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Image Defect Identification with Orthogonal Polynomials Model

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Abstract: In this study, a simple technique for defect identification based on Orthogonal Polynomials (OP) model is presented. Initially, the input image under analysis is applied with OP model and gradient estimation scheme is employed to locate the edges present. The resulting binary image is again applied with OP model, and a simple computation scheme that finds the ratio between selected transform coefficients is proposed to identity the defects present in the image. Experiments have been conducted with different images consisting of both homogeneous and non homogeneous regions. The proposed technique is found to perform well, for unshaped defects, and is found to outperform the existing schemes.

Key words: Edge detection, defect identification, orthogonal polynomials, weight factor, gradient estimation

INTRODUCTION

The process of identifying and classifying defects in digital images is a high priority operation and has wide applications. Image defect detection algorithms are generally developed for homogeneous regions where local anomalies that break the visual homogeneity from their surrounding background are identified as defects. Defect detection task is confidential as qualitative inspection which involves detecting ill-defined, no quantifiable faulty items such as scratches, cracks, stain and wear. Most of the defect detection methods for uniform surfaces use simple thresholding or edge detection techniques but they are also focused on non textured surfaces such as sheet steel, aluminium strips, glass panel and web materials. Wilder (1989) has reported a scheme to identity the defect in uniform surface images that arises in glass plate. Shankar and Zhong (2006) reported alternatively a non referential method based on wavelet decomposition and morphological operations for wafer die inspection. It requires a specific design of structuring elements for individual defect types and assumes that local defects and parts of the background are structurally different. Since, each image has some unique patterns, local defects could be structurally similar to edges. Hence, the currently available defect inspection algorithms for patterned wafers cannot be extended for defect detection in non homogeneous region.

Serdaroglu *et al*. (2006) applied Independent Component Analysis (ICA) technique for surface defect detection of textile fabrics and Liquid Crystal Display (LCD) panels in manufacturing. But, ICA-based defect detection methods are only applicable to non-textured or homogeneously-textured surfaces. They cannot be extended for defect detection in images with inhomogeneous background patterns. Tsai *et al*. (2012a) reported a shift-tolerant dissimilarity measure for defect detection in gray-level images. Chao and Tsai (2010) designed an anisotropic diffusion model in low-contrast images of backlight panels, LCD glass substrates and brightness enhancement films.

Yang *et al*. (2005) described a subjective evaluation of the visual quality inspection of aesthetic parameters in architectural work. But the experimental results suggested the unreliability of visual quality inspection because it cannot quantify defect values and determine all possible defect positions due to the limits of human perception. Tsai *et al*. (2013) reported defect detection methods based on independent component analysis basis images to detect defective solar cell subband of a large solar module in the Electro Luminescence (EL) image. The line and barshaped defects of micro-cracks, breaks and finger interruptions in the solar module can be well presented as dark regions in the EL image. But, EL image displayed dislocations and grain boundaries of the multicrystalline solar wafer as dark regions and results in a random inhomogeneous background. The dark regions of defects and those in the defect-free background can be visually observed in the EL image, but they are extremely difficult to be distinguished automatically. Liu *et al*. (2010) applied spectral subtraction to detect defects in the Integrated Circuit (IC) image. Tsai *et al*. (2012) suggested a self-reference scheme based on the fourier image reconstruction to detect various defects in multicrystalline

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solar cells. To identify defects in the inhomogeneous surface of an EL image, the Fourier image reconstruction process is applied by setting the frequency components associated with the line and bar shaped defects to zero and then back transforming to the spatial image. But, this process takes a serious computation cost.

Jiang *et al.* (2012) investigated the cause of visual defect by driving the display under different settings. But, it failed in non-periodic defects. Uttwan *et al.* (2012) automated fast defect detection system and applied combination of coefficient of variation and Log-Gabor filters bank based features. Using the coefficient of variation as a homogeneity measure, defects are approximately localized in a preprocessing stage. Tolba (2011) reported a system that provided a crack probability measure for each detected potential crack. Landstrom and Thurley (2012) reported a system for multi-class defect detection and classification in weld radiographs using both geometric and texture features to capture the visual properties. But, it failed to produce promising results.

