Defect Detection and Classification of Optical Components : A Review

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Abstract - *Optics engineering is a field that is rapidly changing, inventive, and developing. To address the growing demand for optical components, product quality requirements must be maintained. Automatic optical inspection (AOI) is a non-destructive technology used in product quality inspection. This technology is regarded reliable and may be used to replace human inspectors who are tired and bored while doing inspection chores. Hardware and software configurations make comprise a fully automated optical inspection system. The hardware setup is responsible for acquiring the digital picture, while the software portion implements an inspection algorithm to extract the attributes of the collected images and categories them as defected or non-defective depending on the user requirements. To distinguish between faulty and excellent items, a sorting system might be utilized. This study examines the numerous AOI systems utilized in the electronics, microelectronics, and optoelectronics sectors. The imaging, pre-processing, feature extraction, and classification technologies used to detect flaws in optical components are reviewed.*

***Key Words*: Automatic optical inspection (AOI), Defect detection and Classification, Machine Learning, Deep Learning, Digital Holography (DH).**

1. INTRODUCTION

Defect detection and classification is an important task in manufacturing industries, to ensure the quality of products. The past few years, have been characterised by growth in emerging markets and invention of new products, which leading more people to buy new the new one. Therefore, ensure that the manufacturing process is under control and prevent the defect formation. Based on the type of materials defect detection and classification methods are different. Early defect detection helps to replace the defected parts of the system. Moreover, it helps to reduce the material wastage. There are two classifications in quality check, destructive and non-destructive testing. Most of the testing are non-destructive type of testing. They are visual-based method, dye penetrant inspection, radiography, ultrasonic testing, Eddy current approach, thermography, X-ray, circuit probe testing and optical inspection[1][2].

In an optical system, optical components are the most important components. Transparency and reflection are the main properties of optical components. The system's dependability is impacted by optical component defects. Surface quality checking is essential in the manufacture of optical components. Several sorts of errors develop as a result of imperfections in the manufacturing process. The traditional dark‐field imaging approach is unsuitable for this purpose because optical components have radically different reflection and scattering properties than regular clear glass. Throughout the production process, errors in precision optical components always arise, posing a hazard to the entire optical system. Images with minor faults have low contrast and a skewed grayscale distribution, making scrutiny difficult.

Optical elements are employed in a variety of devices that are significant in a variety of sectors, including semiconductor manufacturing, defense, space, astronomy, and medicine. Optical surfaces should be accurately constructed, polished, handled, and maintained dust-free for imaging applications. Even the minute scratch, crack, irregularity in period, or other form of imperfection in the optics may scatter the incident light, generating noise signal and thereby affecting the findings. The dispersed light can cause severe ghost interference patterns, which can lead to inaccurate findings. A scratch or dust particle might also influence the desired outcomes in non-imaging areas by generating noise signal. For accurate readings, it is critical to keep the optics clear of scratches and dust. To identify these flaws, several approaches such as spatial filtering, diffraction-based methods, interferometric, holographic, and digital holographic methods are used. The majority of these approaches are only useful for detecting defects in periodic items. Time is running out to create a system that can analyses both periodic structures like semiconductor wafers and gratings, as well as non-periodic components like mirrors and glass plates. The detection and categorization of defects in periodic as well as non-periodic patterns will be discussed in the next session.

2. DEFECT DETECTION AND CLASSIFICATION METHODS

Tao[3] proposed a binarization method by combining the LSD (line segment detection) method and Hough transform. Using a coarse-to-fine detection strategy in dark field imaging for weak scratch detection. First a bionic vision used to detect all possible scratches. Then connect all the scratches using LSD and a priori knowledge. For classification GIST (global image descriptor) method is used. In this method the defects and interference are classified with accuracy 94.44%. But have two disadvantages: the detection result is not accurate enough and it is sensitive to threshold parameters.

Hong-Yan[4] proposed a method to overcome the disadvantages of Tao[3] proposed method. The MDSI (Microscopic dark-field scattering imaging) system is used in front end of system. MDSI consist of a ring light source, a zoom microscope, XY-DOF translation stage and a high-resolution CCD. Therefore, system provide original information of defects on the optical surface. This method has automatic processing capability (i.e., positioning, clustering and estimation of length of scratches), efficiency and accuracy. But microscope have small field of view (FOV), So it difficult to imaging large scale optical components. For that it should be transform in to a platform and allow the microscope to scan the entire surface for complete inspection. Have error rate less than 5%. LSD method works well for straight scratches or line segments but less in the case of curvature scratches. This algorithm can be used for glass like surface. But not proved through the experiment.

