



HOKKAIDO UNIVERSITY

Title	Accumulated and Aggregated Shifting of Intensity for Defect Detection in Uniform Background Regions
Author(s)	Yan, Yaping
Degree Grantor	北海道大学
Degree Name	博士(工学)
Dissertation Number	甲第14145号
Issue Date	2020-03-25
DOI	https://doi.org/10.14943/doctoral.k14145
Doc URL	https://hdl.handle.net/2115/78534
Type	doctoral thesis
File Information	Yan_Yaping.pdf



SSI-DT79175032

Doctoral Thesis

**Accumulated and Aggregated Shifting of Intensity for
Defect Detection in Uniform Background Regions**

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November, 2019

Division of Systems Science and Informatics
Graduate School of Information Science and Technology
Hokkaido University

Doctoral Thesis
submitted to Graduate School of Information Science and Technology,
Hokkaido University
in partial fulfillment of the requirements for the degree of
Doctor of Philosophy.

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Accumulated and Aggregated Shifting of Intensity for Defect Detection in Uniform Background Regions*

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Abstract

Quality control is one of the most important procedure in modern industrial manufacturing. Product surface inspection is an important step in quality control to guarantee that the products show good impressions to consumers. In the past decades, product surface inspection was usually performed by human beings. Manually inspection is reliable for small number of products. However, it is impossible for human beings to inspect large number of products one-by-one. On one hand, it is too slow for human beings to do such kind of huge work. On the other hand, it is very expensive to hire workers for inspecting huge amount of products. Therefore, automatic vision inspection (AVI) is highly desirable.

Conventional AVI algorithms can be classified into two categories: hand-crafted features based ones and data-driven features based ones. Hand-crafted features based approaches can be further classified into four categories: statistical methods, structure description and analysis, domain transformation, and data separation model based methods. Data-driven features based methods are generally based on deep learning techniques. These two kinds of algorithms have their own merits and demerits. Hand-crafted features based methods usually have clear algorithmic meanings. For different application scenarios, suitable features can be designed for the unique goal. Hand-crafted features based methods are usually efficient, because they do not rely on learning from huge amount of data. Data-driven methods tend to design some learning parameters in a model and then train the model with data. The training data usually contains both of images and corresponding annotations manually marked by human beings. Although data-driven methods show high accuracy and high generalization ability, they need huge learning data and manual annotations. The training process also need huge computational resources and time.

This dissertation focuses on detection of low-contrast defects in uniform background regions. To achieve this goal, an accumulated and aggregated shifting of intensity (AASI) has been proposed for detecting defects on micro 3D textured surfaces and an improved AASI approach with golden template picture (AASI-GTP) has been proposed for detecting defects on curved and highly-reflective surfaces. About AASI, two novel features,

*Doctoral Thesis, Division of Systems Science and Informatics, Graduate School of Information Science and Technology, Hokkaido University, SSI-DT79175032, November 10, 2019.

named absolute intensity deviation and local intensity aggregation, which are associated with the probability of abnormality, are firstly designed to measure the saliency at pixel level. By considering the dynamic property during iteration and the salient features from initial image, AASI can iteratively shift the intensity of each pixel depending on its saliency, i.e., defect probability. The AASI output sequence along iterations of defective pixels follows an exponential function, while that of defect-free pixels can be formalized as a linear function. So the detection process can be regarded as a problem of fitting to two statistical models. About AASI-GTP, a multiple-pairwise reflective observation system is first introduced. Multiple-pairwise cameras and diffused lights are fixed in specific positions and angles to capture all defects on the whole curved surfaces while avoiding shadows and highlights. Then a golden template picture (GTP) is introduced to represent the pixel-wise brightness of the defect-free background. By replacing mode intensity in AASI with GTP, the AASI-GTP is constructed for detecting defects on surfaces with uneven intensity.

The overall dissertation is organized as follows.

Chapter 1 introduces the importance of product quality control, the background of defect detection, conventional defect detection methods, challenges in defect detection, and contributions of this dissertation.

Chapter 2 introduces the proposed accumulated and aggregated shifting of intensity (AASI) to solve the problem of detecting defects on micro 3D textured surfaces. Two salient features which measure the saliency in pixel-level are introduced. These two features are further used to construct an iterative pixel-level enhancement procedure, which can iteratively shift intensity of each pixel according with its defective probability. And then, an original fitting-based classification rule was proposed. Two statistical models are utilized to judge whether each pixel in the given image is defective or not. Finally, the parameter setting was discussed.

Chapter 3 introduces the improved AASI with golden template picture (AASI-GTP) for defect detection on curved and highly-reflective surfaces. Firstly, the reflection property of highly specular surfaces is analyzed. And then, a multiple-pairwise reflective observation system is introduced. Multiple-pairwise cameras and diffused lights are utilized to capture all defects on the whole curved surfaces while avoiding shadows and highlights. Finally, the golden template picture (GTP) is introduced to replace the mode intensity in AASI, so that the AASI-GTP to be effective for surfaces with uneven intensity.

Chapter 4 shows the dataset, experimental setting, experimental results and analyses. Experimental results demonstrate that our method generally outperforms state-of-the-art unsupervised defect detection methods in terms of Precision and F-measure. AASI performs well even for low-contrast defects and small-sized defects with 3×3 pixels, and is robust to uniform illumination variations. And the AASI-GTP shows satisfied performance on curved and highly-reflective surfaces.

Chapter 5 concludes the whole dissertation and introduces future works.

Keywords: Defect detection, Accumulated and aggregated shifting of intensity (AASI) procedure, Saliency description, Illumination invariance

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Chapter 1. Introduction

1.1 Computer vision based defect detection systems

With the fast development of electronic and manufacture techniques, millions of products are being produced everyday, as shown in Fig. 1.1. Meanwhile, customs have higher and higher requirements on product quality. That's the reason why product quality control is extremely important in modern industrial manufacturing. In the field of product quality control, product surface inspection is one of the most important aspect. Because product surface gives the first impression to customers.

