Digital Correlation based on Wavelet Transform for Image Detection

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Abstract. In this work is presented a method for the optimization of digital correlators to improve the characteristic detection on images using wavelet transform as well as subband filtering. It is proposed an approach of wavelet-based image contrast enhancement in order to increase the performance of digital correlators. The multiresolution representation is employed to improve the high frequency content of images taken into account the input contrast measured for the original image. The energy of correlation peaks and discrimination level of several objects are improved with this technique. To demonstrate the potentiality in extracting characteristics using the wavelet transform, small objects inside reference images are detected successfully.

1. Introduction
The images pattern recognition is a discipline whose goal is the classification of objects into a number of categories or classes. A specific example of this work area is the vision machine, in which images are captured from a camera and after analyzed to generate descriptions about them. Many applications can be found in the images pattern recognition field: computer-aid illness diagnostic [1]-[2], fingerprint identification [3]-[4], signature authentication, optical characters recognition faces and hand gestures detection, image registration, and others [5]-[7]. Generally speaking, all of these applications used images, as input patterns, captured from cameras of different resolutions. When working with optical signals, it is necessary to maintain the almost perfect conditions in the environment where the image is captured in order to obtain the same pattern each time we want to process one. Unfortunately, an acquired image always differs from the previous one by several reasons: image distortions introduced by the camera (because of lenses problems), illuminations conditions, and focus problem as well as scale and pose variations. In this sense, the image enhancement and denoising algorithms are fundamentals processes for image recognition and detection applications.

The last decade, the problem of low contrast of images has been treated by the use of many approaches of image enhancement [8]-[9].

The images digital correlation is a method that allows to compare and to determine the similitude grade between two bidimensional signals (images), being this technique one of the principal methods in the field of pattern recognition and feature detection. This method is commonly known as template matching [10]. Traditional architectures of correlators such as the Vander Lugt correlator or...
conventional matched filtering (CMF), and the joint transform correlator (JTC) have been a subject of constant research [11]-[12], and combinations of techniques have been proposed to improve the performance of the digital correlator [13]. These methods employ the Fourier transform as the basic operation to compare two images.

Since images are complex in detail and they can contain a great amount of information is much more convenient, for applications that requires only the comparison of precise details, the use of the high frequency component of the image instead of using the correlation of the complete signals. In general, the image correlation algorithms are divided in two groups according to the domain in which the analysis is made [14]. Taken into account the space of representation of the information, the image processing can be carried out in the spatial or spectral domain.

Many works have been proposed to identify pattern in several application using the images optical correlation [15]-[16]. For instance, in [5] correlation filters are used at the frequency domain for faces authentication from cell phone cameras images. Here, several training images are used to design a correlation filter in the frequency domain. The performance of the correlator is measured by computing the PSR (Peak-to-Sidelobe Ratio).

The Wavelet transform is a mathematical tool that allows the decomposition of a signal in scaled and translated versions of a mother signal [17]. For digital application is of great utility to employ the discrete wavelet transform, which has been used for multiple purposes in image analysis [18]-[19], becoming one of the most powerful methods of multiresolution representation. In [20], [21] and [22] are depicted the advantages of the discrete wavelet transform for image contrast enhancement. In combination with this technique several algorithms have been developed with the aim of enhancing and recognizing images once the multiresolution representation of the signal has been obtained [13], [23]. For instance, Suarez et al. uses wavelet decomposition for extracting the detail or high frequency information of the original image at different level of resolution. After this, the digital correlation is computed using either the horizontal or vertical or diagonal subband of representation. Moreover, the algorithm is evaluated with images in the presence of noise.

In this work is proposed an approach, in which the properties of signals decomposition of the Wavelet transform and the optical correlation techniques used to match a template with a reference image are combined in order to detect important characteristics from images as a method of pattern recognition. A non linear filter has been designed at the level of subband for the enhancement of the high frequency components of the image. The method is evaluated using images of different characteristics, resolutions and illumination as well as unfocused images.

The rest of the paper is organized as follow. In section II, the correlation algorithms are depicted; section III shows concepts of the discrete wavelet transform and describe the non linear filter designed at level of subband. Section IV illustrates a general overview of the proposed method; section V shows results of the method, performance measurement and discussions. Finally, in section VI is treated the conclusions of the work.

