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A GAUSSIAN-MIXTURE BASED APPROACH TO SPATIAL IMAGE BACKGROUND MODELING AND COMPENSATION

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ABSTRACT

In an optical inspection instrument, there is an undesirable image background which is often due to the nonuniform illumination characteristics of the system. The background however may also involve other, hard-to-model effects such as stray light. In the present paper, we report on our efforts to achieve robust elimination of smooth image backgrounds so as to achieve improved inspection of flat patterned media. We consider a uniform two-dimensional array of bivariate Gaussian functions on the image plane and consider the optimal approximating model to the smooth image background signal. The representation and associated algorithm effectively captures the background while being minimally effected by the high frequency pattern on the inspection surface. The set of linear weights of the Gaussian kernel offers a compact representation of the background and is used to eliminate the background for further processing (e.g., defect detection) of the surface image. Performance results are illustrated on a representative problem of TFT-LCD panel inspection for finding production defects. This process involves a sub-pixel resolution pattern subtraction scheme and therefore is sensitive to background variations, effectively forming a good case study.

1. INTRODUCTION

Automated optical inspection (AOI) using Machine Vision techniques has recently become a very important tool for the manufacturing industry as a means to detect and deal with production defects[1][2]. This trend results from the fact that mass production plants in many areas of consumer products experience increasing market competition and require to lower the costs of their products while increasing the product quality. AOI techniques promise to eliminate the subjectivity and large variation in the performance of human operator based quality inspection and meet the throughput requirements of the production process.

A particularly competitive industry is TFT-LCD manufacturing which is experiencing exponential growth in the recent years with the penetration of the LCDs into the consumer TV market. Automated optical inspection solutions are being proposed as a solution for high speed inspection of the production defects occurring during TFT-LCD production[3]. Another important application for computer vision and particularly automated optical inspection is the inspection of textiles [4]. In both of these applications, the surface to be inspected can be held flat under the inspection system and a controlled illumination is possible. In the latter case, the fabric is composed of a regular pattern which is violated by the defects. Although not perfect, there is an inherent periodicity of the pattern on the fabric. The defects are often features that violate this periodicity.

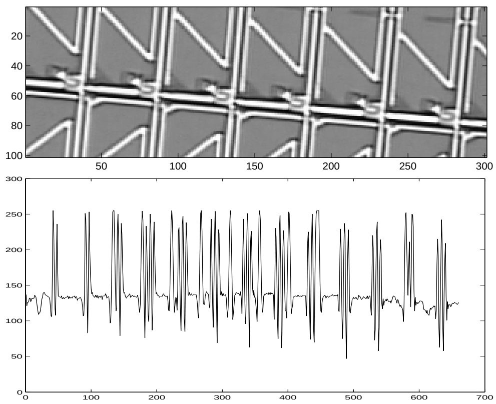


Figure 1: (a) An example TFT-LCD sub-pixel array which is periodic within the limitations of the masking process. Defects manifest as points or small regions violating the periodic structure. (b) Line-profile through the array exposing background variation

In the former case of TFT-LCD inspection, the non-defective surface is composed of high intensity and high frequency, periodic TFT pattern. This pattern is composed of the electronic circuit forming the color sub-pixel array. Here, the pattern is perfectly periodic within the limitations of the masking process. An example TFT array is illustrated as a partial image frame in Figure 1. The wast majority of the defects are composed of singular points or regions which violate this strict periodicity of the TFT pattern. As such, defect detection techniques often resort to a popular spatial "pattern subtraction" approach in which, two suitably chosen regions from either a single image or a pair of images are carefully aligned with respect to each other and spatially subtracted. This is usually done at sub-pixel resolution through correlation techniques due to high intensity aliasing noise resulting otherwise. The residual signal, ideally a black background, is then inspected for defect points showing nonzero image intensity. A simple thresholding technique is then used in most of the cases.

The paper is organized as follows. In Section 2 we briefly overview the existing literature with an emphasis on similarities and differences in applications and approaches. Section 3 presents the details of our approach as well as some details on the subsequent defect detection method employed in the experiments. This is followed by Section 4 which presents the results of background correction in the TFT-LCD inspection application considered. The paper concludes with Section 5.

