ADAPTIVE DIRECTIONAL MORPHOLOGICAL OPERATORS

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ABSTRACT

This paper proposes a new method of nonlinear filtering based on the classical morphological operators. The originality of our method consists in assigning to each pixel an adaptive structuring element depending on the local orientation of the image. Several examples of applications are presented and a comparison with the classical operators is done. Our method can be applied for early vision tasks.

1 INTRODUCTION

The mathematical morphology operators for grey tone functions were first introduced by Serra [1]. A morphological operator is a set operation performed between the input image and a given set, called structuring element **(B)**. Usually the structuring elements used to compute the basic morphological operations (dilation, erosion) are isotropic, then they do not take into account the local morphological properties of the input image.

This paper presents a new method for computing the basic morphological operations by taking into account the local orientation of an object. This information is supplied by a Principal Component Analysis (PCA). The analysis is performed on the local image gradient map. The output data e.g. the mean orientation of the gradient field is supplied as conditional input to the morphological operator. The orientation based operator, by adjusting the structuring element, acts in the direction given by the second eigenvector obtained through the PCA analysis,.

2 PRINCIPAL COMPONENTS ANALYSIS

The *Principal Components Analysis* is a multidimensional data analysis technique which transforms a set of variables in a new set with the same number of elements (p). Each variable is computed as a linear combination of the original variables. The main interest of the PCA lies in the fact that the output space can be represented by hierarchical axis, each of the axes containing the maximum possible residual information. By keeping only the most significant components (k, k<p) with the most important variances, it is possible to reduce the dimension of the space[2].

An *oriented field* (directional field) is a vector field whose elements define the direction and the intensity of a given physical phenomenon (electrical field, force field, gradient field, etc.)

A directional field $V = \{v_i\}_{1\le i\le N}$ of N bidimensional vectors can be represented by a scatter diagram (Fig. 1).

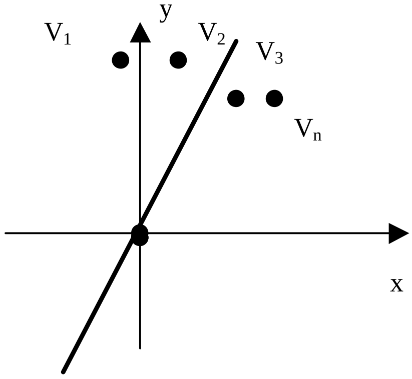

Fig.1 Bidirectional orientation field

An end point • in Fig.1 represents the extremity of the gradient vectors computed in the surrounding window for the pixel under study.

As a direction is modulo-π the mean orientation can not be found by a arithmetical mean on V.

The mean orientation [3] of the field shown on Fig . 1 is obtained by searching an axis that maximizes the squared sum of the vectors projections onto this axis :

$$J = \sum_{i=i}^{N} (v_i^T u)^2 \qquad (1)$$

where u is the unit vector of the desired axis.

The solution is obtained by computing the eigenvector corresponding to the strongest eigenvalue of the moment tensor M :

$$M = \frac{1}{N}\sum_{i=1}^{N} V_i V_i^T \qquad (2)$$

In Fig. 1 the orthogonal of the principal axis associated with the scatter of points is represented by a continuous line.

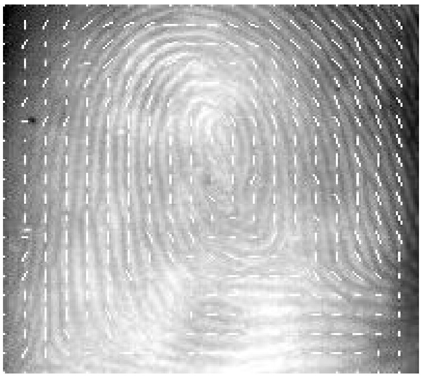

Fig.2 Mean orientation of a gray scale image

In the case of gray scale images the local directional field is represented by the gradient field. A result of the mean orientation of PCA analysis is given on Fig.2.

The vector field in Fig. 2 was obtained by performing a Sobel gradient on the inital image, then a PCA analysis on rectangular windows of 7x7 points. The orientation of the white dotted lines represent the mean orientation of the second eigenvalue of the matrix (2).. The lenght of each dotted line represents the confidence when estimating the orientation.

It can be also noticed that a PCA analysis will affect also the neighbouring pixels. Fig . 3 shows an example of several broken lines. On the original image an orientation image obtained by a PCA analyis was imposed.

