Driving segmentation and recognition phases using multiscale characterization

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***Abstract*—Half away between edge detection and pattern recognition this study aim to characterize singularities in order to build closed edges and to classify object within an image.**

Keywords : wavelet transform, segmentation, pattern recognition, singularity

I. INTRODUCTION

This study is an extension of Lipschitz Exponent for non-standard signals. In fact, most of the objects present in a real scene could not be modeled with a unique signal (a dirac, a sinusoidal, …) but are combination of more complexe structures. We adapt the characterization made with Lipschitz exponent to classify the image ruptures and so split the scene into object.

The article is organized as follows. Section II present the multiscale analysis and the extension of the Lipschitz exponent (generalized maxima chains). It also deals with supervised and unsupervised classification of the chains which is the base of segmentation and pattern recognition. Section III to IV deal with the integration of the maxima chain to the segmentation and recognition phases and show the way to use multiscale characterization. Section V present an application with the main results. Current work and perspectives are presented in section VI.

II. MULTISCALE ANALYSIS

We present a summary of the more precision could be found in [5] and [6]. The multiscale is obtained using a dyadic discrete wavelet transform based on a biorthogonal dyadic wavelet. The image I is decomposed on n approximation ($\{W_i\}$, $0\leq i\leq n$) and details ($\{D^x_i\ ,\ D^y_i\ \}$, $0\leq i\leq n$) images (orthogonal projection on affine spaces obtained with the wavelet bases [6]) :

$$I = W_1 + D^x_1 + D^y_1 \qquad (1)$$

$$W_i = D^x_{i+1} + D^y_{i+1}\ ,\ 0\leq i\leq n \qquad (2)$$

Then we compute the modulus of the details images for each scale of the decomposition.

$$(|D^x_{i+1}|^2 + |D^y_{i+1}|^2)^{1/2},\ 0\leq i\leq n \qquad (3)$$

Finally, we extract the maxima of each modulus.

A. *Maxima chains*

We now have a set of maxima for each scale of the wavelet transform. To characterize a structure present in the first scale (thus within the original image *I*) we analyze the evolution of the maxima of the details images through the different scales.

A maxima of the details modulus represent a rupture in the image, that is to say an edge point.

Starting from a maxima, $m_0(x_0,y_0)$, in the first scale we now have to found a maxima , $m1(x_1,y_1)$, in the next scale, which is representative of m_0.

To found this new maxima we explore the neighborhood of (x_0,y_0) in the next scale inside the cone of influence as defined in [1]. Repeating the process across the different scales we obtain the set $\{m_{i,}\ 0\leq i\leq n\}$ which is a maxima chain.

Many different cases could appear during this process: if there is only one maxima in the next scale the choice is easy. If there is many maxima in the next scale, the choice is ambiguous and we have to define a criteria to choose between them. If there is no maxima the chain stop at the correspondent level. We can also have a fusion between two or more maxima chains. Figure 1 illustrates the maintenance, the fusion and the disappearance of a chain.

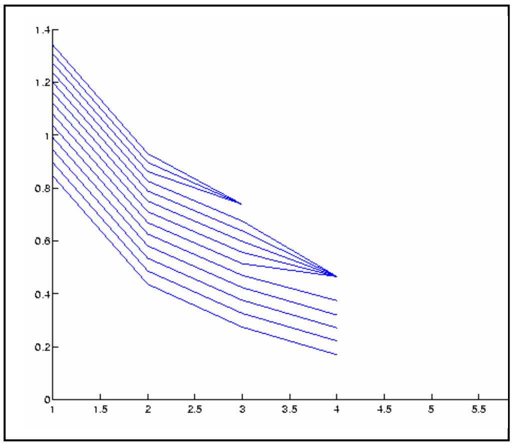


Figure 1. Maxima chain : Value of the maxima

B. *Extension of Lipschitz exponent*

Initially the regularity of a signal was measure with Lipschitz exponent (signal characterization). This exponent is numerically computed with the evolution of a maxima chain across the different scale. The evolution of the value of the maxima is typically closed to an affine function. The correspondent coefficient is the Lipschitz exponent [2].

We extend the Lipschitz exponent by considering not only affine maxima chains. In fact, in real scene, the evolution of a maxima is linked to the other one present in the neighborhood. The evolution function of a maxima is no more affine and we could not reduce the characterization of a signal to the expression of the Lipschitz exponent. Figure 2. illustrate different maxima chains.

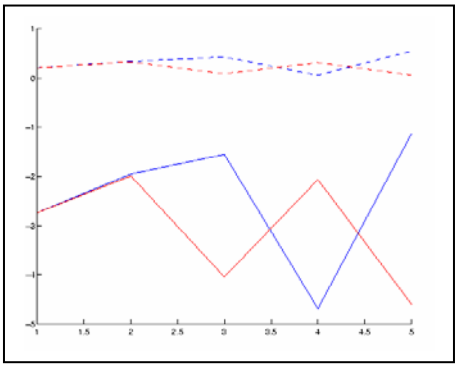


Figure 2. Non standard maxima chains

The extension of the Lipschitz exponent is made by integrating all the characteristics of a chain: the position (x_i,y_i) and the value of the maxima at the different scales; the evolution across the scales (fusion, stop, …).

The construction of the chain is also revisited. In fact, we integrate the neighborhood and the evolution of other maxima chain to choose the successor of the current maxima. This step is necessary to choose between many potential successors and to control (guide or avoid) the fusion of maxima chains [5].

C. *Classification*

The classification process is applied to the set of maxima chains. All characteristics are used to guide the classification.

Two kind of classification could be used: supervised and not supervised.

The choice of the method is linked to the information we have about the scene and to the object we want to detect.