2. Image Correlation Algorithms

The correlation operation between two images is a standard approximation for characteristics detection, in which is analyzed the similitude of the two signals [24]. As mentioned before, the correlation can be carried out by using either spatial or spectral domain.

2.1. Correlation in the spatial domain

In the spatial domain the correlation (cross-correlation) is applied to identify a pattern, which corresponds to a subimage that maps other reference image in order to find some similarities between them. The mentioned subimage, called as image template, represents the sample containing the wanted information inside the reference image. The bigger the similitude between the reference and the mapped image is, the bigger the correlation coefficient results. Generally speaking, in pattern recognizing system several filtering techniques are used in combination with normalized cross-correlation, which is defined as:
\begin{equation}
    \text{corr}(u,v)=\frac{\sum_{x=1}^{J}\sum_{y=1}^{K} f(x,y)g(x-u,y-v)}{\left(\sum_{x=1}^{J}\sum_{y=1}^{K} f^2(x,y)\right)^{1/2}\left(\sum_{x=1}^{J}\sum_{y=1}^{K} g^2(x-u,y-v)\right)^{1/2}}
\end{equation}

where \( f \) is the reference image and \( g \) the sample subimage positioned in point \((x,y)\) inside the reference image \( f \). In general, coefficients \( c(x,y) \) must be calculated for all possible translations of the sample image over the reference image [25].

2.2. Correlation in the spectral domain

Correlation in the spectral domain is based on convolution theorem and the Fourier transform. It is necessary to get the two-dimensional discrete Fourier transform of both simple and reference images in order to find the correlation coefficients. Taken into account this, the correlation is calculated through the convolution theorem in the spatial domain for discrete signals:

\begin{equation}
    \text{corr}(u,v)=\sum_{x=1}^{J}\sum_{y=1}^{K} f(x,y)g^*(x-u,y-v)
\end{equation}

where * denote the conjugate complex of the function \( g \). When working with images of big size is completely convenient to employ this operation in the spectral domain by using the discrete Fourier transform (DFT), in which it is necessary to use the correlation theorem [26] to obtain the output coefficients by the multiplication of the Fourier transforms of the images to be compared. To return to the spatial domain the inverse transform is calculated:

\begin{equation}
    \text{corr}(u,v)=F^{-1}\left\{ F(f(x,y))F^*(g(x,y)) \right\}
\end{equation}

where \( F \) denote the Fourier transform of the function and \( F^{-1} \) the inverse transform. This method is commonly known as Joint Transform Correlator (JTC) [26].

3. Two Dimensional wavelet transform for multiresolution representation

Wavelet decomposition produces a family of hierarchically organized decompositions; it mean, a signal is decomposed into hierarchical set of approximations and details. The wavelet analysis procedure is to adopt a wavelet prototype function, called an analyzing wavelet or mother wavelet [27]. The main advantage of using wavelet transform is that it is well-suited to manage different image resolution and allows the image decomposition in different kinds of coefficients, while preserving the image information. This work uses the Two-Dimensional Discrete Wavelet Transform, which can be defined as:

\begin{equation}
    C(a,b)=C(j,k)=\sum_{x \in Z} \sum_{y \in Z} f(x,y)g_{j,k}(x,y)
\end{equation}

with \( a=2^j \), \( b=k2^j \), \( j \in N \), \( j \in N \)

where \( f \) is the original image, \( g \) is the wavelet function, \( a \) is a scale factor of the wavelet function, \( b \) is a location parameter of the wavelet function, and \( C(a,b) \) is the set of coefficients obtained. Inverse process is calculated by:

\begin{equation}
    f(x,y)=\sum_{j \in Z} \sum_{k \in Z} C(j,k)\psi_{j,k}(x,y)
\end{equation}

where \( \psi \) is the wavelet function used to reconstruct the image.
The multiresolution representation carried out by 2-D discrete Wavelet transform fragment the frequency spectrum of an image \( I \) into a low-pass subband image \( cA \) and a set of band-pass sub-band images with horizontal orientation \( cDH \), vertical orientation \( cDV \), diagonal orientation \( cDD \), \( j = 1, \ldots, L \), where \( L \) denote the number of levels for a representation [28]. Generally speaking, multiresolution representations are implemented by a cascade of analysis/synthesis (A/S) filter banks. The discrete wavelet transform uses two different wavelet mothers: \( h(x) \) for multiresolution decomposition (analysis) and \( g(x) \) for reconstruction (synthesis) of the original image from its multiresolution representation. An efficient method to implement discrete wavelet transform using filters was developed by Mallat [29]. Figure 3 shows the implementation of one-level (\( L = 1 \)) multiresolution representation of the discrete wavelet transform, which partitions orientations into three bands. As seen in Figure 3, the forward 2-D wavelet transform is implemented using a bank of 1-D low pass \( (h_1(x)) \) and high pass \( (h_2(x)) \) analysis filters. The reconstruction process, or inverse wavelet transform, is likewise computed via 1-D synthesis filters, \( g_1(x) \) and \( g_2(x) \).

