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Pattern recognition using sequential matched filtering of wavelet coefficients

Roberto A. Maestre, Javier García, Carlos Ferreira

Universitat de València, Departament Interuniversitari d'Optica, C / Doctor Moliner 50, 46100 Burjassot, Spain

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Abstract

A bank of wavelets is used for pattern recognition by means of sequential filtering. Each element of the bank is matched to a different wavelet coefficient of the target. A sequential process leads to a set of correlation outputs. Post-processing by means of a fast blending method provides the final output correlation. Both computer simulations and optical experiments are presented, showing the discrimination capability for this implementation.

Keywords: Pattern recognition; Wavelet transform; Wavelet filters

1. Introduction

The field of pattern recognition has been a subject of interest in the optical community during the last thirty years. Since the first patents and experiments in the decade of 60 with incoherents correlators, there has been a great progress, but the problem is still alive owing to its intrinsic complexity. A pattern recognition process usually involves three steps. First, a preprocessing of the input target is made in order to prepare it for filtering. Later, the filtering is performed and a correlation image is obtained. Finally, some post-processing technique is carried out. Thus in the final correlation output the recognition peaks are enhanced and the possible false alarms are rejected.

Between the differents methods to perform a pattern recognition process (joint transform correlators [1], neural networks [2], feature analyzers [3], etc.) the optical coherent correlation by means of holographic filters has been extensively studied. Since the introduction by Vander Lugt of the classical matched filter (CMF) [4] many other holographic filters have been developed. The performance capabilities of these filters depend on the particular feature to be stressed. For example, the CMF has low sensitivity to additive Gaussian noise, the phase-only filter (POF) [5] yields an excellent light efficiency, the synthetic discriminant function (SDF) filter [6] allows the recognition of various targets, and so on. It is well stated that improving one performance parameter means deteriorating another one [7]. Thus the study of possible trade-offs between different parameters have become an interesting item. As a result there have been reported filters like the optimal trade-off (OT) filter [8], the minimum average correlation energy (MACE) filter [9], and so on. The use of passbands allows the improvement of the discrimination and the signal-to-noise ratio but the price is a reduction in the ligth efficiency [10,11].

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On the other hand, the wavelet transform is a subject of interest in optics and others fields as astrophysics, mechanics, geophysics, and so on. The wavelet transform allows the decomposition of a one- or two-dimensional signal into a time-frequency or a space-frequency joint representation. The signal to be analyzed is correlated with a bank of functions, called wavelets. Each of the wavelets are derived from an original mother wavelet by means of dilation and shift operations. The interest showed by the optical community can be seen in the extensive literature produced in the last years [12]. Szu et al. [13] showed the advantages of the wavelet transform over the Fourier transform and the windowed Fourier transform and considered the wavelets as a bank of Vander Lugt matched filters. Several architectures for the optical generation of the wavelet transform have been developed. Zhang et al. [14] made an optical system for performing the wavelet transform of a one-dimensional signal. An intensity-modulated wavelet mask represented as a group of bandpass filters was used to filter the incoming signal. Sheng et al. [15] implemented the wavelet transform of a one-dimensional signal using an optical multichannel correlator with a bank of matched filters encoded as optical transmittance masks. Medlovic and Konforti [16] implemented the wavelet transform of two-dimensional objects by the use of a conventional coherent correlator with a multireference matched filter. The wavelets of the bank are spatially multiplexed with different reference-beam directions. Joseph et al. [17] employed holographic recording in a photorefractive material for the implementation of a wavelet transform of two-dimensional images. The derivation of the wavelets of the bank was achieved by the use of an optical feedback loop. Stolfuss et al. [18] used coding methods of diffractive optics to transform the original complex-valued distributions of multiwavelets filters into light-efficient quantized phase-only distributions preserving the original filter functionality. Sheng et al. combined wavelet filters and classical matched filters for optical pattern recognition purposes [11]. Later, Roberge and Sheng analized the combination of wavelet filters and phase-only filter in order to increase the light efficiency of the wavelet matched filter [19] and implemented it using an on-axis optical correlator by means of a liquid-crystal television [20]. This wavelet matched filter shows improved discrimination capability with respect to the classical matched filter and improved signal-to-noise ratio with respect to the phase-only filter. Nevertheless, in order to obtain a good compromise between their performance parameters it is necessary to look for suitable scale factors of the wavelets encoded in the filter. This is not an obvious task and could be excessively time consuming.

In this paper we present a sequential approach for pattern recognition tasks based on the use of a bank of filters matched to different wavelet coefficients of the target. A subsequent post-processing of the correlations obtained with the different filters in the bank leads to a better recognition ability. As we will see later, the use of an appropiate bank of wavelets, in combination with the post-processing of the outputs correlations, eliminates the necessity of looking for suitable parameters of the wavelets for each input object to be detected and improves the recognition ability with respect to the classical matched filter (CMF), the phase-only filter (POF), the inverse filter (IF), and the previous wavelet matched filter (WMF). Section 2 recalls the wavelet transform theory. Section 3 deals with the recognition procedure. In Section 4 computer simulations are presented. Experimental results are shown in Section 5, and finally Section 6 sets out the conclusions.

2. The wavelet transform

The wavelet transform (WT) of a bidimensional function $f(x, y)$, for instance an image, is defined as the correlation between that function and a set of functions $\{h_s(x, y)\}$, called wavelets

$$W_f(a, \boldsymbol{b}; x, y) = f(x, y) * h_s(x, y). \quad (1)$$

Wavelets are generated from a mother wavelet function $h(x, y)$ as following

$$h_s(x, y) = \frac{1}{s} h\left(\frac{x - b_x}{s}, \frac{y - b_y}{s}\right), \quad (2)$$

where s is the scale parameter and $\boldsymbol{b} = (b_x, b_y)$ the translation parameter. For a function to be considered as a wavelet it must oscillate in such a way that it has zero mean. This is known as the admissible condition. The correlation with a particular daughter wavelet, for example of scale parameter s_0, is called the wavelet coefficient of scale s_0. The wavelet transform can be written in the frequency domain as [21]

$$W_f(s, \boldsymbol{b}; x, y) = s\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} F(u,v)\, H^*(su, sv) \times \exp\left[2\pi i(b_x u + b_y v)\right] \mathrm{d}x\,\mathrm{d}y, \tag{3}$$

where a capital letter indicates a Fourier transformation. As we will see below, the factor $H^*(su, sv)$ can be interpreted as a frequency filter and implemented in an optical correlator. It operates like a passband filter. When the scale parameter s varies the filter is reduced or dilated, so it is possible to work in different zones of the frequency spectrum of the image $f(x, y)$.

