Non-linear Fourier optics in computers: a challenge for hybrid digital-optical image processors

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In the paper, a family of methods that work in the domain of Discrete Fourier and Discrete cosine transforms and proved to be very efficient for adaptive and local adaptive image restoration and target location is reviewed and possible ways for their implementation in analog optical image processors that work with the speed of light are discussed. © Anita Publications reserved. All rights reserved.

1 Introduction

Digital image processing and optical image processing date back to 1960-1970-th, and the latter to even earlier times, if one considers photographic methods. Since that time digital image processing has made a tremendous progress and has become ubiquitous in applications, where image processing is required. Such advantages of digital image processing as its versatility and programmability turned out to be decisive, whereas the main advantage of optics, its capability to perform point-wise non-linear as well as linear integral transformations of optical signals with a speed of light are still far from being realized by virtue of the absence of appropriate hardware. Obviously, optimal solution would be hybrid digital-optical processing, which, however is still up to now not veryfeasibly for the same reason of the absence of fast and high precision electronically controlled spatial light modulators, capable of modulating, under computer control, both amplitude and phase of optical signals, and of non-linear optically and electronically controlled media capable of performing fast and accurate point-wise non-linear transformations.

However recent advances in photonics and nano-materials promise that this shortage of the appropriate hardware might be soon overcome, and smart magic digital-optical “magnifying” glasses, binoculars, spyglasses, and alike working with a speed of light and enabling direct viewing and analyzing images in viewer’s comfortable real time are coming. The purpose of the present paper is to summarize available up to now ideas that look potentially implementable in such digital-optical image processors. Specifically, we overview methods of image denoising, deblurring and enhancement as well as methods of target location in images, which are basic operations to assist visual and automated image analysis. We sketch also possible options of digital-optical image processing system design and formulate what is missing and thus preventing these systems from coming into being.

2 Adaptive transform domain filters for image restoration

The first candidate for digital-optical implementation is the family of adaptive and local adaptive linear filters for image denoising, deblurring and enhancement [1-3]. Generally, these filters work in domain of image transforms, such as Discrete Fourier Transform (DFT), Discrete Cosine Transform (DCT), Walsh Transform, Wavelet Transform and alike, and implement Empirical Wiener filtering principles. DFT and DCT Transform processing proved to be in majority of applications the most efficient. DFT and DCT are transforms that represent in computers integral Fourier Transform [1,3]. In what follows we will mean working with image Fourier spectra in domain of the Fourier Transform, which is the basic optical transform.

There are three modifications of the filters: (i) Proper Empirical Wiener Filters, (ii) Signal Spectrum Preservation Filters and (iii) Rejecting filters. For image denoising from additive signal independent noise and image deblurring they modify input image Fourier spectra \( \hat{S}_{inp}(f) \) at each frequency component \( f \) according to the equations, correspondingly:

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Empirical Wiener Filter:

\[
Sp_{out}(f) = \frac{1}{ISFR(f)} \max \left\{ 0, \frac{[Sp_{inp}(f)]^2 - Sp_{noise}(f)}{[Sp_{inp}(f)]^2} \right\} Sp_{inp}(f);
\]  
(1)

Signal Spectrum Preservation Filter:

\[
Sp_{out}(f) = \frac{1}{ISFR(f)} \max \left\{ 0, \frac{[Sp_{inp}(f)]^2 - Sp_{noise}(f)}{[Sp_{inp}(f)]^2} \right\}^{1/2} Sp_{inp}(f);
\]  
(2)

Rejecting filter:

\[
Sp_{out}(f) = \begin{cases} 
\frac{Sp_{inp}(f)}{ISFR(f)} & \text{if} \quad [Sp_{inp}(f)]^2 > Sp_{noise}(f) \\
0, & \text{otherwise}
\end{cases}
\]  
(3)

where \(Sp_{out}(f)\) is Fourier spectrum of output image, \(Sp_{noise}(f)\) is power spectrum of additive noise, assumed to be known or to be empirically evaluated from the input noisy image [1,3], \(ISFR(f)\) is Imaging System Frequency Response on frequency \(f\), assumed to be known from imaging system certificates. Division of image spectra by \(ISFR(f)\) means “inverse” filtering that compensates image blur in the imaging system, i.e. performs image deblurring.

