How to Compensate the Effect of using an Incomplete Wavelet Base for Reconstructing an Image?
Application in Psychovisual Experiment

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Abstract: One way in psychovisual experiment to understand human visual system is to analyze separately contents of different spatial frequency bands. To prepare images for this purpose, we proceed to a decomposition of the original image by a wavelet transform centered on selected scales. The wavelets used are Difference Of Gaussians (DOG) according to works modeling the human visual system. Before rebuilding the visual stimulus, various transformations can be performed on different scales to measure the efficiency of the observer, for a given task, according to the spatial frequencies used. The problem is that if we use an incomplete wavelet basis during decomposition, there is a significant loss of information between the original image and the reconstructed image. The work presented here offers a way to solve this problem by using coefficients appropriate for each scale during the decomposition step.

1 INTRODUCTION

In psychovisual experiment we have to present a lot of images to observers in order to understand how visual human system working. The interest is to understand which information is helpful for performing a task as pattern recognition, distance computation, categorization…. Objects present in the scene are shown on different background. To construct the psychovisual stimuli we normalize images and we perform a wavelet decomposition of the images to analyze, scale by scale, the observers answer. Some experimentations have been done in order to analyze visage perception (Gosselin, 2001) or spatial frequencies influence on pattern recognition capacity in complex environment (Giraudet, 2001); (Kihara, 2010). All these experiences and some other data obtained from electrophysiological measures in macaque cortex (Wilson, 1983) lead researchers to assume that it is possible to describe the human visual system with only a four or six frequencies channel.

The aim of this paper is to propose a method to compensate the loss of information during image reconstruction for a psychovisual experiment, if the initial image decomposition has been made with few scales, as the human visual system works.

The first part of this paper explains the choice of Difference Of Gaussians (DOG) as wavelet functions in the decomposition stage and the problem when using an incomplete set of wavelets, i.e. the loss of information problem which occurs in the reconstruction step. We explain then the proposal method to reduce this effect. The fourth part is dedicated to comparative results to show how the proposal approach reduces the explained problem. Conclusion and some future works are given to finish.

2 POSITION OF THE PROBLEM

Enroth-Cugell and Robson (Enroth-Cugell, 1966) showed that the responses of the retinal ganglion cells were type "on / off" or “off/on”, the incoming signal on the central part being compared with the signal arriving on the periphery of cells. This comparison would be modeling by a DOG. Later, models of human vision have been developed using this type of function and applied to images, to validate this concept (Watson, 2005). In spatial plane (x,y), or image plane, the DOG is given by equation (1).

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$$\mathrm{DOG}(x,y) = (C_1 e^{-\left(\frac{x^2+y^2}{2\pi a^2}\right)} - C_2 e^{-\left(\frac{x^2+y^2}{2\pi a^2 \sigma^2}\right)} \quad (1)$$

In this equation, (x,y) are the pixel coordinates in the spatial plane, a is the scale of the DOG, C_1=1.8 and C_2=0.8 in order to obtain that the Fourier transform of the DOG is equal to zero for u=v=0 in the frequency plane and σ is equal to 2.25 (Schor 1983). The Fourier transform of a DOG is another DOG, here called DOGTF, which is given by (2).

$$\mathrm{DOGTF}(u,v) = e^{-2(\pi a)^2\left(\frac{u^2+v^2}{M^2}\right)} - e^{-2\left(\frac{(\pi a)^2}{\sigma^2}\right)\left(\frac{u^2+v^2}{M^2}\right)} \quad (2)$$

In this equation, (u,v) are the frequency coordinates and M is the number of lines (or columns) of the image. Theoretically, when we reconstruct an image by using its wavelets decomposition (Mallat, 1998), final and original image would be the same. This is partially true, if we use all the available wavelets. Figure 1 illustrates this situation. Scale of DOG is ∊ [0.125, 256], related to the size M of image (here we put down M= 512). When minimum value is fixed (SCALEINI) and total number of wavelets (NBW) too, scale value "a" for the wavelet rank "i" is obtained by using equation (3).

$$a = \mathrm{SCALEINI} \times 2^{i-1} \quad (3)$$

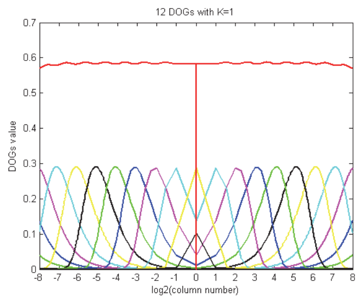

Figure 1: Twelve wavelets and their sum in red.

The DOG value (y axis) is presented related to the binary logarithm of the vertical pixel position (column number) as it is following defined (4).