The particular wavelet function varies according to the specific application. A few examples are: the D4 wavelet (Daubechies's wavelet) in analysis of vibrations [22], the Haar's wavelet in analysis of fractal objects [23], the Meyer-Yamada's wavelet in seismic phase identification [24], and so on. In the field of optical pattern recognition a useful wavelet is the bidimensional Mexican-hat wavelet, as was pointed out by Sheng et al. [11]. Its analytical form is

$$h(x, y) = \left[(x^2 + y^2) - 2\right] \exp\left(-\frac{x^2 + y^2}{2}\right), \tag{4}$$

i.e. the second derivative of the Gaussian function. Its Fourier transform is

$$H(u,v) = 4\pi^2(u^2 + v^2) \exp\left[-2\pi(u^2 + v^2)\right]. \tag{5}$$

It can be seen that this function has revolution symmetry. This is not a necessary requirement. If we wish to enhance the target in some particular direction a wavelet without revolution symmetry as, for example, the Arc wavelet or the separable Mexican-hat wavelet can be used.

3. Sequential wavelet matched filtering

The recognition operation has been implemented in a conventional variable scale correlator working under spherical illumination. Let us suppose that $f(x, y)$ represents the object to be recognized and $h_s(x, y)$ a daughter wavelet. We define one filter of the bank of filters as

$$F^*(u,v)\,|H(su, sv)|, \tag{6}$$

where the first factor operates as a classical matched filter. We will refer to it in the following as the matched factor. The second factor acts, as was mentioned before, like a passband filter, selecting the zone of the Fourier transform of the object to be correlated. We will refer to it as the wavelet factor. In the recognition procedure the wavelet factor implicitly performs a preprocessing of the input scene. So, it may be interpreted as that the matched factor does not operates over the scene itself but over the wavelet coefficient obtained. Sheng et al. called that filter wavelet matched filter [11]. The definition given by us basically is almost equal in its analytical form, but our goal is to go deeply into the wavelet transform concept taking into account a set of daughter wavelets, i.e. a bank of wavelets filters, instead of only one of them. Thus each wavelet filter enhances only the spectral content of the object carried by it. As different wavelets act over different zones of the spectrum of the object then the correlation process will be carried out among several versions of it, i.e. several wavelet coefficients. The matched filter has been made in two separate elements. The first element consists of a holographic filter, either a classical matched filter (CMF) or a phase-only filter (POF), and corresponds with the matched factor. Let us recall that this factor is $F^*(u, v)$ for the CMF and $F^*(u, v)/|F(u, v)|$ for the POF. The second element consists of a bank of photographic filters. A wavelet factor with a different scale parameter has been recorded in each plate. The matched filter is the superimposition of both elements. We will refer to it in the following as wavelet coefficient matched filter. In Fig. 1 the modulus of the amplitude distribution for two filters matched to different wavelet coefficients are shown. In a CMF there is a matching to the phase of the target and, at the same time, an amplitude filtering according to the modulus of its Fourier transform. A POF eliminates this last filtering allowing for the selection of any desired spectral range. For instance, parts of the target spectrum can be blocked in order to optimize the signal-to-noise ratio and the peak-to-correlation energy [10,11]. The

