AUTOMATIC PARAMETER COMPUTATION FOR EDGE DETECTION BY THE ZERO-CROSSING METHOD

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RESUME

Beaucoup de techniques pour la détection de bords ont été proposées dans la littérature, parmi lesquelles la technique développée par D.Marr et E.Hildreth est une des plus intéressantes. Cette technique est basée sur les points de croisement zéro du Laplacien d' une transformation de Gauss de l' image d' input, et dépend de quelques paramétres, dont les valeurs doivent être fixées par l' usager. En particulier, il est critique de fournir la valeur du seuil qui choisit les poits de bord significatifs parmi ceux qui ont été extraits par l' essai basé sur le croisement zéro. En effet, ce paramètre présente des valeurs très variables, qui comprennent des ordres de grandeur différent, selon les caractéristiques de l' image et les autres paramètres utilisés. Une valeur très basse de ce seuil offre l' avantage des bord bien fermés, mais malheureusement elle produit aussi beaucoup de points de bord faux à cause du bruit. Au contrair, une valeur haute permet une bonne insensibilité au bruit, mais elle cause aussi beaucoup de trous sur les bords vrais.

Le but de ce travail est de présenter une étude sur la dépendance du seuil pour la sélection des points de bord d' autres paramètres de l' opérateur Laplacien de la transformation de Gauss et du niveau du bruit de l' image d' input, et un critère pour calculer automatiquement la valeur de ce seuil. En particulier, nous avons trouvé que, dans quelque hypothèses, on peut obtenir de bons rèsultats à l' aide de une formule que depend de la deviation standarde du bruit et d' autres paramètres du Laplacien de la courbe de Gauss. Cette formule a été obtenue en faisant beaucoup d' experiences sur des images uniformes caractérisées par de bruit de Gauss non-correlées, additifs et avec une moyenne zéro, qui presentaient des variances différentes. Les résultats ont été confirmés sur des image médicales de résonance magnétique. A' présent nous faisons des expériences sur d' autres types d' image.

SUMMARY

Many techniques for edge detection have been proposed; among them, one of the most interesting was proposed by D.Marr and E.Hildreth. This technique is based on the zero-crossing points of the Laplacian of a Gaussian trasformation of the input images, and depends on some parameters whose values must be fixed by the user. In particular, it is critical to provide the value of the threshold that selects meaningful edge points from among those extracted by the zero-crossing test. In fact this parameter exhibits very variable values that span over various orders of magnitude, depending on the image features and on the other parameters employed. A very low threshold value has the advantage of well-closed edges, but, unfortunately, also causes many false edge points due to noise. By contrast, a high threshold value allows good insensitiveness to noise, but also causes many holes on true edges.

The purpose of this paper is to present a study on the dependence of the above threshold for edge-point selection on the other parameters of the Laplacian of a Gaussian operator and on the noise level of the input image, and a criterion to compute automatically the value of such threshold.
In particular, we have found that, under some hypotheses, good results can be obtained by means of a formula that depends on the noise standard deviation and on the other parameters of the Laplacian of a Gaussian operator. This formula has been derived from many experiments carried out on uniform images with zero-mean, additive, uncorrelated Gaussian noises of different variances; results have been confirmed on Magnetic Resonance images of the medical type. We are currently conducting experiments on other kinds of image.

1. INTRODUCTION

Edge detection is one of the most important process involved in low-level image processing; consequently, many interesting techniques have been proposed in the literature to accomplish this task.

Some techniques are based on the detection of sudden changes in the grey-level function. To this end, a spatial convolution with an appropriate mask can be performed to enhance local differences (operators of the gradient type); a well-known operator of this type was proposed by Sobel [Gonzalez, 77]. A local analysis can also be performed by applying non-linear operations, e.g. by taking the maximum local difference, or some combination of the absolute values of local differences. Another approach is represented by the application of high-pass filters in the spatial frequency domain.

In general, after the above processing, a thresholding operation is required in order to binarize the image in two kinds of points: background and edge points. This is a critical issue, which often is solved by an interactive help by the user. However, in computerized image processing, it is preferrable to solve it by some automatic computation. To this end, some interesting approaches have been presented, among which we recall the work of Canny [Canny, 86] based on a hysteresis process.

A different approach performs the edge detection by extracting the zero-crossing points in the second derivative of the grey-level function of the input image [Marr, 80; Haralick, 84].