![Figure 1. Wavelet decomposition algorithm.](image)

Let \( A_N(x,y) \) denote a two dimensional image, \( h_1 \) and \( h_2 \) be the analysis filters used to compute the two dimensional discrete wavelet transform, in which \( h_1 \) and \( h_2 \) respresents the Low Pass and High Pass filter coeficients respectively. Then the j-level of the wavelet trasform:

\[
\{cA_{n,m}(x,y), cDH_{n,m}(x,y), cDV_{n,m}(x,y), cDD_{n,m}(x,y)\}
\]

of \( A_N(x,y) \) can be calculated as [13]:

\[
cA_{n,m}(x,y) = \sum_{m,n} H_1(m)H_1(n)A_n(2x-m,2y-n)
\]

\[
cDH_{n,m}(x,y) = \sum_{m,n} H_1(m)H_2(n)A_n(2x-m,2y-n)
\]

\[
cDV_{n,m}(x,y) = \sum_{m,n} H_2(m)H_1(n)A_n(2x-m,2y-n)
\]

\[
cDD_{n,m}(x,y) = \sum_{m,n} H_2(m)H_2(n)A_n(2x-m,2y-n)
\]

where \((x, y), (m, n)\) are the coordinates in the spatial domain.

3.1. Non Linear enhancement of Detail Subbands

One of the principal advantages of using multiscale enhancement is that the designed filter can be focused on improving separately each detail information, taken into account the need of a specific application. In addition, denoising algorithms can be incorporated into the multiresolution representation.
A problem for image enhancement in some applications is the ability of emphasizing image edge features and sharpening high frequency components while reducing the enhancement of noise. For the last twenty years, algorithms of contrast enhancement have been created. Many of them use histogram modification techniques [30], adaptive unsharp masking [31] morphological enhancement [32], spectral definition [9] whilst others have employed image multiresolution representation through Wavelet transform to design the desired filters. As an example, Laine et al. propose a set of multiscale filters using a dyadic wavelet for enhancement of mammograms, in which several non linear functions were introduced at each level of the decomposition wavelet to modify the high frequency-subband coefficients using local and global contrast enhancement. In spite of this filters present a good performance on applications like mammograms, neither of them has a direct dependence of the local contrast measured in the input image.

For the enhancement, we developed a filter based on an exponential function whose argument depend on the local contrast measured on the detail subbands at each level of decomposition:

$$F_{H,V,D}(x,y) = cD_{H,V,D}(x,y)\{k \times \exp\left[1 - c(x,y) / C_{max}\right]\}$$

(11)

where $c(x,y)$ is the local contrast calculated and centered on the current pixel surrounded by a window $W$ whose size is an odd number, $C_{max}$ is the maximum contrast calculated on the detail subbands at each $j$-level, and $k$ constant. The expression $k \times \exp\left[1 - c(x,y) / C_{max}\right]$ is seen as a parameter of gain controlled by the local contrast and the constant $k$.

This method has the property of enhancing areas of low contrast more than areas of high contrast, what means that for small values of $c(x,y)$, the current pixel is incremented by a larger gain. Moreover, sharp edges are not blurred. Zones of high contrast, near the maximum contrast, are maintained without modification. Figures 2a, 2b and 2c show the obtained enhancement when using the filter defined in the above equation and its visual perception is compared with a commonly used filter based on unsharp masking.

