La Correlación Nolineal Dual en el Reconocimiento Óptico de Patrones (I):
Principio y Realización Optoelectrónica

Dual Nonlinear Correlation in Optical Pattern Recognition (I): Principle and Optoelectronic Implementation

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RESUMEN:
La Correlación Nolineal Dual (DNC) es una operación general en reconocimiento óptico de patrones en la que el preprocesado nolineal introducido en el canal de referencia puede diferir del introducido en el canal de entrada. Abarca un gran número de métodos de filtrado lineal y nolineal y puede realizarse mediante un correlador optoelectrónico de transformadas conjuntas (JTC) en dos pasos. La capacidad del sistema depende finalmente de algunas condiciones experimentales tales como la discretización, el rango dinámico de niveles de gris, la saturación y otras características técnicas de la cámara y el modulador utilizados en el JTC. En este trabajo, presentamos una revisión de las técnicas de reconocimiento basadas en la DNC, centrándonos en primer lugar en la descripción de los fundamentos, las propiedades y la realización óptica de la correlación nolineal dual. Las posibilidades de la DNC en el reconocimiento de patrones con sensibilidad ajustable se presentan en un segundo trabajo (K. Chalasinska-Macukow et al., Dual Nonlinear Correlation in Optical Pattern Recognition II, Óptica Pura y Aplicada 38, núm. 2, 85-97, 2005).

Palabras clave: Reconocimiento de patrones, capacidad de discriminación, correlación óptica, correlador de transformadas conjuntas (JTC), procesado nolineal, cámara CCD, modulador espacial de luz (SLM).

ABSTRACT:

Dual Nonlinear Correlation (DNC) is a general operation in optical pattern recognition where the nonlinear pre-processing introduced in the reference channel may differ from that introduced in the input channel. It involves a number of popular linear and nonlinear filtering methods and can be implemented by an optoelectronic two-step joint transform correlator (JTC). The eventual capabilities of the system depend on some experimental conditions such as quantization, gray-level dynamic range, saturation, and other technical characteristics of both the camera and the spatial light modulator used in the JTC. An overview of the pattern recognition techniques based on DNC is presented in this paper. Firstly, we focus our attention on the description of the principle, properties and optical implementation of the dual nonlinear correlation. The potential of DNC to achieve pattern recognition with adjustable sensitivity is presented in a second work (K. Chalasinska-Macukow et al., Dual Nonlinear Correlation in Optical Pattern Recognition II, Óptica Pura y Aplicada 38, núm. 2, 85-97, 2005).

Keywords: Pattern recognition, discrimination capability, optical correlation, joint transform correlator (JTC), nonlinear processing, CCD camera, spatial light modulator (SLM).
REFERENCES.

1.- Introduction.

Pattern recognition is an important task of human vision that has been intended by using machine vision systems along the last four decades. Due to the complexity and variety of operations involved as well as the huge diversity applications, there is not a complete and definitive solution to the problem. However, it can be also said that a long way has been already done. Thus, one may find artificial vision systems installed in robots, surveillance devices or other machines capable to “see an object” in the sense of recognizing its pattern, locating it, identifying it, distinguishing it from others, classifying it, tracking it, etc. even when there are some difficulties in the input signal such as noise, occlusions or distortions.

Pattern recognition based on optical correlation has rendered a large number of well established methods and techniques with the common valuable capability of parallel processing in real time. It became then a motivation to build a general model that grouped the methods having similar formulation. The common study of filters and processors unified within a model gives a better insight into their properties and enables one to compare them in a more systematic and reliable way. As it has been reported in the literature, this sort of models often leads to optimized methods or new performances.