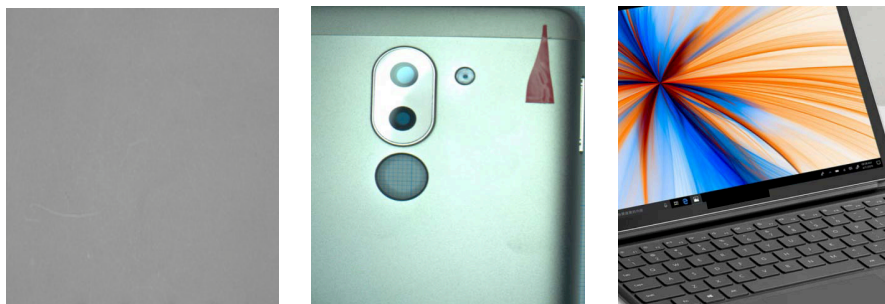


Figure 1.1: Several examples of products whose surfaces should be inspected.

In the past decades, product surface inspection was usually performed by human beings, as shown in Fig. 1.2 (a). Manually inspection is reliable for small amount of products. However, in nowadays, large amount of products, such as mobile phones and personal computers, are being mass produced. It is impossible for human beings to inspect every products one by one. On one hand, it is too slow for human beings to do such kind of huge work. On the other hand, it is very expensive to hire workers for inspecting huge amount of products. Therefore, we should find a way which is of high accuracy and low cost for ensuring high quality of product appearances.

A straightforward way to solve the above mentioned problems is to develop automatic inspection techniques, as shown in Fig. 1.2 (b). Automatic inspection means the work should be done by machines. To this end, one possible solution is to achieve inspection through checking the product surfaces by sensors, such as microwave sensors, infrared sensors, and visible-light sensors. The signals from sensors can be further processed and analysed to extract useful information on the defects of product surfaces. Among all the potential sensors, cameras are the most cheap and reliable ones. Because microwave sensors and infrared sensors are not so robust to small defects and the defects without

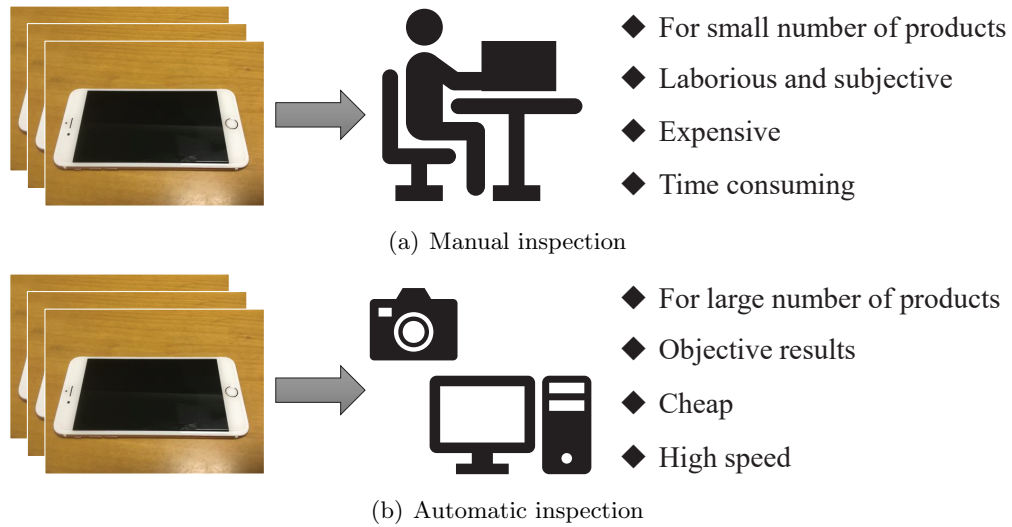


Figure 1.2: Illustration of two ways for product surface inspection: (a) manual inspection and (b) automatic inspection.

concave-convex surfaces. But cameras can find out even micro and low-contrast defects. Recent years, with the fast development of computer vision technologies, camera-based visual inspection has been paid increasing attention. This kind of potential solutions use cameras as sensors to take pictures of products, and then design reliable computer-vision algorithms to point out the pixels which corresponds to defects on product surface.

1.2 Conventional visual inspection methods

As the most important and challenging part in visual inspection systems, accurate and efficient computer vision algorithms are highly desirable. This subsection reviews the existing visual inspection methods. Just like other commonly studied computer vision techniques, visual inspection methods also first preprocess images, then extract distinctive features from images, and finally analysis the extracted features to recognize defective pixels and defect-free pixels in the image. From the point-of-view of development history, feature extraction methods can be classified as handcrafted ones and data-driven ones. In the past decades, most of the methods are based on handcrafted features. However, in recent years, with the rapid increase of computational ability and fast development of deep neural networks, data-driven end-to-end learning also becomes popular in defect detection.

Handcrafted-features-based methods and data-driven methods have their own merits and demerits. In particular, handcrafted-features-based methods are usually have clear algorithmic meanings. For different application scenarios, suitable features can be designed for the unique goals. By doing like this, the specific defect detection problems can be solved according to different materials, illumination conditions, and background

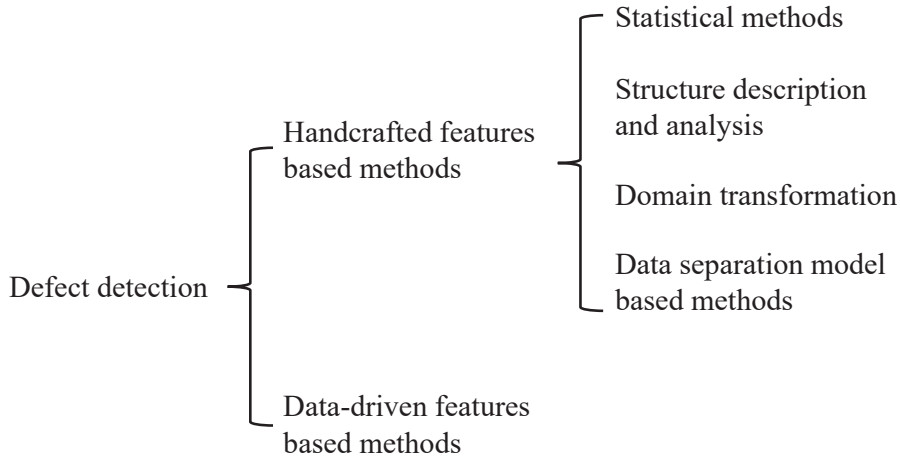


Figure 1.3: Graphical summary of the defect detection approaches.