2. PREVIOUS WORK

Spatial pattern subtraction is a major technique in common use in the inspection of periodic structures such as the TFT-LCD array. A major factor limiting the performance of pattern subtraction based techniques is the non-uniformity of the image background. In image processing and in particular image feature detection framework, any features of the image which does not belong to the event of interest (e.g., defects) can be classified as background. As such, elimination or compensation of this non-uniform background is a very broad topic and its consideration within each particular domain presents new challenges and associated solutions. The focus of the present study is within the context of flat media inspection as in the case of TFT-LCD inspection. However, the methods proposed are equally applicable to other flat or near flat media imaging problems with non-uniform background. A good example is camera based digitization of text documents. Unlike scanner applications, this process is much faster and at a distance (desirable) but non-uniform image background is significant, largely due to illumination problems.

The literature on background elimination in image processing shows a considerable number of studies on processing of moving video images for the detection of objects of interest. In a recent study Bhandarkar and Luo discusses background correction in the context of real time traffic monitoring [5]. The focus is particularly on dynamic scenes. They categorize the background correction methods based on their usage of single or multiple color values per pixel to represent the background image. All methods discussed essentially segment the image and try to determine which pixels belong to the background and which pixels to the objects of interest by means of the background being stationary in the image.

This category of background correction problems belong to a fundamentally different class than the one discussed in the present study. We call them "static background segmentation". In all of the methods that are dominantly discussed in this group, the focus is on dynamic images with moving objects and the background is defined as a static or slowly varying image that characterizes the scene when no objects of interest are present. When such objects are present, the image pixels are tried to be segmented into background and non-background. Pixel values belonging to the objects of interest (non-background) are not modified as part of the background elimination process but masked out from further processing. The background makes a distinction between the "moving" and the "stationary" in the image. [6]

Other studies of the aforementioned class of background modeling include for example a study by Cristani et al. [6] where they improve on isolated pixel statistics based background segmentation by predicting and using the motion of objects in the image through particle filtering. The same study also summarizes the conventional use of the Gaussian Mixture as a statistical model of the background pixel color generation process. Effectively, the mixture is used as a multi-modal probability density function predicting the probability of occurrence of a pixel value as part of the background scene. Zhou also proposes combining a Gaussian mixture statistical model with optical flow and temporal differencing within the context of motion video segmentation[7]. Range data from stereo vision has been introduced within the same context in an earlier work [8].

The background correction addressed in the present study on the other hand primarily focuses on isolated or sequences of images where the intensity of each pixel needs correction before even the defect detection stage is activated. We define the "background" as the collection of unwanted intensity variations in pixels of the image belonging to the same type of surface or object. The focus hence is on eliminating or correcting this variation and not the segmentation of the image. I fact, a segmentation of the image into defect/non-defect is a separate process which follows our background correction step and can be tought analogous to the previously discussed "background elimination". The type of background correction we address arises in particular within the context of the illumination of an field-of-view (FOV) of an inspection instrument since the non-uniformity in the illumination system results in a nonlinear and possibly slowly time varying intensity variation which is not due to feature variations of interest on the inspection surface. E.g., if this intensity variation was static, a gray sheet of calibration paper in the FOV would reveal the background signal and would allow it to be later used. However, since the signal slowly varies with time, it has to be approximated from the actual images.

A similar difference exist in the use of the Gaussian mixture model in the present study for the modeling of the intensity background. Our use of the Gaussian mixture model here is not in the context of a statistical density function as introduced by [9] and later extended for the adaptive case [10]. The Gaussian Mixture is rather used as a direct nonlinear approximator to the smooth, low-spatial-frequency intensity profile of the background and hence is fundamentally different from its statistical usage.

In terms of similarity of the application to our case and the type of background correction considered, one can mention some recent studies for the background correction for document images [11][12]

3. PROPOSED APPROACH

Our approach in the present paper considers the image background modelling task as a spatial smooth surface approximation. We assume that the features of interest in the image are of sufficiently high frequency to allow us an approximation to the background by using the full image data, without resorting to a preliminary segmentation. This assumption is reasonably valid in the application domain considered, namely the inspection of TFT-LCD panels for production defects. The assumption also seems reasonable for illumination correction for documents. Therefore, the method presented here should be applicable in the latter case as well. The background consist of a weighted sum of M bivariate Gaussian functions given by

