

Research on the Application of Optical Flow Method in Complex Local Deformation Edge Defect Detection

Wenfeng Li¹, Aolin Li², Ruilin Li³

¹MTI(Suzhou)Intelligent Technology Co., Ltd, Suzhou, Jiangsu, 215100, China

²Beijing Jianhua Experimental Yizhuang School, Beijing, 100039, China

³Beijing University of Posts and Telecommunications, Beijing, 100876, China

ABSTRACT

In the quality control process of the label printing industry, accurately identifying complex and variable local edge defects has become a core challenge. The dynamic variations, irregular shapes, and subtle printing deformations of these defects pose significant obstacles to traditional inspection methods. Consequently, this study introduces optical flow tracking technology. We firstly employ the optical flow method to achieve high-precision alignment and mapping between the image to be inspected and the reference standard image. Following this, we conduct a meticulous extraction of edge regions and ultimately adopt grayscale analysis and defect judgment for defect detection. Experimental results demonstrate that our approach achieves an precision rate of 95.66% and a recall rate of 98.60%, markedly enhancing the efficiency of label printing quality control.

KEYWORDS

Optical flow; Local deformation; Edge defect detection

1 Introduction

In the field of quality control for label printing, the precise detection of complex local deformation edge defects has become a crucial task. These defects are typically characterized by dynamic variations, irregular shapes, and subtle printing deformations, significantly increasing the difficulty of detection and posing stern challenges to conventional methods. Existing techniques are constrained by evident limitations such as low recognition accuracy, poor adaptability, and sensitivity to environmental changes, necessitating the development of novel detection strategies to address these technological gaps. There is an urgent need to advance label printing quality control towards higher precision and efficiency.

Analysis of challenges in complex local deformation edge defect detection: Dynamic Variability, during the inspection process, factors such as thermal expansion and contraction, and mechanical stress can lead to temporal changes in the edge condition. This dynamic nature necessitates detection technologies that are capable of real-time tracking and adaptation. Irregular Shapes, the edges of label products exhibit a wide variety of forms, with non-standard geometric shapes making it difficult for detection methods based on predefined templates or rules to accurately identify them. This diversity significantly increases the complexity in designing recognition algorithms. Subtle Local Print Deformations, Slight variations in font thickness occurring during the printing process due to differences in techniques. While these minute changes may be deemed insignificant by experts in the label printing industry concerning the overall quality of the finished product, they pose a substantial adaptability challenge to detection systems. Traditional vision inspection technologies often struggle to meet these demands.

Optical flow methods ^[1-6], a technology based on analyzing object motion information from image sequences, calculate the displacement of pixels between consecutive frames (the optical flow field), effectively capturing motion features in dynamic scenes. Within the area of edge defect detection, optical flow presents unique advantages: it not only furnishes ample motion information, aiding in distinguishing minute deformations caused by defects from background noise, but also mitigates the effects of varying illumination to some extent, thereby enhancing the robustness of the detection process. By meticulously examining the abnormal distribution or discontinuity within the optical flow field, one can indirectly reveal the potential location and nature of local defects.

While direct research progress in edge defect detection specifically for labels has been limited in recent years, the domain of edge defect detection in other industries remains highly active ^[8-10, 12-21]. Notably, Wang of Zhejiang University ^[8] addressed the issue of edge defect detection for optically film die-cutting products, proposing a method that firstly corrects and locates images, then employs the Canny algorithm and Zernike algorithm for edge detection in different regions, followed by geometric primitive segmentation and fitting of the cutting contour. Defect presence is determined through comparing the fitted equation with the minimum mean square error of corresponding pixel points in the region, achieving an accuracy rate above 95%. However, the effectiveness of this method is heavily dependent on the fitting outcome; suboptimal fitting for complex, irregular printed edges can lead to reduced detection precision. Furthermore, efforts have been made to combine optical flow methods with other image analysis techniques to enhance detection accuracy and efficiency. Among these, Feng ^[11] and colleagues investigated algorithms for remote sensing image

registration using optical flow correction, achieving high-fidelity and high-precision alignment even in complex terrains with changing landforms. This work significantly inspires the application of optical flow in the domain of defect detection.

In summary, given the limitations of current technologies in detecting complex local deformation edge defects and the unique advantages demonstrated by optical flow methods, this paper aims to delve into the innovative application and advancement of optical flow, integrating advanced image processing and machine learning techniques. The objective is to develop a highly adaptable and precise new detection method, thereby providing a feasible solution to address the challenges confronted in this field.