textures. Further more, handcrafted-features-based methods are usually efficient, because they do not rely on learning from huge amount of data. So this kind of algorithms are computational fast and do not need to collect large amount of training data. The demerits are also clear. The generalization ability of handcrafted-features-based methods are not as high as data-driven ones, because handcrafted-features-based methods are usually designed for specific materials or some unique tasks. Therefore, it is difficult to transfer handcrafted-features-based methods to other materials or other conditions. In the past five years, data-driven methods attracted much attention. Most of data-driven methods show high potential in defect detection, especially using deep learning. Data-driven methods design some learnable parameters in a model, typically a neural network, and then train the model with prepared training data. The training data usually contains both of images and corresponding annotations manually marked by human beings. Although data-driven methods show high accuracy and high generalization ability, they need huge learning data and manual annotations. The training process also need huge computational recourses and time. For some application scenarios, collecting large amount of training images is difficult, even impossible. For pixel-level defect detection, manually marking annotations for large amount of images is also very arduously.

According to the above discussions, Fig. 1.3 listed four categories of existing handcrafted-features-based visual inspection methods [1], including statistical methods, structure description and analysis, domain transformation, and data separation model based methods. The four categories of methods will be introduced one-by-one at below.

1.2.1 Statistical methods

Statistical methods, which utilize statistics to describe the spatial distribution of texture intensities, are generally applicable to irregularly-textured surfaces. As the graphical illustration in Fig. 1.4, statistical histograms are the most widely used approach for

texture description. One of the common approaches is that using Otsu method [2] to find an optimal threshold for gray-level histogram. The global optimal threshold can be

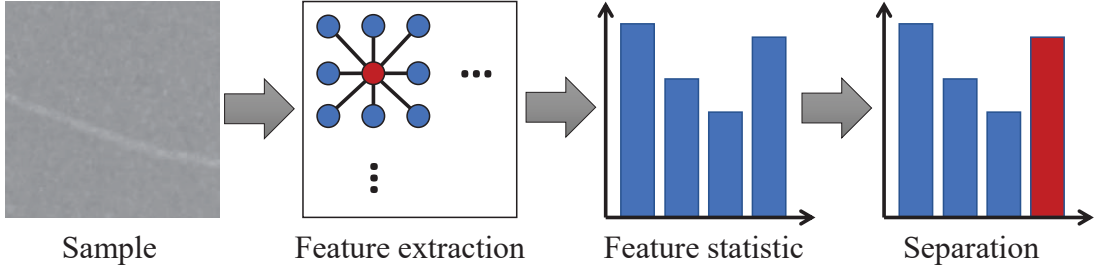


Figure 1.4: Graphical illustration of the supervised and unsupervised data-driven defect detection.

utilized for segmenting defects from background. Inspired by the thresholding method, many approaches attempted to improve it for various specific tasks. To inspect defects on dusty wood boards, Ng [3] found that Otsu method is suitable for image histograms of clear bimodal or multimodal distributions. To overcome the problem that defects in images vary from small size to large size, Ng proposed a valley-emphasis method which not only maximizes the between group variance as Otsu method does, but also tries to find out the valley in gray-level histogram. Niskanen *et al.* [4] propose to use both of color histogram and texture description to locate defective pixels in image.

Besides simply thresholding gray-level histograms, various method utilize co-occurrence matrix [5, 6] as statistical representation for defect detection. For example, Li *et al.* [7] revised the local binary patterns (LBP) [8] and proposed to combine multidirectional binary patterns (MDBP) and the gray-level co-occurrence matrix (GLCM) as discriminative features for fabric-defect detection. Su *et al.* [9] combined color features and the gray-level co-occurrence matrix to detect defects on ceramic tiles. Instead of calculating co-occurrence matrix from grey-level image directly, Chen *et al.* [10] proposed to extract graylevel-gradient co-occurrence matrix for detecting defects on rail track surface.

Many approaches also use local statistical feature descriptors, such as local binary patterns (LBP) [11, 12] and rotation invariant measure of local variance (RIMLV) [13] are also commonly utilized as effective statistical features for detecting defects. For example, Song and Yan [14] proposed to use local binary pattern to detect defects on hot-rolled steel strip surface. Based on local binary pattern, Fu *et al.* [15] designed a new feature named adaptive local binary pattern by using frequently occurred patterns as features, and tried to locate defects on fabric. Huang *et al.* [16] proposed a higher order statistics (HOS) based harmonics extraction method which uses fourth-order cumulants slice to estimate a power spectrum and then extracts harmonic frequencies from the power spectrum.

1.2.2 Structure description and analysis

From image point-of-view, defects can be regarded as abnormal structures in image. Because of this reason, structure description and analysis can be performed to achieve defect detection. In spatial image domain, various features have been designed for describing image structure. Sezera *et al.* [17] attempted to simulate the mechanism of human vision system and to describe the regularity and anisotropy of textures through independent component analysis. Chetverikova *et al.* [18] also studied the textural properties of regularity and anisotropy, and then regarded defects as inhomogeneities in regularity and orientation fields. Tsai *et al.* [19] proposed a morphological method with arc-shaped SE for defect detection on surfaces with circle patterns. Chen *et al.* [20] proposed a skeleton based approach of defect detection by first thresholding image histograms and then mapping it into skeleton presentation. After that, some statistical measurements are defined according to the location histogram and length histogram of skeletons. Wen *et al.* [21] proposed to find out defects according to the information of edges in image. In particular, with the candidate edges, they are verified by checking the edge strength, edge length and the distributions of grey level values of the pixels located in an edge neighbourhood. Song *et al.* [22] utilizes both color and texture information to extract structure features. In particular, each image is first clustered into segments according to color information, the binary image is then processed by morphological smoothing. After that, structure features, such as area, perimeter fractality, elongatedness, and spatial information, of each blob in the binary image is extracted. Finally, defect identification is achieved through color inspection and blob defect identification. Other works, such as [23, 24], also employ morphological operations to achieve defect detection.