Tuyen[5] proposed a novel framework based on machine vision known as the optical film based real time defect detection and classification. This method is applicable for reflector sheet, diffuser sheet and light guide plate (LGP). To obtain high quality optical film images a high-resolution camera with custom made lighting field. Then the defect is detected by localized cross projection based adaptive energy analysis method. To enhance the defects from background kirsch operation, energy analysis and adaptive single value decomposition (ASVD) methods are used. Then using SVM (support vector machine) classify the defect image into two categories: dark and bright. Dark category represents defects like foreign materials and stain. Bright category represents defects like point and scratch. This method provides 99.6% defect detection rate and 100% classification accuracy rate. But this method is not explained for the transparent optical components as well as the weak scratch detection. Lighting field in this system will cause scattering noise when imaging an optical component.

Tan[6] proposed morphological operation based FCM (fuzzy c- mean) clustering method for defect detection of piezoelectric ceramic plate. This system consists of both hardware and software portion. Hardware portion consist of a two strip light sources, a lens with distortion, an industrial camera and piezoelectric ceramic plate on conveyor belt. Camera and lens are mount above the conveyor belt. After taking the image, extract the information about scratch using FCM algorithm and morphological character. Usually, uneven texture and a random gray value affect the accuracy of detection. But this algorithm achieves the detection rate 100% and false rate of 5.63%. but efficiency of the system has to improve by parallel processing of morphological feature extraction. And the imaging system is not apt for transparent optical components.

Ruifang[7] suggested an artificial neural network based on deep learning for defect detection and classification. To cope with enormous amount of data quickly, a graphics processing unit (GPU) card was used. The classification accuracy ranged from 96 to 100 percentage. The speed of detection and classification is higher than the traditional method. The defect features seen on glass and mirror surface are limited to 11 characteristics in the current category. However, by further training the algorithm to catalogue distinct defect categories and associated feature characteristics, it is possible to perform more classifications for multiple flaws on various items.

Song[8] described a deep convolutional neural network (DCNNs)-based approach for identifying faint scratches on metal component surfaces. A DCNN is first trained using labelled scratch pictures. The trained DCNN then separates the scratches from their backgrounds. The trained DCNN then detects scratches and certain flaws, and most of the faults may be removed by properly thresholding based on the size of connected regions. Finally, the skeleton extraction yields the scratch length divided by the number of pixels. The results of the experiments reveal that the suggested technique can successfully deal with background noise, resulting in accurate scratch detection. The method described in this paper does not require image pre-processing, and a good model can be built with only a few training data. It can withstand variations in lighting and uneven surface illumination. This algorithm is applicable to metal surfaces. However, the imaging technology used in this method is insufficient for optical components.

Gwang Myong[9] presents a modelling-based approach for combining defect information (meta data) with defect image. Classification model includes a separate model for embedding location information in order to use the defective locations classified as defective, as well as an ensemble model to improve overall system performance. The system includes a class activation map for pre-processing and augmentation for image acquisition and classification via an optical system, as well as feedback on classification performance via a defect detection system. The proposed system achieved 97.4 percent accuracy in a real-world dataset experiment. Rather than treating problems purely with images, created a fusion network to boost detection performance by integrating meta-data for defect detection. The system capability improved but, there is room for improvement in the early outlined ensemble of distinct meta data that affect fault detection, as well as in the deep learning model's optimization.

Jiang[10] presented a coaxial bright-field (CBF) and low-angle bright-field (LABF) imaging system, both of which use 8K line-scan complementary metal oxide semiconductor (CMOS) cameras to capture pictures. The CBF method is used for minor flaws like scratches and discolouration, whereas the LABF system is used for large defects dents.

Based on U-net, a symmetric convolutional neural network with encoder and decoder architecture is suggested, which delivers semantic segmentation of the same size as the original input picture. The average accuracy is above 91 percent, and the average recall rate is over 95 percent. The procedure is ideal for inspecting screen printing mobile phone rear glass for surface defects. Without much adjustment, the method also shows tremendous promise for additional surface examination jobs. However, it must achieve strong detection performance with less defect samples while also increasing computing efficiency. Meanwhile, there is a need to improve how to annotate defect images with more precision and efficiency.

