Design of Detection System Based on Digital LCD Touch Screen

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Abstract: ***Traditional Liquid Crystal Display (LCD) touchscreen manufacturing processes are often hampered by testing systems characterized by low levels of automation. These legacy systems suffer from significant limitations, including an inability to seamlessly exchange test data with other devices in the production line and a lack of flexibility to accommodate products with multiple specifications. This data siloing and inflexibility create bottlenecks, impede statistical process control, and hinder the transition towards smart manufacturing. In response to these challenges, this paper presents the design and development of a novel, digitized detection system specifically for LCD touchscreens. The core of the proposed system utilizes an industrial image acquisition card to capture high-fidelity digital images of the unit under test. Subsequently, a suite of advanced image processing algorithms is applied. Key to its operation is the capability to filter and analyze specific regions of interest (ROI) based on configurable area thresholds, enabling precise and automated screen inspection for defects such as dead pixels, scratches, and Mura effects. The system's architecture is designed for versatility, allowing it to be easily reconfigured to test different specifications of LCD touchscreens and associated Flexible Printed Circuit (FPC) boards. Its functionality comprehensively covers critical assembly stages, including the inspection of plug-in components, the quality of hot-pressing (e.g., for FPC attachment), and continuity or wiring tests. The implementation of this system facilitates fine-grained management of the production workflow, empowers intelligent defect recognition, and establishes complete data tracing from raw materials to finished goods. Empirical results from deployment demonstrate tangible benefits, notably a significant reduction in manual labor requirements, a marked improvement in testing efficiency and throughput, and a substantial elevation of the overall digitization level within the production environment. This research provides a practical and scalable solution for modernizing quality control in display manufacturing.***

Keywords: LCD Touchscreen, Automated Optical Inspection (AOI), Digital Detection System, Image Processing, Smart Manufacturing, Quality Control, Data Tracing, Flexible Production.

1. INTRODUCTION

The automation level of traditional LCD touch screen detection is low, and a series of steps such as plug-in, hot pressing, and line testing require manual independent or auxiliary completion. However, manual operation and manual detection speed are slow. It takes about 12 seconds for skilled workers to complete the detection of a 5.99-inch touch screen, and the data detected in this way cannot be communicated with other production equipment, resulting in the formation of a "data island".

In response to this, this article developed a digital based LCD touch screen detection system, which can complete the plug-in, hot pressing, and line testing between different specifications of LCD touch screens and FPC circuit boards; Realize refined management, intelligent recognition, and data traceability of the production process. Achieved the reduction of workstations and increased efficiency, meeting the production and testing needs of enterprises for multi specification products.

Chen, Yang et al. (2025) proposed SyntheClean, enhancing large-scale multimodal models through adaptive data synthesis and cleaning techniques [1]. Concurrently, question answering systems evolved with Jiang et al. (2025) introducing a knowledge-enhanced multi-task learning model [2], followed by Zhuo et al. (2025)'s intelligent-aware transformer incorporating domain adaptation and contextual reasoning [3]. Cross-modal generation advanced through Zhang, Hanlu et al. (2025)'s dynamic attention-guided text-to-video framework with multi-scale synthesis and LoRA optimization [4]. For knowledge maintenance, Zhao et al. (2025) developed KET-GPT, a modular framework for precision knowledge updates in pretrained language models [5]. Dialogue systems saw innovations via Shih et al. (2025)'s DST-GFN, a dual-stage transformer with gated fusion for pairwise preference prediction [6]. Multimodal detection capabilities improved with Li et al. (2025)'s MLIF-Net, fusing vision transformers and LLMs for AI image detection [7]. Business intelligence tools advanced through Xie and Chen (2025)'s CoreViz, featuring context-aware reasoning for dashboards [8], while diagnostic systems benefited from Zhu, Bingxin (2025)'s TraceLM for temporal root-cause analysis [9]. Deployment safety was addressed by Zhang, Yuhan (2025) via SafeServe's scalable tooling for release testing [10], and Hu, Xiao (2025) introduced UnrealAdBlend for immersive 3D ad creation using game engines [11]. Healthcare AI progressed with Qin et al.