1.2.3 Domain transformation

The defect inspection approaches reviewed above are all in the spatial domain. Another kind of approaches transform the image into other domains, and then solve the problem of defect detection through analysing of the features of non-spatial domains. As the graphical illustration in Fig. 1.5, this kind of methods are referred to as domain transformation. Unlike conventional wavelet based methods which analysis wavelet coefficients in individual decomposition levels to obtain useful information, Li *et al.* [25] proposed to use not only the wavelet coefficients in individual decomposition levels as features, but also the difference of the coefficient values between two consecutive resolution levels as the weights to distinguish local defects from the crystal grain background. Yapi *et al.* [26] utilized the redundant contourlet transform (RCT) to represent fabrics patterns instead of using the traditional contourlet transform. The coefficients of the redundant contourlet transform are modeled using a finite mixture of generalized Gaussians to obtain statistical signatures that can be used for distinguishing defects and non-defects. To detect defects on steel surface, Liu *et al.* [27] uses an anisotropic

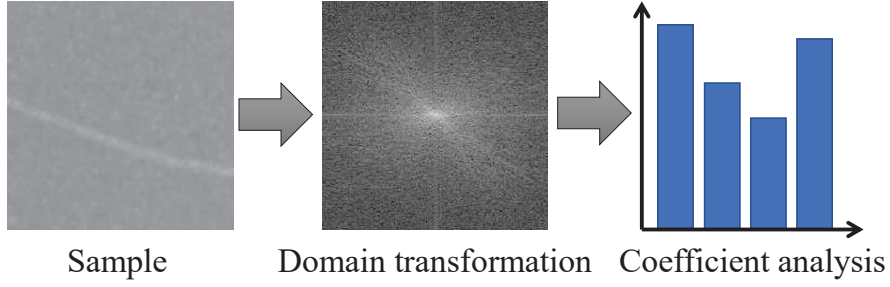


Figure 1.5: Graphical illustration of the supervised and unsupervised data-driven defect detection.

diffusion model as preprocessing to reduce the background noise, and then proposes a Haar-Weibull-variance (HWV) model to describe the local patch level texture distribution. After that, the HWV parameters are modified, and threshold is determined adaptively. Defects are identified by the adaptive threshold. The method is unsupervised and robust to arbitrary type of defect on the homogeneously textures. To detect defects on tire laser shearography image, Zhang *et al.* [28] use the curvelet transform to enhance the edges in the image. Specifically, they keep only large coefficients in sub-highest frequency band and delete small coefficients to make the edges in image to be more clear, and then use improved edge detectors, such as improved Canny operator, to locate edges in the inversely-transformed image. Instead of using discrete Fourier transform (DFT), Tsai *et al.* [29] utilized the Fourier transform (FT) coefficients to reconstruct images. Aiger *et al.* [30] proposed a phase only transform (PHOT). The phase only transform is able to find out defects by removing all regularities from image, and the remained irregular patterns are likely to be defects. Besides analysing in frequency-domain only, Ma *et al.* [31] designed Gabor filter banks to generate the energy maps, and then used hysteresis thresholding to segment the energy maps for locating defects. In addition, spatial information was combined with frequency coefficients for defect detection [32, 33, 34, 35, 36]. Domain transformation based methods are efficient and simple for implementation, but they are not very effective in detecting micro defects.

1.2.4 Data separation model based methods

The problem of defect detection can be regarded as data separation. From image point-of-view, defect detection is actually separating defective pixels from defect-free pixels, as the graphical illustration in Fig. 1.6. Based on this concern, researchers attempted to achieve data separation models which segment defect from background by designing or learning a data separation model. The random field model [37, 38] exhibits satisfied performance. Xie *et al.* [39] split images into patches, and then use the Markov random field model to learn texems. The learned texems contain primitive textural information of given images. The image can be generated from superposition of a selection

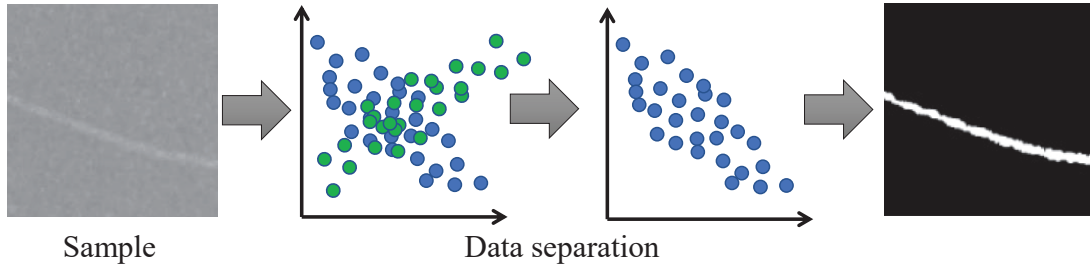


Figure 1.6: Graphical illustration of the supervised and unsupervised data-driven defect detection.

of texems. Gao *et al.* [40] proposed a nonnegative matrix factorization (NMF) algorithm for analysing the frequency spectrum characteristics of the reflected signal between the defect and nondefect areas. The approach is scale-invariant and has a smoothness constraint. Tsa *et al.* [41] proposed to generate a set of basis images from defect-free image to represent non-defect surfaces. With the basis images, a given image can be formulated as a linear combination of the basis images. Then, following an independent component analysis (ICA) model, uneven-brightness defects are detected by comparing coefficient vectors of test image and the learned coefficient vectors from clear surfaces. Bibiloni *et al.* [42] proposed the curvilinear structure model which requires pixels in an image satisfy some geometric and photometric characteristics. Diffusion is also fully studied. For example, Chao *et al.* [43] proposed an anisotropic diffusion model which has a generalized diffusion function with the curve can be adaptively changed. To defect defects on low-contrast glass substrates, Chao *et al.* [44] proposed a diffusion model to perform smoothing and sharpening in a simultaneous way. Through the simultaneous operations, the resulting image can be segmented by a simple threshold. By doing like this, the drawbacks of conventional diffusion models which passively stop the diffusion process are overcome.