Filtering the techniques using the joint spatial/spatial-frequency Gabor transforms (Clausi and Jernigan, 2000) are also commonly used to design a filter bank that represents the characteristics of the textured patterns, with application to the inspection of wooden surfaces granite (Kittler, 1985) steel surfaces (Wiltschi *et al.*, 2000) and textile fabrics (Bodnarova *et al.*, 2000). Kumar and Pang (2002) used a set of finite impulse response filters for defect detection in textiles. The optimal filters were selected based on discriminate analysis from defect-free and defective regions in training images. Xianghua and Mirmehdi (2007) generated a set of texture exemplars by exploring a Gaussian mixture model from defect-free image patches, and used them for defect detection on ceramic tiles. The abnormality is measured by the likelihood of each patch in the inspection image and a low likelihood indicates a possible defect region. A homogeneously textured surface generally presents repetitive, periodical patterns in the image. Therefore, the self-similarity property can also be used as a cue for defect detection.

Valavanis and Kosmopoulos (2010) reported a method to identify the defects that involve relatively scattering and blurring edges on inhomogeneous solar wafer images. However, a severe micro-crack defect showing thin and sharp edges in the multicrystalline solar wafer cannot be effectively detected by this method. Li *et al.* (2011) have suggested a method based on seed growing approach, characterized by its nonparametric and unsupervised nature of threshold selection. But, it is applicable to only zeroth and first order cumulative moments of the gray-level histogram. A review of defect detection in fabric has been reported by Ngan *et al.* (2011) with defects resulted from machine faults, yarn problems, poor finishing, excessive stretching etc. Li and Tsai (2011) reported a defect detection scheme based on Fourier image reconstruction and Hough-like non-stationary line detection to identify saw-mark defects in multicrystalline solar wafer images.

Tsai and Luo (2011) designed an automated visual inspection scheme for multicrystalline solar wafers using mean-shift technique. In this research, defect types involve random gradient directions, while the normal grain edges generally present more consistent gradient directions in a small spatial window. It cannot be directly extended to other defect types such as holes that show only line-shaped figures and presented a low variation in gradient directions. While many techniques have been developed to limit the adverse effects of these parameters on image, many of these methods suffer from a range of issues such as computational involvement of algorithms to suppression of useful information. In few image processing applications, use of transformation has been made effective for edge identification, such as wavelet (Sun *et al.*, 2009). Besides texture, edge plays a significant role in defect detection, especially to compensate or fill the defected area. Good number of works are reported for exclusive edge extraction. It includes Roberts (1965), Prewitt (1970), Canny (1986) and Sobel (1970) operators. All these operators are first order derivatives. Marr and Hildreth (1980) suggested laplacian, a zero-crossing operator, as a second order derivative and is used to establish the location of edges present in the image. Bhattacharyya and Genesan (1997) reported the detection of zero crossings in the second directional derivatives of the image region. Use of edge in defect identification requires careful analysis and need to tackle many issues including non-supression of low level information and computational cost. Also, it can be observed that most of the existing defect detection schemes are reported to be application dependent and no generic model based system exist that can be computationaly less costly. Hence in this paper, a simple computational model for defect detection based on orthogonal polynomials is proposed. The detected defects are represented in a binary form to visualize the detection results and to find accurate defect position, shape and size.

MATERIALS AND METHODS

Orthogonal polynomials model: In this study, the orthogonal polynomials model for the proposed defect detection is presented. This model is built on top of set of orthogonal polynomials functions defined in

(Bhattacharyya and Ganesan, 1997). From these polynomials u_0 (t), u ($_1$t), ...u $_{n-1}$which are of sizes are degrees 0, 1, 2... n-1, a point spread operator M of different sizes is constructed as:

$$|M| = \begin{vmatrix} u0(t0)u1(t0)\cdots un-1(t0) \\ u0(t1)u1(t1)\cdots un-1(t1) \\ \vdots \\ u0(tn-1)u1(tn-1)\cdots un-1(tn-1) \end{vmatrix}$$

for n≥ 2 and t_i = i. This operator, that defines linear orthogonal transformation for defect identification can be obtained as |M|⊗|M|, where: |M| = Is computed and scaled to integers as follows:

$$|M| = \begin{vmatrix} 1 & -1 & 1 \\ 1 & 0 & -2 \\ 1 & 1 & 1 \end{vmatrix} \quad (1)$$

The class of orthogonal polynomials function characterizes the local regularity of signals by decomposing signals into elementary building blocks that are well localized in frequency plane and capture the underlying mechanism of classical texture feature detector. A remarkable property of the proposed orthogonal polynomials model is its ability to characterize the local regularities. The size of the kernel operator can be adaptively fixed and its use to separate signal components from noise, as the responses of the operator is highlighted. A remarkable property of the proposed orthogonal polynomials model is its ability to characterize the local regularities and its use to identity defect area is investigated. This is presented in the next study.

