Reforming Mass-Scale Gel Pen Manufacturing: An AI-Enhanced Writing Mechanism for Improved Quality Control and Defect Detection

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Abstract

The advancement of technologies has introduced a significant development in automation systems into almost all manufacturing fields in today's world. Automated systems have enhanced the manufacturing industry by considering productivity, safety, reliability, and quality while reducing shortcomings associated with human labor. This study focused on designing a gel pen writing mechanism with a writing verification method for mass-scale pen assembling in the stationery item manufacturing industry. The main objective of this research is to automate the gel pen writing and verification mechanism which is currently based on a semi-automated method that involves manual labor. The development involved attaching pen writing and a verification mechanism to the existing pen assembling machine. Automation techniques to verify the writing of gel pens are crucial as they are prone to fail on first writing when a customer purchases the product at the retail store which leads to a loss in profit and customer dissatisfaction. Sequential techniques are being practiced by many stationery companies, which slows down the production rate and work-in-progress. In this study, the techniques to synchronize online verification of the pens are mentioned and an adaptable attachment for full-functioning defect detection was developed by training an Artificial Intelligence model.

Keywords: **defect detection, gel pen, writing fluidity, design, artificial intelligence**

Introduction

With the increasing demand for stationery items, the production process has become a prominent aspect of today's manufacturing industry. The use of semi-automated techniques for the assembling of pens leads to drawbacks such as production time, accuracy, efficiency, and production rate. Gel pens typically use low-viscosity ink [1], which can lead to reduced reliability during the centrifugal process to eliminate air bubbles trapped inside the ink tube and tip. Consequently, there is a higher likelihood of gel pens experiencing failures after production. As a result, every pen undergoes a quality check in a separate process before being released to the market. The continuous flow of ink is expected but practical manufacturing introduces many challenges and fine defects which leads to discontinuity that may cause writing failure. This results in a significant impact on production rates and work-in-progress (WIP). As a result, an automated pen writing mechanism was introduced by this study with an online verification system that will identify the defects of writing using computer vision.

The ballpoint pen is a microfluidics-type device where capillarity gravity drives the ink [1,2] and this study emphasizes having an even film of ink on the ball surface that does not break is essential for a high-performance pen. In our design, the mechanically generated ‘Z’ shapes would be written in equal pressure conditions. Tang et al. [3] evaluate a possible quality inspection of the pen tip in the necked-in area which is vital to ensure the writing fluidity of a pen. The method involves detecting the defective pen tips by using sub-pixel edge detection and least square methods. The study by He et al. [4] measured the quality of writing fluidity by calculating the pixel area of a predetermined drawn pattern and breakage of the writing path and ink accumulation. Our study also involved using a similar technique to generate a standardized drawing pattern of the letter 'Z'. According to Hase, [5] writing performance is affected by design, tip, and ink components, and the design for the writing testing mechanism was limited to generating straight lines only, to better test the pens our design was improved to generate a zigzag ‘Z’ shape which covers both straight and slanted lines.

Methodology

The study involved generating data for analysis of properly written ‘Z’ shapes on a paper that closely resembles human writing form. A mechanical design was developed to simulate handwritten ‘Z’ shapes while the pen was being assembled along the pen assembling machine. The data generated was captured by a USB camera module which was accessed by the OpenCV-based Python 4.7.0.72 program running on the PC. The detection mechanism was based on Tensorflow 2.10.1 and object detection API 2.12.0 which was used to detect defective written samples. During the study, an algorithm was developed to generate perfect ‘Z’ samples within the resolution of 250 x 250 pixels. Based on these perfect ‘Z’ samples, defect samples were generated by varying the allowed defected pixels per location and a fixed number of random locations along the selected perfect ‘Z’ sample to create a base model that closely resembles the quality requirements of a particular organization.

Table 1 shows the parameters used to generate accepted and rejected ‘Z’ samples to create the base model. For this study, 150 samples were generated from each font size with five defective locations which accounts for a total of 1800 samples.

Table 1. Sample Classification

Font Size	*Allowed defective pixels per location for passed sample generation*	*Allowed defective pixels per location for defective sample generation*
5	20	30
6	25	35
7	25	35
8	25	40
9	25	40
10	30	45

The total locations along the ‘Z’ shape depend upon the total number of pixels in the ’Z’ shape and the allowed defective pixels per location.

$$\text{Total locations} = \frac{\text{Total pixels in Z shape}}{\text{Allowed pixels per location}} \quad (1)$$

By using this method, we can make sure that defective areas are not affected by the size of the ‘Z’ shape. The defects are then populated among a fixed number of randomly selected locations from the total number of locations computed along the shape. A random grayscale value of 0-255 is assigned to the pixels in the randomly selected location to generate the defects. Figure 1 shows the samples generated for a font size of 10.

