Data fusion by segmentation. Application to texture discrimination.

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Nous présentons un algorithme de segmentation multi-canaux qui est déduit de la fonctionnelle de Mumford et Shah. La méthode est un algorithme de croissance sur une image "vectorielle". Les applications présentées sont la discrimination de textures et la détection d'objets sur fond naturel.

We present a multichannel segmentation algorithm which is related to the Mumford and Shah functional. The method we use is a region growing applied on a vector valued picture. Applications which are presented include texture discrimination and decluttering (removal of background textures).

1 Introduction.

Image processors today are often presented with multiple data for the same scene, obtained using various sensors. Typical examples include satellite pictures using multispectral data or medical data such as MR images. It thus seems quite natural to include this information in image processing algorithms. This not only should improve analysis of the data but should also help to obtain more stable algorithms since there is more information available.

Another way to obtain multichannel input is by preprocessing a textured picture. Indeed in order to characterize textures the common method is to get information about orientation, terminators, corners and so on.

We present a multidimensional segmentation algorithm which has been presented in [KMS] for the gray-level case. This note completes the description of the possibilities of the simple segmentation model given by the Mumford and Shah functional (see [MS]) and the corresponding region growing algorithm. The outline is as follows, in the next section we briefly present the mathematical model and the algorithm in the multichannel case. In section 3 we discuss the application to texture discrimination and in section 4 we present some results in object detection developed at Cognitech Inc.

2 Mathematical model and algorithm.

We consider the following, simplified Mumford and Shah functional

$$E(K) = \int_{\Omega\setminus K} ||u-g||^2 dxdy + \lambda \ell(K)$$

here g is a vector valued function, whose components are the different channels, defined on the rectangle Ω, u is the piecewise constant approximating vector function, and K is the set of boundaries with total length $\ell(K)$. When g is scalar the norm $||.||$ is just the absolute value. For multichannel data a weighted norm $||.||$ is used. It is specific to each application and to the importance the user wants to give to each of them.

Typically an energy normalization is done in some of the presented algorithms. As we shall note in section 3 this is a very important point in real applications.

It has been shown (see [KLM]) that the minimization of the above energy can be related to region growing methods. The decision to proceed to a merging of two regions O_i and O_j depends on the sign of

$$E(K \setminus \partial(O_i, O_j)) - E(K)$$

The algorithm looks for a decrease of the global energy by merging those regions. This is the criterion of 2-normal segmentations introduced in [KMS]. Indeed the set of these segmentations verifies a compactness property and the minimum obtained in this class of segmentations verifies a priori estimates on the size of the regions.

The explicit form of the merging criterion is the following

$$E(K \setminus \partial(O_i, O_j)) - E(K) =$$

$$\frac{|O_i|\cdot|O_j|}{|O_i|+|O_j|}\cdot ||u_i-u_j||^2 - \lambda\cdot\ell(\partial(O_i,O_j))$$

Suppose $g = {}^t(g^1, \ldots, g^n)$, then to each region O we associate n channels, i.e. g restricted to O. These yield the values for u on O : $u_O = {}^t(u_O^1, \ldots, u_O^n)$ by simply computing the mean value of each g^l over O.

More details about the algorithm can be found in [KLM]. Finally note that the algorithm is pyramidal and is very fast, just as the scalar/grey level version. The range of execution time goes from 10 seconds for a 512 by 512 grey level segmentation to 6 minutes (including preprocessing) for multichannel segmentation as presented below (execution time obtained on Cognitech's workstations).

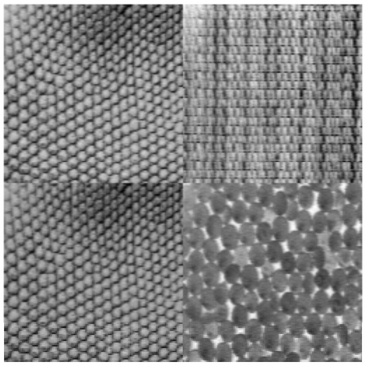

Figure 1: Three different Brodatz textures.

3 Texture discrimination.

Let us first consider the classical **Brodatz textures** (see figure 1 and [B]). These sort of textures are well discriminated by a wavelet transform, indeed most of the channels introduced by the algorithms of [MP, VP, BCG, U] are linear operators which, according to the Wavelet theory, can be computed at each scale in linear time by a pyramidal scheme.
The initial datum for the experiments related below is given in our experiments by an oversampled Haar-Wavelet transform of the picture g. More precisely the image is convolved with a bank of linear filters F_k, followed by half-wave rectification.

$$R_{2k} = (g \star F_k)^+ (x, y) \ \ ; \ \ R_{2k+1} = (g \star F_k)^- (x, y)$$

It should be noticed that all the filters F_k are of zero mean and separable:

$$\begin{aligned} H_a^1(x,y) &= \chi_{[-a,a]}(x) \left(\chi_{[0,a]}(y) - \chi_{[-a,o]}(y)\right) \\ H_a^2(x,y) &= \chi_{[-a,a]}(y) \left(\chi_{[0,a]}(x) - \chi_{[-a.0]}(x)\right) \\ H_a^3(x,y) &= \left(\chi_{[0,a]}(x) - \chi_{[-a,o]}(x)\right) \left(\chi_{[0,a]}(y) - \chi_{[-a,o]}(y)\right) \end{aligned}$$

where χ is the characteristic function on $I\!R$ and $a = 2^j$, $1 \leq j \leq J$, J is the decomposition order of the analysis.
The R_is are then filtered by Gaussians in order to obtain texton densities. The size of these Gaussians corresponds to the "Δ-neighbourhoods" of Julesz. Finally we obtain the components of our initial datum as the filtered versions of the R_i channels.