In this paper we review the Dual Nonlinear Correlation (DNC) model that covers not only well-known linear and nonlinear filtering operations but also realizes a variety of intermediate methods. The basic performance of the DNC and the comparison of various linear and nonlinear correlation methods within the model are analysed digitally according to the peak-to correlation energy criterion. The optoelectronic implementation of the DNC is based on a Joint Transform Correlator architecture. Power-law nonlinearities are separately introduced to the input and the reference channels and the power-law values play the role of parameters which control the processor performance. As a result, the recognition system based on the DNC has an adjustable discrimination capability (DC). The DNC method can be considered as a generalization of the nonlinear joint-transform correlator, for which the general case of nonlinearity applied to the joint power spectrum and the particular cases of the hard limiter and the kth-law device, were mathematically analysed in ref. [4]. In comparison with DNC, these symmetrically nonlinear processes apply the same level of nonlinearity to both the reference and the input scene transformations. In nonlinear correlators, it has been already pointed out that the DC of the system can be varied simply by changing the severity of the nonlinearity whereas, for instance, conventional matched filter and phase-only filter have a fixed discrimination capability. In addition, nonlinear joint-transform correlators provide optimum solutions in terms of discrimination and input noise robustness.

2.- Principle and properties.

Let s(ν) denote the input signal, which is to be analysed, and r(ν) the reference object that we seek (we use one-dimensional notation for simplicity). Their Fourier transforms will be denoted with capital symbols as S(ν) and R(ν), respectively. In a
conventional linear correlator, the location of the reference object \( r(x) \) in the input scene \( s(x) \) is estimated from the maximal values of the intensity distribution of the correlation between \( s(x) \) and \( r(x) \), which can be obtained from their spectra according to the expression

\[
s(x) + r(x) = IFT \left\{ S(\nu) R^*(\nu) \right\},
\]

where * indicates correlation, and \( IFT \) the inverse Fourier transform. The definition of the Dual Nonlinear Correlation\(^6\) extends eq. (1) in a way that enables to include in the same mathematical expression the filtering techniques that could not be realized by a linear correlator.

\[
DNC_{L,M}^{(\nu)} \{ s(x), r(x) \} = IFT \left\{ S(\nu)|R(\nu)|^{L-1} S(\nu) R^*(\nu) T(\nu) \right\},
\]

where \( L \) and \( M \) are some real coefficients and \( T(\nu) \) is introduced as a real positive function. Function \( T(\nu) \) is a weighting function in the Fourier domain that modifies the filter according to the effective aperture of the optical setup or, more general, the region of support\(^{17-19}\) providing additional control over the filter performance by introducing zero level in the transmittance of some filter areas. Particular filtering operations covered by the DNC model can be obtained by choosing specific values of \( L \) and \( M \) (Table I).\(^{6,10}\) The expression of DNC given in eq. (2) can be written more compact using the power-law nonlinear operator defined by the formula

\[
P(z) = \begin{cases} P, & \text{for } z > 0 \\ 0, & \text{for } z = 0 \end{cases},
\]

where \( z \) represents the complex argument and \( P \) is a real number or, in general, a real function of spatial frequency \( \nu \). Taking eq. (3) into account, eq. (2) can be rewritten as

\[
DNC_{L,M}^{(\nu)} \{ s(x), r(x) \} = IFT \left\{ N_L \left[ S(\nu) \right] N_M \left[ R^*(\nu) \right] T(\nu) \right\},
\]

where \( N_L \) and \( N_M \) are power-law nonlinear operators introduced in the input channel (scene) and in the reference channel, respectively, to control the system performance.

Regarding the properties of DNC, we analyse the system performance for different values of \( L, M \). We assess this performance using standard measures widely used to compare optical correlation filters\(^2\): the peak-to-correlation energy (PCE) and the discrimination capability (DC) will be considered in this work.

In the DNC the PCE takes the form

\[
PCE = \frac{\text{correlation peak energy}}{\text{correlation plane energy}} = \frac{\int \left| IFT \left\{ N_L \left[ S(\nu) \right] N_M \left[ R^*(\nu) \right] T(\nu) \right\} \right|^2 d\nu}{\int \left| IFT \left\{ N_L \left[ S(\nu) \right] N_M \left[ R^*(\nu) \right] T(\nu) \right\} \right|^2 d\nu},
\]

Table I Filtering and correlation operations covered by the DNC model with \( T(\nu) = 1 \).