1.2.5 Data-driven approaches

The methods reviewed above are all based on handcrafted features. As mentioned in the beginning of this section, data-driven features based defect detection methods are also an important kind of approach. Driven by the fast development of machine learning, defect-aware features can be learned from large number of training samples. As the graphical illustration in Fig. 1.7, some machine learning tools are also utilized by most of these approaches to learn some separation criterion and further divide the whole image into defective and defect-free regions. Some of the methods needs pixel-level manual annotations as label to train the model, this kind of approaches are called supervised defect detection. Another kind of approaches do not rely on manual labels, they are correspondingly called unsupervised defect detection. Basically, the data-driven approaches need large number of samples for training. It is very laborious and time

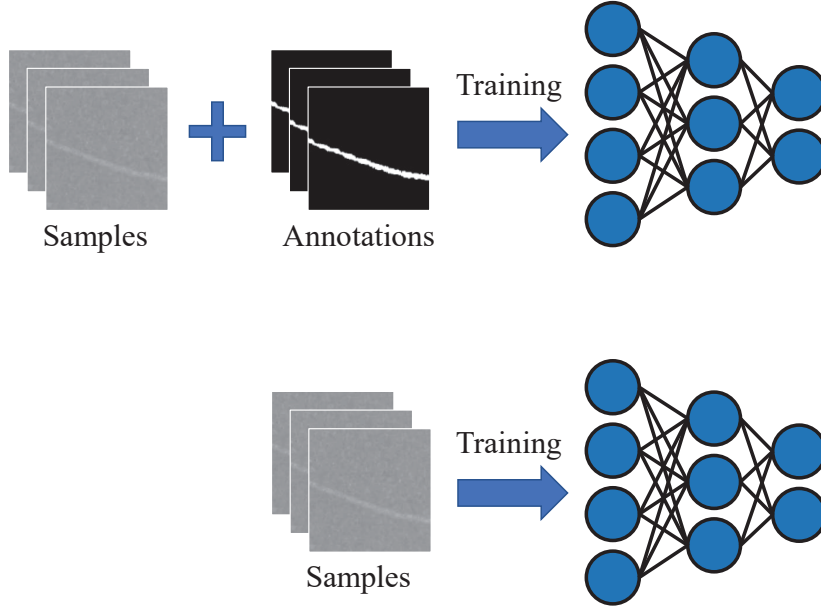


Figure 1.7: Graphical illustration of the supervised and unsupervised data-driven defect detection. Top: supervised defect detection; Bottom: unsupervised defect detection.

consuming for human beings to annotate the pixel-level ground-truth, especially when the number of images is large and the resolution of each image is high. Therefore, unsupervised defect detection is more practical. However, it is also very challenging to achieve unsupervised defect detection.

In [45], both of gray information and geometric relations were utilized for classifying defects. Then sparse representation was utilized to design a classifier which divides defects into different types. In [46], to achieve high performance of defect detection, wavelet transform was leveraged by neural network. In [47], the Elo rating system was applied to defect detection on patterned fabric, in which fabric inspection is regarded as sportsmanship. In [48], an adaptive support vector data description is proposed to handle deviations caused by illumination change. Although machine learning based approaches achieved high performance, they rely on large-scale training data.

In recent years, deep neural network driven defect detection approaches [51, 52] are also attracting much more attention, because of the great successes achieved by deep learning in other fields. Krummenacher *et al.* [49] utilized general wavelet features and features learned by deep neural networks to detect wheel defects. Mei *et al.* [50] reconstructed image blocks by using convolutional denoising auto-encoder network. The defects are finally synthesized from different Gaussian resolution levels. Ren *et al.* [53] utilized the convolutional neural network (CNN) to classify blocks. The trained network is then used to conduct pixel-wise classification. Chen *et al.* [54] proposed a coarse-to-fine defect detection method for fasteners on the catenary support device. Three deep convolutional neural networks (DCNNs) are utilized to locate, extract, and classify de-

fects, respectively. However, unlike other applications which are easy to collect training samples, defective samples are difficult to obtain because of the probability of defect occurrence is very low in industrial manufacturing. Moreover, manually labeling images is a time-consuming and laborious task.

1.3 Challenges in defect detection

Although conventional defect detection methods have achieved great successes, there are still several challenges that need to be overcome. Because the properties of defects in image, such as shape, size, contrast, and orientation, are very complex, one of the most challenging problem is to locate various kinds of defects. Not only the properties of defects, but also background makes the defect detection problem more difficult. Detecting defects on simple background has been well solved, but complex backgrounds, such as complex textures and nonuniform contrast, make a lot of illusions which are easily to be incorrectly recognized as defects. Flatten surfaces are easier to be inspected than curved ones. Once a surface is a 3D curve, the inspection becomes difficult. Nowadays, since the appearances of products vary a lot, many products use metal or glass as surfaces. These kinds of materials have high reflectance. The illumination reflectance also brings difficulties to the task of defect detection. In general, the open problems in defect detection can be summarized as follows.

- **Irregular properties of defects.** The properties of defects in images, are very complex. As the examples shown in Fig. 1.8, some defects are large, and some are

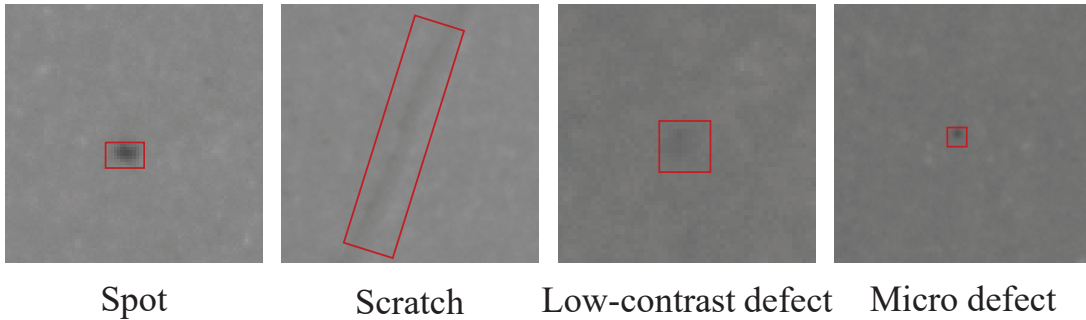


Figure 1.8: Examples of various shapes, sizes, and contrasts of defects.