2 Basic Principles

Optical flow, a key concept in computer vision, aims to infer the motion (velocity and direction) of points in a scene from a sequence of consecutive images. Its fundamental principles rest upon several core assumptions:

Assuming 1. Brightness Constancy – Assumes that the brightness of a physical point in the scene remains unchanged over very short time intervals. This means changes in brightness observed in the image are solely due to the displacement of the point on the image plane, not variations in lighting or the object's intrinsic brightness.

Assuming 2. Spatial Coherence (Small Motion) – Postulates that between successive frames, object movement is relatively minor. This permits linearization of the motion model, simplifying computations. Based on the assumption of brightness constancy, the following equation(1.1) can be derived:

$$I(x + \delta x, y + \delta y, t + \delta t) = I(x, y, t) \quad (1.1)$$

Where, $I(x, y, t)$ represents the grayscale value at the coordinate (x, y) position at the moment t of the image.

Using the Taylor expansion approximation to describe the brightness change between two frames, ignoring higher order terms, we can obtain equation(1.2):

$$I(x + \delta x, y + \delta y, t + \delta t) \approx I(x, y, t) + \frac{\partial I}{\partial x} \delta x + \frac{\partial I}{\partial y} \delta y + \frac{\partial I}{\partial t} \delta t = I(x, y, t) \quad (1.2)$$

Subtracting the same term $I(x, y, t)$ from both sides of the equation yields the following equation(1-3):

$$\frac{\partial I}{\partial x} \delta x + \frac{\partial I}{\partial y} \delta y + \frac{\partial I}{\partial t} \delta t = 0 \quad (1.3)$$

In the equation(1.3), $\frac{\partial I}{\partial x}$, $\frac{\partial I}{\partial y}$ represent the gradient of the image in the x and y direction, and $\frac{\partial I}{\partial t}$ represents the rate of change in time, respectively.

Divide the above equation(1.3) by δt at the same time, and the following basic constraint equation(1.4) for optical flow can be obtained:

$$\frac{\partial I}{\partial x} u + \frac{\partial I}{\partial y} v = -\frac{\partial I}{\partial t} \quad (1.4)$$

Where, u and v represent the optical flow component along the x and y axis respectively, that is, the speed of the image point. However, this equation group is two unknown(u, v), so additional constraints are usually required to solve the optical flow.

The LK algorithm was proposed by two scientists, Lucas and Kanade in 1981. Under the conditions of the above two basic assumptions, this method introduces the following assumptions three:

Assuming 3. Spatial consistency, neighboring pixels, because they belong to the same surface or have similar motion attributes, usually have similar movement speed. This assumption helps reduce the complexity of calculation and improve the stability of estimates.

According to assuming(3), considering the light current of the image in a rectangular range of a size $m \times m = n$, it can be consistent with the formation of the equation(1.5):

$$A\mathbf{x} = \mathbf{b} \quad (1.5)$$

Where, $A = \begin{bmatrix} \frac{\partial I_1}{\partial x_1} & \frac{\partial I_1}{\partial y_1} \\ \frac{\partial I_2}{\partial x_2} & \frac{\partial I_2}{\partial y_2} \\ \vdots & \vdots \\ \frac{\partial I_n}{\partial x_n} & \frac{\partial I_n}{\partial y_n} \end{bmatrix}, \mathbf{x} = \begin{bmatrix} u \\ v \end{bmatrix}, \mathbf{b} = \begin{bmatrix} -\frac{\partial I_1}{\partial t} \\ -\frac{\partial I_2}{\partial t} \\ \vdots \\ -\frac{\partial I_n}{\partial t} \end{bmatrix}$

Multiplying A^T on both sides of the upper formula at the same time:

$$A^T A \mathbf{x} = A^T \mathbf{b} \quad (1.6)$$

Therefore, the final formula(1.7) of optical flow current calculation is as follows:

$$\mathbf{x} = (\mathbf{A}^T \mathbf{A})^{-1} \mathbf{A}^T \mathbf{b} \quad (1.7)$$

3 Edge Defect Detection Algorithm

In this study, we propose a complex edge defect detection methodology based on optical flow field analysis and grayscale feature identification, aimed at achieving efficient and accurate quality monitoring of product labels on the production line. The method comprises five core steps to ensure high sensitivity and reliability in defect detection.