(2025) optimizing deep learning to combat ALS progression [12], while Ding and Wu (2024) conducted a systematic review of self-supervised learning for ECG/PPG biomedical signals [13]. For low-resource settings, Restrepo et al. (2024) proposed multimodal deep learning with vector embedding alignment [14]. Financial AI applications included Zeng et al. (2025) analyzing education investment's impact on household financial participation [15], and Wang, Hao (2025) developed joint propensity-prediction modeling via targeted learning for MNAR recommendation systems [16].

2. HARDWARE DESIGN

2.1 Overall hardware design

The system divides the screen detection process into the following steps: the handling arm grabs the screen to be detected, the mechanical arm loads the material, sends lighting requests, captures screen images, compensates for defect parameters, and turns off lighting requests, which can improve detection efficiency. The motion control hardware mainly consists of Mitsubishi Q series PLC and its expansion modules, handling arms, robotic arms, photoelectric switches, Proface human-machine interaction interface, multi station turntable drivers, and ARM processors for machine vision modules. The entire screen detection device is centered around PLC, and the designed PLC program can transmit data in real-time with the detection device and upper computer program. Enable real-time feedback of the screen detection results to the upper computer. If the detection result is abnormal, the upper computer can send a retest instruction to the PLC to form a complete closed-loop detection system.

2.2 Automated collection device

In this detection system, the automated acquisition device is an important component of data acquisition, which determines the imaging quality of the collected data. In the actual production line of the factory, the production environment is complex and varied, and background light sources and dust are important factors that affect the detection results. Therefore, when designing the automatic acquisition device in the screen detection system, the work related to data acquisition should be completed in a dark box. A dark box can avoid the influence of environmental light sources. The blower in the cassette can remove interference factors such as dust and non panel surface defects, and then different screen images are collected by CCD image sensors. These images are processed and converted into digital signals, which are then transmitted to a computer for future detection algorithm processing. The 3D effect of the automated acquisition device is shown in Figure 1:

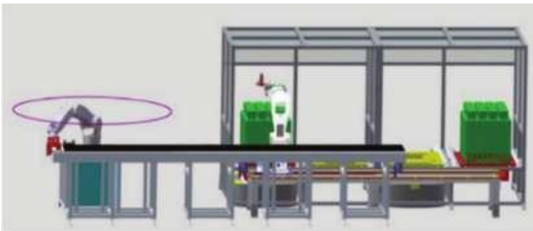


Figure 1: Automated collection device

2.3 Image acquisition card

An image acquisition card is a connecting device for image acquisition and processing, which is a hardware device capable of acquiring digital image information and storing or outputting it. The function of a digital imaging system is to first convert photons into electrons, and then convert analog electrical signals into digital signals. The digital imaging system used in this system is shown in Figure 2. The system mainly includes optical system, image sensor, control system, image processing and analysis system, and storage system.

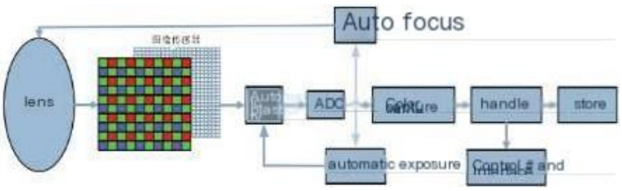


Figure 2: Block diagram of digital imaging system II. Software design

3. SOFTWARE DESIGN

3.1 System detection process

Firstly, open the detection software on the upper computer, initialize the communication port, and determine if the number of cycles is less than 4. If so, send data to the system to drive the camera to take photos and output information to the PC for image preprocessing. Then, perform image processing and determine if the detection passes. If it passes, output the result. Otherwise, return to determining if the number of cycles is less than 4; If the number of cycles is less than 4, output the result directly.

3.2 Image Preprocessing

In order to accurately and effectively judge images, in the LCD screen detection system designed in this article, a series of preprocessing operations are required before the image of the LCD screen to be detected enters the network model, including distortion correction, cropping, gamma transformation, filtering, and enhancement. The specific process is shown in formula (1).

$$\begin{bmatrix} \theta 1(x,y) = \frac{1}{2}[h(x,y) + h_1(x,y)] \\ \theta 2(x,y) = \frac{1}{2}[h(x,y) + h_2(x,y)] \end{bmatrix} \tag{1}$$

3.3 Image Processing

The region based segmentation method used in this design relies on the spatial local features of the image, such as grayscale and statistical features of pixels. In different segmentation methods, the selected region features and the criteria for judging the similarity of region features are different.

