Multiresolution approach for image processing

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Abstract

Multiresolution approaches provide a powerful tool for image processing. In this report,we propose an overview of different types of multiresolution. We show this methodology is composed of two main complementary steps, the bottom-up and the top-down strategies. We also present some important existing applications like filtering and features extraction. Finally, a brief comparison of the different techniques is given and some new interesting possible use of this tool are exhibited.

1 Introduction

Image processing is an important and huge research domain. For several years, a lot of studies have been done on image analysis and image understanding. One approach which has shown very interesting results is the multiresolution. To handle processing like filtering and features extraction, it has been proved that it cannot be efficiently done just by using the initial image resolution. In most of the cases, pyramidal schemes are used to implement this strategy. In this report, we propose an overview of different types of multiresolution and the most important fields of application.

In the next section, we describe a signal based methodology which treats the image in a regular way. Section 3 deals with the graph based approach doing an irregular treatment which allows a more semantic oriented analysis. In section 4 we show some important applications and we propose other possible applications of this tool in section 5. Finally, we conclude over the interest and efficiency of multiresolution.

2 Signal based treatments

The signal based treatments are very usefull to filter and extract features of images. The two predominant ways to do these operations with this technique are the Gaussian and Laplacian filters [3]. We describe these operators in the following paragraphs.

2.1 Gaussian filter

This type of operator is used to perform smoothing or bluring on images. Smoothing an image eliminate the noise and allows to have a more simple and more regular subsequent processing. Moreover, image features can be extracted by adjusting the amount of smoothing at different levels (features occur at different spatial scales).

There are two techniques for the Gaussian multiresolution. The first one is the space scale representation. The second one is a pyramidal representation. These two methods are described in the following paragraphs.

2.1.1 Space scale representation

To construct a series of images at different levels of space scale, we use variable kernel sizes to do the convolution but the image size stays constant like in [3]. To control the kernel size, a *scale parameter* σ is used :

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

Figure 1: Gaussian smoothed versions of a zebra using increasing kernel size

Figure 1 shows different images computed by increasing the kernel size. The interest of such a method is that we compute a level directly from the initial image with only one parameter, thus we do not need to calculate the intermediate levels.

2.1.2 Pyramidal representation

In the previous method, as the kernel scale increases, the bandlimit of the image decreases. Thus, we can reduce the image size proportionnaly to this bandlimit reduction without loosing any information. So, we obtain what we call a *Gaussian Pyramid*.

Each level of the pyramid is half the size of its predecessor and also has a bandlimit one octave lower. An exemple of such a pyramid is given in figure 2.

Moreover, this pyramid is regular since we have regular links between the pixels of two consecutive images.

One of the most important properties of this filter consists in the fact it is the only one which does not create zero-crossings of the Laplacian of an image as the filter size increases. This is very important for contour extraction for exemple since the zero-crossings represent the frontiers between areas of different brightness.

2.2 Laplacian filter

We use the Laplacian filter to detect spatial changes in brightness. This allows to find edges in an image by tracking the zero-crossings of the Laplacian. By combining the Laplacian with the Gaussian filter, we obtain the operator:

$$\nabla^2 G(x,y) = \frac{1}{\pi\sigma^4}\left[\frac{x^2+y^2}{2\sigma^2} - 1\right] e^{-\frac{x^2+y^2}{2\sigma^2}}$$

As for the Gaussian filter, we can construct a *Laplacian Pyramid* to detect edges at various scales (see figure 2). The interest of the multiscale edge detection has been shown several years ago. In the next paragaph, we explain how to construct such a pyramid.

