order statistics for smoothing homogeneous region and geometrical criteria to enhance discontinuities. The advantage of using both statistical and geometrical information is to obtain a maximum noise reduction, in addition to contrast enhancement.

The main features of this filter are:

- adaptivity with respect to noise amplitude distribution.
- adaptivity with respect to orientation of structures.
- adaptivity with respect to local anisotropy measures.

This operator can be regarded as an extension of previous operators proposed by Zamperoni [1], D. R. K. Brownrigg [2], Vila and al. [3], J. Astola and al. [4], O. Yli-Harja and al. [5].

## 2. WEIGHTED $d\alpha$ FILTER

Let  $\{x_1, \dots, x_M\}$  be the set of data inside a filtering window

centered at location  $k$ . The output  $y_k$  of a weighted  $d\alpha$  filter [6] is defined by:

$$y_k = \underset{y}{\text{Argmin}} \left( \sum_{j=1}^M c_{k,j} |y - x_j|^\alpha \right) \quad (1)$$

$c_{k,j}$  are the filter coefficients, and  $\alpha$  is its parameter ( $\alpha > 0$ ), when  $C_{k,j} = 1$ , the filter output is the maximum likelihood estimate for noises with a probability density function:

$$f(x, \gamma) = k \exp(-c \cdot |x|^\gamma) \quad (2)$$

The exponential density function is obtained for  $\gamma = 1$ , the gaussian density function is obtained for  $\gamma = 2$ , and the uniform one with  $\gamma \rightarrow \infty$ .

Since the absolute value function is not analytic, the output of eq. (1) can be regarded as a nonlinear function of the order statistics  $x_{(i)}$  of the data inside the filtering window:

$$y_k = \underset{y}{\text{Argmin}} \left( \sum_{i=1}^M c_{k,(i)} |y - x_{(i)}|^\alpha \right) \quad (3)$$

The weighted median filter [2] is a special case of weighted  $d\alpha$  filter ( $\alpha=1$ ). If  $\alpha < 1$  the weighted  $d\alpha$  filter has a joint effect of noise smoothing and contrast enhancement. In the adaptive version,  $\alpha$  and  $c_{k,j}$  depend on location  $k$  and are chosen as follows:

- $\alpha$  is chosen according to the local noise distribution in stationary regions. Small  $\alpha$  values are adapted to heavy tailed distributions (exponential) and large values to shallow ones (uniform).
- Coefficients  $c_{k,j}$  are chosen according to a geometrical criterion.

## 3. SELECTION OF $\alpha$ VALUE

We need to characterize the local noise distribution, in order to select a proper value for  $\alpha$ . To achieve this purpose we use the method proposed in [7], which is based on the statistic  $V(\beta)$  [8] defined by:

$$V(\beta) = \frac{U(\beta) - L(\beta)}{U(0.5) - L(0.5)} \quad \beta=0.05, 0.1 \text{ and } 0.2 \quad (4)$$

$U(\beta)$  (resp.  $L(\beta)$ ) is the average of upper (resp. lower)  $\beta M$