High Resolution Analysis for Defective Pixels Detection using a Low Resolution Camera

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Abstract

A system for high-resolution analysis of defective elementary cell (R, G or B) on Flat Panel Display (FPD) is described. Based on multiple acquisitions of low-resolution shifted images of the display, our system doesn't require a high-resolution sensor neither tedious alignment of the display, and will remain up to date even facing an important increase of the display dimensions. Our process, highly automated and thus flexible and robust, is expected to perform a full analysis in less than 60s. It is mainly intended for production tests and display classification by manufacturers.

1. Introduction

Flat Panel Displays (FPD) inspection requires numerous production tests to assess their quality. One of them consists in counting the defective elementary cells (R, G or B) and precisely identifying their coordinates. Such a knowledge could allow manufacturers to correct some defects, to classify displays in groups of different qualities (with different prices), or to quickly identify a degradation on the production mask. Production tests are mostly visually done, which leads to a subjective rejection decision that depends -for example- on the operator's tiredness. Moreover only two groups of displays are created: the rejected ones -which remain numerous-, and the good ones.

Localization of every defect cannot be directly obtained from a usual video camera because of a definition conflict between the Charge Coupled Devices sensor (CCD) and the display matrix - which has much more pixels per row than usual CCD sensors -. One solution to get a high-resolution image of the display consists on using a high-resolution sensor. However, men skilled in the art agree to say that at least a 4-time more resolved sensor is needed. That means that at least a 23 Mpixels sensor is needed to test UXGA displays. This solution is very expensive and would need to be updated for future QXGA display definition.

We develop in this article a new method for the reconstruction of high-resolution images of FPD. It is based on the acquisition of multiple low resolution images with a low cost sensor while a periodic image - in which some pixels are regularly switched on and off - is sequentially displayed. Our process doesn't require a precise alignment with -for example- a specific ratio between the sensor pixel relative dimension and the elementary cell of the tested display. Moreover, it can cope with large range of ratio between display and sensor dimensions. The proposed system reaches sub-pixel resolution and precise localization of defects, thanks to a spectral approach, which allows the best use of the strong a priori knowledge got through the periodicity of the displayed test pattern.

2. Theory

2.1 Coping with sensor degradations

Image acquisition through a CCD camera introduces three main degradations. The first one is the low-pass filter that mainly corresponds to the optical blur and CCD integration. That filter prevents us from precisely localizing the defect. The second degradation is called aliasing and is tied to sampling. Intensity swing due to the Moiré pattern may introduce more intensive variations of intensity than that corresponding to a defect (Figure 1). That can generate errors in defect analysis. Thus, we are looking for about a dozen of defect and we can't accept to forget one or to identify some ones that do not exist. The third degradation is the noise introduced by the CCD cell and by the electronic chain. Perfect knowledge on each elementary cell requires the compensation of the two first degradations (restoration task and super-resolution task), while taking into account the added noise (and minimizing its effect).

2.2 The use of the a priori knowledge

The main idea of our system is to exploit the periodic and sampled structure of our substrate. This induces a periodicity of its spectrum, which is generally handled as a drawback (because of Shannon rule). Thus we use it positively by saying that the knowledge of the spectrum on a single period allows us to reconstruct it perfectly at any wavelength by "periodisation" (Figure 2).

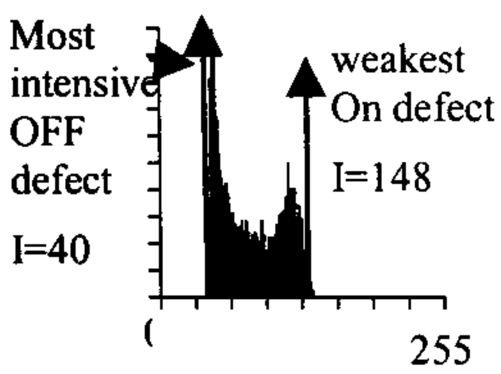

Figure 1: Histogram from the image of a red screen with some simulated defects. It shows the distribution of intensity due to aliasing. The arrow shows the position of the lowest –highest- intensity of simulated defects. They are mixed into the Moiré pattern.