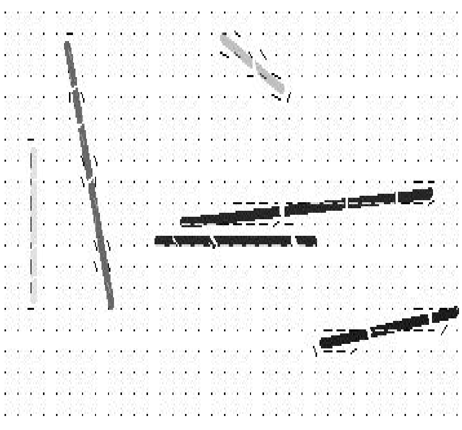

Fig.3 Original and superimposed orientation image

The dots and small lines in Fig. 3 represent the orientation vectors superimposed on the original images

3 DIRECTIONAL MORPHOLOGICAL OPERATORS

Approaching image processing from the vantage point of human perception, morphological operators simplify image data, preserving essential shape characteristics and eliminating irrevelancies.

The classical definition of the morphological transformations can be found in [1].

The extension of the classical defintions for grey scale images is given also in [1]:

$$f \Theta B = \{\min\ f(y) : y \in B_x\} \qquad (3)$$

$$f \oplus B = \{\max\ f(y) : y \in B_x\} \qquad (4)$$

The structuring element used in (3) and (4) on a square grid of points, is usually a centered window with an odd number of elements. If B is an isotropic convex set then the erosion (dilation) is performed on the same manner in all the directions defined on a square grid.

In certain applications the aim is to perform conditional dilations and erosions in order to transform the objects under study in preferential directions.

There are several approaches for this purpose [4],[5]. Gleason and Tobin [1] proposed a directional approach to merge disconnected objects in a given image in order to obtain, for example, a curvilinear object. The principle of this approach based on gravitational force is to dilate each object along a direction corresponding to the nearest and biggest objects. Finally a dilation kernel is obtained and applied to the whole object.

Our approach makes use of the supplementary informations supplied by the PCA analysis and changes the isotropic convex structure of B in order to compute the desired directional dilation or erosion.

Let B denote a small 3x3 centered window; In the case of binary images B is usually chosen as:

B= (5)

1	1	1
1	(1)	1
1	1	1

The small circle denotes the center of the structuring element. It can be easily seen that all the directions are treated in the same way. By preprocessing the image with a PCA analysis, for each pixel the mean orientation can be found. Then the structuring element is selected taking into account the mean orientation.

On a square grid on the 3x3 window, only 4 directions can be defined: horizontal, first bisector , vertical, secondary bisector. By enlarging the size of the structuring element the number of possible directions increases, the structuring element are then drawn corresponding to a given direction by the Bresenham line drawing algorithm

For a [3x3] square grid Table 1 presents for each orientation the corresponding structuring element.

Direction	B
Horizontal	0 0 0 1 1 1 0 0 0
First bisector	0 0 1 0 1 0 1 0 0
Vertical	0 1 0 0 1 0 0 1 0
Secondary bisector	1 0 0 0 1 0 0 0 1

Table 1. Structuring elements used on a 3x3 window grid

Where : 1 means that the pixel is taken into account
0 means that the pixel is not taken into account

It can be easily seen that different structuring elements lead to a different oriented transformation

As can be seen from Fig. 3, due to the fact that the PCA analysis also affects the neighbouring pixels, a straightforward implementation of an oriented erosion(dilation) will also thicken (thin) the black lines. This fact can be avoided by performing a supplementary check at the beginning in order to restrict the support of the erosion (dilation) to the broken zones areas. The algorithm is the following:

- compute the inner morphological gradient of the image e.g. the difference between the original image and the image eroded with a structuring element of size one according to (3).
- starting from the edges, detected in the previous step, the broken areas are detected by trying to find similar gray levels in the directions given by the PCA gradient analysis.

4 EXPERIMENTAL RESULTS

Fig. 4 shows the results several broken straight lines. The commonly used method to reconstruct the lines is to filter mophologically the image with a classical opening[1]. The result is shown on Fig. 5. The main drawback of the classical method is the merging of neighbouring lines together.

The final result of the directional erosion is shown on Fig.7

Fig 6 shows the support of the directional erosion operator.

Our method can reconstruct the lines withouth tickening or undesired merging together.

Fig.4 Original image of several broken lines

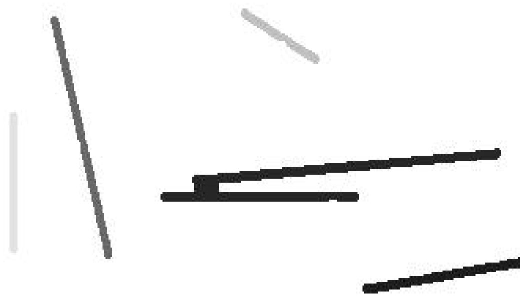

Fig.5 Results using classical opening with a 7x7 structuring element

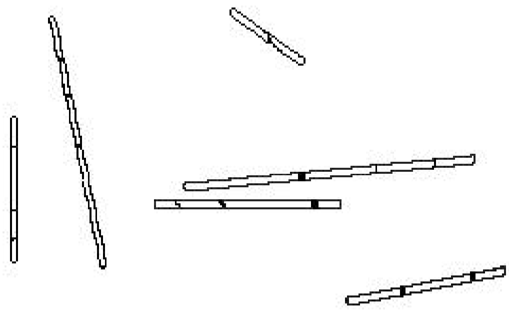

Fig.6 Broken areas detection

Fig.6 Final result

The final result shown in Fig. 7 was obtained by 3 consecutive directional erosions. Once the lines have been reconstructed the directional erosion has no effect on the image.