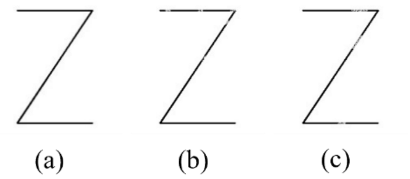


Figure 1. (a) Perfect Z, (b) Allowed Z, (c) Defected Z

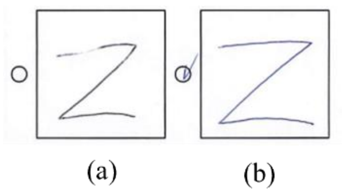


Figure 2. (a) Detect Sample, (b) Passed Sample

The model was trained using 100,000 steps with a batch size of 4. A transfer learning process was used on the ssd-mobilenet-v2-fpnlite-320 which was trained on the COCO data 2017 dataset. To adapt the base model to detect real-world samples, an adapted model was trained on 490 samples obtained by fifteen people. The users were allowed to select among 20 gel pens randomly to draw ‘Z’ shapes and mark the properly written ‘Z’ samples based on their own judgment. A sample is illustrated in Figure 2.

The collected data was labeled into two classes named ‘defected’ and ‘passed’. The pre-trained model that we generated using computer-generated ‘Z’ samples was used as the starting point for the training on real-world data. The model was trained using 50,000 steps and with a batch size of 4. The base model and adapted model were evaluated for their performance.

Design and Implementation

Designing was done and two assemblies were developed as a Paper Reel Rolling Unit and a Writing

Unit as follows which could be attached to the pen assembling machine.

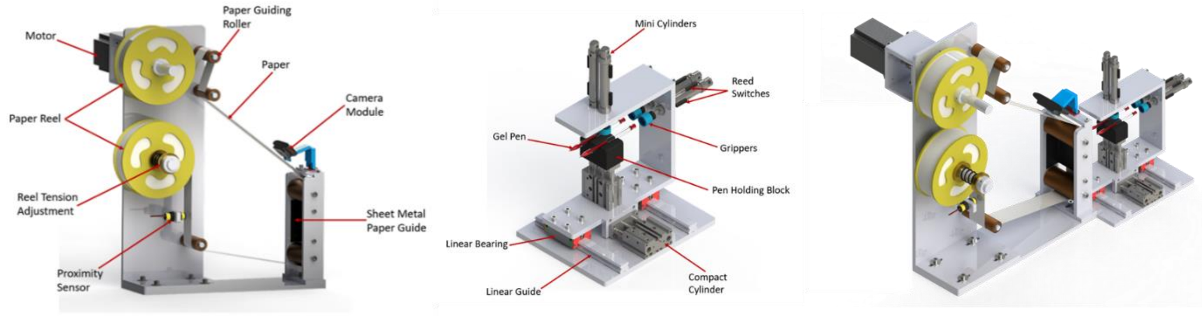
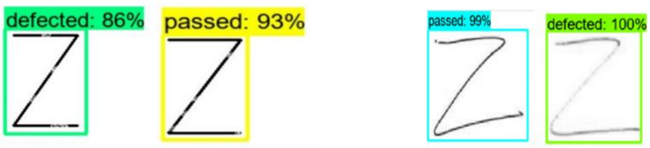


Figure 3. 3D Design

The paper is fed and moved through the writing unit to draw the 'Z' shape which would be captured by the attached camera module. The image data was then processed using image processing and the AI model. The writing mechanism actuates two parallel pens along the horizontal axis to generate the straight-line sections at the start and the end of the ‘Z’ shape. Retrieval of the pneumatic cylinders, while the paper is being rolled, generates the inclined mid-section of the ‘Z’ shape. Reed switches attached to these cylinders were used for feedback control and to adjust the stroke as necessary.

Results and Discussion

The base model trained was adapted to recognize real samples from the camera. Figure 4 shows the predictions made on defective and passed samples of the base and the adapted model.



(a) (b)

Figure 4. Predictions on Defective and Passed Samples of (a) Base Model, (b) Adapted Model

By using the evaluation script available on the TensorFlow object detection API, the following measurements were obtained.

Table 2. Evaluation Summary

Parameters	*Base Model*	*Adapted Model*
Average Precision	0.912	0.913
Average Recall	0.934	0.936

The adapted model has a mean average precision of 91.3% which is fairly accurate enough to verify the writing fluidity of commercially manufactured gel pens. Further precision could be achieved by generating diverse passed and defective ‘Z’ samples by using the algorithm that we developed in the studyFor this demonstration, we have considered only five defective locations along the generated ‘Z’ shapes. By using better matching font, stroke, color, and font size the base model could be further improved depending on the requirements of the manufacturing plant. The adapted model could be enhanced by capturing real-world training samples with similar hardware such as the type of camera used in the final deployment stage.

Conclusion

This study aimed to standardize data sets for verifying gel pen writing fluidity. Algorithms were introduced to train a base model and then an adapted model for real-world samples which was crucial for inspecting writing quality. Future research should refine algorithms to closely resemble the 'Z' generation which matches real-world writing form. The base model used a white pixel array, enhancing it could be done using real paper images as backgrounds for further testing. Proposed improvements are to include an algorithm analyzing real samples to determine thickness, size, defective pixels, and common defect-prone areas to enhance the model. Using a manual focus camera is recommended as the focus could remain fixed, as most of the USB cameras tend to autofocus, which may result in blurring as the paper moves across the detection area The methods could be extended to verify other writing products as well. Ultimately, these techniques could enhance customer satisfaction and reduce manual labor in checking pen writing quality. The stationery manufacturing industry could benefit from this study by applying the proposed techniques by adjusting the parameters as necessary which has less tendency for error and false positive verifications involved with human writing and eye verification techniques

Conflict of Interest

None.

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