Proposed defect identification scheme: The proposed defect identification scheme has the following two stages:

- Gradient estimation and edge extraction with orthogonal polynomials model
- Identification of defects based on ratio between highest frequency coefficients and sum of other coefficients in iterative orthogonal polynomials model with weight factor

These two stages are presented in the subsequent subsections.

Gradient estimation on defect images: In this proposed research, the image under analysis is assumed to have low level features such as edge, texture and uniform background in both defect and non-defect area. To facilitate the identification of low level features, the following symmetric differences that estimate the partial derivatives at (x, y) of gray scale image I, excluding O_{00} are determined from the orthogonal polynomials model described in the previous study:

$$\left.\frac{\partial I}{\partial y}\right|_{x,y} = \sum_{i=-1}^{1}\left[I(x-i,y+1)-I(x-i,y-1)\right]$$

$$\left.\frac{\partial I}{\partial x}\right|_{x,y} = \sum_{i=-1}^{1}\left[I(x+1,y-i)-I(x-I,y-i)\right]$$

$$\left.\frac{\partial^2 I}{\partial y^2}\right|_{x,y} = \sum_{i=-1}^{1}\begin{bmatrix} I(x-i,y-I)-2I(x-i,y) \\ +I(x-i,y+1) \end{bmatrix}$$

$$\left.\frac{\partial^2 I}{\partial y^2}\right|_{x,y} = \sum_{i=-1}^{1}\begin{bmatrix} I(x-I,y-i)-2I(x,y-i) \\ +I(x+I,y-i) \end{bmatrix} \quad (2)$$

and so on. In general:

$$\frac{\partial^{i+j}}{\partial x^i \partial y^j} = |O_{ij}|$$

$$\frac{\partial^{i+j} I}{\partial x^i \partial y^j} = (|O_{ij}|,|I|) = \beta'_{ij}, 0 \le i, j and i = j \ne 0$$

where | | indicates the arrangement in dictionary sequence and (,) indicates the inner product. Hence, O_{ij}s are symmetric finite difference operators, β_{ij} are the coefficients of linear transformation and are defined as follows:

$$|\beta'_{ij}| = |M|t|I| \quad (3)$$

where | M | = Is the 2-D point-spread operator. We then compute the mean squared amplitude responses of these operators O_{ij} and group the operators whose response are due to the low level features (edges, texture etc). Based on the visual properties of edges, responses of operators are O_{ij}s at i = 0, 0 < j = 2 and j = 0, 0 < i = 2 are modeled to be responses towards edges and the remaining operators are assumed to be responses towards non-edge. In otherwords, the linear contrasts considering one direction (either x or y direction) at a time is modeled to be responses towards edge present and the linear constrats considering both the directions x and y are modeled for non-edge.

Now, for the purpose of computing gradient, from the orthogonal polynomials model coefficients, we consider only the first order differences, β'_{01} and β'_{10} and the strength of the gradient Gf_i is determined as:

$$Gf_1 = (\beta'^{2}_{01} + \beta'^{2}_{10})^{1/2} \quad (4)$$

This gradient strength is to be verified with a threshold ι, for detection of edges, as their large values having prominent edges being separated with small values contributing towards nearly uniform gray level area. This scheme, when applied to the defect images, shall produce binary image. The selection of threshold τ is described in the following subsection along with relevant literature on thresholding.

Threshold selection: Thresholding plays a significant role in many image processing operations and applications. A simple but standard approach for thresholding, analyses the global image intensity histogram. But, it has drawbacks when dark peaks of histogram are minuscule in size. Hence, good number of works based on variance of pixel values are reported in the literature (Otsu, 1979; Kittlev *et al*., 1985; Abutaleb, 1989). A review of thresholding schemes can be found by Sezgin and Sankur (2004). Few works based on the pixel distribution are also reported by Davies (2007) and Coudray *et al.* (2010). In use of Rayleigh distribution for noise and devising heuristics to analyse the overall distribution of pixel values is reported (Carnicer *et al*., 2011). Besides variance based schemes, approaches based on entropy, (Hannah *et al*., 1995) Max-Likelihood, global-valley approach, are also reported (Davies, 2007; Ng, 2006). But, these schemes basically use the distribution of probability of original pixel values. In the case of proposed gradient strength, as we are already in the frequency domain with orthogonal polynomials variance based thresholding, in terms of difference operators are devised.