As an example, if only one on three pixels is switched on, the spectrum will have a minimal period of 1/3. No need to clean the spectrum in the [-0.5,0.5] frequency domain. We can simply clean it on the [-1/6,1/6] domain and reproduce it periodically. The use of multiple shifted images allows us to be sure that the [-1/6, 1/6] domain isn't disturbed by aliasing. Moreover, the use of a small spectral domain allows a simple inverse (or quasi-inverse) filtering to compensate the sensor blur, without incurring a huge increase of the noise. Indeed, the transfer function of the sensor doesn't take zero intensity for so low frequency values.

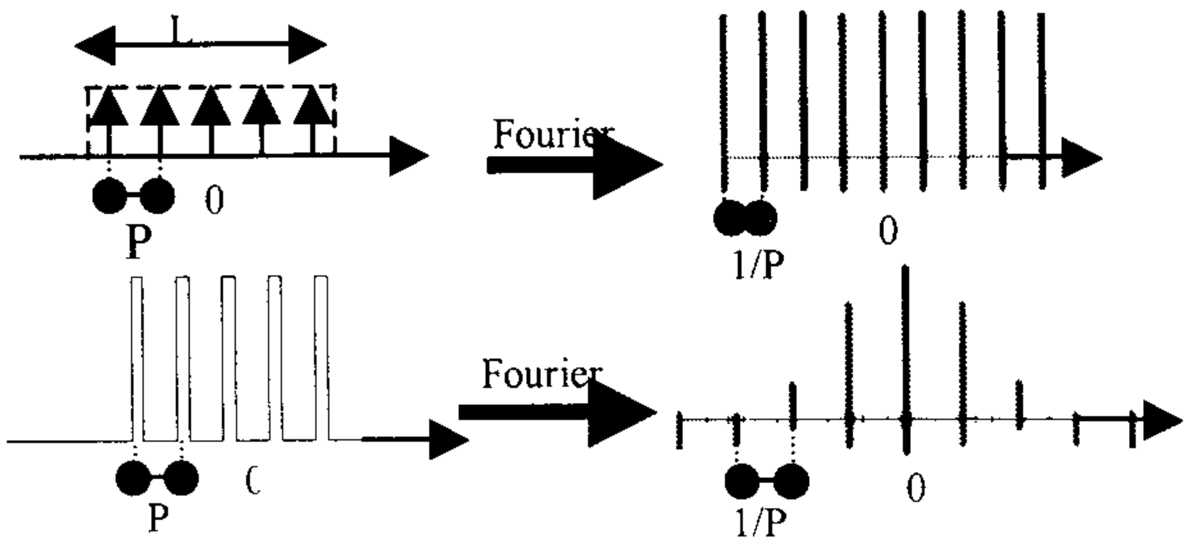

Figure 2: Spectrum of a periodic pattern in its sampled form and in its sampled-hold form. The first spectrum shows that the knowledge on a 1/P wide frequency interval allows reconstructing the whole spectrum. In reality, pixels are not Dirac impulse, what is described in the second spectrum by the cardinal-sine frequency response. The knowledge of the elementary cell dimension is sufficient to compensate for that attenuation.

3. The algorithm

The multiple images have first to be interleaved into a single huge image. A Fourier Transform is then computed. This involves that the images have to be almost regularly spaced, with the shift step smaller than the CCD pixel relative dimension, that is N x Shift = CCD relative dimension (being stated that we use N images shifted along one dimension).

The frequency intensities can be computed only for wavelengths in the smallest period of the spectrum, which significantly reduces the computational complexity of the algorithm.