$$B(x,y) = \sum_{m=1}^{M} a_m g_m(x,y) \quad (1)$$

$$g_m(x,y) = e^{\{(x-\mu_{mx})^2(y-\mu_{my})^2/2\sigma_m^2\}} \quad (2)$$

where x and y are image pixels, μ_{mx} and μ_{my} are means

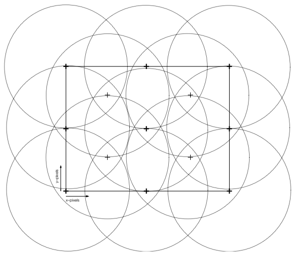


Figure 2: Layout of the Gaussian functions on the image frame

of the Gaussian functions along each axis, σ_m^2 are variances which are assumed to be the same along each image axis (circular) and a_m are the linear weights in the weighted sum. Due to the assumed smoothness of the background, A 2D uniform grid of Gaussian mean locations is constructed over the image plane with the extend of this grid matching the image frame size so that image edges can be modelled accurately. The variances of the Gaussian functions are all taken the same and is a design parameter for the algorithm. The choice can be made based on the expected smoothness of the background signal so that a sufficient overlap is achieved between the Gaussians. The algorithm is quite robust to the selection of this parameter. There are $M = 13$ Gaussians and variances are selected as $\sigma_m^2 = 350^2$ pixels The layout of the bivariate Gaussian functions on the image frame are illustrated in Figure 2. The circles are for illustration of Gaussians and do not reflect the actual variances.

The linear weights of the Gaussian kernel thus formed can be determined optimally in order to achieve the best approximation to the given background data. This is a convex optimization problem with a unique solution and becomes one of solving a linear system of equations. Let a set of N background samples be given by coordinates (x_n, y_n) and the intensity v_n for $n = 1, 2, \cdots, N$, the set of equations can be expressed in matrix form as

$$\begin{bmatrix} G_{11} & G_{12} & \cdots & G_{1M} \\ G_{21} & G_{22} & \cdots & G_{2M} \\ \vdots & \vdots & \ddots & \vdots \\ G_{M1} & G_{M2} & \cdots & G_{MM} \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_M \end{bmatrix} = \begin{bmatrix} H_1 \\ H_2 \\ \vdots \\ H_M \end{bmatrix} \tag{3}$$

where $G_{ij} = \sum_{n=1}^{N} g_i(x_n, y_n) g_j(x_n, y_n)$ and $H_i = \sum_{n=1}^{N} v_n g_i(x_n, y_n)$. The solution for $\mathbf{a}$ is obtained by inverting the $\mathbf{G}$ matrix. The derivation of this result follows defining an objective function based on squared sum of approximation errors over background samples and using standard necessary and sufficient conditions (see for example [13]) for minima for convex functions.

A number of additional processing steps are necessar before the model is constructed. The flow-chart of the GMM based background modeling and compensation algorithm is presented in Figure 3. The processing start by converting the input image to gray scale. Instead of averaging, selecting the green channel has proved to provide the best feature contrast for the task considered.

This is followed by a histogram analysis. Since high contrast features of the TFT-LCD lattice occupy comparatively small are of the array, the dominant gray level is identified as the transparent, mostly uniform area of the array. Histogram analysis provide the mean intensity value of this region which is considered to be the data source for reliable background estimation. Other features of the array are either saturated or too dark to provide useful information about the background.

Once this “background” level is determined, thresholding on a symmetric band around this level is used to segment pixels of the image that are the best candidates for background modeling. It should be noted that this set of samples is not the background itself and the modeling process is robust, through its smooting property, to some amount of outlier pixels leaking into this background region. Since it is assumed that these regions are large, contiguous regions of samples to be used for background modeling, a sequence of morphological dilation and closing is applied to the background sample regions to eliminate any small, isolated, outlier islands of pixels.

The valid background data regions thus constructed are sampled by a uniform rectangular grid, at a much lower density than that of the image pixels in order to reduce the amount of data that needs to be processed for background modeling. This data is then used to construct the system of equations to be solved to determine the optimum linear weights of the Gaussian mixture background model by means of Eq. 3.

Once the background model is obtained, a background “image” is constructed by evaluating the model at each image pixel. Finally, the original background corrupted image is corrected through a multiplicative correction procedure: The image is divided by the background image normalized by the average background value. The normalization is necessary to keep the image average intensity unchanged through the process. Image samples exceeding maximum possible intensity level are klipped at the maximum.

The intermediate steps and the results of this process are illustrated in the following section dedicated to experimental results.

4. EXPERIMENTAL RESULTS ON TFT-LCD INSPECTION

The quality of the background compensation is quite subjective for general images. However, the pattern subtraction based defect detection in TFT-LCD panels is very sensitive to background variations and hence is a suitable test bed for evaluating the performance of background compensation. Therefore, the proposed background modeling and compensation algorithm is applied within the context of TFT-LCD inspection through pattern subtraction. The example TFT-LCD array given in Figure 1 contains a defect within the transistor at the center. The small transistor defect is hidden inside the high contrast features and cannot be detected However, a sub-pixel aligned pattern subtraction with a precisely estimated period is capable to reveal the defect provided we have a flat background. This section demonstrates the use of the background correction algorithm by presenting intermediate data and the final detection image.