This paper adopts a simple and effective measurement of image contrast local based on the intensity difference in a window $W$, which has been used in [8]:

$$c(x,y) = \max(W(x,y)) - \min(W(x,y))$$

(12)

where $W(x,y)$ represents the local image of $cD_{H,V,D}$ centered at the position $(x,y)$ at the $j$-level of decomposition. In figures 3a, 3b and 3c is illustrated the local contrast measurement obtained.
In the same way the inverse algorithm for the discrete Wavelet transform can be described from the \( F_h, v, d(x, y) \) coefficients as:

\[
A_{h, v}(x, y) = 4 \sum_{m, n \in Z} g_1(m)g_1(n) A_{h, v}(x-m, \frac{1}{4}(y-n)) + \]

\[
+ \sum_{m, n \in Z} g_2(m)g_2(n) F_h(x-m, \frac{1}{4}(y-n)) + \]

\[
+ \sum_{m, n \in Z} g_3(m)g_3(n) F_v(x-m, \frac{1}{4}(y-n)) + \]

\[
+ \sum_{m, n \in Z} g_4(m)g_4(n) F_d(x-m, \frac{1}{4}(y-n)) \]  

(13)

where \( g_1, g_2 \) are the synthesis filters used to reconstruct the image. If there are problems of noise in the image, several techniques of image denoising using wavelet representation can be applied [20], [22]. In addition, for many years several analysis and synthesis filters for the discrete wavelet transform have been proposed. In this paper, daubechies, haar, symlets and biorthogonal families are employed.

4. Algorithm overview

The algorithm consists of several processing stages as illustrated in figure 4. Firstly, the subband decomposition must be obtained using the 2D DWT over the images involved in the comparison.

Once the DWT is calculated, several images are obtained showing the low and high frequency components of the original image. The idea of using multiresolution representation is due to the possibility of changing the characteristics of the image, manipulating the resulting subband through different decomposition level, which is useful when working with images of different level of contrast. This leads the system to employ a specific filter depending on the contrast of the input image.

As shown in figure 4 the next step corresponds to a filtering process over the detail information of each input image. The non linear filter defined above is then used.

The inverse wavelet transform is finally obtained after the subband filtering is finished. In here, a new image is visualized remarking the high frequency components of the original image. It is important to note that the original image can be reconstructed from the subbands only to show either the high or low frequency components. This is carried out by eliminating either the low or high frequency components at the level of subband. Once the image is recovered, the digital correlation is applied using one of the two methods depicted in section II. If target detection is needed, the final correlation peaks are selected through a thresholding process defined by a step function:

\[
P(x, y) = \begin{cases} 
1, & \text{if } \text{corr}(u, v) > \max(\text{corr}(u, v)) - l \\
0, & \text{if } \text{corr}(u, v) < \max(\text{corr}(u, v)) - l
\end{cases}
\]  

(14)
where $corr(u,v)$ are the correlation coefficients obtained and $l$ is a constant that allows decreasing the threshold to a smaller value than the maximum peak of the final correlation matrix.

![Figure 4](image_url)  
**Figure 4.** Developed method.

The resulting correlation peaks show the position in which the sample subimage is located inside the reference image.

5. Results and Discussions

In order to evaluate the findings, different reference images were employed to match with a template image. Autocorrelation is used and its result is compared with the correlation using blurred and enhanced images with the wavelet-based filter. The idea is to demonstrate how the correlation peaks energy is improved when using this filter.

Figure 5 shows a face image used to evaluate the autocorrelation and its blurred version, which can be seen as an unfocused image and was obtained as a result of applying a media filter several times. This picture was captured by a commercial webcam camera.

![Figure 5](image_url)  
**Figure 5.** Face image to prove the autocorrelation, a) Original Image; b) Blurred version of the the original image; c) Enhanced contrast of the original by the wavelet-based filter, d) Enhanced image of the blurred version by the non wavelet based filter.

The edge version of each image in figure 4 is taken to evaluate the method. Firstly, autocorrelation is calculated using the original image and in the same way it is computed with the rest of the images. Figure 6 shows findings of this process. As a first intuitive result, it is notable that the maximum correlation peak is increased when employing the wavelet-based filter. However, others correlation performance methods can be used. Some of these approaches are described in [5], [33]-[34] and we developed three of them as follow.
5.1. Metrics of the correlator

There are several forms of evaluating the correlator performance: Signal to Noise Ratio-SNR, which is a measure that represents the noise tolerance of the system, Correlation Peak Intensity-CPI, Peak to Correlation Energy-PCE and Peak to Sidelobe Ratio-PSR. In this paper is explored the last three metrics. Taken the equations (1) and (2) as the final correlation coefficients calculated, these parameters are computed as:

5.1.1. Correlation peak intensity – CPI

With this parameter is calculated the maximum amplitude of the correlation matrix, it means, the maximum peak:

\[ CPI = \max(\text{corr}(u, v)) \]  

(15)

Some results of this measure are shown in figure 6.