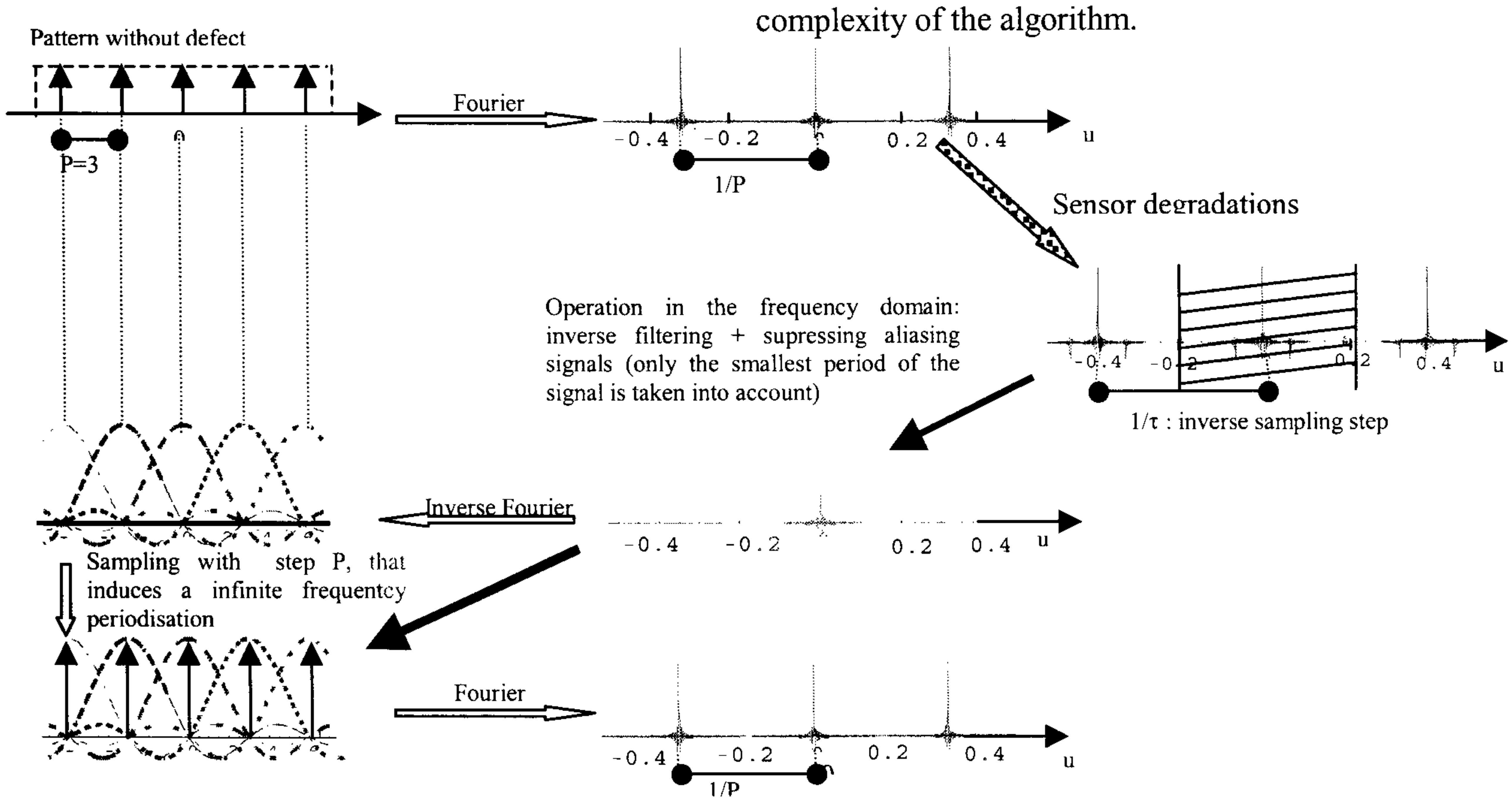

Figure 3 : Main steps of the reconstruction algorithm. Only plain arrows represent real task. Empty arrows just help to have a representation of the modifications introduced by a task in the complementary domain.

The low pass filtering induced by the sensor is then compensated on the smallest period by inverse filtering. That simply means that we divide the spectrum by the transfer function of the sensor (or its estimate). For a CCD pixel dimension that not exceed 2P times the dimension of the elementary cell under test, the transfer function doesn't null, which also insures that the noise won't be hugely increased by that inverse filtering. The restriction of the frequency domain to the smallest period corresponds in the spatial domain to the convolution of each Dirac impulse with a sinus-cardinal form (see figure 3).

Then, the spectrum has to be "periodised". The data can be duplicated P times before computing a huge inverse Fourier transform. This operation can be tacitly done by sampling the spatial result with a P step. That insures that the cardinal-sine forms are sampled according to their maximum and their zeros, and allows a perfect reconstruction. Whatever we choose, a condition for a perfect analysis is that the 1/P, smallest frequency domain, be precisely imaged by an integer number of frequency samples.

3.1 Two groups of defects: two reconstruction processes

We can identify two groups of defects: the ones switched OFF for an ON command, and the ones switched ON for an OFF command. The first group is perfectly suited for the previous theory. They are thereby perfectly reconstructed (Figure 4: $\varphi = 0$).