<table>
<thead>
<tr>
<th>Filtering method</th>
<th>( L )</th>
<th>( M )</th>
<th>DNC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Classical Matched Filter (CMF)(^1)</td>
<td>1</td>
<td>1</td>
<td>( DNC_{1,1} { s,r } = IFT \left{ S \cdot R^* \right} )</td>
</tr>
<tr>
<td>Phase-Only Filter (POF)(^20)</td>
<td>1</td>
<td>0</td>
<td>( DNC_{1,0} { s,r } = IFT \left{ S \cdot R^* \overline{R} \right} )</td>
</tr>
<tr>
<td>Inverse Filter (IF)(^21)</td>
<td>1</td>
<td>-1</td>
<td>( DNC_{1,-1} { s,r } = IFT \left{ S \cdot R^* \overline{R} \right} )</td>
</tr>
<tr>
<td>Fractional Power Filters (FPF)(^2)</td>
<td>( k+1 ) real number</td>
<td>1</td>
<td>( DNC_{1,1+k} { s,r } = IFT \left{ S \cdot \left</td>
</tr>
<tr>
<td>Locally Nonlinear Matched Filters (LNMF)(^22)</td>
<td>1</td>
<td>( M(\nu) ) real function</td>
<td>( DNC_{1,M} { s,r } = IFT \left{ S \cdot \left</td>
</tr>
<tr>
<td>Pure Phase Correlation (PPC)(^23-26)</td>
<td>0</td>
<td>0</td>
<td>( DNC_{0,0} { s,r } = IFT \left{ S \cdot R^* \overline{R} \right} )</td>
</tr>
<tr>
<td>Nonlinear Joint Transform Correlation (NJTC)(^4)</td>
<td>( k+1 ) positive real number</td>
<td>1</td>
<td>( DNC_{k+1,1+k} { s,r } = IFT \left{ S \cdot \left</td>
</tr>
<tr>
<td>Optimal Filter (OF)(^27)</td>
<td>-1</td>
<td>1</td>
<td>( DNC_{-1,1} { s,r } = IFT \left{ S \overline{R} \cdot R^* \right} )</td>
</tr>
<tr>
<td>Dual Nonlinear Correlation (DNC)(^6)</td>
<td>( L(\nu) )</td>
<td>( M(\nu) )</td>
<td>( DNC_{L,M} { s,r } = IFT \left{ S \cdot \left</td>
</tr>
</tbody>
</table>
and gives information about the sharpness of a correlation peak and the energy distribution in the output correlation plane. A reference object included in a scene will be precisely located and easily detected if a sharp peak projects over a low energy background. In this case the PCE value will be close to 1. However, the PCE will approach 0 if a broad correlation peak appears and/or an important energetic background is present.

The discrimination capability (DC) is defined by the expression \(^2, 28\)

\[
DC = \frac{1 - \text{CC}}{\text{AC}},
\]

where \(\text{CC}\) and \(\text{AC}\) are, respectively, the cross-correlation and the autocorrelation intensity values. The recognition decision is conditioned on the value of DC at a selected level \(u\). For instance, if DC \(\leq u\) for the object of a segmented input scene, then the system recognizes it as the reference object because it cannot be sufficiently discriminated. On the contrary, if DC \(> u\), then the object is discriminated from the reference signal and the system considers it as to be a different object. In the following, we will take for \(u\) the common but arbitrary value of \(u = 0.5\). Thus, it can be derived from eq. (6) that the system is able to discriminate two objects if their cross-correlation peak value differs by more than 50% of the autocorrelation peak value. Conversely, it is able to recognize two objects as the same if their cross-correlation peak value differs by no more than 50% of the autocorrelation peak value.

In addition, we point out that independently of the choice of \(L\) and \(M\), the DNC operation is shift-invariant, and assures that, in the absence of noise, the maximum of the autocorrelation signal is located at the actual position of the reference object. \(^5, 8\) In this sense the DNC really generalizes the linear correlation-based pattern recognition methods.