In particular, the technique proposed by D.Marr and E.Hildreth defines edge points as the zero-crossing points of the function obtained by applying the Laplacian of a Gaussian operator to the grey levels of an image. This technique depends on some parameters, whose values must be given by the user. One of them, i.e. the value that selects the meaningful edge points from among those extracted by the zero-crossing test, is quite critical. In fact, this parameter exhibits very variable values, spanning over various orders of magnitude, depending on image features and on the other parameters employed.
Various works have been proposed on the topic of the parameters of 'zero-crossing' techniques, like the predicate technique [Huertas, 86] and the edge-focusing in [Bergholm, 88].

The purpose of this paper is to present a study on the dependence of the threshold for edge-point selection on the other parameters of the Laplacian-of-Gaussian operator and on the noise level of the input image, and a formula to compute automatically the value of this threshold. This formula has been derived from experiments on synthetic images; the result was confirmed on Magnetic Resonance images of the medical type. We are currently carrying out experiments on other kind of images.

2. MATERIALS AND METHODS

The technique proposed by D.Marr and E.Hilreth requires that the following three processes be applied: a preliminary smoothing filter to reduce noise in the original image, then a second derivative operator, finally a test to extract the zero-crossing points from the transformed image.

The shape of the smoothing filter is chosen so to obtain the optimum compromize with respect to two opposite requirements, i.e. the definition of a narrow band in the frequency domain to reduce (high-frequency) noise, and of a small size operator (in the spatial domain) to consider only local edges. The optimal shape (both in space and in frequency) is the Gaussian one, as can rigorously be proven.

The Gaussian filter requires the definition of the covariance matrix, which is usually considered isotropic and with null cross-correlation terms ($\sigma_{xx} = \sigma_{yy} = \sigma$; $\sigma_{xy} = \sigma_{yx} = 0$).

If the user wants to save small (or thin) details, it is better to select a low σ value; otherwise it is more convenient to select a higher σ value to obtain a stronger noise reduction. Typical values of this parameter range from 0.5 to 5.0.

The second step (computation of the second derivative) can be performed by a Laplacian operator. It exhibits the advantage of being independent from edge orientation, so it not necessary to execute more computations in different directions.

These first two steps can be carried out in a single step by combining the Gaussian and the Laplacian in a Laplacian-of-Gaussian (LoG) operator. Besides some normalization of the coefficients of the LoG operator, it is necessary to fix an amplitude parameter which influences its height and width. To this end, it has been proven that the best results are obtained by requiring that the total size of the operator be 3 times the size of the Gaussian (defined as $2\sqrt{2}\sigma$). This constraint allows the computation of the amplitude parameter.

The last step consists of the extraction of the zero-crossing points. As a matter of fact, not every zero-crossing point generally corresponds to true edges. In fact, noise usually gives rise to false edge points. Consequently, it is useful to select those pixels for which there's not only a change of sign (zero-crossing), but also a difference of value, in the transformed image, above a given threshold.

While it is clear how to select both the variance of the Gaussian function and the value of the amplitude parameter, it is rather critical to select the threshold for edge-point selection. In fact, it has very variable values, depending on image features and on the other parameters mentioned above.

Moreover, a very low threshold value (e.g. equal to 0) has the advantage of well-closed edges, but unfortunately also causes the presence of many false edge points (due to noise). By contrast, a high value allows a good insensitiveness to noise, but also causes many holes on true edges.

In our study, we have considered that a strategy for the computation of a good (even if not always optimum!) value of the above threshold can be based just on false-edge analysis, regardless to true-edge closure. In fact, we can find a false-edge situation that does not creates any problem to the subsequent processing stages, but such that a worst one could begin to create some problems. This is a good situation in the sense that it is not important to reduce false edges (so it should be avoided to maintain as closed edges as possible), and it is dangerous to accept more false edges.

We have found that, at least with a particular type of noise, the threshold value which leads to a given false-edge situation (in particular to the good situation defined above) can be computed, by a good approximation, by means of a formula depending on the noise standard deviation and on the other parameters of the LoG operator.

This formula was obtained by carrying out many experiments on uniform images (i.e. without true edges) with zero-mean, additive, uncorrelated gaussian noises of different variances. In all cases, the threshold value was interactively provided, and after some attempts, the value which led to a desired situation of false edges was obtained. In particular, we imposed that no long or closed chains of edge points be present in the final edge map.