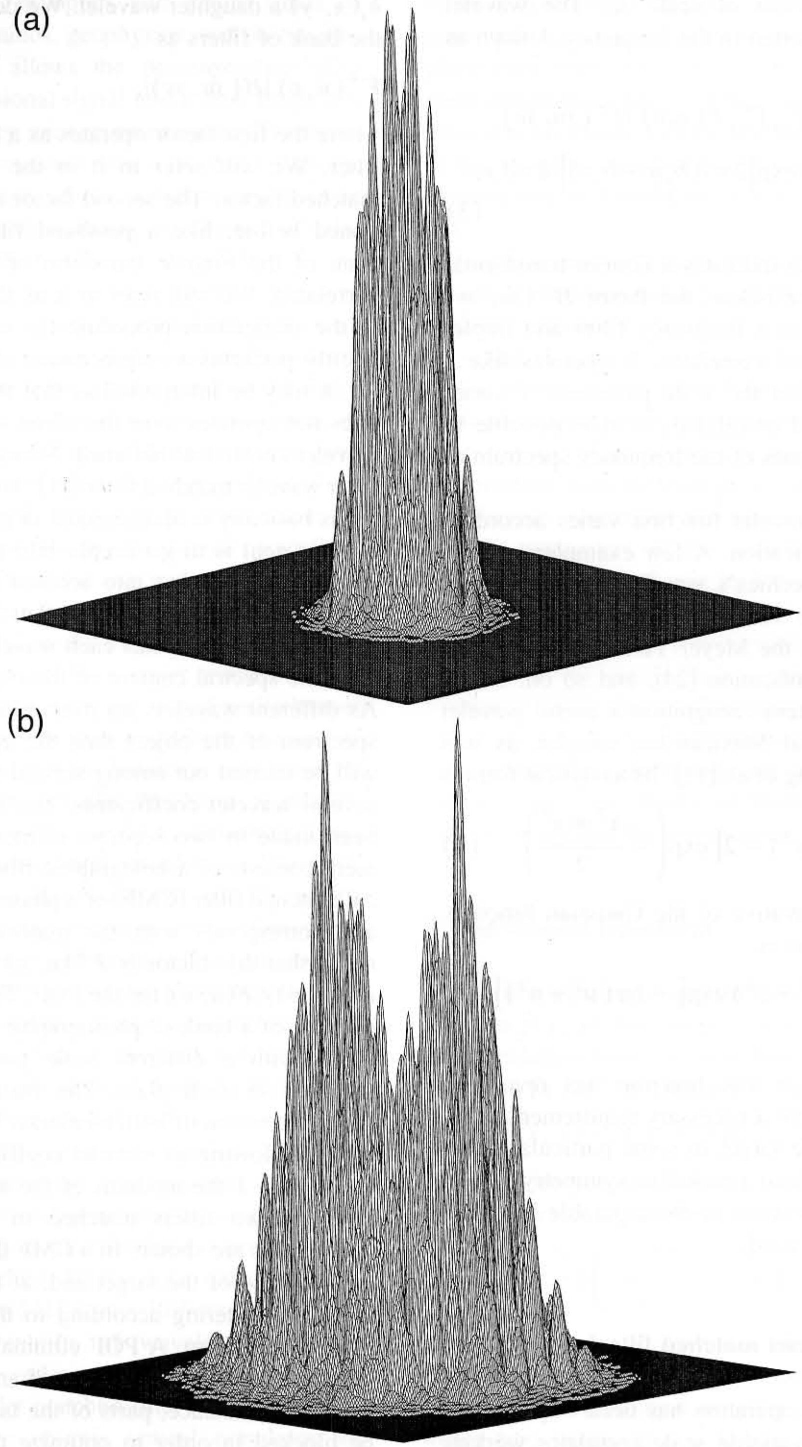

Fig. 1. Modulus of the amplitude distribution for two filters matched to different wavelet coefficients, (a) $s = 20$, (b) $s = 50$.

use of wavelets as pass-bands permits to modulate the amplitude and to select parts of the object spectrum providing a good discrimination and avoiding the problem of the high sensitivity to noise of POFs.

The proposed recognition algorithm is as follows: given a particular scene $g(x, y)$ as the input of the correlator, we introduce in the setup a filter, the wavelet factor of it corresponding to a given scale parameter, namely s_1. The correlation output $C_1(x, y; s_1)$ is grabbed in a computer for a posterior processing. Next, the wavelet factor of the filter is changed for other corresponding to a different scale parameter s_2 and the correlation $C_2(x, y; s_2)$ is grabbed. This process is repeated until all the wavelet factors of the bank are used and a set of correlations $\{C_j(x, y; s_j)\}$ is obtained. A digital recombination at a high rate of the elements of this set yields the final output correlation. The chosen method consists of building an output image from the cascade of correlations for all wavelets, by simple multiplication of these images, pixel by pixel, i.e. the final output is $\Pi_j\ C_j(x, y; s_j)$. If a pixel has a high intensity on every correlation, the final image pixel will have a high intensity value, while a pixel having a low intensity in one or more correlation results in a low-value output pixel. The pointwise combining operation can be accomplished at a high rate, yielding a single output plane in reduced analysis time. Moreover, this method greatly reduces not only the false alarm peaks but also the sidelobes in the output plane. Another simple blending of the images is also possible [25,26].

Several remarks about this filtering approach must be done. The first one refers to the sequentiallity of the process. In recent papers image analysis by means of optical wavelet transform have been made using parallel methods. For instance, Mendlovic and Konforti [16] encoded with different reference beams several daughter wavelets on a holographic filter. The result is a multireference matched filter that provides a simultaneous wavelet transform representation. The wavelet coefficients are spatially separated of each other at the output plane. Nevertheless, it can be problematic to multiplex wavelets overlapping each other; the efficiency of the filter reduces and crosstalk appears. So the number and the shape of wavelets to be encoded is restricted. Also, an interesting approach was made by Stolfuss et al. [18]. They obtain several coefficients simultaneously by means of a multifunctional wavelet-filter element. This filter is coded by iterative techniques as a diffractive phase element. This way, the packing of filter responses and the diffraction efficiency are improved. In the output plane a nonoverlapping distribution of wavelet coefficients is obtained. A disadvantage of the iterative-coding techniques is their high degree of computational complexity. Unlike this parallel approach we have worked with a sequential one. There are several reasons for this. If we work with a bank of separate wavelet filters then the wavelets are not multiplexed as in the parallel process and the output distributions corresponding to the correlations with the different wavelet coefficients appear in the same spatial position. Thus, there is no problem for centering the different outputs and the pixel by pixel post-processig can be performed easily. Additionally, a bank of separate filters provides more flexibility than a multireference wavelet filter. We have not to decide which wavelets will be coded in a multireference filter. We can have a large bank of wavelets and introduce only those we think that are interesting. If a wavelet provides no relevant information we can simply remove it and introduce another one. This is particularly interesting because although we have implemented the wavelet component of the matched filter as a photographic mask it is also possible to do it by means of a spatial light modulator. Finally, the problem of the overlapping of different wavelets in the filter plane is avoided. Anyway the sequential process is not intrinsically better than the parallel one. It is only an alternative with its advantages and disadvantages. For instance, the sequentally approach may be problematic in real time applications owing to the fact that applying filters of a filter set needs a high computational effort.

4. Computer simulations

In this section, results of numerical simulations of the recognition process are presented. For testing the performance of the sequentially wavelet matched filtering we used the scene shown in Fig. 2. It corresponds to a snapshot from a CCD camera, of a real scene, on a 256×256 matrix, and with an

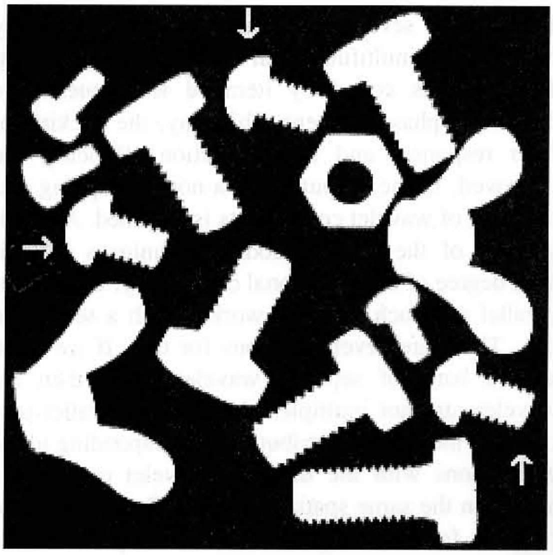

Fig. 2. Input scene. The targets to be recognizeded are marked by arrows.