The input scene to analyse by the system may be of different sorts: a segmented scene, multiobject scene, noisy scenes, and scenes with partially hidden objects. Let us study the PCE in such cases.\(^{6, 29}\)

**Segmented input scene.** If the input scene is identical to the reference object, \(s(x) = r(x)\) in eq. (2), the DNC gives a correlation signal with a maximum located at the origin of the coordinates, that is,

\[
\text{DNC}^{\tau(v)}_{L,M} \{r(x), r(x)\} = \text{IFT} \left[ R(v) F_L^{L+M} T(v) \right] = \text{DNC}^{\tau(v)}_{L,M} \{r(x), r(x)\} = \text{IFT} \left[ |D(v)|^{2} \right].
\]

If the searched object is shifted in the input scene by a given distance, the location of the maximum of the correlation signal is shifted by the same amount in the output plane (shift-invariant property). These two properties are well known for the linear case and do not require any further explanation. We point out that the nonlinear autocorrelation (Eq. 7) depends on \((L+M)\) and not on \(L\) and \(M\) separately. When \((L+M) = 0\) (IF, PPC, OF in table I) the shape of the correlation peak can be approximated by a delta function. It can be simply proved that this condition optimizes the DNC according to the PCE measure. A similar optimization carried out on the fractional power filters leads to the inverse filter, which also satisfies \((L+M) = 0\). When \((L+M) \neq 0\), the correlation peak becomes wider.

**Linear filtering.** Defined in terms of DNC with \(L = 1\), produces an output whose intensity is proportional to the input intensity. This is not generally true for other values of \(L\). If the input scene changes its intensity by an illumination scaling factor \(I_{in}\), then the intensity in the output plane of the DNC processor is

\[
I_{out}(x) = \left[ \text{DNC}^{\tau(v)}_{L,M} \{I_{in}^{1/2} s(x), r(x)\} \right]^2 = I_{in} \left[ \text{DNC}^{\tau(v)}_{L,M} \{s(x), r(x)\} \right]^2,
\]

\[L = \text{const}(x).
\]

When \(L = 0\), the DNC output is independent of the illumination scaling factor \(I_{in}\) of the input scene. This property has already been studied for the cases of PPC and joint transform correlator.\(^{31}\)

**Multiobject input scene.** Let us consider the simple case of a noise-free multiobject input scene just consisting of reference objects. Then, the input function can be expressed as the convolution of the reference function with a set of delta functions

\[
s(x) = r(x) \otimes d(x) = r(x) \otimes \sum c_i \cdot \delta(x - x_i).
\]

where \(\otimes\) denotes convolution.

In eq. (9), function \(d(x)\) contains all the information about the reference object positions \(x_i\) and their intensities \(\{c_i\}\) in the input plane. In this case, DNC takes the form

\[
\text{DNC}^{\tau(v)}_{L,M} \{s(x), r(x)\} = \text{DNC}^{\tau(v)}_{L,M} \{r(x) \otimes d(x), r(x)\} = \text{DNC}^{\tau(v)}_{L,M} \{r(x), r(x)\} \otimes \left[ \text{IFT} \left[ N_{L+M} D(v) \right] \right],
\]

where \(D(v)\) is the Fourier transform of \(d(x)\). Eq. (10) can be rewritten in the form

\[
\text{DNC}^{\tau(v)}_{L,M} \{s(x), r(x)\} = d(x) \otimes \left[ \text{DNC}^{\tau(v)}_{L,M} \{r(x), r(x)\} \right] \otimes \left[ \text{IFT} \left[ |D(v)|^{2-1} \right] \right].
\]

We analyse eq. (11) as the convolution of three terms: the first one, \(d(x)\), provides the desired ideal
recognition result (each target is represented by a delta function of adequate height and placed in its position). Unfortunately, the other convolution terms of eq. (11) disturb this desired output. The second term is the nonlinear autocorrelation already described by eq. (7). If only the distances between the targets in the input scene are larger than the autocorrelation peak width, the convolution of the first two terms of eq. (11) yields copies of the autocorrelation peak separated enough. We remind that the peak shape depends on \((L+M)\) and that delta-shaped autocorrelation peaks are obtained for \((L+M) = 0\). The third convolution term of eq. (11) usually contains a distribution of narrow peaks that may be approximated by delta functions. The convolution with this term can be a source of intermodulation false alarms. Intermodulation affects mostly those input scenes involving some periodicity in the object location.\(^{32-34}\) There are no intermodulation effects for segmented input scenes, which contain a single object, and linear systems \((L = 1)\). The intermodulation represented by the third term of eq. (11) does not depend on the shape of a given object. It must be emphasised that the output light distribution given by the convolution of three terms (Eq. 11) is valid only for noise-free input scenes. Otherwise, the analysis of the output result becomes more complex.

