Robust Printing Quality Inspection on SHIBO Surfaces by Multiple Paired Pixel Consistency of Orientation codes

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1　Abstract

A new method for printing quality inspection in SHIBO surfaces is proposed, called multiple paired pixel consistency (MPPC). In this method, we utilize orientation codes as basis. Since orientation codes can against the illumination changes. The proposed method consists of two major components, as illustrated in Fig. 1: training stage and detecting stage. Training stage is for making defect-free model based on multiple paired pixel consistency and orientation code difference. Detecting stage is to identify whether the target pixel match its model.

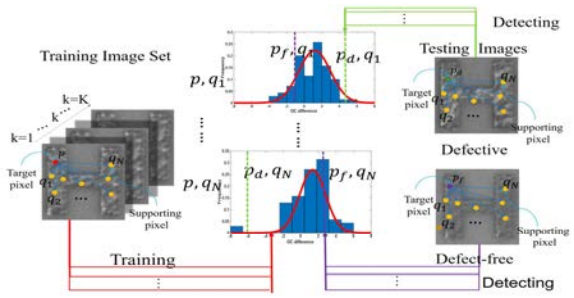

Fig.1 The framework of proposed method

2　MPPC defect-free model

MPPC is inspired by the previous work in [1], and it utilize orientation codes [2] as basis. The training stage can be divided to two steps. Select supporting pixels which have high consistency with target pixel. In other words, the selected supporting pixels have similar trend of change with target pixel. And make the model of each pixel pair by using a single Gaussian model to fit orientation code difference histogram.

2.1 Definition of new differential operator

Here we propose a new definition of differential operator for computing horizontal and vertical derivatives. And comparing the previous used Sobel operator, our new operator is smaller in size, so it has less influence on the boundary pixels and can extract more effective pixels. This is especially important for small-sized templates. The expression is shown in following.

$$G_x = \begin{bmatrix} -1 & 1 \\ -2 & 2 \end{bmatrix} \; and \; G_y = \begin{bmatrix} 2 & 1 \\ -2 & -1 \end{bmatrix} \tag{1}$$

2.2 Selecting the supporting pixel

Fig.1 shows the fundamental definitions of the image data. In this algorithm, we select the supporting pixel q by utilizing the Pearson's product moment correlation coefficient $\gamma(p,c)$. We select the pixels which are the highest N components of $\gamma(p,c)$ as the supporting pixels q_n for each target pixel p, and record the position (u'_n, v'_n).

2.3 Modeling

We build the model for each pixel pair (p, q_n) by a single Gaussian model:

$$\Delta(\mathrm{p}, q_n) \sim N(\hat{\mu}_n, \hat{\sigma}_n^2) \tag{2}$$

where $\Delta(\mathrm{p}, q_n)$ is the OC difference between the target pixel and supporting pixel. Through the training, the $\hat{\mu}_n$ and $\hat{\sigma}_n^2$ can be determined. The defect-free model is a list consist of $[u'_n, v'_n, \hat{\mu}_n, \hat{\sigma}_n]$ for each target pixel p.

3　Defect detection

In the defect detection stage consists of two procedures: (1) to identify the normal/abnormal state of

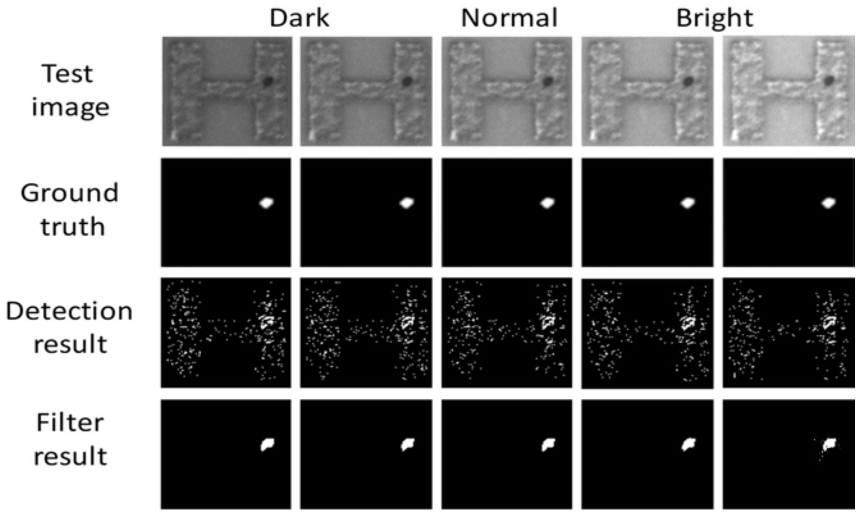

Fig.2 some example of inspection results under different illumination conditions.

the pixel pair; (2) to determine target pixel is defective or defect-free pixel.

3.1 Pixel pair state

For each pixel pair (p, q_n), we utilize a binary function $\beta(q_n)$ for identifying the normal/abnormal state which can be estimated by following expression.

$$\beta(q_n)_{n=1,2,\ldots,N} = \begin{cases} 1 & \|\Delta(p, q_n) - \hat{\mu}_n\| \geq C * \hat{\sigma}_n \\ 0 & otherwise \end{cases} \quad (3)$$

where *C* is a constant. The constant *C* can be set from 1.0 to 3.0 to contain approximately an area of 68%-99% of its probability density function.

3.2 Decision function

In order to identify the defective/defect-free state of target pixel *p*, we define a decision function. The expression is shown in following.

$$\xi(\mathrm{p}) = \frac{1}{N}\sum_{n=1}^{N} \beta(q_n) \quad (4)$$

where N is the total number of supporting pixels. if $\xi >$ T, the target pixel can be considered as defective. And T is a global threshold that can be adjusted to achieve desired result.

4 Experimental evaluation

We utilize the real production image from the real factory. Due to the difficulty to collect any real defects, in this we utilize some artificial defects. We cut out a sub image from the background, then add this sub image to the printed part. It is a simulation of missing print.

Fig.2 shows the inspection results. In these images, the white pixels are detected as defective pixels. The first row shows some example of test image under different illumination conditions, the second row shows the ground truth image, the third row shows the inspection of results, and the last row shows the filtering result. From the results, we can see that our proposed method can locate the almost part of defect. And for quantitative analysis, we utilized three evaluation metrics, *Precise, Recall* and *F-measure.* After filtering, the precision of all character is about 0.93, the recall is about 0.70, and the *F-measure* is about 0.80.

5 Conclusion

MPPC is a robust printing quality inspection on SHIBO surface under dynamic illumination change. For the future work, we want to modify the filtering algorithm that may make the result more accurate. And we also want to modify the present version of defect detection method for improving the recall of defect.

Reference

[1] Liang, Dong, et al. "Co-occurrence probability-based pixel pairs background model for robust object detection in dynamic scenes." Pattern Recognition 48.4 (2015): 1374-1390.

[2] Farhan Ullah, and Shun'ichi Kaneko. "Using orientation codes for rotation-invariant template matching." Pattern recognition 37.2 (2004): 201-209.