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       With M2=M/2 and u=M2
if v< M2 ➔ abscissa=-log2(M2-v)
if v> M2 ➔ abscissa= log2(v-M2)        (4)
       if v= M2 ➔ abscissa=-0
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As you can see on figure 1, sum of all the wavelets is not equal to one. Then, previous work (Plantier, 1992) proposes to use the equation (5) with K=1.7. With this equation, the sum of all the wavelets is equal to 1 on almost all space.

$$\mathrm{DOGTF}_i(u,v) = K(e^{-2(\pi a)^2\left(\frac{u^2+v^2}{M^2}\right)} - e^{-2\left(\frac{(\pi a)^2}{\sigma^2}\right)\left(\frac{u^2+v^2}{M^2}\right)}) \quad (5)$$

But if we use an incomplete set of wavelets to reconstruct the image, there is a loss of information for the frequencies not, or weakly, used by the wavelets during image decomposition. These situations are illustrated on figure 2. We use only six DOGs with scale ∊ [1, 32]. So, in comparison with figure 1, three wavelets are suppressed in high frequencies (scales 0.125, 0.25 and 0.5) and three wavelets are suppressed too in low frequencies (scales 64, 128 and 256). Figure 2 shows the situation, when the DOGs are computed with equation (5) with t K=1.7, sum of wavelets is closer to one, but only in a limited area. To conclude, if we want to simulate an image, by using only frequencies channel related to the human visual system, as it is previously described with scales ∊ [1, 32], we have to found how is it possible to compensate this loss of information.

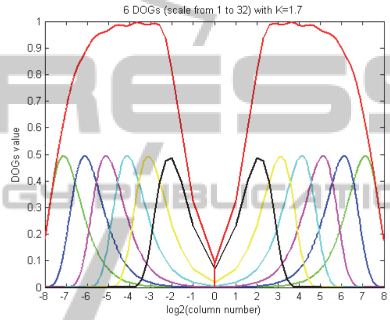


Figure 2: Six wavelets and their sum in red.

3 PROPOSAL METHOD

To solve this problem, we propose to make a weighted sum of all the wavelets. So we must give a value to each coefficient Ki as illustrated on the equation (6).

$$\mathrm{SDOG}(u,v) = \sum_{i=1}^{NBW} K_i \times \mathrm{DOGTF}_i\,(u,v) \quad (6)$$

To find the value of each K_i, we solve an equation system with as much unknowns as wavelets we use to decompose the image. We work on one dimension (u=0) and we use the symmetry of the wavelets. For each value "v" leading to a maximum value of one of the wavelets, called "$vmax_a$" with "a" the wavelet scale, we put down the equation (7).

$$\sum_{i=1}^{NBW} K_i \times \mathrm{DOGTF}_i\,(0, vmax_a) = \mathrm{Sol}(a) \quad (7)$$

Sol(a) is the value requested for the sum of wavelets at the position "$vmax_a$". When all the values "$vmax_a$" have been found, we have the equation system to solve. In a first time we put down, Sol(a)=1, ∀a. With these solutions, sum of wavelets

Table 1: Coefficient values obtained with Sol(a)=1, ∀a and optimal solution.

NBW=6 - Size of image: 512x512 -SCALEINI=1						
Scales: value and color	***a=1 (green)***	***a=2 (blue)***	***a=4 (magenta)***	***a=8 (cyan)***	***a=16 (yellow)***	***a=32 (black)***
Sol(a)	**1,00**	**1,00**	**1,00**	**1,00**	**1,00**	**1,00**
Coefficient values	**3,11**	**1,33**	**1,79**	**1,75**	**1,55**	**1,70**
Sol(a)	**0,95**	**0,97**	**0,99**	**0,97**	**0,90**	**1,00**
Ki coefficients	**2,94**	**1,31**	**1,79**	**1,74**	**1,25**	**2,25**

is over “1”, for a lot of value of “v” as we can see on figure 3. Correspondent Ki values are given in table 1. If we are over the value “1”, the reconstructed image will be, for some frequencies different than the original image. The goal of this work is to obtain a reconstructed image as closer as possible to the original image. To obtain a correct solution, we perform an iterative resolution under two constraints which are given by (8) and (9).

$$\sum_{i=1}^{NBW} K_i \times DOGTF_i\,(0,v) \le th \quad \forall v \qquad (8)$$

$$\sum_{v=0}^{M2} \left(1 - \sum_{i=1}^{NBW} K_i \times DOGTF_i\,(0,v)\right) \to 0 \qquad (9)$$

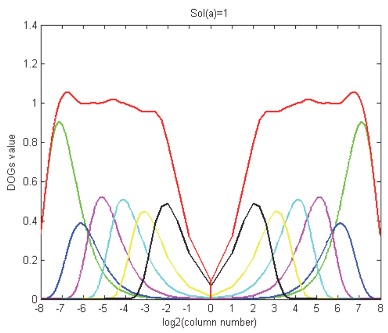


Figure 3: Six wavelets and their sum with Sol(a)=1 ∀a.