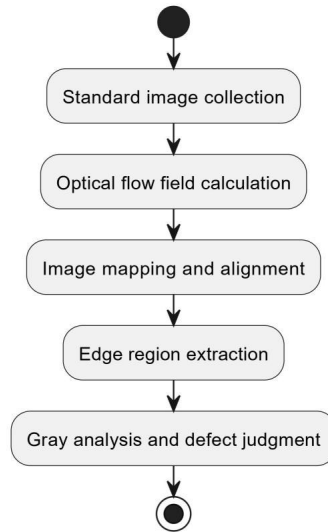


Figure 1 Algorithm flow

In this research, we propose a complex edge defect detection approach based on optical flow field analysis and grayscale feature recognition, designed to facilitate efficient and precise quality monitoring of product labels in the production line. The method consists of five principal stages, ensuring high sensitivity and dependability in defect detection.

Step 1: Standard Image Acquisition and Establishment. Initially, representative samples are meticulously selected from defect-free product labels, and high-quality standard images are captured using high-precision imaging equipment. These standard images serve as reference benchmarks for subsequent processing, requiring clarity and the absence of imperfections to fully manifest the visual characteristics inherent to the labels. Through this process, a high-quality database of standard images is constructed, laying a solid foundation for subsequent comparative analyses.

Step 2: Optical Flow Field Calculation. In real-time monitoring, the system continuously acquires label images and employs optical flow algorithms to compute the optical flow fields between these live images and pre-established standard images. Optical flow field analysis captures minute movements between images and effectively reflects pixel displacements caused by printing deviations or deformations, providing precise motion parameters for subsequent image registration.

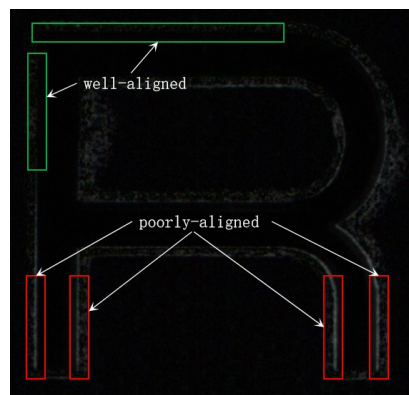


Figure 2 Comparison results between the standard image and real-time image

Step 3: Image Mapping and Alignment. Leveraging the calculated optical flow fields, real-time captured label images are precisely mapped onto the standard images, achieving spatial alignment. This step ensures that, even with minor positional shifts or deformations, a consistent analytical basis is provided for subsequent defect detection through pixel-to-pixel correspondences.



Figure 3 Comparison results between the standard image and real-time image after mapping

Step 4: Edge Region Extraction. On the standard image, critical edge positions of the label are predetermined either manually or through intelligent algorithms as regions of interest (ROI). Utilizing the mapping relationship, these ROIs are accurately transferred to the real-time images, extracting the edge regions from the live label images. This strategy focuses on the portions of the label most prone to defects, significantly enhancing the targeted and efficiency of the detection process.

Step 5: Grayscale Analysis and Defect Judgment. Lastly, detailed grayscale analysis is conducted on the extracted edge regions, comparing their grayscale distribution with that of the corresponding regions in the standard image. By setting reasonable thresholds and indicators for grayscale variation, the system swiftly identifies grayscale anomalies caused by uneven printing, stains, or other factors, thus determining if the label harbors potential defects. This approach, combining morphological features with grayscale statistical analysis, ensures the accuracy and robustness of defect detection. In summary, the proposed label defect detection scheme based on optical flow fields and grayscale analysis, through meticulous image processing and analytical techniques, realizes efficient monitoring of label quality on the production line and is poised to play a pivotal role in elevating the standard of product quality control.

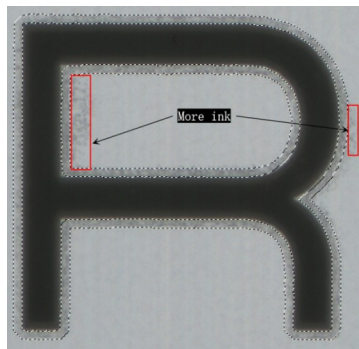


Figure 4 Result of Grayscale Analysis

4 Experiment

4.1 Data Set Description

This study focuses on garment labels, collecting three types of labels with defects including ink deficiency at edges, ink overflow at edges, glue detachment, insufficient glue, and excessive glue, as illustrated in the accompanying figures. For each type of label, a dataset comprising 200 images was gathered, with the distribution of defective samples detailed in the table below.