Pyramidal representation

There are different ways to construct it. For example, the Gaussian pyramid can be used. Each level of the Laplacian pyramid is computed by applying the Laplacian operator to the corresponding level in the Gaussian pyramid. Another way is to compute each level directly from the initial image by modifying the σ parameter (this is a space scale representation [2]. Finally, an efficient method is to compute each level as the difference of two consecutive Gaussian levels. Since the levels of the Gaussian pyramid are not of the same size, to compute the difference between two levels, we have to expand the smallest image to the

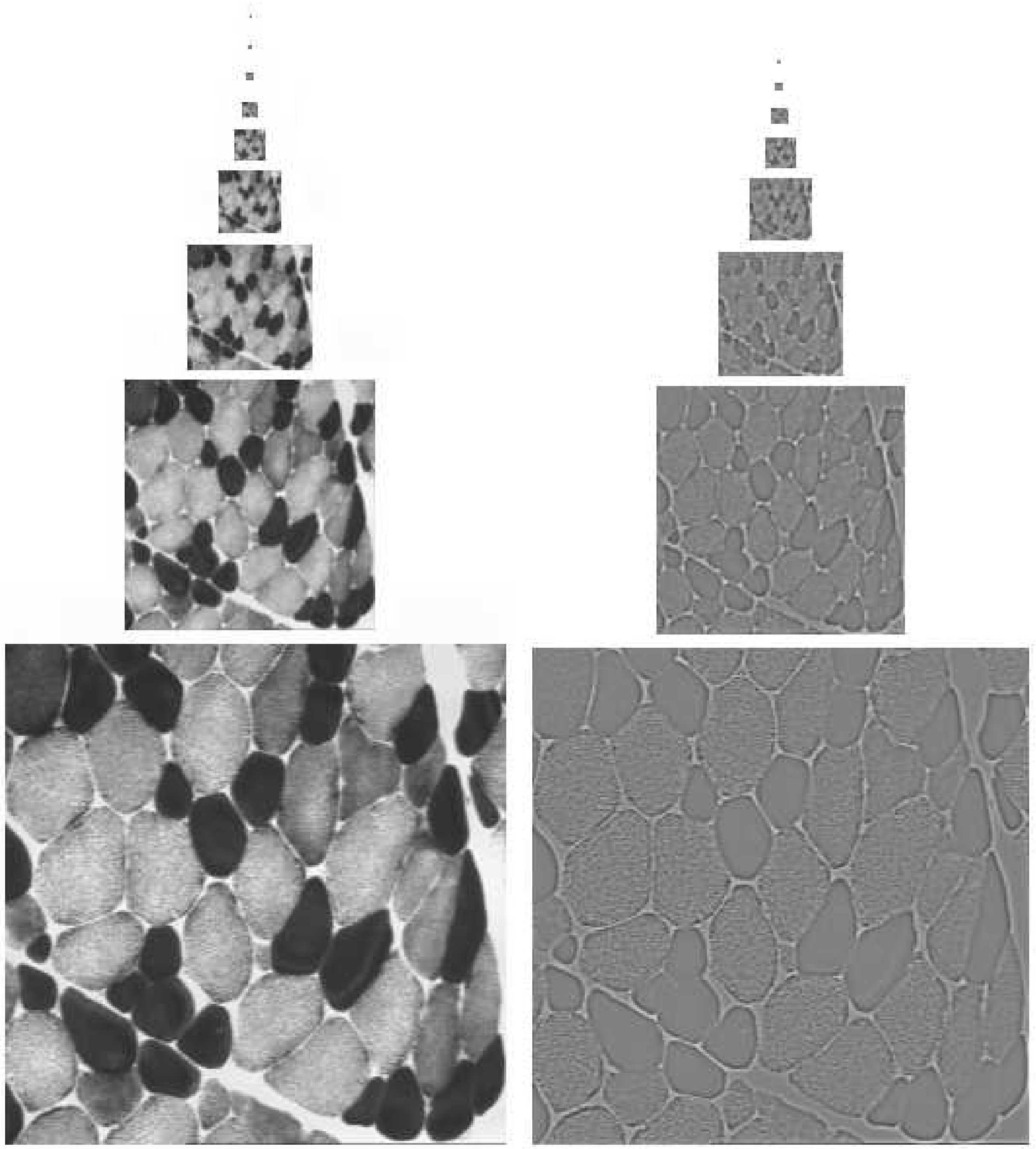

Figure 2: Exemple of a Gaussian pyramid (on the left) and a Laplacian pyramid (on the right)

size of the biggest one. This works well since the physical edges of interest can be found at several scales of smoothing, so the difference between two different scales smoothed images will mark these edges.

