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Enhancement of low-contrast edge detection through deep learning approach

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Abstract

In the large-scale production of thin film products such as flexible electronics, roll-to-roll processes play a crucial role. The slot-die printing method of coating is commonly used in roll-to-roll as it offers a simple yet precise dispensing of conducting ink onto a wide flexible flat substrate. Optimisation of slot-die coating processes can be further achieved by integrating systems that control the key operating parameters. This work focuses on designing a feedback approach that incorporates a machine vision surface inspection. Analysing the edges of the printed ink on the substrate can provide meaningful information about the process performance. For edge detection, the authors have previously reported that using a standard computing method that uses the Sobel operator, enables the extraction of quantitative information related to the printed ink edge consistency and hence track width regularity. The authors have observed that in some cases where the edges are blurred, poorly illuminated, or have thin transparent coatings resulting in low contrast between ink and substrate, they are difficult to detect. Two different printed ink samples have been used in the present work. Here, the authors present a deep learning-based approach to enhance edge detection. It has been found that the Faint-Edges-Detection approach performed better at identifying low-contrast edges compared to traditional approaches such as Sobel and Canny operators. The lateral arithmetic average Ra^{LAT}, was used as an indicator of the edge regularity along the printed track. Calculated Ra^{LAT} of difficult to quantify edges was found to be 0.65 micron through application of the deep learning-based algorithm. This process is achieved with no time penalty compared to Sobel-based methods.

edge detection, low contrast, neural network, slot-die printing.

1. Introduction

Modern large scale flexible electronic manufacturing predominantly relies on the roll-to-roll (R2R) process for the production of a wide range of devices such as printed sensors, solar cells, organic light-emitting diodes, and electric vehicle batteries [1-4]. Large scale adaptation of R2R is due to its scalability, cost-efficiency, and the ability to integrate multiple layers and materials in a continuous process [1]. One of the key steps in the R2R manufacturing process is coating, where a thin uniform layer of usually conductive ink is applied to the substrate [5-6]. Among various coating techniques, such as Gravure printing, spray coating, screen coating; slot-die coating is often the first choice. This is because of its precise dispensing of ink, high throughput and large area coverage, as well as superior production speed [7-8]. Slot-die coating parameters can be further optimised by integrating feedback quality control systems. Despite having these advantages, a common coating defect at the ink edge often occurs as "ragged" edge patterns at during the coating process. Analysing the edge of the printed ink on the substrate can provide meaningful information about the ink-based coating process. Camera based optical quality control systems offer the advantage of low cost, non-contact, real-time, and can provide simple to use solutions [9-12]. Previously, the authors have reported on edge detection using a standard computing method that uses a Sobel operator to extract the quantitative information concerning the printed edge consistency and track width regularity [9]. However, there are cases where the edges are blurred, poorly illuminated, or have thin transparent coatings resulting in low contrast between ink and substrate, the ink track edges are difficult to detect.

This study employs a deep learning-based approach to enhance the edge detection. Due to the hierarchical nature of feature learning, using a convolution neural network (CNN) is promising for many tasks including contrast-enhancement [13]. A faint edge detection approach (FED-CNN) has been employed to detect blurry and low-contrast edges. This approach is fast and accurate for binary edge (where only the edge pixels are highlighted as white against a black background) detection in noisy and low-contrast images. It has been proven to be orders of magnitude faster as well as achieving higher accuracy by training the network on a dataset of binary images [14]. In this work, the authors suggest the use of a pre-trained model of FED-CNN for detection of edges of the printed ink on the substrate.