Figure 5 Defect examples (a)Less ink (b)More ink (c)Glue off (d)Less glue (e)More glue

Table 1 Each type of defect distribution

	OK	Less ink	More ink	Glue off	More glue	Less glue
A Label	101	35	27	17	11	9
B Label	125	8	11	15	27	14
C Label	143	7	11	10	23	6

4.2 Comparisons with other Inspection Methods

Experiments were conducted on the above data sets, verified by Halcon software, and the hardware configuration of the running platform was 2.3GHz CPU and 8G memory.

This experiment comprehensively examines the effectiveness of algorithms by evaluating the two key performance indicators precision and recall rate. The accuracy rate specifically refers to the situation where the algorithm fails to accurately identify the real cases, and it is misjudged to the right, the calculation formula is,

$$FNR = \frac{TP}{FP + TP}$$

Where, TP is the correct number of regular identification, and FP is the negative number of misjudgment. This indicator can reflect the misunderstanding of the defect detection. The larger the value, the less the misunderstanding.

The recall rate refers to the situation where the algorithm is wrongly ordered to be the positive sample error standard as the negative case, the calculation formula is,

$$FPR = \frac{TP}{FN + TP}$$

Among them, FN is a positive number of misjudgment as a negative case. This indicator can reflect the missed report of defect detection. The larger the value, the less the missed report.

Under the strict requirements of label printing quality control, these two indicators are particularly important. The accuracy and reliability of the detection system is directly associated to the detection system, which will affect the overall product quality and production efficiency.

The comparison experiments are designed, and the global imitation transformation method and the algorithm proposed in this article are tested to test the above data sets. The experimental results are summarized as follows:

Table 2 Comparison of precision and recall rate of each label

Algorithms	A Label		B Label		C Label	
	precision	recall	precision	recall	precision	recall
Global Affine Trans.	78.22%	94.05%	72.80%	96.81%	59.44%	97.70%
Ours	95.05%	97.96%	96.80%	98.37%	95.10%	99.27%

Table3 Comparison of precision and recall rate of all

Algorithms	total precision	total recall
Global Affine Trans.	69.11%	96.23%
Ours	95.66%	98.60%

The experimental results revealed that our proposed algorithm outperforms the global affine transformation algorithm in both reducing false negatives and false positives. Specifically, our algorithm achieves an overall precision rate of 95.66%, significantly higher than the 69.11% of the global affine transformation algorithm. This highlights its superiority in minimizing false detections and enhancing detection accuracy. Similarly, our algorithm's total recall rate stands at 98.60%, a slight improvement over the 96.23% of the global affine transformation algorithm, demonstrating its greater efficacy in identifying and correctly classifying actual defects.

Moreover, our algorithm exhibits broader adaptability and stability across various label products, maintaining consistently high levels of performance in both precision and recall, whereas the global affine transformation algorithm shows more variability in its performance.

In conclusion, our algorithm holds significant value for enhancing the finesse of quality control in printed materials. This innovative achievement not only enriches the theoretical and practical aspects of defect detection but also provides robust technical support for related industrial applications.

5 Conclusion and Future

Optical flow, as a potent image analysis technique, has demonstrated remarkable advantages in the detection of complex local deformation edge defects. It enables the precise tracking of pixel motion trajectories in image sequences, inferring the direction and speed of object movement. In defect detection scenarios, optical flow not only captures subtle surface variations but also effectively discriminates between genuine motion and artifacts, enhancing detection accuracy and robustness, thereby reducing false positives while improving the detection of false negatives. This underscores its extensive potential in industrial quality control applications.

Despite its prowess in complex local deformation edge defect detection, optical flow still encounters challenges: the computation time is relatively long, limiting its efficiency in real-time applications. Future studies might explore less computationally intensive optical flow calculation methods or parallel processing accelerations of existing algorithms to decrease computation times. Moreover, the accuracy of optical flow estimation is susceptible to image noise, occlusions, and rapid motions. Developing more resilient algorithms, such as those incorporating deep learning into optical flow estimation, can bolster resistance against these detrimental factors.

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