Because of an additive phase, the reconstruction of defects from the second group is more difficult. Indeed, the spectrum of switched ON defects doesn't accept 1/P as its smallest period. Therefore, the spectrum of such defects is corrupted by the forced "periodisation" and the reconstruction isn't perfect (Figure 4: φ 0). In the spatial restored image, the intensity of an abnormally switched-on pixel is then split between different pixels, through a cardinal-sinus distribution. The analysis of the main samples corresponding to the defect allows us to localize it precisely whenever the pattern period isn't too important (i.e. doesn't exceed 5).

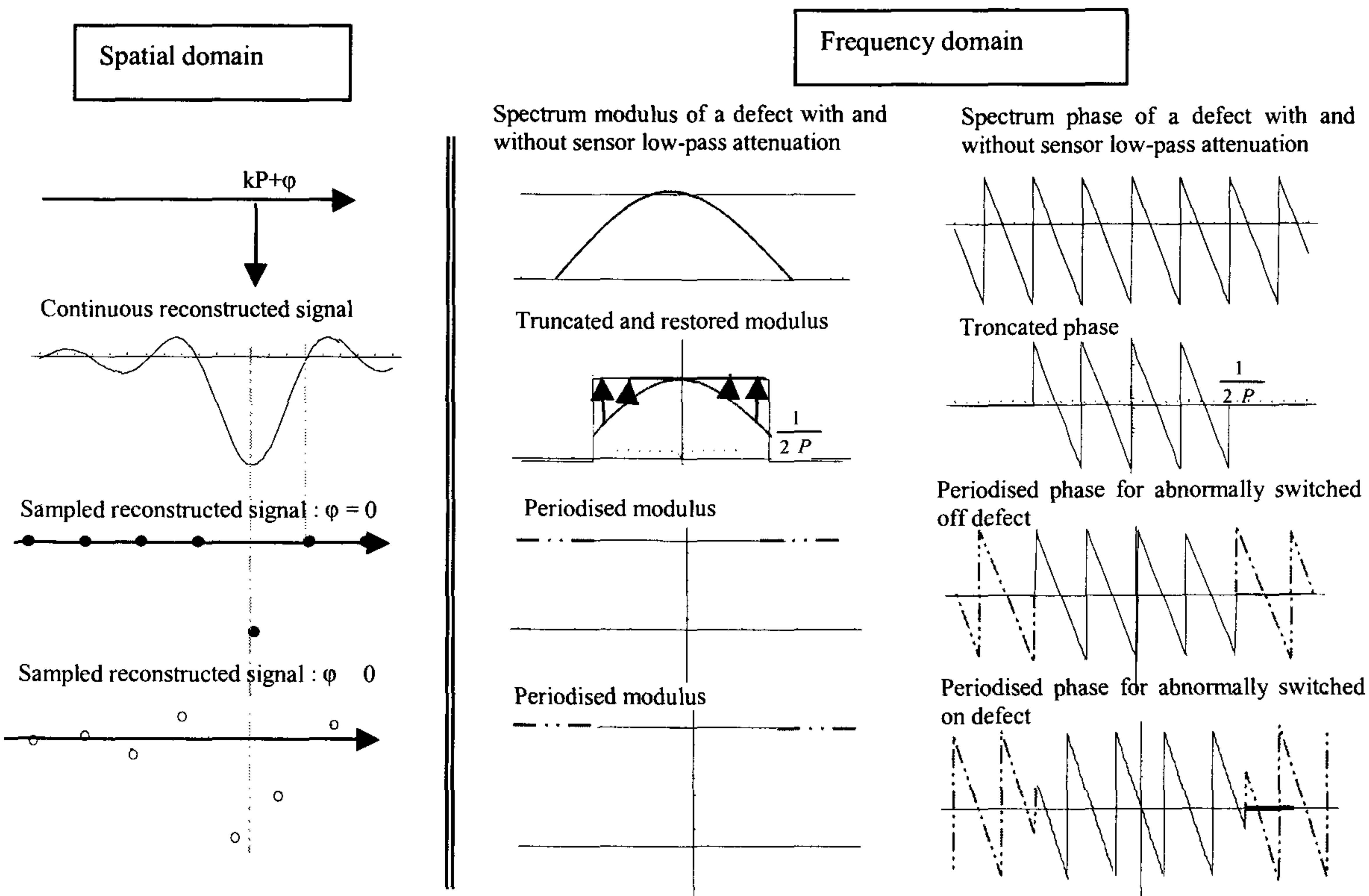

Figure 4 : Reconstruction of abnormally switched off and on defects. The first group is perfectly reconstructed because the cardinal-sine curve is sampled according to its maximum and its zeros: one defect influence only one reconstructed pixel. The second group is worse reconstructed because the cardinal-sine curve isn't well sampled and the intensity of a single defect is spread on several reconstructed pixels. However a simple fit allows finding precisely its position and intensity.