increased contrast (quasi-binary). The target used to perform the matched component of the filter is marked with an arrow. We checked both classical matched filter and phase-only filter. Regarding the wavelet factor we made a bank of six Mexican-hat wavelets. The more convenient analytical expression actually used to compute the wavelet is

$$H\left(\frac{u}{s},\frac{v}{s}\right)=\left(\frac{u^2+v^2}{s^2}\right)\exp\left(-\frac{u^2+v^2}{s^2}\right). \qquad (7)$$

Thus the scale parameter also represents the distance, measured in pixels, from the coordinate origin to the maximum of the wavelet (realize it has revolution symmetry). Moreover, the normalization factor including the scale parameter is removed, in order to get an improvement in light efficiency. The scale parameter lies in the interval [15, 50] pixels, thus any zone of the Fourier transform of the target has at least one wavelet filter acting on it. For clarity we will refer to a matched filter combined with a wavelet factor as wavelet coefficient matched filter (WCMF), and to a phase-only filter combined with a wavelet factor as wavelet coefficient phase-only filter (WCPOF).

Some comments before the explanation of the results must be done. We will compare the WCMF and the WCPOF with some popular filters like the classical matched filter, the phase-only filter and the inverse filter (also named as non-wavelet filters in the text). Each of these kinds of filters has its way of working and we should be careful in their comparison. The non-wavelet filters act in one single step. The correlation of the input object and the filter yields an output that after a post-processing, for example, a threshold process, leads to a recognition response. Unlike this, in the WCMF and WCPOF we have a bank of filters. The use of a bank of wavelets means that we are splitting the information of the input object in several channels, i.e. its wavelet coefficients. We should not compare the performances of a single filter of the bank with those of a non-wavelet filter. Before this, we need to blend the different correlation outputs obtained with the wavelet filters. It can be said that the recognition procedure using a bank of wavelets includes not only the generation of the filters but also the strategy of post-processing the information provided by each filter. In our case we have chosen the multiplication pixel-by-pixel followed by thresholding of the final output. Its is very important to remark that the application of this post-processing over the correlation output obtained with a non-wavelet filter does not necessarily improve the performances; on the contrary, the output could degrade. It is clear that if a correlation signal has a false peak then, for instance the multiplication process by itself does not remove it. On the contrtary, the wavelet process splits the information contained in the scene into several channels, i.e. the wavelet coefficients. The correlations obtained for each wavelet coefficient are different. A false object and a right one differ at least in one wavelet coefficient (usually in more than one). So, the false peak does not appear in all the correlations and therefore the multiplication process removes it. A similar explanation may be done in the case of false peaks owing to noise in the scene. Some wavelet coefficients are more affected by the noise than others (depending on the spectral distribution of the noise). So the influence of the noise in the correlation varies according to the wavelet coefficient and therefore the multiplication process improves the noise tolerance. An example of this can be seen in Fig. 3. The correlation intensity distribution between the scene of Fig. 2 corrupted by additive Gaussian noise (SNR = 0.64) and a POF is shown in Fig. 3(a).

It is not possible a correct identification of the targets. If we apply the post-processing algorithm to the correlation obtained with the POF, the final correlation never permits the recognition of the objects, as can be seen in Fig. 3(b). Nevertheless, in Fig. 3(c) we can observe how the sequential correlation with a bank of three wavelet coefficient phase-only filters leads to a recognition of the targets and the false peaks can be removed with a threshold of 58% (it should be noted that in one of the wavelets channel false alarms also occur).

In a first step the correlations for each of the six filters were calculated. They were normalized, in order to equalize the maximum of the different correlation outputs and be able to mix them, and stored in memory. Later, was performed, as mentioned above, the multiplication of these images, pixel by pixel. Fig. 4(a) shows a 3-D plot of a representative example of the correlation obtained with a single WCPOF ($s = 30$), whereas Fig. 4(b) shows the blending of three correlation images ($s = 30$, 40, 50) also for WCPOFs. Before explaining the results it should be mentioned, regarding non-wavelet filters, that the classical matched filter does not permit the recognition of the target in the scene and the inverse filter misses the recognition with scenes containing even a low level of noise. So, we will stress the comparison of results with the phase-only filter. Table 1(a) gives the perfomance parameters of the POF.

The discrimination ability can be defined as one minus the ratio of the maximum correlation peak value obtained for any false target and the minimum correlation peak value obtained for the true target. The POF yields a discrimination of 0.89. The discrimination ability obtained with the sequential filtering in Fig. 4(b) is 1 (the highest possible value). The necessary threshold to detect the true targets is as low as 1% (for comparison, the threshold obtained for a POF is 10%). This is due to the multiplication of the different information carried in each correlation output. A peak corresponding to a false target will have a low intensity at least in one of the correlations (probably in the greater part of them), so the multiplication will make that the final value drops to a very small quantity. However, there is a risk. If the number of wavelets is very large perhaps some of the peaks corresponding to a true target could be diminished in excess. Thus the target could not be detected. With additional computer and optical experiments we have found that a suitable number of wavelets is between three and six (alternative post-processings that avoid this problem are actually under study). Table 1(b) gives the evolution of the minimum and maximum threshold allowed for a

Table 1

(a) Performance parameters of the phase-only filter

Discrimin.	Min. Th. (%)	Max. Th. (%)	PCE ($\times 10^{-2}$)	SNR_{min}
0.89	10	91	6.17	0.66

(b) Evolution of some performance parameters of the wavelet coefficient phase-only filter as a function of the number of wavelets used in the recognition procedure

	1 wav.	2 wav.	3 wav.	4 wav.	5 wav.	6 wav.
Discrimin.	0.90	0.90	1.00	1.00	1.00	1.00
Maximum Thres. (%)	92	85	75	65	54	38
Minimum Thres. (%)	8	2	0	0	0	0
PCE ($\times 10^{-2}$)	15.54	34.32	44.82	51.51	55.31	57.82
SNR_{min}	0.66	0.64	0.61	0.56	0.50	0.41