2. Methods

The faint edge detection convolutional neural network uses a multi-scale U-net network architecture that captures both fine and coarse features, which is crucial for accurate edge detection. It uses a custom edge preservation loss function that is designed to maintain the integrity of edge structure during the denoising process, ensuring essential features are retained. The model is trained on a dataset of binary images, enabling it to distinguish between edges and non-edges under various noise level. It operates with linear complexity with respect to number of pixels in an image, which makes it suitable for real-time applications. A detailed description about the model architecture and methodology is available in literature [14]. In this work, authors use the pre-trained model weight of the FED-CNN in training the dataset [14]. This approach enhances the training efficiency and improves detection performance on the test samples by taking advantages of learning from a large dataset. It provides a good starting point for the model with less training data which can be then optimized for a given task. Two types of printed ink samples were used in this work: silver ink on a polyethylene terephthalate substrate (ink 1) and polymer blend ink on a titanium substrate (ink 2). For both cases, the printing parameters were set to a flow rate of 2.4 mL/min, a speed of 6 m/min, and a 100 µm gap between the slot-die head and the substrate. Multiple categories of images have been collected using a CMOS camera (Baumer VCXG-15C.PTP, pixel size 3.45 µm x 3.45 µm). The training collected images have low visible edge contrast, very low edge contrast on transparent substrates and blurry edges as well as images where edge is clearly defined. The assessment camera was mounted perpendicular to the printed substrate to capture the image frames. Augmentation has been implemented to increase the number of training dataset images. A total of 80 images (used in the ratio of 80:20) were used for training and validating. No other pre-processing of the images has taken place besides conversion to grayscale.

3. Results

Firstly, a sharp edge image was used for the extraction of edges (see Figure 1 a). The deployed network was able to detect edges along with a residual edge as can be seen in Figure 1b. Residual edges occur due to the drying up of the ink from the edges. From the output of the detected edge images, the edge profile of the ink was extracted as shown in the Figure 1c.

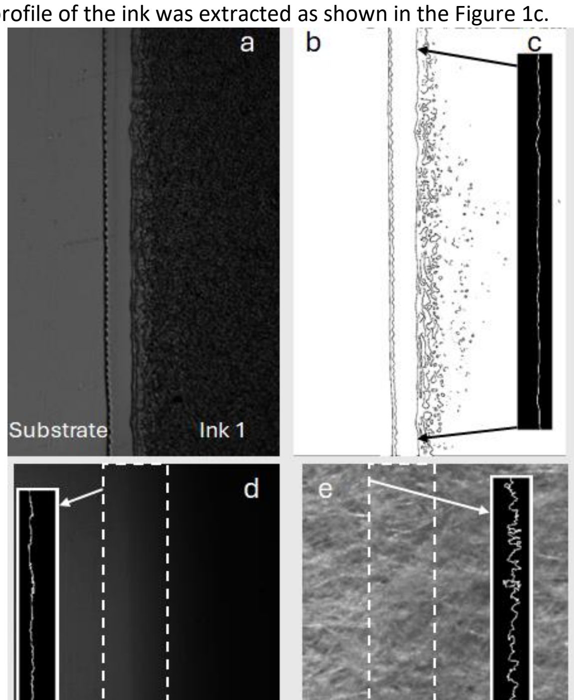

Figure 1. Results of the edge detection. a) An image with a visible edge contrast between substrate and ink 1 and b) image showing detected edge profiles as an output of the network. c) The snippet shows the extracted edge profile of the detected edge for calculation of Ra^{LAT}. d) An image with low edge contrast between substrate and ink 2, and e) shows an image with very low edge contrast on a transparent substrate and ink 2. Snippet in images d) and e) shows the extracted edge profile for calculation of lateral roughness average.

Further analysis was carried out to extract the ink edge for calculation of edge roughness average, Ra^{LAT} [9], in the lateral direction to assess print track straightness and consistency. This "roughness" value was calculated as the mean absolute deviation from the fitted line of the extracted lateral edge profile. The calculated value was found to be 0.65 µm. Subsequently, images with low edge contrast (see Figure 1d) and a very low edge contrast (see Figure 1e) on a transparent substrate were used for extraction of edges, and calculated Ra^{LAT} value was 0.90 µm and 2.82 µm respectively. Although the edge at very low contrast can be detected, the high roughness value may suggest that detection performance has decreased. The increased roughness value might be caused by weak feature extraction, or inconsistencies along the edge boundary.

5. Conclusions

These preliminary results indicate that blurry and low-contrast edges can be detected using FED-CNN. The calculated roughness parameter in the case of visible edge contrast is comparable to that of other reported methods [9]. However, the accuracy of detection of edges in the case of blurry and low-contrast images of transparent substrates may benefit from further improvement. In theory the accuracy could be by increasing the number of training images manifold. Such a vision system could be implemented into a feedback loop for printing control and provide a powerful tool for optimising R2R production parameters. This process is achieved with no time penalty compared to Sobel-based methods. Since this method is not dependent on material-specific properties, it can be extended to other ink and substrates combinations with appropriate parameter adjustments.

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