3.2 An automated process

The proposed algorithm requires the knowledge of two main parameters: the relative dimension of the CCD pixel and the relative position of the CCD matrix with respect to the flat panel display. The extension from 1D to 2D approach works well if X and Y axis of the screen and CCD are almost aligned. This can be achieved by software and adds the need of knowing the rotation parameter. Moreover, we can take care of the optical distortion factor whenever it has been identified. In order to make our process friendly and robust, we propose a fully automated process, which performs parameters identification so that the reconstruction is fully unsupervised. Parameters identification is mainly achieved by a functional minimization from the image of a calibration pattern

3.3 Required relations for a perfect reconstruction

The perfect reconstruction of the LCD pattern requires meeting the relations:

$$\frac{1}{T_{Rx}} - \varepsilon_x > \frac{1}{2P_x} \quad \text{and} \quad \frac{1}{T_{Ry}} - \varepsilon_y > \frac{1}{2P_y} \quad ,$$

Where T_R represents the relative dimension of the CCD pixel, P_x represents the period of the pattern on the index direction and ε represents a tiny margin of error to avoid noise amplification even in the case of a non-ideal optic.

The algorithm may work with any period pattern, but we recommend to use a $P_x = 3$, $P_y = 1$ pattern which often corresponds to a monochrome screen (R, G or B) and prevents the reconstruction from chromatic degradations. It is perfectly suited for the test of current LCD, since the use of a 1024*768 CCD allows the full analysis of UXGA LCD.

4. Results and discussion

We have tested the algorithm in different conditions: with irregular sampling step, with a small amount of shifted images and with errors in the parameters identification. It has proven to be very robust, being able to give acceptable results even far from ideal conditions. The result evolves slowly under non-critical conditions.

The only drawback of that algorithm is the computational complexity (because of the Fourier Transform). However, a wired FFT is currently in development, which would run very rapidly and performs a full analysis in less than 60s.

The algorithm was meant to work with saturated ON or OFF defects. It has been proven to perform a very good reconstruction (Figure 5), which clearly distinguishes defects from background and precisely identify their coordinates. Current results allow us to trust in sorting defect in intensity levels. We forecast to be able to classify the defects in at least four classes of intensities within the available scale.

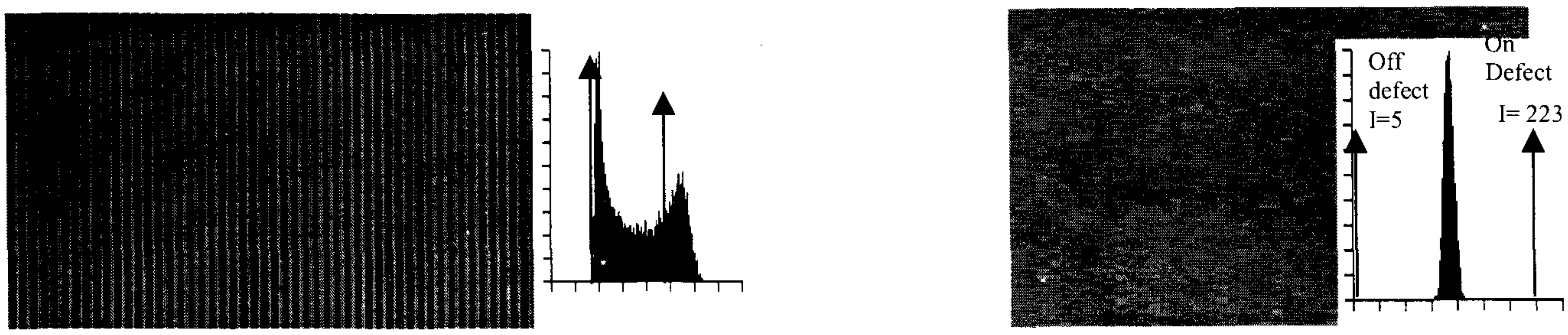

Figure 5 :Super-sampled image obtained from the multiple shifted images, then, reconstructed image. In the initial image the defects get bogged down in Moiré pattern. Each defect can be perfectly reconstructed at the good location, even for adjacent defects

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