As one can see in these equations, all the filters eliminate image spectral components that are less intensive than those of noise and the remaining components are corrected by the “inverse” filter with frequency response \(1/ISFR(f)\). In addition, empirical Wiener filter modifies image spectrum through de-amplification of image spectral components according to the level of noise in them. Spectrum preservation filter modifies image spectrum as well to make it equal to its empirical estimate as difference between spectrum of noised signal and spectrum of noise. Rejecting filter does not modify remaining, not rejected, spectral components at all.

These filters can be applied both globally to entire image frames and locally to individual image fragments. Global application is effective for removing so called narrow band noises, such as banding and moire noise. Local application of the filters to image fragments of about several tens to several hundreds of image resolving elements (pixels) proved to be an effective mean for cleaning images from wide band noise, such as white noise. When implemented in computer, local filtering is carried out in a moving row-wise/column-wise window, generating, in each window position, an estimate of the window central pixels or, as an option, accumulating estimates of the pixels overlapping in the process of image scanning by the filter window. Deblurring can be performed practically equally efficiently in both global and local filtering.

Image enhancement is yet another application of adaptive linear filters acting on image spectra in the domain of Fourier transform. These filters can be exemplified by a Spectrum Compressing filters (SC-filters) that compress image spectra dynamic range. Image spectra dynamic range is, as a rule, extremely high. Low frequency image components, which carry information on general shapes of imaged objects, carry a lion share of image energy, whereas high frequency components, which carry crucial for object recognition and discrimination one from another information on object boards, are substantially less intensive. This is a direct consequence of the fundamental fact that object borders contain much less pixels than objects themselves. Low intensity of image high frequency components cause poor visibility of object borders, and this hampers image visual analysis, object detection, discrimination and recognition. Compressing image
spectra dynamic range redistributes image energy in favor of low intensity high frequency image spectra components and results in amplification of object border contrast and thus in improvement of image visual quality and “readability”. Simple and easily controllable SC-filters are $P$-th law spectrum compression filters that modify image power spectra $|S_{p_{in}}(f)|^2$ to be equal $S_{p_{in}}(f)^{2P}$:

$$S_{p_{out}}(f) = \frac{1}{|S_{p_{in}}(f)|^{(1-P)}} S_{p_{in}}(f),$$  \hspace{1cm} (4)

where $P \leq 1$ is a parameter that controls the degree of spectrum dynamic range compression and, by this, the degree of image enhancement.

Amplification of image high frequency components by this filter can, in practice, result in amplification of image noise as well. Therefore, practical solutions are $P$-th law SC-rejecting filters, described by the equation

$$S_{p_{out}}(f) = \begin{cases} \frac{1}{|ISFR(f)|S_{p_{in}}(f)^{1-P}} S_{p_{in}}(f), & \text{if } |S_{p_{in}}(f)|^2 > S_{p_{noise}}(f) \\ 0, & \text{otherwise} \end{cases}$$ \hspace{1cm} (5)

They combine image dynamic range compressing, suppressing image noise and compensation of image spectra distortions in imaging systems.

Image enhancement SC-filters can also be used for both global processing of entire image frames and for processing of image fragments in running window. Figures 1, 2 and 3 illustrate image denoising, deblurring and enhancement capability of adaptive and local adaptive linear filters.

![Before](image1.png) ![After](image2.png)

Fig 1. Removing banding noise from a satellite image by means of separable (row-wise and column-wise) high pass rejecting filtering. Fiducial cross marks were removed from the image before the processing and restored afterwards.
Fig 2. Denoising and deblurring of a satellite image by means of local adaptive filtering. Top row: raw image and its magnified, for better viewing, fragments (marked by arrows); bottom row: resulting image and its corresponding magnified fragments.
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2.1 Adaptive transform domain filters for reliable target detection

When people speak on optical information processing, optical correlators for target detection in images first come to mind. This application of coherent optics has been known since A Vander Lugt’s publication [4], which introduced an optical implementation of the so-called “matched filter” for object detection. Matched filtering is described in Fourier Transform domain by the equation:

\[ Sp_{MFcorr}(f) = TgSp^*(f)Sp_{inp}(f), \]

where \( Sp_{inp}(f) \) is Fourier spectrum of the input image on which a target object is sought, \( TgSp^*(f) \) is complex conjugate to the spectrum of the target object, \( Sp_{MFcorr}(f) \) is spectrum of correlation between the input image and the target object. It is assumed that target detection is accomplished by detecting the highest signal peak in the image/target correlation found by inverse Fourier transform of its spectrum \( Sp_{MFcorr}(f) \).