Results have suggested the following heuristic formula:

$$T = k \frac{\sigma_n * S_+}{\sigma_{op}^2} \qquad (1)$$

where T is the threshold for edge-point selection, k is a constant (k=2.61), σ_n is the noise standard deviation in the input image, S_+ is the sum of the positive coefficients (equal to the sum of the negative coefficients, by normalization) of the LoG operator, σ_{op} is the standard deviation of the Gaussian curve.

As one can expect, the curve is directly proportional to the noise standard deviation; obviously, it also depends on the features of the LoG operator.

While we are still considering this formula from a theoretical point of view, in our opinion this result is interesting, since it provides T values in good agreement with the manually selected ones, as shown in Tab.1.

TABLE 1

σ_{op}	T_{man}	S_+	T
1.4	5.5 e+3	4.3 e+2	5.7 e+3
1.5	7.7 e+6	5.8 e+5	6.7 e+6
1.6	1.4 e+6	1.3 e+5	1.3 e+6
1.7	4.0 e+5	4.3 e+4	3.9 e+5
1.8	1.3 e+5	1.7 e+4	1.4 e+5
1.9	5.5 e+4	7.6 e+3	5.5 e+4
2.0	2.5 e+4	3.9 e+3	2.5 e+4
2.5	1.1 e+5	2.7 e+4	1.1 e+5

Results obtained on a uniform image with additive, uncorrelated, zero-mean gaussian noise of standard deviation σ_n=10.

Legend:
σ_{op}=standard deviation of the Gaussian curve
T_{man}=manually selected threshold value
S_+=sum of positive LoG operator coefficients
T=automatically computed threshold value

Only in one case the error is considerable, being equal to 13% (second line of Tab.1). Anyway it can be noted that the final result (edge map) is not very sensitive to T value; consequently, the result obtained by using the automatically computed threshold value is not so much different from the desired one.

Results are satisfactory since on an average the error is small (i.e. about 4%) and in some case it reduces to 0.

Similar results have been obtained on other uniform images with the same kind of noise, but with different standard deviation values.

The formula in eq.(1) can be employed when analyzing images containing structures to be revealed by means of the edge detection process. A procedure for the automatic computation of σ_n can be developed to avoid the need for user interactions.

Results can be worse in the case of different types of noise: e.g. it is worth investigating the case of multiplicative, correlated noise, like the speckle noise.

Considering the disadvantages of our approach, the major risk is in the case of very noisy images, for which the reduction of false edges causes too many holes on true edges. In such a case it could be better to accept a lower threshold value representing a better compromize.

Another unpleasant behavior could be revealed for images with very low noise levels: in these cases closed true edges could be obtained without introducing false edges.

Anyway these problems are partially overcome if we consider the edge-detection process inserted in an image-processing environment that interacts with it. For example, we have developed a procedure to fill small gaps in edge maps and to delete open chains of few edge pixels. In this way the edge map quality is improved, and edges can be used to extract regions by segmentation.

Finally, some different values of the constant k (see eq.(1)) can be a priori fixed, corresponding to different situation of false edges (e.g. no false edges,; few false edges; just tolerable situation of false edges). If the edge detection module is managed by a knowledge-based system, then the k value can be selected, and possibly changed accordingly to results, by the control structure.

3. RESULTS

The formula presented in the previous section has been applied to some Magnetic Resonance images of the head of human patients.

For a comparison, we have implemented the predicate technique proposed in [Huertas, 86], and we have applied it to the same images, considering the same values of σ_{op}. This technique does not employ any threshold for edge-point selection, so it is sensible to compare its results with ours, for which a threshold is needed, but it is automatically computed.

In Fig.1 an original image is shown, with a display of the LoG transformation for two different values of σ_{op}. This two values (1.6 and 2.0) corresponds to two different levels of details. As regards the transformed images, the one with the lower operator size looks like a better-focused image, as compared with the other one.

The corresponding edge maps obtained with the manual threshold is almost identical to the image in the left portion of Figs.2,3, so we do not present it. The predicate technique provided rather different images, as can be observed in the right portions.

The situation about false edges is similar in the two images obtained with the automatic threshold computation (left portions of Figs.2,3), even though the former contains more details. This confirms that also for this kind of images the criterion for threshold computation holds. As a matter of fact, the value of k could be reduced without problems, since the false-edge situation is still a good one.

A comparison with the result of the predicate technique points out that our approach causes some more holes in true edges (recoverable by a postprocessing algorithm), but strongly reduces false edges; false edges seem to be too many in the result obtained by means of the predicate technique.