The parameters that are experimentally determined to provide good performance and used for the illustration in this section can be summarized as follows: *Number of bins for histogram analysis*: 256 (one for each gray level), *Thickness of the symmetric band around histogram maximum*: 40 gray levels, *Image dilation order*:3, *Size of background sampling*

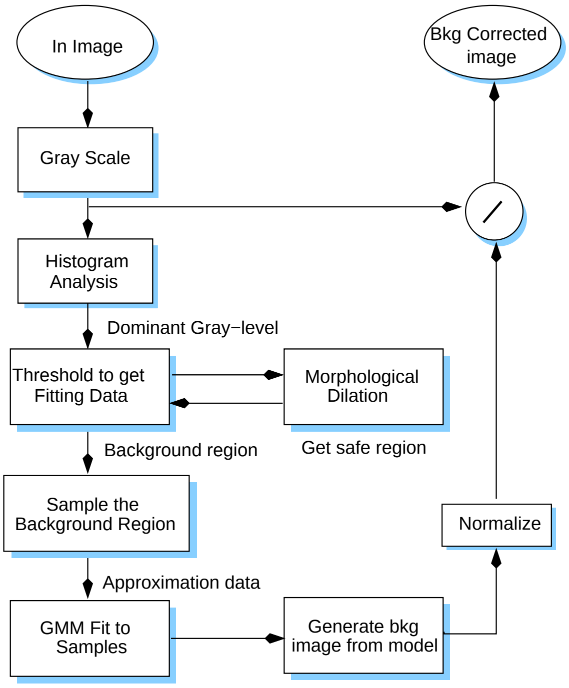


Figure 3: Algorithmic outline of preset approach: GMM based background modeling and compensation

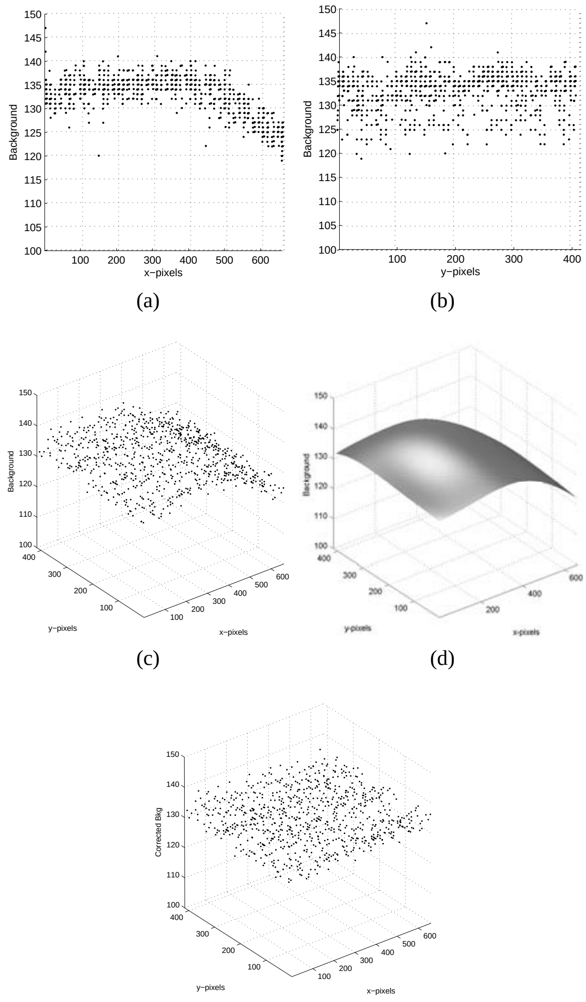


Figure 4: Background samples and GMM model. (a) and (b) illustrate the projections of the background samples on x and y image axis respectively. (c) is the 3D plot of the samples and (d) illustrates the GMM approximation of the background while (e) is the compensated background samples.

grid: 40x40, *Number of uniformly distributed Gaussian functions*: 13, *Gaussian variances*: 350^2.

Figure 4 illustrates the 3D background samples corresponding to the TFT-LCD array illustrated in Figure 1 together with their projection onto x-axis and y-axis. In the same figure, the compensated 3D samples of the background are also illustrated.