5.1.2. Peak to correlation energy – PCE

This parameter measure the concentration of energy into the correlation peak:

\[ PCE = \frac{\text{corr}(0,0)}{\sum_{x} \sum_{y} |\text{corr}(x,y)|} \]  

(16)

with \(\text{corr}(0,0)\) being the Correlation Peak Intensity-CPI calculated in equation (14).

![Figure 6](image_url)

**Figure 6.** Correlations Coefficients when it is processed, a) Original Image – autocorrelation; maximum peak = 1153, b) Image Initial and Blurred Image; maximum peak = 700, c) Initial Image and Enhanced Blurred Image; maximum peak = 710, d) Enhanced Initial Image and Enhanced Blurred Image; maximum peak = 722.
5.1.3. Peak to sidelobe ratio - PSR

This measure emphasizes in calculating the sharpness of the correlation peak and it is typically high for similar patterns:

\[
PSR = \frac{CPI - \overline{SL}}{std(SL)}
\]  

(17)

where the CPI is the largest value of the correlation output, \( \overline{SL} \) and \( std \) the mean and standard deviation of the sidelobe region, which is an annular window surrounding the peak as shown in figure 6.

5.1.4. Numeric results

In the next table are summarized findings for each parameter explained using correlations for images shown in figure 7.

|                | CPI  | PCE  | PSR   |
|----------------|------|------|-------|
| Face vs Face   | 1153 | 0.0254 | 116.6516 |
| (Autocorrelation) |    |      |       |
| Face vs Blurred Face | 700 | 0.0086 | 66.4655 |
| Face vs Enhancement Blurred Face | 710 | 0.0112 | 79.5320 |
| Enhanced Face vs. Enhanced Blurred Face | 722 | 0.0138 | 86.3233 |

It is notable that the performance of the correlator is improved by using image enhancement with wavelet-based filtering into the two images.

5.2. One example on target detection

In this part, it is evaluated an example of the proposed method in detecting target in a clutter reference image. Figure 8(a) shows a reference image, which consists of a parking zone and the template image to be compared is illustrated in figure 8(b), which corresponds to a sign (cross) showing that a specific parking site is not busy.

In order to compare the effectiveness of the algorithm to detect targets in scenes, it was employed the correlation without using the wavelet-based image enhancement algorithm; findings of this process are shown in figure 9.
It can be noted that in this case was necessary to use the final peaks selection algorithm illustrated by the equation (14). As result 18 from 29 objects were detected for a percentage of 62% in performance.

The next step is to calculate the correlation once the wavelet-based filter is applied over the images (the reference and the target). In this example 26 from 29 objects were detected inside the reference
image and 2 false positive for a percentage of 89% in performance. The following values of parameters were used: wavelet decomposition level $L=1$, wavelet family $= \text{Symlet – order 4 (sym4)}$, gain of the subband filter $k=1$, constant $l=0.7$. For this specific case, both spatial and spectral domain correlators were used, obtaining the same results. In figure 10 is then observed the position of the detected objects after employing the developed method.

Because of the type of target to be detected inside the reference image, it was only necessary to use the diagonal high frequency component of the target and reference image for this example.

![Image](image_url)

**Figure 10.** Obtained correlation matrix using wavelet-based filtering, seem as a graphic a) in 2D, b) in 3D; c) in 2D with final peaks detected.

6. Conclusions

It was presented a system in which the discrete wavelet transform was used to improve the capacity of objects recognizing when using image digital correlation. The method increases the performance of the correlator when employing the filtering process of wavelet detail subbands. The algorithm is then proved in detecting single targets in a reference image, showing an increase in the performance compared with correlation system that does not use filtering. The filtering process emphasizes in enhancing the high frequency details of images by using the wavelet decomposition. It can be seen that the multiresolution decomposition allows manipulating the information of the image while it is preserved the initial form of the image. As it was demonstrated in the example, the choice of specific detail information to be correlated depends directly on the type of images that are being compared. The direct dependence of the enhancement algorithm over the initial contrast of the image makes that the general method work different for each input image, which is useful for real applications because not all the images have the same contrast. As a future work, it is (planned to create an automatic system that involves the initial contrast of the image in order to select an adequate wavelet family for the decomposition.
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