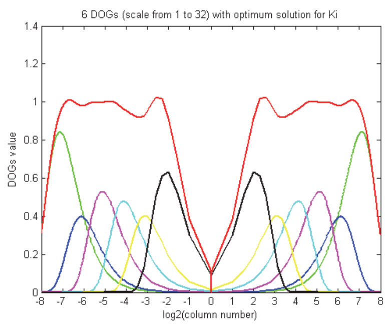


Figure 4: Wavelets and their sum for optimal Ki values.

So we compute 9000000 of iterations, with different values of Sol(a) bounded by “0.8” and “1”. The threshold th is set to 1.01. Around 85% of possible solutions lead to a result of the equation (8) up to the fixed threshold. To finish we obtain the Ki coefficients given in table 1, with a gap as defined in equation (9) equal to 0.0171. On figure 4 we show the case for six wavelets. Sum of wavelets is more regular and closer to “1” than in previously solutions. A last interesting result is that Ki coefficients obtained are almost constant for a given number of DOGs, whatever are the size of original image and the initial scale.

4 DISCUSSION

To evaluate the interest of these coefficients, we first present some visual results on a natural image (figure 5a) and its reconstructions (figure 5b and 5c). Figure 6a and 6b display the difference between, original and reconstructed images from figure 5. To finish figures 6c and 6d illustrate edges detection computed on the difference images with the Matllab function called “Canny”. Figures 5b and 5c give a good representation of original image with a slight lack of contrast, as standard deviation values (STD see table 2), illustrate it. STD is less important in reconstructed images, and this drop is more marked when we use the only coefficient K=1.7.

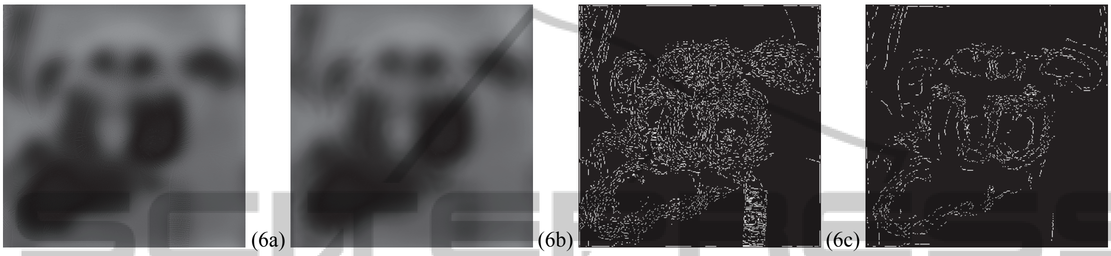
Table 2: STD and percentage of edge points in difference images from original and reconstructed images.

	Original image	Reconstruction with K=1,7	Reconstruction with different Ki
STD measure	52,97	24,65	26,71
% of Edges in Difference image		9,71%	4,13%

The images 6a and 6b are visually close, but when we see the edges obtained on these images, we notice that edge points are more present in images obtained with coefficient K=1.7 (see table 2). When we use different coefficients K_i in the decomposition step, a lot of high frequencies are preserved in

(5a) (5b) (5c)

Figure 5: 5a Original image "Ginko", size 512x512 pixels. (5b) et (5c) reconstructed images after a decomposition by five DOGs.(7b) by using only coefficient K=1.7 and (7c) by using proposal method.



(6a) (6b) (6c) (6d)

Figure 6a and 6b : Images of differences between 5a and 5b or 5c. Figures 6c and 6d: Edges of 6a and 6b.

reconstructed images, leading to reduce the edge point number in the difference images.

To finish, we compared these two methods on 150 images, from the Corel Draw database. These images are grey level converted and normalized to a size of 512² pixels. We have chosen different kind of images: outdoor scenes, animals, areas… Table 3 shows the results obtained by the two methods. During the decomposition stage, five or six DOGs have been used. As we can expect, the quality of reconstructed images grows with the number of wavelets used during the decomposition step. The results confirm the interest of our approach. With the use of Ki coefficients, we have a mean gain around 4% on the standard deviation of the reconstructed images, and edge point number in difference images have been divided by two, or more, when we use five DOGs only.

5 CONCLUSIONS

This work shows the problems of image preparation in the field of psychovisual experiment to understand the human visual system. We could show the problem using an incomplete wavelet basis during the decomposition step of the image. The proposed solution, based on assigning a special coefficient for each scale of decomposition, has proved effective in increasing the standard deviation and reducing information loss for high frequencies (edges) of the reconstructed image. Now we will use this method in the preparation of images for psychovisual experiments about perception and pattern recognition in night vision images.

Table 3: Comparison of the two reconstruction methods on 150 natural images from Corel Draw Database.

		Reconstruction with K=1,7	Reconstruction with different Ki
Original Images	Mean of STD	53,98	
5 wavelets	Mean of STD	29,26	31,43
	Mean% of edges	12,16%	4,82%
6 wavelets	Mean of STD	36,43	38,54
	Mean% of edges	14,73%	7,16%

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