Scratches on metal surfaces, solar panel surfaces, and railway surfaces, among other materials, are commonly detected using machine vision technologies. Optical components, on the other hand, are highly reflecting and high-transmittance materials when compared to the materials indicated above. Visual inspection techniques find it difficult to image flaws properly due to these features. For optical components, Hou and Tao[11] introduced an end-to-end weak scratch inspection approach based on innovative scratch enhancement algorithms and a convolutional neural network (CNN). A local maximum index (LMI) and a direction sensitive convolution (DSC) module are presented to construct multilevel-feature maps utilizing prior information about scratch to improve weak scratches. These multilevel characteristics are utilized as inputs to the encoder-decoder CNN module for training, with raw dark-field picture as network input. On the test dataset, the suggested model achieves pixel accuracy of 92.48 percent and IoU of 77.27 percent. This is the first strategy for reducing dataset size, decreasing computing time, and increasing computation performance by combining prior knowledge with CNN. However, applying prior information will impair the system's efficiency due to inexpert human eye assessment. The inspector will not detect the weak scratches owing to the fatigue of labour.

In the dark field, weak scratch imaging has an ambiguous edge and poor contrast, making automated defect identification challenging. Due to the lack of attention-aware features, traditional vision inspection methods based on deep learning cannot successfully analyse weak scratches. Xiang Tao[12] offers the "Attention Fusion Network," a convolutional neural network that generates attention-aware features utilising an attention mechanism created by hard and soft attention modules to address challenges emerging from industry-specific characteristics. The hard attention module is implemented by integrating the network's brightness adjustment operation, while the soft attention module is made up of scale and channel attention. The suggested model is tested against various defect inspection methods using a real-world industrial scratch dataset. In comparison to traditional scratch detection methods and other deep learning-based methods, the proposed method has the best performance in detecting weak scratch inspection of optical components. However, it is unable to detect unlabelled mild defects and discontinuous point-like defects. Segmentation networks may identify discontinuous points such as scratch faults. Furthermore, because manual defect labelling is a time-consuming and costly operation, defect identification utilising only normal samples would be a very promising task. GANs (generative adversarial networks) are used to extend and check faulty samples. As a result, automated flaw identification without labels can overcome this disadvantage.

Optical components play a crucial role in high-power laser equipment. Particles on the optical element diminish system performance and can potentially destroy it. Hou and Tao[13] offer a particle inspection model based on self-supervised convolutional neural networks (CNNs) and transfer learning. To convert the picture from grayscale to rotation-flip-invariant, a self-supervised network based on a rotation-flip-invariant pretext task is utilised. The learnt feature is then applied to the central-pixel classification network, which is fine-tuned using a small labelled dataset. The suggested technique has a 97.90 percent classification accuracy. The central-pixel classification network is converted to the particle inspection network easily with minimum changes for the entire picture prediction, to feature reuse and pointwise convolution. To accomplish the impact of particle segmentation, a central-pixel network is constructed, which leverages the self-supervised learning characteristics and classification results of the centres, in contrast to current approaches. With a short-labelled dataset, the suggested model achieves high particle inspection accuracy, which fulfils the inspection criteria. A self-supervised network eliminates the need to manually identify a large number of samples. The approach has the potential to be employed in industrial production since it uses a large amount of unlabelled data and is fine-tuned on a small number of labelled samples. Furthermore, the suggested classification network can only generate image-level classification results or approximate fault sites by using sliding windows or class active maps (CAM). The system's examination of various defects has to be improved.

In vision inspection, imaging of flaws in optical components is crucial. Sonia[14][15] illustrates how digital holography is used to evaluate periodic and non-periodic optical components for faults like as scratches, dust particles, and irregularities. Digital holography is a non-contact, largely non-invasive method of recording and reconstructing three-dimensional data of test items. In comparison to other methodologies, it has the benefits of quick, parallel, and dry processing, numerical analysis, and compactness. In this proposed method Mach–Zehnder off-axis Fresnel holography is a technique for detecting faults in both periodic and non-periodic components. The object wavefront and the reference wavefront interfere. Fresnel–Kirchhoff reconstruction is carried out numerically. On the reconstructed wavefront, integral and spatial filtering is done digitally. With spatial frequency filtering, periodic components such as gratings and semiconductor wafers may be readily suppressed, leaving only frequencies linked to defects/flaws in the observation plane to be digitally detected using a complementary metal–oxide–semiconductor (CMOS) detector. Further digital post-processing of the image yields more information about abnormalities and imperfections, making them easier to spot. Similarly, non-periodic items' reconstructed pictures are digitally processed for efficient flaw identification and assessment. The system shows that this approach may be used to check both periodic and non-periodic components, and hence could be valuable in the optical and semiconductor industries for quality testing of produced optical components, masks, and circuits. However, setting up a Mach–Zehnder system on an industrial scale is problematic.