(c) Evolution of some performance parameters of the wavelet coefficient matched filter as a function of the number of wavelets used in the recognition procedure

	1 wav.	2 wav.	3 wav.	4 wav.	5 wav.	6 wav.
Discrimin.	0.85	0.97	0.99	1.00	1.00	1.00
Maximum Thres. (%)	100	100	99	98	96	92
Minimum Thres. (%)	15	3	1	0	0	0
PCE ($\times 10^{-2}$)	2.66	11.09	16.01	19.42	21.48	22.87
SNR_{min}	0.27	0.27	0.26	0.28	0.29	0.31

correct recognition as a function of the number of wavelets for the scene of Fig. 2. The minimum threshold is very small in all cases and stable. However, the maximum allowed threshold drops from 92% down to 38%. Even though in all cases recognition is achieved (with a threshold of 10%, for example) it would be desirable to have a security rank as high as possible. A similar behaviour regarding discrimination is reached with WCMFs as is illustrated in Table 1(c). It is important to remark that the stability of the peaks is very good. In the worse case the maximun threshold only drops to 92%.

The peak-to-correlation energy (PCE), defined as the ratio between the correlation peak energy and the whole correlation plane energy, gives a measure of sharpness of the correlation peaks. Again, Tables 1(b) and 1(c) give the values of this parameter for WCPOF and WCMF respectively, as a function of the number of wavelets used. As it was expected the PCE increases with the number of wavelets. In this example, the PCE increases from 15.54×10^{-2} for one wavelet up to 57.82×10^{-2} for six wavelets in the case of WCPOF and from 2.66×10^{-2} up to 22.87×10^{-2} in the case of WCMF. As a reference, the POF (which is a standard filter that behaves well in many cases) yields a PCE of 6.17×10^{-2}. It should be mentioned that the value of the PCE grows slowly after having made use of a few wavelets. This is another reason to maintain between three and six the number of wavelets in the initial set.

The Horner efficiency [27] (peak value over the input object energy) gives a measure of the light

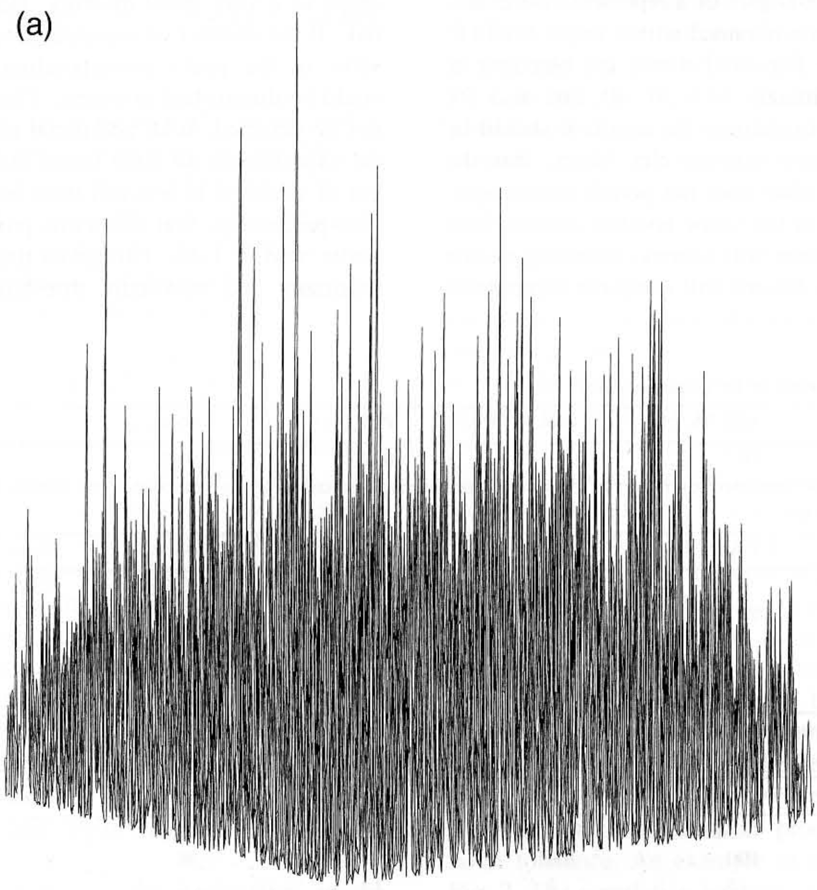

Fig. 3. Computer simulation results. Correlation intensity distribution between the scene of Fig. 2 corrupted with additive Gaussian noise (SNR = 0.64) and (a) phase-only filter, (b) phase-only filter with post-processing of the output correlation, (c) bank of three wavelet coefficient phase-only filters.

efficiency of the filters. As it was expected, due to the bandpass nature of the wavelets filters, the light efficiency is reduced in comparison with non-wavelets filters. We have checked that typical values of the Horner efficiency are between 0.1% and 1% for WCMFs, and between 5% and 20% for WCPOFs. Also, as different wavelet filters have different light efficiencies, a normalization of the correlation signals registered by the CCD must be done before combining them into the final correlation output.

To consider the sensitivity of the filter to noise, we computed the minimum SNR (SNR_{min}) that allows for the detection of the target. Gaussian additive noise is used for calculating this parameter. The POF has a SNR_{min} of 0.66 which can be considered a good value. The inverse filter fails the recognition with a very low noise level present in the scene input. Its SNR_{min} is as high as 1.95. For this reason we have not mentioned it in the previous performance parameters. Table 1(c) shows that the WCMF is a very robust filter, with values of the SNR_{min} between 0.27 and 0.31. The improvement of noise tolerance is great. Regarding the WCPOF, its SNR_{min} is between 0.41 and 0.66. These results show a behaviour of the same order or better than the POF.