**Noisy input scene.** The influences of input scenes affected by white additive noise in the PCE and in the intermodulation effect are studied in ref. [6]. It is possible to determine an optimised DNC method, defined in terms of ref. [6]. It is possible to determine an optimised and in the intermodulation effect are studied in scenes affected by white additive noise in the PCE. Otherwise, the analysis of the output result becomes more complex.

Scenes with partially occluded objects. This case is studied in more detail in ref. [29]. Let the scene \(s(x)\) contain the reference object \(r(x)\) partially occluded. The scene can be expressed either by

\[
s(x) = r(x) - h(x),
\]

where \(h(x)\) is the hidden part, or alternatively, by

\[
s(x) = A(x) r(x),
\]

where \(A(x)\) is an aperture function. From eqs. (12) and (13), it is clear that \(h(x) = [1 - A(x)] r(x)\). Taking into account eq. (12), the correlation of the scene containing a partly occluded reference and the reference gives

\[
s(x) \ast r(x) = [r(x) \ast r(x)] - [h(x) \ast r(x)].
\]

The first term of eq. (14) is the autocorrelation and the second term is the result of the mismatch between the hidden part and the reference. Thus, the problem of the recognition of a partly occluded object leads to developing methods that minimize the effect of mismatch while maximize the autocorrelation. A DNC processor was proposed in ref. [29] for such a purpose and some experiments by numerical simulation were carried out and the results discussed. By changing the severity of the nonlinearity in the input channel (through the \(L\) value), optimised PCE for each aperture input scene was obtained. We remark that the condition \((L+M) = 0\) is no longer the optimal condition, as it was in the case of non-distorted and noise-free segmented input scenes. The contribution of the high frequency component is very important in this recognition procedure and it can be assured by choosing high-pass filters in the reference channel and high frequency enhancement in the input channel. A proper choice of \(L\) value can improve the PCE several times. For a given \(M\) value, the best \(L\) value depends on the level of occlusion and the high frequency content of the actual visible part of the scene.

In the following, only segmented scenes containing a single object will be considered. As it has been just described, this is to avoid the false alarms produced by the undesired intermodulation effects that appear when the input consists of a multibject scene and nonlinear methods are applied for recognition.\(^{32-34}\)

### 3.- Algorithm and optoelectronic realization.

The simplest optoelectronic implementation of DNC\(^7\) is based on a two-step joint transform correlator (JTC) architecture (Fig. 1). As in the cases of the quasi-phase correlator,\(^{35}\) the nonlinear JTC with various thresholds,\(^{33,36}\) the modified fringe-adjusted JTC\(^{37}\) or the spatial envelope-free nonlinear JTC,\(^{38}\) to implement the DNC we need to capture several intensity distributions in the Fourier plane with a charge-coupled device (CCD) camera.
In the first step of JTC, three power spectra are sequentially captured by the CCD camera:
- the reference object power spectrum:
  \[ I_R(v) = |R(v)|^2 \]
- the input scene power spectrum:
  \[ I_S(v) = |S(v)|^2 \]
- the joint power spectrum:
  \[ I(v) = |FT(r(x+d) + s(x-d))|^2 \]

The first two spectra are obtained by successively displaying the reference object \( r(x) \) and the input scene \( s(x) \) on the electronically addressed spatial light modulator (SLM). The joint power spectrum \( I(v) \) is captured when displaying both the reference and the input scene, symmetrically shifted a distance \( d \) from the centre of the SLM, as usually for a JTC. Once the three power spectra \( I(v) \), \( I_R(v) \) and \( I_S(v) \) are stored, the modified joint power spectrum \( I'(v) \) is computed according to the formula

\[
I'(v) = I(v) I_R(v)^{\frac{L-1}{2}} I_S(v)^{\frac{M-1}{2}} \tag{15}
\]