In this proposed work, we first compute the variances Z^2_{ij} corresponding to the responses of the (n^2-1) basis, difference operations O_{ij} (excluding the averaging operator O_{00}). For selection of single threshold τ the criterion to be maximized is the ratio between variances due to edge response (Z^2_e) against variance due to total response (Z^2_T):

$$\tau = \frac{(Ze^2)}{(ZT^2)} \quad (5)$$

The identifying defect detection scheme of the image based on edge with the orthogonal polynomials model coefficients is presented in the next subsection.

Proposed defect detection scheme: Having obtained the gradient based edge extracted binary image, our next task is to identify defect region present in the image under analysis. In this work, we propose an effientent technique that extracts the boundary of the defect region. The edge extracted ouput (I^e) obtained in the previous stage is again subjected to orthogonal polynomials model, so as to produce the transform coefficients β^r_{ij} by partitioning the image into (n x n) non-overlapping sub blocks. We then define a weight factor, wf, as sum of orthogonal polynomials transform coefficients, excluding the response due to average factor β^r_{00}. That is:

$$wf = \sum_{i=0}^{n-1}\sum_{j=0}^{n-1} \beta^r_{ij}, i = j = 0 \quad 6)$$

We then compute the ratio between the response of orthogonal polynomials transform coefficients due to average factor and the sum of other responses, in terms of wf, so as to model the block under analysis for defectness. In essence, in this proposed work, the block is modeled to contain the defect area, if, $wf/\beta^r_{00}1$; otherwise the block under investigation is modeled to contain the original edge. We then repeat this step for all the blocks of the input image. The defected blocks thus obtained are represented with pixel value 255 and the original edge block with 0. The entire process of the proposed defect identification, in term of low level feature due to orthogonal polynomials is presented as algorithms hereunder.

Algorithm A; to extract edge, based on gradient estimation:

Input: Defect image.
Output: Edge extracted binary image.
Steps:
Begin
1. for i=0 to Row-2 do
Begin
for j=0 to Col -2 do
Begin

Extract a (3×3) block [I] centred at (I+I, j+I)
Compute $[\beta'_{ij}] = [M]^T [I] [M]$

$$|M| = \begin{vmatrix} 1 & -1 & 1 \\ 1 & 0 & -2 \\ 1 & 1 & 1 \end{vmatrix}$$

Compute gradient estimation and threshold

$$Gf_1 = (\beta_{01}'^2 + \beta_{10}'^2)^{1/2} \tau = \frac{(Z_e^2)}{(Z_T^2)}$$

as described in thershold selection

Ig $Gf_1 > \tau$ mark it as edge pixel, else mark it as non-edge pixel.
Go to Step1, until all blocks are analysed.
End
End
End

Proposed Defect Identifying algorithm B:
Input: Edge extracted binary image.
Output: Defect detected binary image.
Steps:
Begin
for i=0 to Row-2 do
Begin
for j=0 to Col -2 do
Begin

Extract a small area I^e of size (3x3) centred at (i+1, j+1)

Compute $\left[\beta_{ij}^r\right] = \left[M\right]^T [I^e] [M]$

where $[M] = \begin{vmatrix} 1 & -1 & 1 \\ 1 & 0 & -2 \\ 1 & 1 & 1 \end{vmatrix}$

Compute a weight factor

Calculate,. wf/β_{00}^r

if (= 1) mark the central pixel as defect area
by representing with pixel 255.
Else no Defect, and hence mark the central pixel with value 0.
Go to step1 until all blocks are analysed.
End
End
End