Taking into account all the performance parameters we can conclude that sequential matched filtering of wavelet coefficients, both with WCMF and WCPOF, permits a pattern recognition with high discrimination ability and noise tolerance. It im-

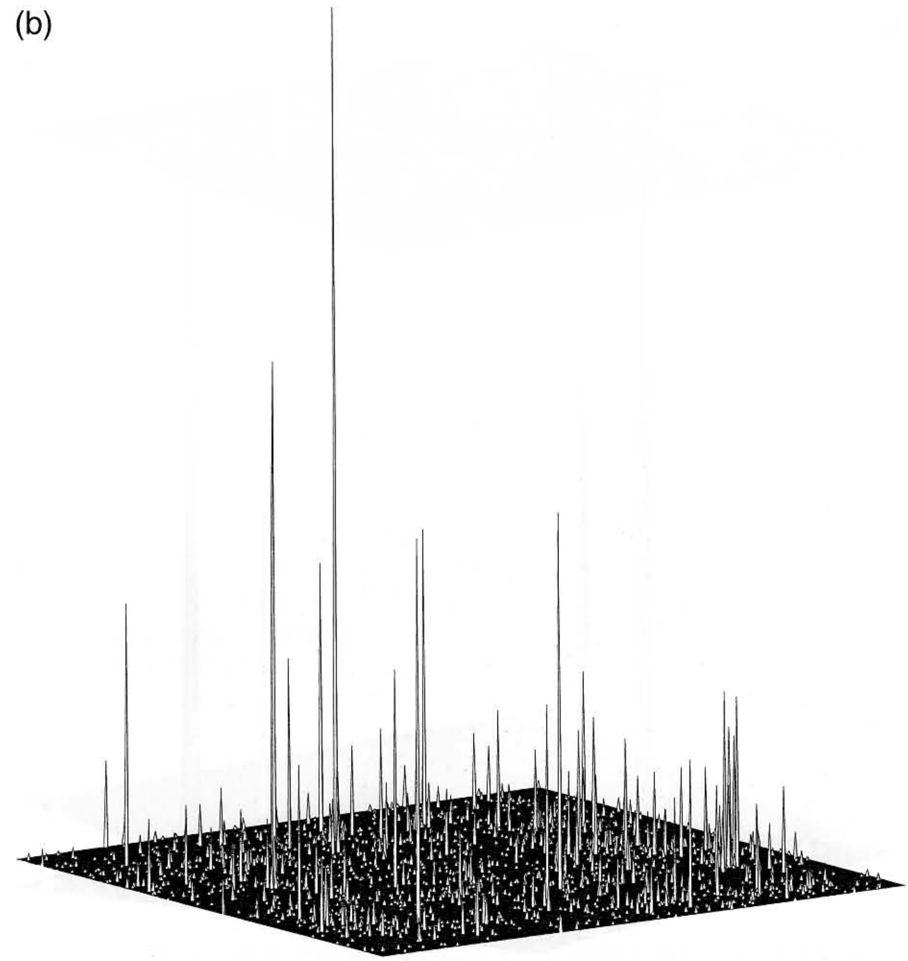

Fig. 3 Continued.

Table 2
Comparison between optical results and computer simulation results of the thresholds needed to detect the target for wavelet coefficient phase-only filters

	1 wavelet		3 wavelets	
	simulation	optical	simulation	optical
Discrimin.	0.90	0.66	1.00	0.97
Upper thres. (%)	92	89	75	75
Lower thres. (%)	8	30	0	2

proves the performance of the classical matched filter, the phase-only filter and the inverse filter. The bandpass nature of the wavelet filters implies reduced light efficiency in the WCMF, which may be alleviated in the WCPOF by the use of a phase-only filter as matched factor of the filter.

5. Optical experiments

In addition to the computer simulations we have checked experimentally the capabilities of filtering. The setup consisted of a conventional variable scale correlator working under spherical wave illumina-

(c)

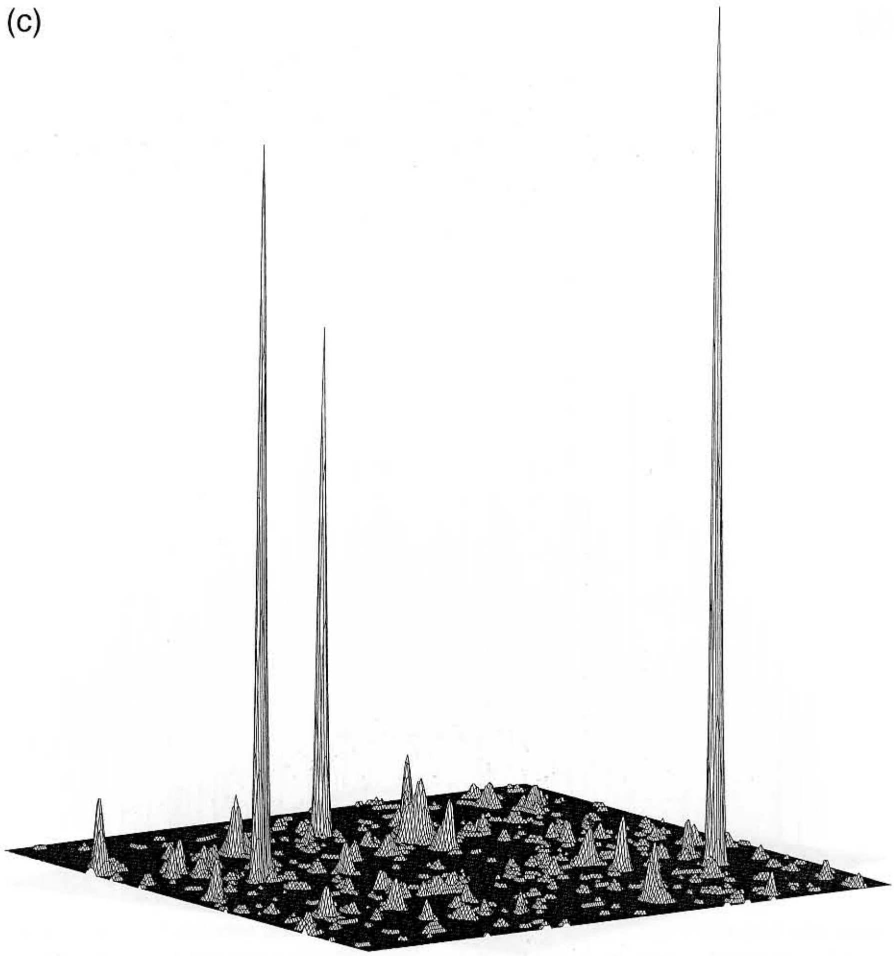

Fig. 3 Continued.