small. The size is unpredictably changing, making the detection hard, because the size of the detection window is hard to be set. In real-world industry environment, the factors which cause defects is impossible to be predicted, so the defects made by these factors are also change a lot on shape. Some shapes frequently caused are lines, dots, circles, and curves. Besides of these shapes, most of the shapes are irregular ones which are hard to be described. Because of the complex shapes of defects, it is difficult to utilize the shape information for detection. On real-world products' surfaces, defects are usually slight damages, which almost share

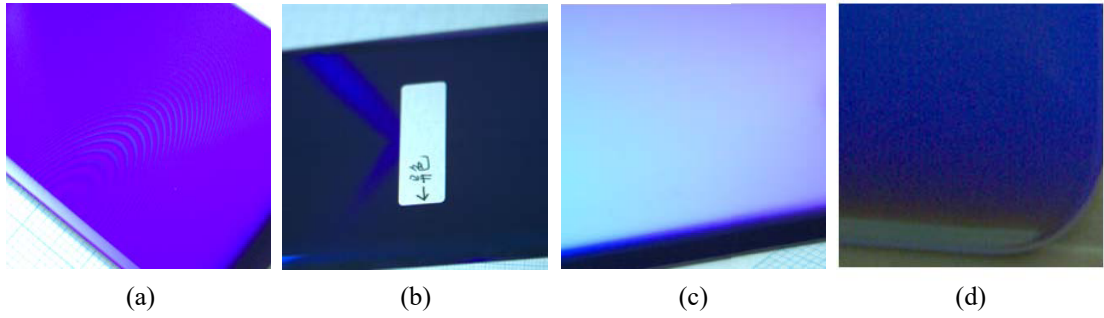


Figure 1.9: Examples of complex background: (a) and (b) are background textures, and (c) and (d) are gradient color.

the same color and brightness with the background, causing low contrast. Since there's no clear boundary between defect and background, pixel-level localization of defects is very challenging. As a summary, the complex properties of defects and the small differences between defects and background make the detection a challenging problem.

- Complexity of background.** Besides the properties of the defects themselves, the characters of background, i.e. the clear surface, also have great influences on the detection results. To achieve good appearances and good hand-feelings, products usually utilize materials such as wood, metal, and plastics, as surfaces. Wood is a common material, but it has irregular and complex textures. Small defects are hidden in the textures and large defects are separated by the boundaries of textures, making defects invisible. Metal is also a good material for products' surfaces, but it is usually carved with small patterns, such as uneven roughness. Although some metal products are clear and have no carved patterns, smooth metal has have reflectance. Either carved pattern or reflectance makes the defect detection problem very difficult, because it is hard to distinguish defects, curved patterns and reflectance. Plastic is cheap and practical, so it is widely used in manufacturing. Plastics are usually colorful and diverse. For example, a plastic bottle may have more than ten kinds of colors on it, and pictures and texts on it are also very complicated. These surface backgrounds have complex textures, curved patterns, reflectance, and colors, preventing the detection of defects. Fig. 1.9 shows two kinds of complex background: textured background and background with gradually varied color, which make defect detection even more difficult.
- Three-dimensional (3D) surfaces.** To attract the attention from consumers, products are designed with various shapes. As the examples shown in Fig. 1.10, not only flatten surfaces are used, but also 3D curved surfaces are utilized on most of the products. Images taken from 2D flatten surfaces is relatively easier to show defects, but defects on the curved surfaces, especially highly-curved surfaces, is not easy to be found. Only using images as input, the geometrical relations between

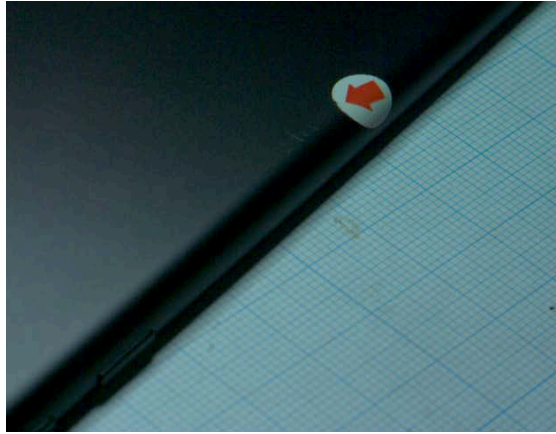


Figure 1.10: An examples of 3D curved surface.

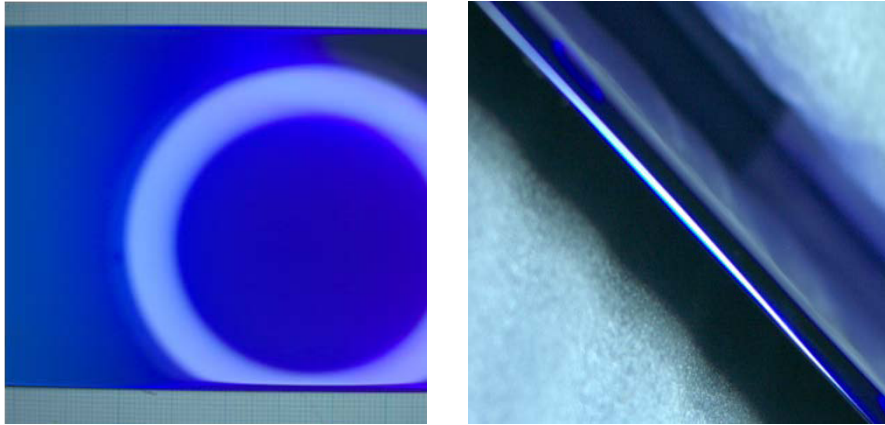


Figure 1.11: Examples of illumination reflectance on highly-reflective surfaces.

surfaces and camera is unknown. When designing defect detection algorithms, it becomes hard to obtain the real shape of the defects which is not always has a fixed distance to the camera. On the other hand, illumination reflectance is usually happened at the curved positions of the product. Because of these reasons, 3D surface becomes a difficulty in defect detection.