The similarity based image segmentation method [3] determines the attributes of adjacent pixels based on whether they have similarity. If two pixels have similarity, they are divided into the same region. If they have no similarity, they will be divided into different regions.

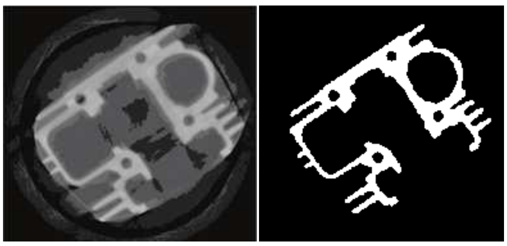
The similarity between two adjacent pixels is determined by their grayscale values. For the 8-domain M of images and pixels (x, y), first, define their similarity metrics θ 1 (x, y) and θ 2 (x, y).

The principle for determining similarity between θ 1 (x, y) and θ 2 (x, y) is: for (k, l) ∈ M, if the interval is satisfied:

$$N = \{(k,t)||f(x,y) - f(k,t)| \leq h(x,y)H(k,t) \in M\}$$
$$h(x,y) = \frac{1}{8}\sum_{(k,t)\epsilon M}|f(x,y) - f(x,l)|$$
$$h_1(x,y) = \min_{(k,t)\epsilon M} h(k,l)$$
$$h_2(x,y) = \min_{(k,t)\epsilon M} h(k,l)$$

So (k, l) and (x, y) are in the same region.

After segmenting similar regions, the experimental results are shown in Figure 4. The source image is 4-1, and the segmented image is 4-2:



4-1 **4-2**

Figure 4: Comparison of Experimental Results of Similar Region Segmentation Before and After

3.4 Testing

By inputting the information processed in the above steps, the corresponding reconstructed image and reconstructed error image will be obtained. The fused image will be obtained through the difference method, and the final defect candidate region information will be obtained through threshold segmentation. Filter the detection results of dust from this information, and filter the remaining part according to the set area threshold. If the condition threshold is met, it indicates that there may be a defect. After marking the defect, record the defect information and have it rechecked by the system. Otherwise, it will be recorded as a good product.

4. SYSTEM IMPLEMENTATION

This system collects production and testing data, performs curve analysis, achieves refined management and data traceability, thereby improving product quality and optimizing production pace. Simultaneously utilizing machine vision [4] and artificial intelligence technology, real-time recognition of on-site thermal conductivity sheets and LCD touch screens is achieved to achieve plug-in, hot pressing, and line testing between different specifications of LCD touch screens and FPC circuit boards. Finally, the data of this system will be transmitted to the cloud to achieve multi terminal remote real-time monitoring and management, improve the timeliness of equipment maintenance and repair, and reduce operating costs. After testing, the output of unqualified products is shown in Figure 5.

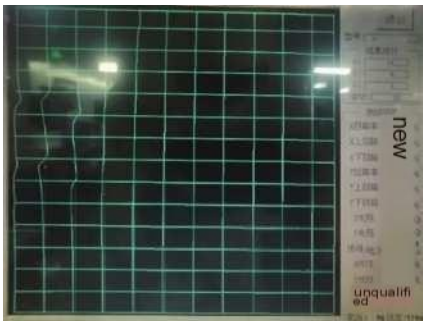


Figure 5: Unqualified product output

5. CONCLUSION

The "Digital based LCD Touch Screen Detection System" is a new intelligent detection system independently developed in this article to solve the problems of low automation, lack of data interoperability, and inability to achieve multi specification product detection in traditional LCD touch screen detection systems. This system realizes the fine management, intelligent recognition, and data tracing of plug-ins, hot pressing, line testing, and production processes between LCD touch screens and FPC circuit boards of different specifications, achieving the goal of reducing staff and increasing efficiency and improving digital level. Therefore, in today's era of widespread use of smart devices, this detection system will definitely be accepted by more and more screen manufacturing and testing companies, and has certain market prospects.

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