tion. The input scene and target were the same as in computer simulations and were recorded in high contrast photographic film. The matched component of the filter was a computer-generated hologram calculated by the Burkhardt method [28], plotted with a 300-dpi laser printer, and photoreduced onto a

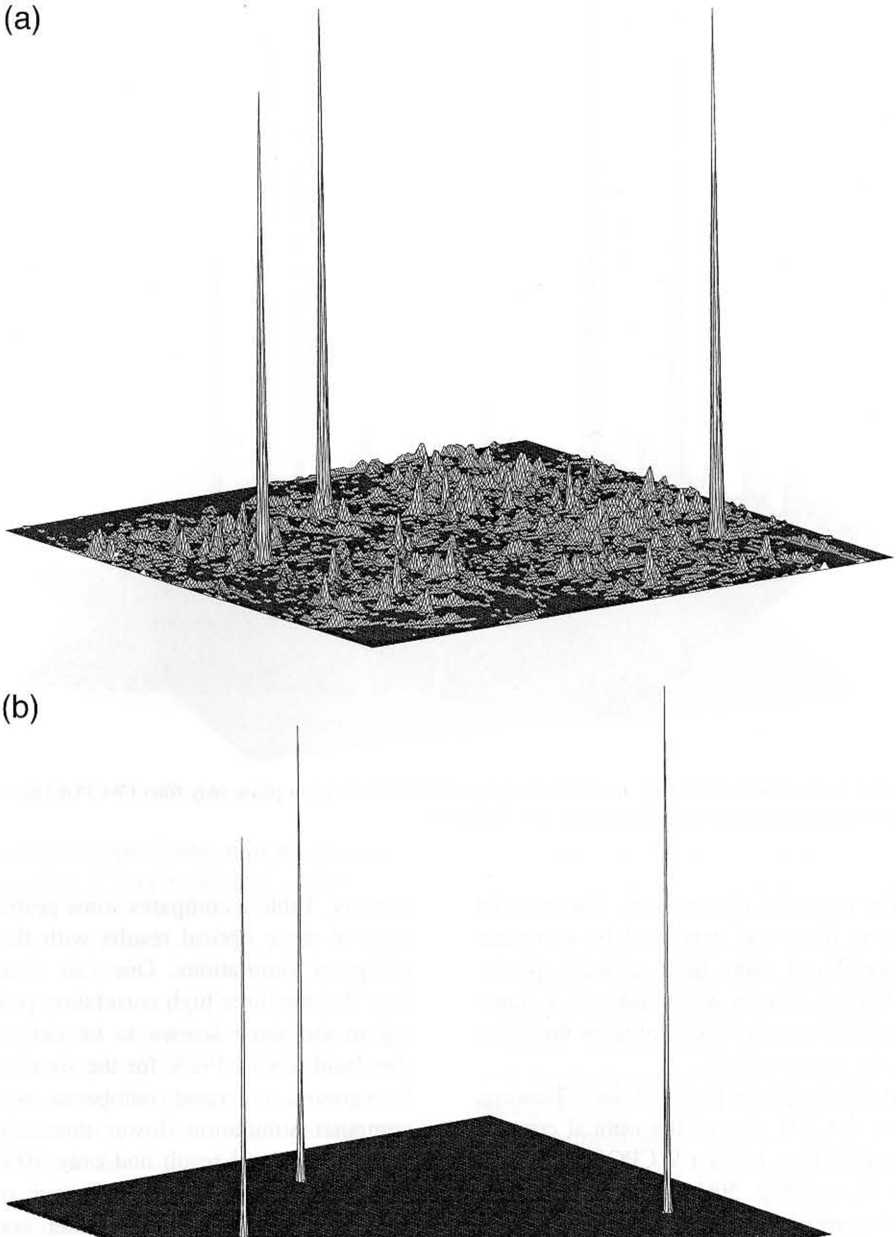

Fig. 4. Computer simulation results. (a) Correlation intensity distribution with the wavelet coefficient phase-only filter (WCPOF) for $s = 30$. (b) Product of the correlations obtained with three scale parameters, $s = 30, 40, 50$.