- **Illumination reflectance.** The factor of illumination reflectance has been mentioned in previous analyses. As the examples shown in Fig. 1.11, highlighted regions usually exist on the highly-reflective surfaces. Detecting reflectance itself is an essential difficult problem in computer vision for a long history. When defect detection meets reflectance, the problem becomes much harder. Because of reflectance, three difficulties may mixture with each other: complex background, curved surface, and illumination reflectance. Solving the mixture of them is very hard.
- **Collection of large number of defective images covering all kinds of**

defects. As reviewed above, many conventional approaches try to train a machine learning approach to extract features of defects and distinguish defects in an end-to-end way. This is of course of a good idea, but the training samples should enough and the samples should cover all the possible scenarios. So the problem becomes how to collect enough samples. With enough samples, supervised approaches need human beings to mark annotations one-by-one. Despite of the laborious task of making annotations. The defective samples are not easy to collect. Since most of the products are defect-free in real industry, so collecting large number of defective samples needs long time. Sometimes when the sample collection is finished, the production itself is also nearly to be finished. Another problem is that samples collected from one product, such as metal computers, can not be straightforwardly utilized to train a model which is for the purpose of inspecting other products, such as wood chairs or plastic toys. As a summary, the collection of large number of defective images covering all kinds of defects is very hard for many applications.

- **Time consumption.** Real-word industries have a high demand on efficiency. As the products are produced more and more quick, the requirement on inspection time becomes shorter and shorter. Even an algorithm can works well in a low speed, it can not be utilized in real industries. Therefore, it is better to consider the time complexity when designing algorithms. Defect detection algorithms are better to be hardware friendly for future parallel accelerations.

1.4 Goals, motivations and contributions

As discussed above, defect detection is very important for industrial manufacturing, but it is also very challenging. In general, it is impossible to overcome all the problems by using one specific approach. Because both defects and textures of backgrounds are very different, it is better to design specific methods for different scenarios. For example, large scale defects and tiny ones are different; flatten surfaces and curved surfaces are different; high-contrast defects and low-contrast defects are also different. Based on these reasons, the dissertation proposes new approaches for some specific flatten surfaces and extends the proposed method to curved surfaces. From texture point-of-view, the dissertation focuses on micro 3D textured surfaces, and detects even low-contrast defects. As a summary, this dissertation aims at detecting defects on the following two kinds of product surfaces:

- **Micro 3D textured surfaces**
- **Curved and highly-reflective surfaces**

As the examples shown in Fig. 1.12, micro 3D textured surfaces are widely used in electronic products, such as mobile phones and personal computers, because of beautiful appearances and good hand feelings. The Micro 3D textured surfaces are also known to

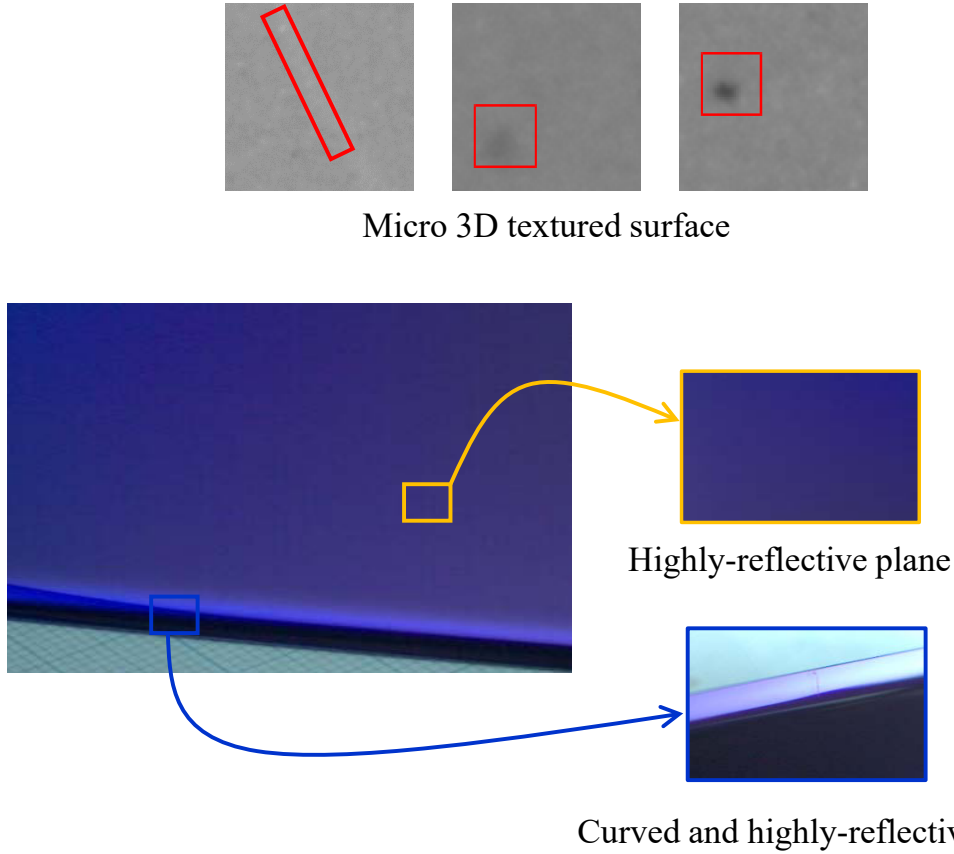


Figure 1.12: Examples of micro 3D textured surfaces and curved and highly-reflective surfaces.

as “uniformly embossed” surfaces. In industrial production, embossing is a process for making tiny raised and recessed patterns on surfaces of metal, plastic, or other materials. These micro three-dimensional (3D) structures embossed uniformly on the surface cause slight shadows under illumination, appearing as random textures in their images. From commercial point-of-view, these embossed surfaces have attractive appearances, good hand feeling, and excellent performance in skid resistance. From industrial point-of-view, complex textures on embossed surfaces make weld lines, sink marks, and even defects less noticeable, which improves the appearance quality of products while avoiding the coating, grinding, and other secondary processes. Therefore, uniformly embossed surfaces have been widely used in the world for many products. Because of these reasons, micro 3D textured surface is studied in this dissertation as the first goal. The above discussed micro 3D textured surfaces are flatten surface. However, real products are all 3D objects. That means every product have non-flatten surfaces. As the curved and highly-reflective surfaces shown in Fig. 1.12, mobile phone surfaces contains both flatten parts and curve parts, so as to other products. Therefore, to enhance the practical ability of our method, this dissertation also takes curved surfaces into consideration. Meanwhile,

as the examples shown in Fig. 1.11, metal and glass are very common materials used for products, which have high reflectance. To solve the problem of illumination reflectance in defect detection, high reflectance surfaces are also taken into consideration. Of course, curved surfaces are more likely to have reflectance, so we also consider the scenario of curved surfaces with high reflectance. As a brief summary, this dissertation aims at both of micro 3D textured surfaces and curved and highly-reflective surfaces.