If we know an object is present in the image and if we have a representative maxima chain we can use it as a sample for a supervised classification. The class we obtain depends on many parameters. The information given by the sample are: the evolution of the maxima value and the position across the scales. The behavior (fusion, …) of the chain.

We can regroup chains based on the value and/or the position in the image and/or the behavior. Figure 3 shows the result of a two-step classification. First step a classification based on the behavior (same shape of the curve). Second step a classification based on the value.

Same kind of evolution but with different value: same kind of structure, fusion or not: difference of size compare to neighbor structures, different position: different location in the image, aspiration to other structure,

Some tolerance threshold must

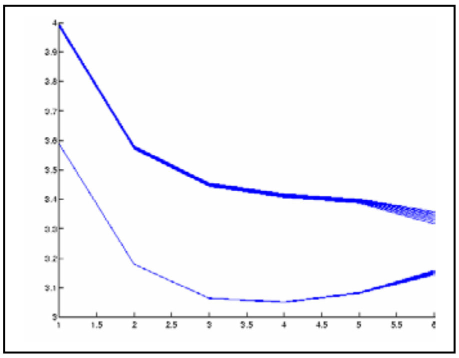


Figure 3. Classification

III. SEGMENTATION PHASE

Let us consider that a maxima of the details image modulus is a part of an edge.

During the segmentation phase, we have to extract edges from object contours and to close this contour.

The way we choose is to use the classification to reject unwanted edges. The information extract from the classification are not only linked to the kind of structure. In fact, an object won't have the same behavior across scales whereas it is isolated in the image or near other objects. For example, if we want to detect closed objects, we will look at the fusion between different kinds of maxima chains. If we are looking for small objects, we will be interested on short maxima chains (chains that disappear before last scale).

In our experimentation we focus on the most important structures and reject small ones. We also try to select particular structures to prepare pattern recognition phase.

After having selected the maxima chains, we have to close the contour. The selection regroup maxima belonging to the same object and we try to find a path that links all this maxima.

If we consider that all the points of a contour are represented by a maxima chain and that all the maxima chain of an object are regrouped in the same class we can wonder why it is necessary to close the path.

The reason is linked to the interactions between objects that modify the composition of the classes. A class will be composed of the most representative object samples. This samples represent a small ratio of the whole contour and.

To close the contour we have to explore the maxima chains by exploiting the localization information they are containing. We apply an optimization process to guide the selection and the construction of the closed contour.

IV. PATTERN RECOGNITION PHASE

Now let us consider that each remaining maxima belong to the contour of the same object (the contour has been closed). A characterization of the entire object is possible by integrating all the maxima chains.
This characterization is useful for pattern recognition. We use a knowledge database containing the characterization of objects potentially present in the scene. Those objects are typical and have been characterized in an isolated context.
After the segmentation process each characterized object is compared to the database and affected to one of the sample.

V. APPLICATION AND RESULT

This algorithm has been applied to both radar and optical (synthesis) images. We present the results obtained with synthesis image. Figure 4 present an image composed of five different objects. Each of them is made of different kind of transition (i.e. different kind of signals): a Dirac, a mexican hat, a low and a high frequency sinusoidal and a step.
This application is not really an object detection case but more a signal characterization. Other application could be presented with object detection and classification but the base of this work is to take advantage of the object structure (the kind of transition, that is to say the kind of signal) to characterize it.

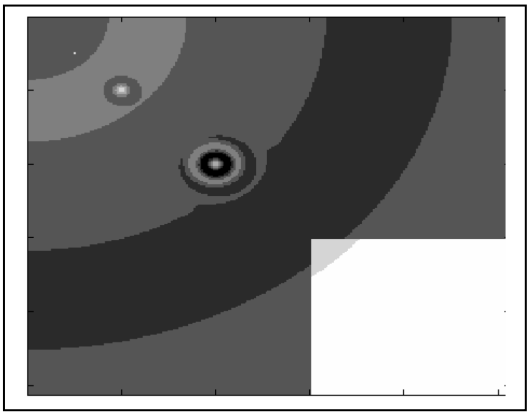
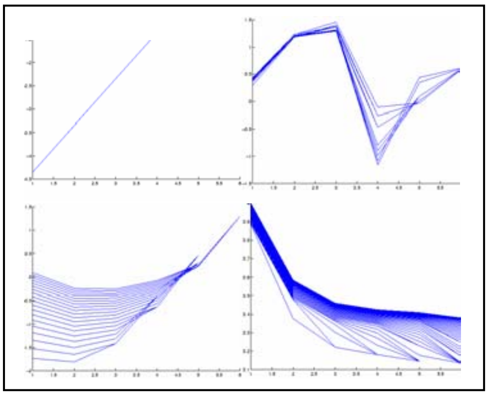


Figure 4. Synthesis image

Figure 5. Classification



The classification is presented in Figure 5: upper-left: the Dirac; upper-right: the Mexican hat; lower-left: the high frequency sinusoidal; lower right: the step.
After this classification, we can easily localize the object.

VI. PERSPECTIVE AND CONCLUSION

Currently, the results are not so satisfying for all the phases. The construction and the classification of the maxima chains are satisfying and allow the separation of objects: maxima chains regroup in the same class represent the same object.
The closing of the contour is less enjoying. The current optimization process is a local search without any specific development. The results are quite satisfying if we consider separated objects or a small object partially recovered by a biggest one. The worst case appears with to object with the same nature and quite the same size. To improve the optimization process used to close the contour of an object we will now use different techniques such as snakes and genetic algorithm.

Best performances are obtained with synthesis images. This result is linked to the speckle and avoids the treatment of points from the same edge separately.
According to this study (synthesis images, accurate knowledge database, separated objects, …) the statistics on object detection and classification reach a very satisfying ratio.

VII. ACKNOWLEDGMENT

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