RESULTS AND DISCUSSION

The proposed orthogonal polynomials based defect identification scheme has been experimented with >200 grey scale images of different types. Two sample images viz. elephant and brick images which are of size (256 x 256) with pixel values in the range 0-255 are shown in Fig. 1a and b, respectively. The input images are partitioned into (3x3) regions, applied with the orthogonal polynomials based transformation, as described in the study and obtain the orthogonal polynomials coefficients β'_{ij}. With the resulting transformed coefficients, we compute the edge estimation and obtain edge extracted image as described in the study. The results of edge extraction, corresponding to the original images shown in Fig. 1 are presented in Fig. 2. We then compute the weight factor wf and threshold ι as described in the study and identify the defect area. The defect identified images with the proposed scheme, corresponding to the original images shown in Fig. 1 are presented in Fig. 3. The performance of proposed defect detection with orthogonal polynomials model is also compared with existing (Ng, 2006; Tsai and Luo, 2011). These results are presented in Fig. 4 and 5, respectively. From Fig. 3-5 it is evident that the proposed defect detection scheme with orthogonal polynomials model gives better results than the exiting schemes. It can also be further observed that the proposed scheme could identify the exact defects, without the original back ground information, whereas the existing schemes display the original background information, besides weak identification of defects. Further Tsai and Luo scheme could not detect defects even for the given sample input images, and the detected defects are very weak.

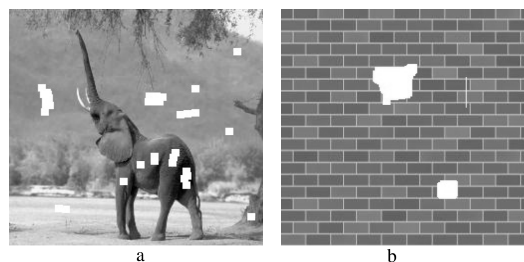

Fig. 1: Sample input images: a) Elephant image; b) Brick image

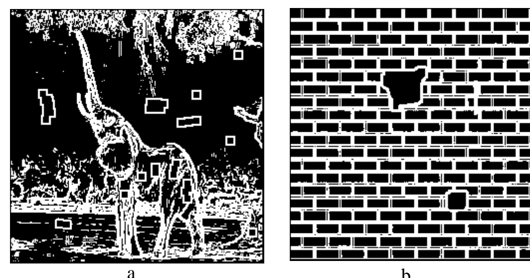

Fig. 2: Results of proposed edge extraction with gradient estimation

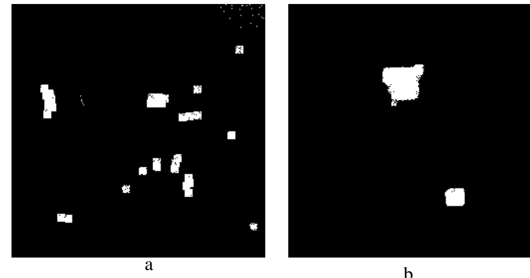

Fig. 3: Results of defect detection with proposed scheme

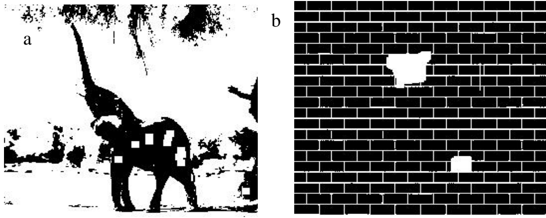

Fig. 4: Results of defect detection with Ng (2006) scheme

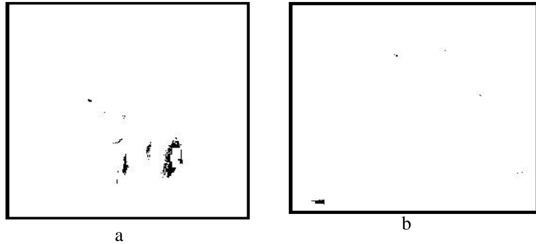

Fig. 5: Results of defect detection with Tsai and Luo (2011) scheme

CONCLUSION

In this stduy, a simple defect identification technique based on orthogonal polynomials is proposed. The edges in the defected images are first detected with the orthogonal polynomials based gradient estimation algorithm. The edge extracted binary image is again applied with the orthogonal polynomials model. A simple computation scheme that finds the ratio between selected transform coefficients is proposed to identity the detects presented in the image. From the experiments it is observed that the proposed scheme is suitable for visually meaningful defect identification and for automated analysis of grey level image. It is also observed that the proposed method fails to detect the crack and scratch faults and experiments and analysis in this direction are in progress in this laboratory.

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