We tested our method for a more complex image shown if Fig. 8. Fig 9 shows the result when applying a classical erosion operator. The erosion will tend to connect the noisy lines from the background of the flag but will also increase the dark areas. A commonly used method for filtering such an image is the opening operator. The result is shown on Fig. 10. As known the opening filters the background but also slightly blurres the image.

Finally Fig.11 shows the result when appying a [3 x 3] directional erosion. This operator allows to reconstruct the lines as well as it preserves the fine details from the original image.

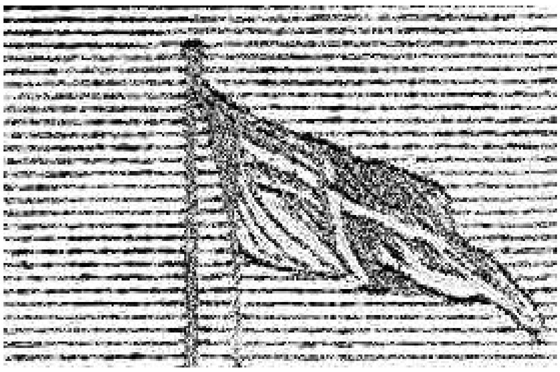

Fig 8 Original image

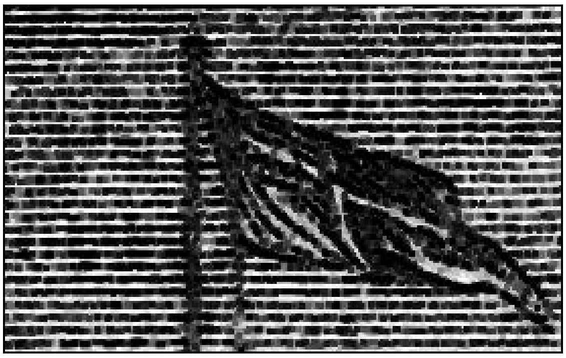

Fig 9. [3x3] Classical erosion

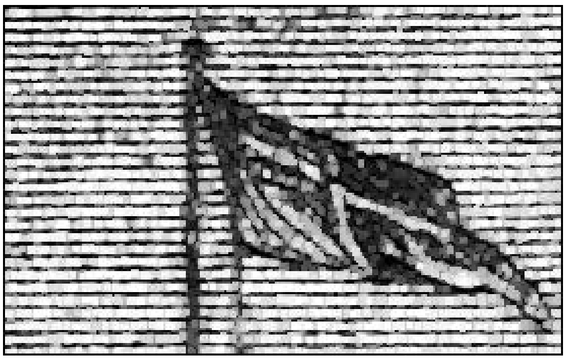

Fig 10. [3x3] Classical opening

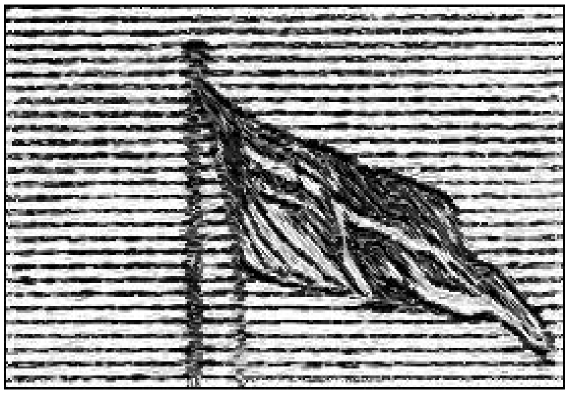

Fig 11. [3x3] Directional erosion

5 CONCLUSIONS

In this paper we proposed a new method based on the definition of the classical morphological operators. The originality of the method is to give a directional feature to each pixel via an PCA analysis and then to use an adaptive structuring element according to this direction. This method gives good results for as well for simple images as for more complex images.

The results of the classical erosion (Fig.9), classical opening (Fig. 10) and directional erosion are showing that the proposed method preserves better the directional features from the original image and also avoids blurring.

Future work will be focused on taking into account the supplementary information given by the estimate of the radii of curvature in each point

6 REFERENCES

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