where the simplest case of \( I(v) = 1 \) has been assumed. Taking the inverse Fourier transform of the modified joint power spectrum \( I'(v) \), we obtain the DNC between the input and the reference images. Thus, it can be written that

\[
IFT[I'(v)] = O(x) + DNC_{L,M}[s(x), r(x)] \otimes \delta(x-2d) + DNC_{L,M}[r(x), s(x)] \otimes \delta(x+2d) \tag{16}
\]

where the on-axis term \( O(x) \) is

\[
O(x) = IFT\left\{ |R(v)|^{\frac{L-1}{2}} S(v)^{-\frac{M-1}{2}} + |R(v)|^{\frac{M-1}{2}} S(v)^{-\frac{L-1}{2}} \right\} \tag{17}
\]

In the second step of JTC, the modified joint power spectrum \( I'(v) \) is displayed on the SLM and then its Fourier transform is obtained in the output plane. Since only direct Fourier transforms can be obtained optically, but not inverse Fourier transforms, the results obtained in the output plane of the JTC only differ from those expressed by eq. (16) in a coordinate inversion \((x \rightarrow -x)\). The on-axis term \( O(x) \) of eq. (16) is non-interesting. It appears in the middle of the two off-axis DNC output signals. In the experiment, the overlapping between the on-axis and off-axis terms can be avoided by introducing \([I'(v)-I_R(v)-I_S(v)]\) instead of \(I(v)\) and an additive constant in the modified joint power spectrum \( I'(v) \) of eq. (15) so that the on-axis term \( O(x) \) in eq.(16) is reduced to \( O(x) = \delta(x) \). \(^6\)

3.a. Constraints: Saturation and quantization effects on the correlation results.

So far, we have assumed that the intensity distributions \( I_R(v) \), \( I_S(v) \), \( I(v) \) and \( I'(v) \) can be accurately captured by the CCD and displayed on the SLM. Unfortunately, the limited dynamic ranges and the quantization introduced by these devices cannot be neglected. Experimental conditions, such as saturation of the CCD camera and the quantization levels of the camera and the SLM, have a strong influence on the eventual capabilities of the DNC processor as we describe in this section. \(^7\)

Let us study the influence of the saturation of the CCD camera in the PCE obtained by the DNC processor. In our digital analysis, a noise-free binary segmented input scene is considered. The reference object is the letter E shown in fig. 2. It has been chosen as a representative example of a general case. The PCE (Eq. 5) will be evaluated for an input scene containing the reference signal. The three intensity distributions in the Fourier plane: the joint power spectrum \( I(v) \), the input scene power spectrum \( I_S(v) \) and the reference object power spectrum \( I_R(v) \) involved in the nonlinear processing usually vary over a wide dynamic range. It is difficult to obtain linear capturing of both high and low frequencies of these power spectra by a CCD camera. If we capture low frequencies linearly, then the high frequencies are lost. That is why a proper level of saturation must be introduced in order to enhance high frequencies. Let us consider \( V_{\text{max}} \) the maximum value of the three intensity distributions \( I(v) \), \( I_R(v) \) and \( I_S(v) \) (Fig. 3). We have established an intensity value \( V_{\text{sat}} \) common to the three distributions, for fixing the saturation level. Values higher than \( V_{\text{sat}} \) are made equal to the maximum CCD grey level in all three recordings. The amount of saturation is related to a parameter \( \alpha \), defined as \( \alpha = \frac{V_{\text{sat}}}{V_{\text{max}}} \times 100\% \). Thus, for instance, a value of \( \alpha \) equal to 100% signifies that there is no saturation at all.
The modified joint power spectrum $I'(v)$ has been calculated according to eq. (15) for various nonlinearities corresponding to $L$ and $M$ chosen between 0 and 1 and for different saturation levels. Fig. 4a presents PCE versus the saturation level of the camera for four particular filtering methods included in DNC. They are the pure phase correlation (PPC, $L = M = 0$), the phase only filter (POF, $L = 1$, $M = 0$), its symmetric case ($L = 0$, $M = 1$) that gives the same results as POF, and the classical matched filter (CMF, $L = M = 1$).

