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Scale insensitive and focus driven mobile screen defect detection in industry

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ABSTRACT

With the wide-spread of smartphones, mobile phone screen has become an important IO device in HCI and its quality is of great matter in interaction. Traditional defect detection process involves heavy labor cost or relies on unstable low-level features and suffers from both scale and model sensitive problems. Screen defect varies in size, shape, intensity and is hard to be described. Efficient and accurate detection system remains an urgent need in mobile phone screen manufacturing.

In this paper, we propose an end-to-end screen defect detection framework. A defect detection network with merging and splitting strategies (MSDDN) to deal with multiple size and shape variations of defect image patches is firstly designed. After training, feature maps of the last layer before the output of MSDDN can be regarded as good representations of a screen image patch. These feature maps are concatenated into a unified feature vector. We then train a recurrent neural network (SCN) to decide which input screen image patch in a sequence is the most likely to contain defects, where the patches are cropped from the same image, and the feature maps are used as input. As SCN emphasizes on the comparison of image patches from one image, it is less sensitive to different screen batches. The patch with the highest probability of containing defects, or called focus area, is further processed with a sliding window to fill in the MSDDN to produce the final results. Finally, to improve the efficiency of the calculation process to fulfill the real industrial demand, we perform both filter selection and weight quantization on the weights in MSDDN under the purpose of building a low-precision version network without great loss in accuracy (MSDDN-l). Experimental results show MSDDN can better handle the defect variations than traditional models and general purpose convolutional neural networks. Meanwhile, SCN can accurately predict the focus area, and MSDDN-l can greatly improve the efficiency.

1. Introduction

With the rapid development of mobile communication technology, the human has entered the mobile Internet era. Smartphones gradually become an indispensable part of people's lives. The function of smartphones has already surpassed the field of text communication and telephone communication. Instead, smartphones have become an important way for people to socialize and get information. The production quantity of global smartphones is raising year by year, making an urgent need of improving quality and ensuring production efficiency for smartphone manufacturers.

As an important component of smartphones, mobile phone screen plays a pivotal role in the user experience. The quality testing of the mobile phone screen is thus a crucial link in production. Mobile phone screen has developed from the black and white screen to the color screen, and then to the current high-definition display. Now the mobile phone screen can display a variety of complex images vividly with rich layering. At the same time, the production process of the mobile phone screen is more and harsher. It is susceptible to the production environment and other factors, resulting in various types of defects, such as dead pixels, light leakage, color difference and so on, as shown in Fig. 1. Considering the yield rate of the mobile phone screen is relatively low, mobile phone manufacturers have to take some means to check the quality of the phone screen to prevent defective mobile phone screen products sold into the market.

The traditional way to detect mobile phone screen defects is to arrange inspectors on the production line, where they use the naked eyes to detect the existence of defects on the phone screen in order. However, with the growing demand for mobile phone

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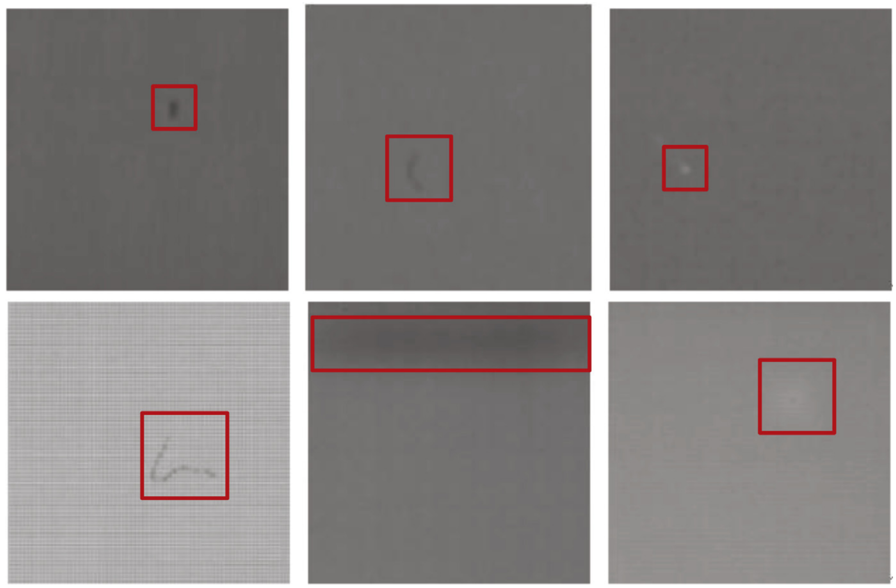