Here again, we have a regular pyramid since the links are regular between the levels. The main problem with these regular pyramids is that they are not image-content guided. All the treatments are systematic. Thus, to have an image-content guided process, we can use irregular pyramids with graph based treatments.

3 Graph based treatments

To make a global efficient interpretation of an image, we need to use a local evidence accumulation. This cannot be done with regular pyramids since it is not very accurate to describe natural shapes with a set of geometrical shapes. That is why the graph based methods were developed since they are well adapted to extract shapes of natural objects.
Among the existing pyramids, there are two interesting approaches, a stochastic one and an adaptative one [5]. We describe these methods in the two following sections.

3.1 Stochastic pyramid

We consider here, cells rather than pixels althought in the first step, they are the same. The process is then to decimate some cells and to attach them to the surviving cells from one level to the other. By this way, we obtain a parallel region growing algorithm.
We need two graphs to generate the pyramid:

- an adjacency graph;
- a similarity graph.

The first one represents the spatial interconnections of the cells. The vertices are the cells (the pixels at the first step) and each edge represents a spatial connectivity between two cells. Thus, at the first level, this graph is a regular grid depicted by the image structure.

The second one shows the relative similarity of neighboring cells in the adjancy graph. The vertices are the cells and each edge indicates that the two cells (connected by this edge) are similar according to a given criterion.
The decimation process is then given by the following rules:

- if a cell survives, its neighbors, in the similarity graph, cannot survive;
- if a cell does not survive, it must be at least one cell in its neighborhood, in the similarity graph, which survives.

Another problem is the selection of the surviving cells. In the case of the stochastic pyramid, each cell is associated with a random number, and we choose the local maxima. Once this is done, we attach the non-surviving cells to the surviving ones using the similarity graph. Hence, for a cell at a given level, it corresponds a set of cells (pixels) at the previous level, this set is called the *receptive field*. Figure 3 shows an exemple of an adjancy graph pyramid and its associated receptive fields pyramid.

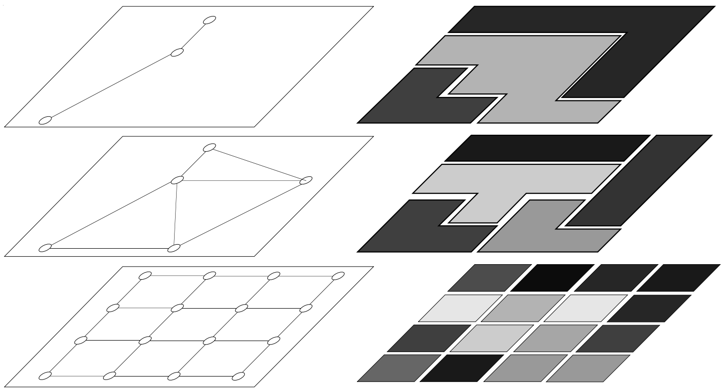

Figure 3: Correspondance between adjancy graph and receptive fields

Because of the random process, we may have different results for a same data. We can then, compare them in order to detect the most occuring cells. We can assume these cells have a strong probability to be semantically representative and therefore, also the objects (recepting fields) they describe.

3.2 Adaptive pyramid

In this approach, we do not use a similarity graph for the decimation. The selection of the surviving cells is done according to the adjacency graph and using an interest operator which is often the homogeneity. Thus, we choose the cells representing the local maximas of homogeneity to survive. The non-surviving cells are then attached to their most similar neighbor.

4 Existing applications

We have seen in section 2 some of the most important applications for the Gaussian and Laplacian pyramids. There are:

- noise elimination;
- feature extraction;

- segmentation by contour extraction.
- shape description [7].