Singh and Mehta[16] proposed Mech–Zehnder Interferometric setup for flaw inspection in glass plates. Optical dislocations can be noticed in the recorded fringes using interferometry. Interference fringes may be utilised to see the stress field that is triggered around the tip of a fracture. An optical wave-front is transmitted through the fracture site of a glass plate in an interferometric setup, causing a local phase jump in the test beam. This phase shift is seen in the fringe pattern as fork fringes, which have branching fringes at the crack tip and down the fracture line. We visually monitor the fracture tip using the Fourier transform fringe analysis approach and phase-unwrapping method. The position and trajectory of the crack tip are determined by the locations of the fork fringes. Through this procedure, an array of optical dislocations is triggered along the crack's route as it propagates in the glass plate, allowing to watch the crack's progression by tracing the course of these optical dislocations. This technology may be used on various transparent materials and provides insight into fracture formation in glass plates.

Chang Chien[17] devised a complex defect inspection (CDI) approach for transparent substrate quality monitoring that employs digital holographic diffraction characteristics and a machine learning algorithm. To expand depth of focus in the effective diffraction zone for numerical reconstruction, a complex pattern diffraction model was created to give two diffraction criteria, the least separation of confusion and the effective diffraction distance. Defect detection was achieved utilising region-based segmentation and a machine learning algorithm to detect and categorise defects (cracks, dusts, and watermarks) in transparent substrates based on an investigation of three-dimensional diffraction characteristics of complicated pictures. The suggested CDI system has a recall of 96.3 percent and an accuracy of 92.8 percent for flaw detection. The suggested CDI system has a recall of 96.3 percent and an accuracy of 92.8 percent for flaw detection. Furthermore, the total multiclass classification accuracy was 95.3 percent, resulting in a 0.96 discrimination area under the receiver operating characteristic curve (Az). Digital holography (DH) is a new 3D imaging method that uses a single-shot capture approach to digitally record the complex wavefront information coming from a target object as a hologram. However, in order to improve the system's reliability and practicability, a bigger dataset of numerous flaws in complex pictures will be collected for use in training and testing methods. A deep learning-based approach will also be used to a large complex dataset to improve flaw identification and classification accuracy.

To identify scratches on glass surfaces with scattering noise, Yeh[18] presented a digital holographic detection approach. He compares the imaging systems based on white light imaging (WIS) and digital holography detection (DHD). Digital holography was also shown to be the best technology for imaging glass surfaces. The digital holographic detection approach is shown to improve the picture contrast of the scratch under strong scattering noise. The high defocus tolerance allows for detection without the need for optical focusing, which is advantageous for high-speed automatic optical inspection. The focusing procedure was carried out digitally rather than manually, which provided substantial benefits in terms of detecting speed and simplicity. The WIS system's defocus tolerance was less than 1 mm under intense scattering. DHD, on the other hand, had a defocus tolerance of more than 10 mm. The high defocus tolerance ensures that no optical focusing is required throughout the detecting procedure. As a result, the high-speed AOI system benefits. The contrast ratio was utilised to compare the performance of the WIS and DHD systems quantitatively (CR). When deep learning is combined with DHD, the system becomes a flawless fault detection and classification approach that improves accuracy, inspection speed, efficiency and reduces electronic waste.

3. CONCLUSIONS

In a wide variety of industries, quality control is an important step in reducing product faults. AOI is one of the most basic and widely used quality control methods in automated industrial inspection. AOI covers a wide range of topics, from image capturing hardware to inspection and decision-making algorithms. As a result, research opportunities in this sector are plentiful and likely to grow in the near future. Various fault detection and categorization approaches are discussed in this work. Each stage in the defect detection process, including imaging, pre-processing, feature extraction, and classification methods, is reviewed.

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