The aim of this experience was to check the discriminating power of wavelets. If the discrimination is successful (i.e the three regions correspond to the textures' location) one can say that the used channels are able to discriminate the given textures (it is important to notice that we don't use the grey-channel information).

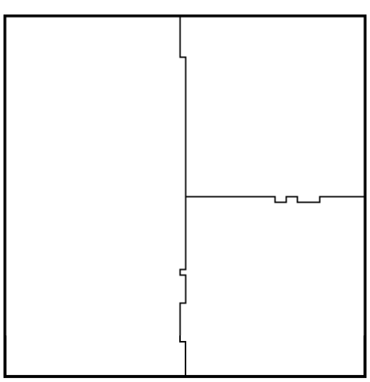

Figure 2: Result of the segmentation.

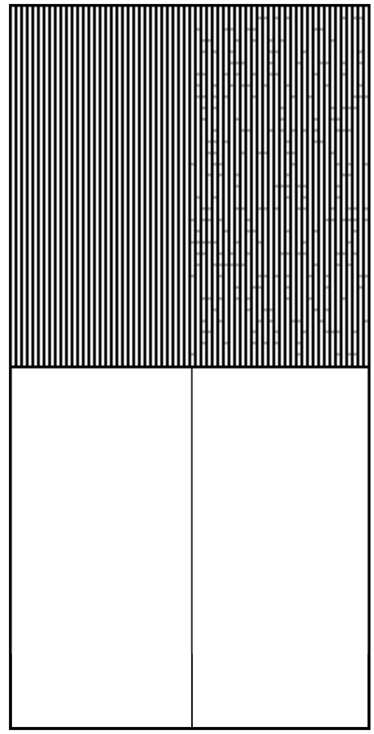

Figure 3: In the upper part are shown the two textures and in the lower part the boundary between the two textures.

In figure 3 we have a synthetic image which illustrates the need to keep all the channels involved in the discrimination process. Indeed most texture analysis devices [BCG, MP, VP] tend to base it on the dominant channel. If the dominant channel is the same in the two regions, no discrimination is possible. It is important to notice that a variational method yields an easy formalization for segmentation based on non-necessary dominant channels. This experiment illustrates the power of the algorithm for discrimination based on nondominant channels.

In order to be able to discriminate **Julesz textures** one has to use other preprocessing techniques. These are explained in [LM], let us just say that the input data is now a multiscale curvature map of the original picture. Using the same technique as above we obtain for the example the result shown in figure 4 (see also the corresponding paper by Lopez and Morel in these pages).

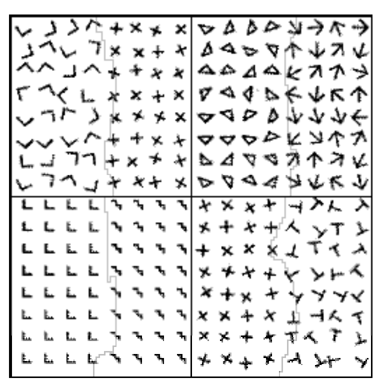

Figure 4: Four examples of Julesz texture discrimination.

Figure 5: Original IPI data base picture: Tank with textured background.

Figure 6: Reconstruction using grey-level segmentation.

4 Clutter removing

This application has been developed at `Cognitech Inc.`, Santa Monica, using still the same multichannel segmentation algorithm. A single gray scale channel segmentation of figure 5 is compared to the segmentation based on 18 wavelet channels. The number of regions was chosen in order to eliminate the grassy background and just keep the object, in this case a tank.

If we use gray level segmentation, it turns out that the object will be eliminated before the background. The reconstruction of figure 6 is obtained by stopping the merging at three remaining regions, the next step would be merging of the tank with its background. This picture shows also that, unfortunately, most of the tank's features are gone. Only gross scale outline features were preserved. This is typical of the difficulties found using clutter removal with only a single channel analysis.

Figure 7: Result of the "declutter" algorithm.

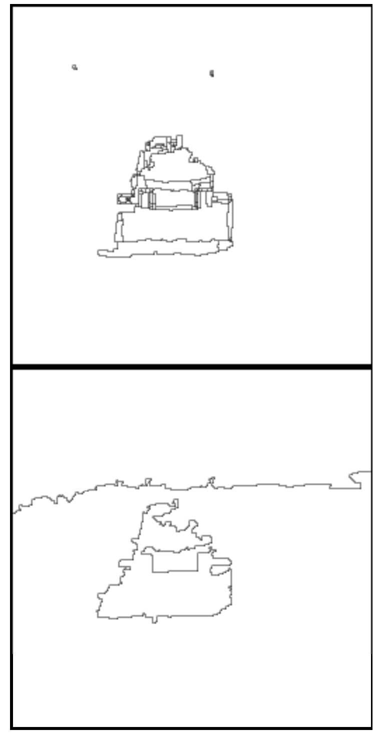

Figure 8: Comparison of the two boundary sets.

In contrast the Haar basis wavelet decomposition basically as described in section 3 above, yields 18 texture/feature channels. Remarkable reconstruction and simultaneous background clutter removal is presented in figure 7. Here the piecewise constant approximations of the channels are used to reconstruct the original picture.

Figure 8 shows in the upper part the boundary obtained using the multidimensional segmentation and below a result you can expect using gray scale segmentation on this kind of pictures.

5 Conclusion.

Other applications developed but not included in this text involve medical data such as MR images taken under different protocols (proton, T2, ...) which give complementary physiological and anatomical information in brain images (see [M]).

We showed how a simple algorithm for grey level segmentation gives an easy to use tool for multidimensional data segmentation. The only parameter for segmentation is the scale parameter, the applications define the respective weights of the channels. This approach is validated by the multiple applications which have been found to the basic algorithm.

References

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