It may be appropriate to briefly summarize some of the steps of the defect detection process used in the application area considered. Namely, after the background correction, the lattice periodicity is estimated through a frequency analysis of the projection onto both axis. In TFT-LCD inspection, the alignment of the inspected panel is known through an alignment process. Therefore, the projection based period estimate can be transformed into actual lattice horizontal and vertical period estimate. The estimated period is then used through a sub-pixel interpolated pattern subtraction process which is often performed on one axis of periodicity, usually the one exhibiting the largest number of cell periods in the image. Figure 5 illustrates the estimation of the lattice period through Fourier analysis followed by finding the first harmonic peak. A section of the original TFT-LCD lattice and the residual image after pattern subtraction is given in Figure 6.

The residual image contains the defect point of interest as the highest intensity object. Due to the property of the two sided pattern subtraction, this object has two "ghosts" along the direction of periodicity. However, these ghosts are always at approximately half the intensity of the real defect and therefore do not constitute a problem for the inspection task. The detail of the defect signal is given in Figure 7 (a) with a shifted gray scale coloring. In the same figure, a longer line-profile through the defect and its pair of ghost artifacts in show that the defect clearly stands out of the background

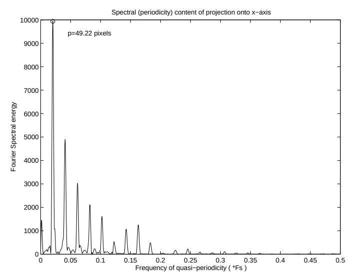


Figure 5: Frequency analysis to find the lattice period for pattern subtraction

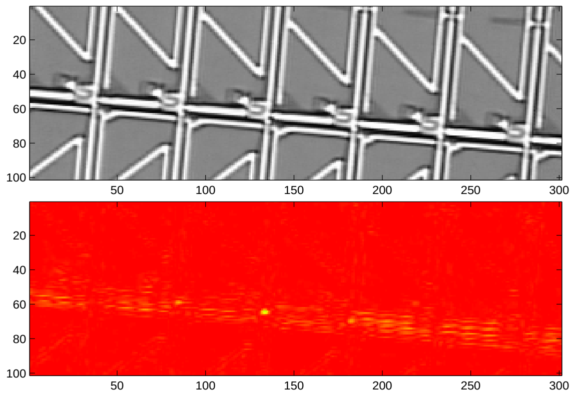
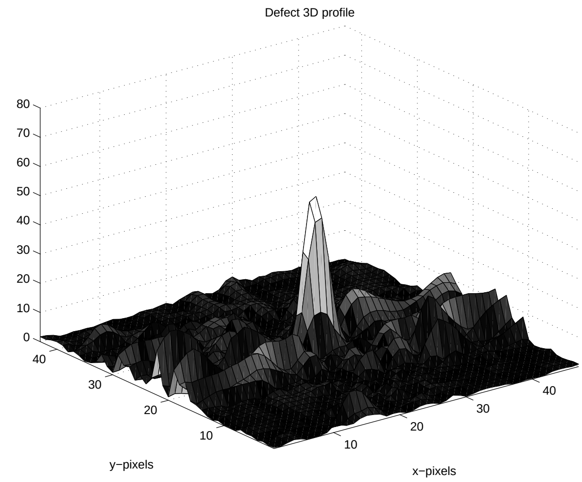


Figure 6: Sections of original and pattern subtracted TFT-LCD lattice

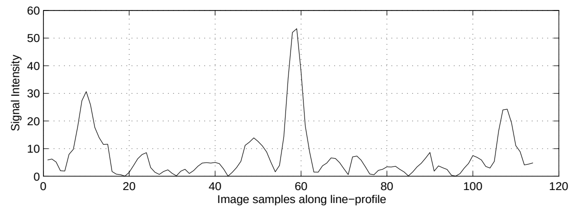
noise and is easily identifiable. The defect SNR is approximately 15.

5. CONCLUSION

Nonuniform and sometimes time varying background is a common and improtant problem for static images of flat media such as in the case of material inspection or document photography. Background correction for the purpose of flattening the overall intensity of such images is useful either for an enhanced image or, as in the case of automated inspection, for improved algorithm performance in subsequent stages of processing. In the present work, we have proposed a Gaussian mixture based background model for modeling and compensation and considered a pattern subtraction based TFT-LCD defect inspection problem as a test case due to its particular sensitivity to nonuniform background. However, the applicability of the proposed modeling and compensation approach is not limited to this particular example and can wey well be used in other areas with flat media and high contrast, high frequency features. Document digitization through photographing is a good example of alternative application.



(a)



(b)

Figure 7: (a) The defect section 3D profile and (b) Line-profile through the defect and its twin ghost artifacts

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