For a given $L$ and $M$, an increase of the saturation (i.e. a decrease of parameter $\alpha$) allows, in general, an improvement of PCE and this is an important achievement. However, if $\alpha$ is too low, the high saturation by itself is enough to achieve hard clipping nonlinearity and the setup also loses its variance on $L$ and $M$. In other words, the different nonlinear processes would obtain similar PCE results. For this reason, if we want the optoelectronic processor to be sensitive to the introduction of different nonlinearities, we must carefully choose the level of saturation. In our experiments we fixed the saturation parameter at $\alpha = 10\%$.

Apart from saturation, the CCD camera introduces quantization in the recorded intensities $I$, $I_S$ and $I_R$. Fig. 4b shows how the PCE depends on the number of the quantization levels (CCD grey levels). In all the analysed cases, the PCE depends highly on the number of quantization levels decrease. We also observe that for few quantization levels (less than 128) the results are similar for different $L$ and $M$ values.

From this study we conclude that the CCD should be tuned to an operating range for which saturation actually occurred. As a result of saturation, the CCD cuts off the intense central peak of the captured power spectra, and the CCD grey levels are advantageously used to register the remaining intensity distribution of the power spectra thus providing a more appropriate representation of the high-frequency information. Moreover, saturation and quantization have a strong influence on the distribution and region of support of the modified power spectrum. Consequently, the light efficiency of the optoelectronic setup is also higher and the processor shows a satisfactory sensitivity to the introduction of nonlinearities.

Let us study the influence of another experimental factor: the number of SLM quantization levels that can be addressed to display the modified joint power spectrum in the second step of the JTC (Fig. 1). The joint power spectrum basically consists of an interference fringe pattern modulated by an envelope function. The number of elements (scene and reference) and their relative position in the input plane are responsible for these interference fringes. The input element shapes determine the central and sidelobe distribution of the
envelope function. The nonlinear process introduced by DNC changes the modulation slopes in the region of support. For instance, the PPC makes the information from the interference fringes quasi-uniform over the whole region of support of the spectrum in such a way that the fringe envelope is almost binary. If POF is considered instead, the modulating envelope is smoother than in PPC, and it is much smoother in the case of CMF. Therefore, applying either POF or CMF, requires many more SLM grey levels to reproduce \( I'(\nu) \) than PPC.

Fig. 5 shows the influence of SLM grey levels on the PCE for four DNC methods (PPC, POF, its symmetric case, and CMF). PCE smoothly varies with SLM quantization and it only decreases significantly when the SLM works with few grey levels. We must be aware that available SLM have a small number of actually addressable grey levels. The nonlinearity that presents the smallest PCE variations corresponds to \( L = M = 0 \) (PPC). This fact could be explained by the nearly binary envelope of the joint power spectrum, for which just few quantization grey levels are enough to reproduce it well. For the rest of filtering methods (POF, its symmetric case, and CMF) the modified spectra are modulated by envelope functions that require more grey levels for an acceptable reproduction. As the number of available SLM grey levels decreases, the PCE decreases as well, particularly quickly in these filtering methods.

Conclusions.

Pattern recognition techniques based on the dual nonlinear correlation (DNC) are overviewed. In this first part, the DNC principle, its most relevant properties along with its optical implementation are introduced and analyzed. The DNC model covers many operations performed in optical linear and nonlinear correlators. This approach allows a better understanding of the properties of specific optical correlation methods and simplifies the comparison and optimization within the model. According to the PCE measure, the most effective DNC methods to analyze segmented noisy input scenes are those based on a symmetric nonlinear filtering. For noise-free scenes, the performance of the PPC is superior. In the case of multiobject input scenes the presence of some low input noise may improve the recognition results of the DNC by reducing the intermodulation effects.

A two-step joint transform correlator is the architecture proposed to implement DNC optically. The experimental realization of DNC is feasible, although it must be taken into account the influence of some practical constraints such as the saturation level and the quantization levels of the CCD camera, and the quantization levels of the SLM. If the saturation level is not properly chosen and the number of quantization levels is too small, the processor looses sensitivity to the introduction of different nonlinearities. In the second part of this work we present a pattern recognition technique based on DNC with sensitivity adjustable to a given aspect of the target (shape, grey level, colour, texture) and variable within a range.

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