The matched filter correlator is the optimal solution for target detection in images that contain only a target object corrupted by uncorrelated normal additive noise. However, it is far from being optimal for detection of targets in images that contain, except the target object, other non-target objects [5] due to its poor discrimination capability with respect to them. A solution of the problem of improving discrimination capability of correlators was found in optimal adaptive correlators [1,6 - 8]. Optimal Adaptive (OA) correlators compute correlation not between input and target images, but between their copies modified by dividing their spectra by the spectrum of the input image as it is described by the first equality in the equation

\[ Sp_{AOcorr}(f) = \frac{TgSp^*(f)Sp_{inp}(f)}{|Sp_{inp}(f)|^2}, \]

Note that the OA-correlator defined by Eq (7) is akin to the above described filters for image denoising, which also contain power spectrum \( |Sp_{inp}(f)|^2 \) of input images in the denominator of their frequency response. This makes the filters and OA-correlator adaptive to input images. Moreover, since
input images may be contaminated by the sensor noise, it is advisable to supplement the OA-correlator with a noise suppressing rejecting filter of the type defined by Eq (5):

\[ S_{\text{out}}(f) = \begin{cases} T_g S_p(f) S_{\text{out}}(f) & \text{if } |S_{\text{out}}(f)| > S_{\text{noise}}(f) \\ 0 & \text{otherwise} \end{cases} \]  

(8)

Improved discrimination capability of the OA-correlator compared to the matched-filter correlator is illustrated in Fig 4 on an example of detection of a fragment of one of two stereoscopic images on the second image.

Fig 4. Comparison of discrimination capability of the matched filter and OA-correlators. As one can see, OA-correlator correctly detects the target whereas matched filter correlator fails. Graphs of rows of correlators’ outputs in right bottom part of the figure show that correlation peak at the OA-correlator is 8.6 times larger than the standard deviation of the correlator output (signal-to-clutter ratio SCR = 8.6); the same ratio for the matched filter correlator is only 2

2.2 Digital-optical image processing systems: a sketch

The main computational burden of described adaptive and local adaptive filters for image restoration, enhancement and target detection is computing image spectra and restoring images from their spectra. All other required operations for their implementation are trivial point-wise transformation, whose computational complexity is negligible compared to that of computation of direct and inverse Fourier transforms. Their implementation and use in digital image processing became possible only after invention of Fast Fourier Transform (FFT) algorithms in year 1965. The per-pixel computational complexity of FFTs is proportional to the logarithm of image size, i.e. it grows with the image size, though with only a logarithmic speed. In this respect optics has an edge: optics can compute image Fourier spectra of whatever large images with a speed of light. In fact, this was the main motivations of advancing ideas of optical image processing in 1960th, before the invention of FFTs and at the very beginning of the digital imaging era.

Several designs of optical image processing systems have been suggested and discussed since then. Figure 5 depicts a version of a so-called “4F” optical system with a nonlinear transparency in its Fourier plane. With the transparency that has amplitude transfer function presented in the right part of the figure, the system is capable of performing image denoising and enhancement rejecting filtering (Eq 5) combined with image magnification with factor \( F_r/F_p \). If the transparency threshold and nonlinearity parameter \( P \) are
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adjustable by an external control, the system will have all flexibility of its digital computer counterparts, while implementing completely parallel processing with a speed limited only by the time response of the transparency.

\[ f (x, y) = \exp \left( \frac{-i 2 \pi k x y}{\lambda f_0} \right) \]

Figures 6 and 7 depict a “4F” optical correlator and a so called “Joint Transform Correlator” for target detection and localization in images. The presence in Fourier plane of the “4F” optical correlator a threshold and “1/x” nonlinear transparency, i.e. transparency with transmittance inversely proportional to the intensity of the incident light, makes it capable of implementing of the adaptive optimal correlator defined by Eq (8). One should note that exact observance of the 1/x law is not required. As it was shown in [6], the discrimination capability of nonlinear correlators with 1/x^n nonlinearity does not vary very much in the range [0.8 < k < 1.2].