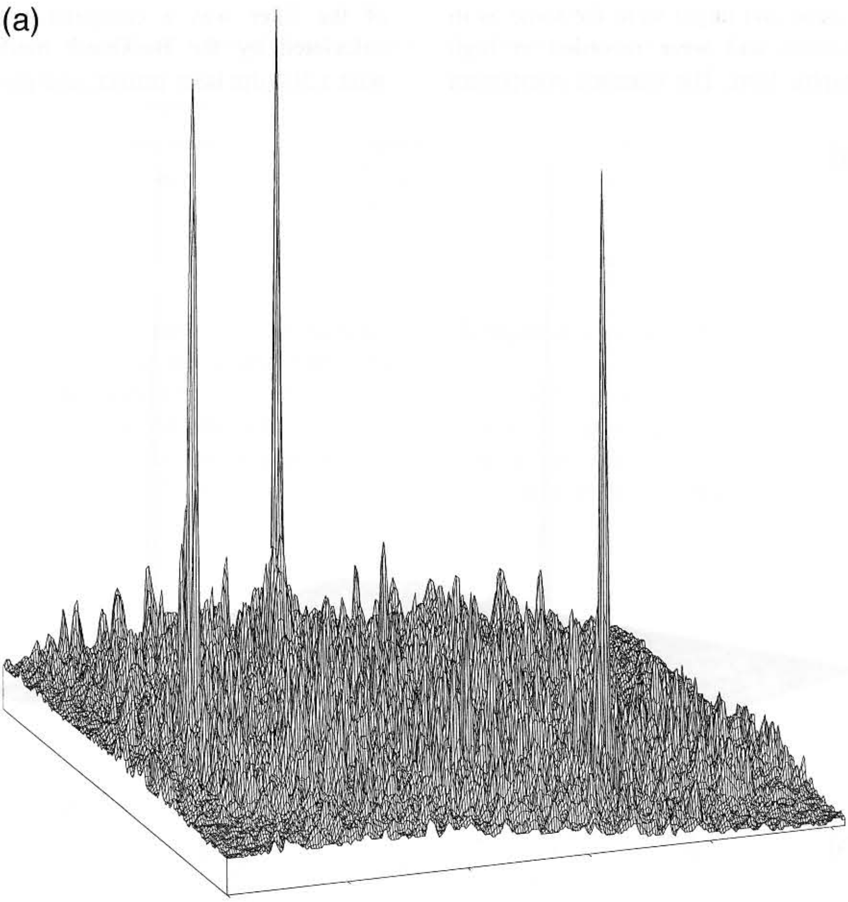

Fig. 5. Optical results. (a) Correlation intensity distribution with the wavelet coefficient phase-only filter (WCPOF) for $s = 30$. (b) Product of the correlations obtained with three scale parameters, $s = 30$, 40, 50.

lithographic film down to 10 mm size. The wavelet component of the filter was generated by computer and also photoreduced onto high contrast photographic film. Output images were taken in a frame grabber with a CCD camera and stored in the computer memory for later analysis.

An illustrative example is given in the following. Fig. 5(a) shows the 3-D plot of the optical correlation for the scene in Fig. 1 and a WCPOF with scale parameter $s = 30$, and Fig. 5(b) shows the blending of three optical correlations obtained with WCPOFs ($s = 30$, 40, 50). Taking as reference the Horner efficiency of the POF (100%), the values of this parameter for these filters are 9%, 13% ans 16% respectively. Although light efficiency is reduced, there was no problem in the detection process. Additionally, Table 2 compares some performance parameters of these optical results with those obtained in computer simulations. One can clearly observe in Fig. 5(a) the three high correlation peaks corresponding to the three screws to be detected. The upper threshold is 89% (92% for the simulated result). The background is worse compared with that of the computer simulation (lower thresholds of 30% for the experimental result and only 10% for the simulated one) because of the influence of the quantization of the hologram and other sources of noise inherent to optical setups. As is illustrated in Fig. 5(b), when the blending method is applied to the optical results, the background decreases drastically and the final correlation is similar to that obtained in numerical simulation. The upper and lower thresh-

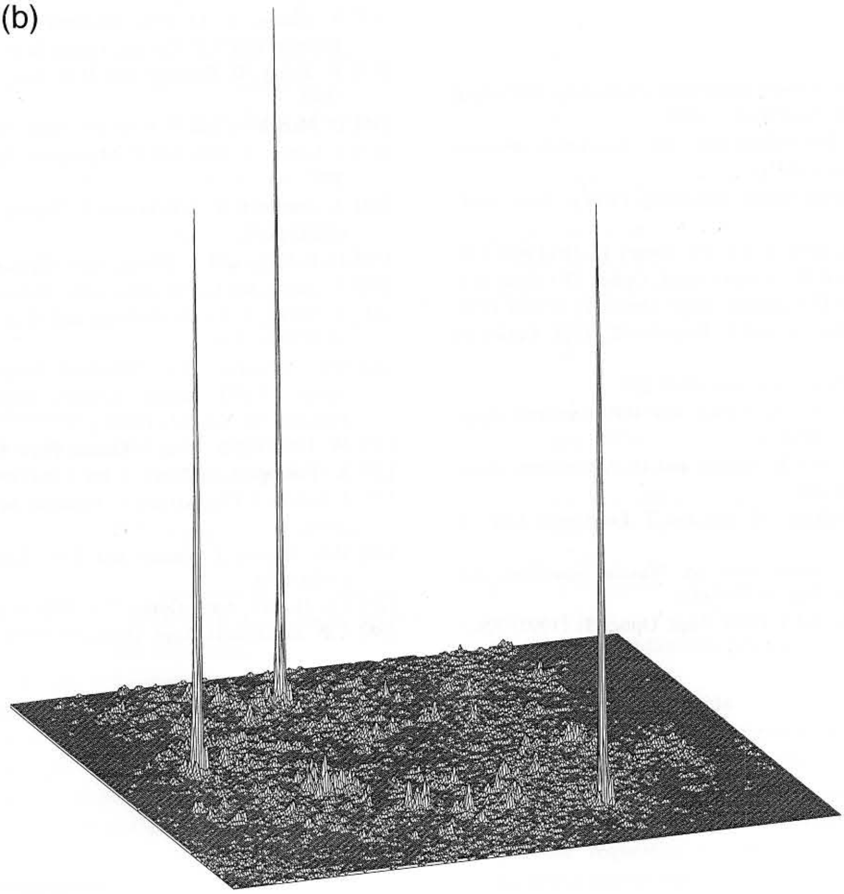

Fig. 5 Continued.

olds are 75% and 2% respectively, thus the discrimination ability reached is very high (DA = 0.97).

6. Conclusions

We have presented a sequential wavelet matched filtering for pattern recognition. The method proposed is independent of the object. It uses a set of wavelet functions with different scale parameters. We have comproved that the suitable number of wavelets in the bank is up to six. Each filter is composed of a matched factor, i.e. a classical matched filter or a phase-only filter, and a wavelet factor. Changing the scale parameter of the latter and performing the correlation for every wavelet one obtains a set of correlation images. Each correlation contains information of the matching between the wavelet coefficient of the scene being analyzed and the matched factor. The fact of splitting the initial target into several wavelet coefficients provides more detailed information than the analysis of the scene in one single step. The blending of the correlation images is made by means of a multiplication pixel by pixel, and provides a unique correlation output with high detection peaks and low sidelobes and background. Both numerical and optical experiments are presented. More research must be done in order to improve the real time capabilities of the process.

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