4. CONCLUSIONS

The technique we have proposed in this paper has provided good results on synthetic and on Magnetic Resonance images; it is interesting also in comparison with the predicate technique.

The formula we have presented is not yet well interpreted from a theoretical point of view; moreover, we are still investigating its validity in particular for images with different kinds of noise.

The major disadvantages of our approach could be reduced by inserting the edge-detection procedure in an image-processing environment managed by a knowledge-based control structure.

Finally, our technique could be improved by making it adaptive not only to the noise level (which is the first approximation we are proposing in this paper), but also to some parameter representing edge quality, i.e., in particular, their sharpness and continuity.

Notwithstanding the above problems and limitations, our study provides an interesting tool for an easier employment of the 'zero-crossing of the Laplacian of Gaussian' technique.

REFERENCES

F. Bergholm, Edge Focusing, IEEE Trans. on PAMI, vol.9, n.6, Nov.87, pp.726,741.

J. Canny, "A computational approach to edge detection", IEEE Trans. on Pattern Analysis and Machine Intelligence, Vol. PAMI-8, No.6, pp.679-698, 1986.

R.C.Gonzalez, P.Wintz, Digital Image Processing, Addison Wesley, Reading (MA), 1977, pp.337-338.

R.M.Haralick, Digital Step Edges from Zero-Crossing of Second Directional Derivatives, IEEE Trans. on Pattern Analysis and Machine Intelligence, No.1, Jan. 1984, pp.56-58.

A. Huertas, G. Medioni, Detection of Intensity Changes with Subpixel Accuracy using Laplacian Gaussian Masks, IEEE Trans. on Pattern Analysis and Machine Intelligence, vol. PAMI-8, No.5, 1986.

D. Marr, E. Hildreth, Theory of Edge Detection, Proc. of Royal Soc. of London, vol. B207, pp.187-217, 1980.

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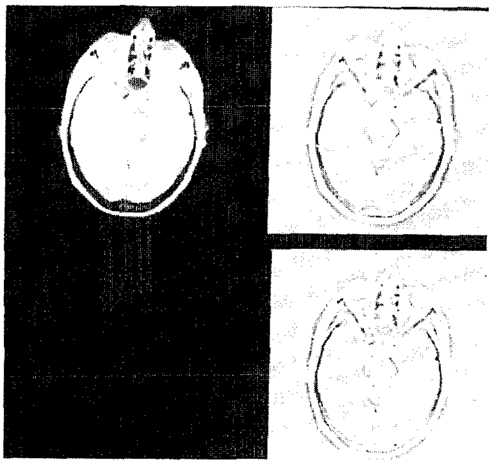

Fig.1. Magnetic Resonance image of a human patient (transversal slice at the eyes' level): original image (top left); LoG transformation with σ_{op} equal to 2.0 and 1.6 (top right and bottom right, respectively.

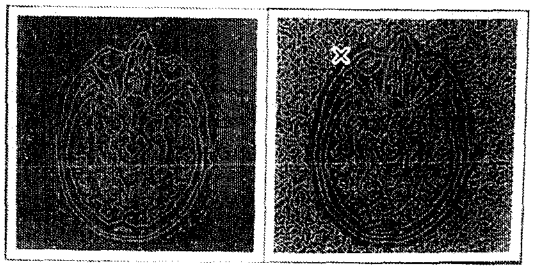

Fig.2. Edge maps derived from the transformed image in the lower left portion of Fig.1 (σ_{op}=1.6) by applying the automatic threshold computation (left) and the predicate technique (right).

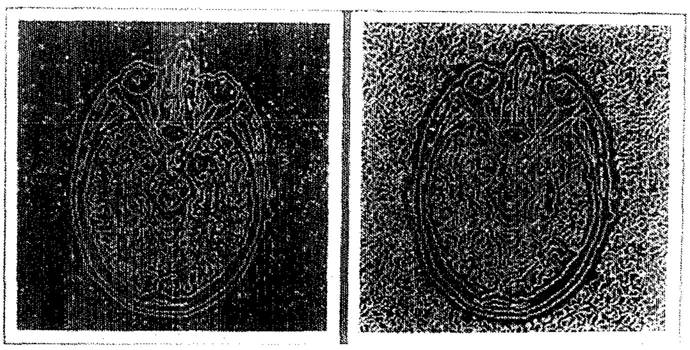

Fig.3. The same as for Fig.2, but related to the LoG transformation with σ_{op}=2.0.