For implementation of the “4F” nonlinear correlator, a transparency with recorded complex conjugated spectrum of the sought target object is required. It can be an optical hologram of the target object image, or it can be a computer generated hologram recorded using one or another computer controlled spatial light modulator. This necessity in a pre-recorded hologram of the target object is avoided in Joint Transform correlators, in which input image and template image of the target object are placed aside in the input image plane and a nonlinear optical light modulator for recording intensity of the sum of Fourier spectra of input and target object images is placed in the Fourier plane. In the logarithmic Joint Transform correlator shown in Fig 7, the optical light modulator has a logarithmic amplitude transfer function, i.e. it records logarithm of the joint input image and target object image power spectrum.

\[ \ln \left[ |S_{inp}(f)| + TgSp(f) \exp \left( i 2 f_x x \right) \right] \approx \ln \left[ |B(f_x, f_y)|^2 + |TgSp(f)|^2 \right] + \frac{S^*_p(f_y) TgSp(f)}{|S_{inp}(f)|^2} \exp \left( i 2 f_x x \right) + \frac{S_{inp}(f) TgSp^*(f)}{|S_{inp}(f)|^2} \exp \left( -i 2 f_x x \right) \] (9)

where \( \vec{x} \) is displacement between input and target object image in the correlator’s input plane, and a natural assumption that \( |S_{inp}(f)|^2 >> |TgSp(f)|^2 \) is made on the base that the size of the target object image is much smaller than the input image size. As one can see, the last term of this approximation implement the adaptive optimal correlator.

\[ |S_{inp}(f)|^2 >> |TgSp(f)|^2 \] (10)
Such implementation, which simplifies the system can be used as image processor for image denoising and enhancement as well.

Yet another option for optical implementation of the described adaptive image denoising and enhancement filters and optimal correlators is associated with the use, as image Fourier Transformers, parabolic mirrors. This option is illustrated in Fig 8 by the sketch of a nonlinear optical correlator. Such implementation has an advantage of being more compact than the “4F” correlators. It also permits direct optical access to the filter plane, which simplifies its external control and enhances its flexibility. With a corresponding replacement of the reflective matched filter by the above-described image restoration filters, the system can be used as image processor for image denoising and enhancement as well.
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3 Conclusion

We reviewed and illustrated by examples of work the family of transform domain adaptive filters for image restoration, enhancement and target location and presented sketches of their possible optical implementation that can take full advantages of working in parallel and with the speed of light on entire images rather than pixel by pixel as it takes place in image processing by computers. Though these ideas go back to 1960-80-th, they are still far from being implemented. The reason is the absence of the required non-linear transparencies and optical light modulators. However, the present author believes that their time will come because, as famous German philosopher Georg Wilhelm Friedrich Hegel wrote, “Was vernünftig ist, das ist wirklich, und was wirklich ist, das is vernünftig. (What is reasonable is real; that, which real, is reasonable).

References


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1995, he had headed a Laboratory of Digital Optics at the Institute for Information Transmission Problems, Russian Academy of Sciences. From 1995 till 2008, he was a full Professor at Tel Aviv University, where presently he is a Professor Emeritus. During his teaching carrier he supervised more than 50 MS and 20 PhD students. He was also a visiting research professor at University of Nürnberg-Erlangen (Germany), National Institute of Health (Bethesda, MD, USA), Institute of Optics, Orsay (France), Institut Henri Poincare, Paris (France), International Center for Signal Processing, Tampere University of Technology, Tampere (Finland), Agilent Laboratories, Palo Alto, Ca, (USA), Gunma University, Kiryu (Japan), Autonomous University of Barcelona, (Spain). Dr. Yaroslavsky’s main fields of interests and expertise include digital imaging and image processing, digital holography and 3D visual communication. He is an author of several internationally published books and more than 150 journal papers.