For Gaussian and Laplacian pyramids, rationnal reduction ratios can also be obtained using special filters [6].
Concerning the stochastic and adaptive pyramids, the typical applications are segmentation by tesselations, object detection and connected component extraction.
We cannot detail all of these applications but we briefly describe here the hierarchical tesselations since it a good exemple of the use of irregular pyramids in multiresolution.

Exemple of mulitresolution process with hierarchical tesselations

The goal of this application is to segment an image at different resolutions according to its content [1]. To do that, we use an irregular pyramid but this is not sufficient since we obtain the multiresolution just in the higher levels. Indeed, once the pyramid is constructed, we need another step which is a top-down process.

The top-down process lies on the fact a pyramid can be seen as a tree from the roots (top of the pyramid) to the leaves (pixels of the original image). If we keep all the levels of the pyramid, we can split each region of any level (excepted the base of the pyramid) into sub-regions. We can then make a tesselation starting from the apex and using an homogeneity criterion, a threshold and the same split process as for the Quadtree structure until each region verifies the given criterion. This approach is recursive but can be transformed in an iterative algorithm in order to reach real time computation.

5 Other possible applications

In this section, we give a little comparison of the different techniques seen and some new ideas of using the multiresolution techniques.

The main difference which appears between the signal treatments and the graph based methods is the image-content oriented process. Moreover, we can say the first approach is a low-level analysis whereas the second approach is high-level, that is to say more semantically oriented. Concerning the irregular pyramids, some experiments [5] showed the stochastic pyramid needs less iterations than the adaptive one. Nevertheless, the adaptive pyramid is better suited to detection and delineation.

Dealing with the applications, there are a lot of domains where we can use this tool. For exemple, to retreive an image in a database, we can use a selective algorithm working at different levels of resolution. We start from the top of the pyramid and then we select, among the candidates (images of the database) of the current level, the possible candidates for the following level using a similarity function.

Another interesting application could be the pattern matching of stereo images for 3D reconstruction since this tool seems well adapted to the features extraction and location. We can begin to match the images at the top of the two corresponding pyramids and then refine the matching by going down to the bases.

Of course, we could probably find many more applications with a deeper study.

6 Conclusion

Different multiresolution approaches have been viewed. The distinction between the signal and graph based strategies has been pointed out. All these techniques show very interesting properties which make them appropriate tools for image processing topics like feature extraction, contour and edge detection, object extraction and also segmentation. Nevertheless, to get a complete multiresolution tool, the alone bottom-up approach is not sufficient, a top-down process adapted to the desired application is required. These techniques have also the advantage to allow a parallelization and then to reduce the computation times of the corresponding applications. In regard to the efficiency of this tool and all the advantages it presents, we can say that multiresolution is very promising and the field of its applications seems to be very extensive and various.

References

[1] P. Bertolino and A. Montanvert. Multiresolution segmentation using the irregular pyramid. In *IEEE ICIP*, Lausanne, Switzerland, September 16-19 1996. To be published.

[2] P.J. Burt and E.H. Adelson. The laplacian pyramid as a compact image code. *IEEE Transactions on Communications*, COM-31:532–540, 1983.

[3] C.R. Dyer. Multiscale image understanding. In Leonard Uhr, editor, *Parallel Computer Vision*, pages 171–213. Academic Press, Inc, Orlando, Florida, 1987.

[4] D. W. Egger, C. R. Dyer, K. W. Bowyer, and H. I. Christensen. The scale space aspect graph. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 15(12):1114–1130, November 1993.

[5] J.M. Jolion and A. Montanvert. The adaptive pyramid: a framework for 2d image analysis. *Computer Vision, Graphics and Image Processing*, 55(3):339–348, May 1992.

[6] M. G. Kim. A prototype filter design approach to pyramid generation. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 15(12):1233–1240, December 1993.

[7] G. Sopiro and A. Tannenbaun. Area and length preserving geometry invariant scale-space. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 17(1):67–72, January 1995.