Fig. 1. Different types of defects indicated by the red bounding boxes. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

screen market, using the manual detection of mobile phone screen defects reveals many drawbacks:

- Both detection efficiency and speed are slow. There are many small defects on the phone screen that are difficult to detect through the human eyes, resulting in low efficiency of manual detection and the production line.
- A lack of criteria. Manual detection is mainly judged by human visual senses, which varies from different individuals. As a consequence, it is difficult to summarize a unified criterion. Different people may hold different test results on the same mobile phone screen product.
- Labor cost is relatively high. Employing a large number of inspectors to detect defects on mobile phone screen will greatly increase the enterprise labor cost and reducing the market competitiveness of industries.

Because of these shortcomings, traditional manual detection methods are unable to adapt to current industrial production requirements of efficiency and accuracy. In this paper, a high-resolution industrial camera is adopted to collect mobile phone screen images. To solve the above shortcomings, we proposed an end-to-end automated framework integrated with two deep networks for mobile phone screen defect detection. The first network (MSDDN) aims at parallel detecting defects under multiple scales. The second one (SCN) is designed for predicting the area with the most probability of containing defeats and eliminating the environmental factors on capturing. Experimental results illustrate that with a combination of the proposed two networks, our framework can achieve robust performance and efficiency.

2. Related work

2.1. Filter based methods

In the mobile phone screen defect detection, the relatively obvious defects can be recognized with edge detection. Common edge detection operators include Roberts operator, Sobel operator, Laplacian operator and Canny operator and so on [1–3]. Roberts operator is one of the simplest edge detection algorithms. However, it is sensitive to the noise in the image and apt to produce isolated points in the calculation results. Sobel operator has a smooth effect on the noise and can produce better edge detection results, but the detection accuracy is not very high, and some false edges are sometimes detected. The canny operator is a relatively complex edge detection method, which includes filtering, enhancement, detection, and other steps. Canny edge detection method can achieve better performance by suppressing the noise.

The edge detection algorithm can handle the relatively obvious dot and linear defects in mobile screens, but can not correctly detect the color difference and conglobate defects. Also, due to the strong dotted noise and specific linear textures on the mobile phone screen image, edge detection algorithms can easily lead to misjudgment of noise and texture as defects.

2.2. Image reconstruction based methods

The methods basing on image reconstruction can be used to detect small defects. Common image reconstruction methods include singular value decomposition and Fourier transform. Lu and Tsai [4] propose the use of singular value decomposition in the image reconstruction, achieving good results in the detection of small defects. In the Fourier transform [5–7] of the images with regular textures, the important features can be effectively extracted. Li et al. [8] propose to integrate User Relevance Feedback (URF) capturing users' intentions to describe the interest parts of an image. Wang et al. [9] put forward the image reconstruction into an extreme visual recovery problem, where a large number of pixel values in a given image are missing. Recently, Wang et al. [10] proposes a principled Tag Disentangled Generative Adversarial Networks (TDGAN) for re-rendering new images for the object of interest from a single image. As the mobile screen image owns this character, the regular textures in the amplitude spectrum image are shown as highlight area, while the dot and linear defects are indicated as dark areas.

The image defect detection methods based on image reconstruction are very sensitive to the small defects in the image, but there are two obvious shortcomings. One one hand, the time cost of the image reconstruction method is generally high, especially when the original image size is large, failing to meet the requirement of real-time detection in the industrial production line. On the other hand, the mobile phone screen detection algorithm based