The motivations behind the methods proposed in this dissertation are discussed as follows.

- Defection of low-contrast defects on micro 3D textured surfaces:** Through observation, it can be found that the micro 3D textured surface looks uniform, but is actually full of random textures and micro grains caused by uneven distributions of materials. In addition, real-world defects, for example, scratches and stains, may be small and have low contrast. Although defective regions can be enhanced by image enhancement algorithms, micro-textures with low contrast on background may also be intensified. And then the defect inspection task becomes even more difficult. Because of such characteristics, traditional enhancement algorithms, gray-value-based segmentation algorithms, and gradient based approaches are incapable to detect defects in our scenario. To overcome this challenge and defect low-contrast defects on micro 3D textured surfaces, this dissertation has the following two observations: 1) defects are local anomalies on the surfaces, which are dissimilar to the texture at other locations; 2) defects are infrequent. Therefore, defects can be considered as salient regions and located by modeling visual saliency. To achieve this goal, Chapter 2 proposes an accumulated and aggregated shifting of intensity (AASI) procedure to iteratively enhance the defect. Two novel features, named absolute intensity deviation and local intensity aggregation, which are associated with the probability of abnormality, are designed to measure the saliency at pixel level. By considering the dynamic property during iteration and the salient features from initial image, AASI can iteratively shift the intensity of each pixel depending on its saliency, i.e., defect probability. The AASI output sequence along iterations of defective pixels follows an exponential function, while that of defect-free pixels can be formalized as a linear function. So the detection process can be regarded as a problem of fitting to two statistical models. Experiments using real-world industrial surfaces demonstrate the feasibility and robustness of our approach.
- Defection of defects on curved and highly-reflective surfaces:** Curved and highly-reflective surface is very different from flatten micro 3D textured surface. First, one camera can shot all the points on a flatten surface, but one camera can not shot all the points of a curved surface. To handle curved surface, multiple cameras are needed. Second, the reflectance part (i.e. highlight part) on a reflective surfaces depends on both the lighting condition (such as the direction of light) and the pose of camera. As we all know, the combination of lighting condition and

camera pose makes some specific parts on the curved reflective surface invisible, because of reflectance. When the defect is right at the position of the invisible part, it becomes impossible to find out defect. Third, although it is inevitable to be invisible parts, it is possible to move the position of the invisible part through changing the combination of lighting condition and camera pose. In other words, gradually changing the combination of lighting condition and camera pose can move the invisible positions, until all the parts of the object is shot. To this end, a multiple-pairwise reflective observation system is introduced. Multiple-pairwise cameras and diffused lights are fixed in specific positions and angles to capture all defects on the whole curved surfaces while avoiding shadows and highlights. As for flatten micro 3D textured surface, the brightness of every pixels is basically uniform. Although defects appear on the uniform surface, the contrast between defects and background is low. So the overall brightness of the surface can be appropriately represented by a fixed value. However, as for curved and highly-reflective surface, it has very bright parts and very dark parts. To extend the proposed AASI for this scenario, a golden template picture (GTP) is introduced to represent the pixel-wise brightness of the surface. By replacing mode intensity with GTP, a extended AASI, named AASI-GTP is proposed for detecting defects on curved and highly-reflective surfaces.

The contributions of this dissertation are summarized as follows.

- **Accumulated and aggregated shifting of intensity (AASI):** The proposed AASI provides two main contributions. First, an illumination invariant AASI procedure is proposed to iteratively highlight defects from the point-of-view of probabilistic saliency. The varied characteristics of real-world defects, including shape, contrast, and size, can all be accommodated. Importantly, AASI is unsupervised and training-free. Secondly, an original rule for two-class classification problem based on statistical distribution fitting is proposed. Only very few samples are needed for determining a reasonable threshold for the classification, so it is free from collecting huge training data. It is worth noting that our method does not utilize any 3D geometrical properties of background textures. The saliency-guided enhancement and statistical fitting-based classification also work well for flatten textures. So AASI is effective for flat-textured and non-textured surfaces. In addition, some local salient regions may exist on the surface. However, the product appearance is settled in industrial production. In other words, the positions of inherent salient regions, such as company logo, are fixed. Therefore, salient regions can be separated by skipping pixels in certain locations.
- **AASI with golden template picture (AASI-GTP):** The proposed AASI-GTP also provides two main contributions. First, a multiple-pairwise reflective observation system is introduced. This system is based on the relationship between the invisible position and the combination of lighting condition and camera pose.

Since the combination of lighting condition and camera pose controls the position of the invisible parts on curved surface, the proposed multiple-pairwise reflective observation system takes multiple images from the product to make every part on it visible in at least one image. By doing like this, even the curved surface itself has reflection, the proposed system removes the negative influence from reflection. Second, a golden template picture (GTP) is introduced to represent the pixel-wise brightness of the surface. By replacing mode intensity with GTP, an extended AASI, named AASI-GTP is proposed for detecting defects on curved and highly-reflective surfaces. Although AASI is not suitable for curved and high reflectance surfaces, the proposed GTP makes it possible to represent overall brightness of the surface itself, making it possible to use the framework of AASI for curved and highly-reflective surfaces.

1.5 Organization of dissertation

The overall dissertation is organized as follows.

Chapter 1 introduces the research background of defect detection, conventional works, challenges in defect detection, and contributions of this dissertation. Since defect detection is one of the most important means of product quality control, it is extremely important in modern industrial manufacturing. Conventional automatic defect detection methods include both of handcrafted feature based ones and data-driven feature based ones. Defect detection is still faced with many challenges, such as irregular properties of defects and complex textures of background. This dissertation proposes an accumulated and aggregated shifting of intensity (AASI) and an improved AASI approach with golden template picture for detecting defects on both micro 3D textured surfaces and curved and highly-reflective surfaces.

Chapter 2 proposes an accumulated and aggregated shifting of intensity (AASI) based framework was proposed to solve the problem of detecting defects on micro 3D textured surfaces. Firstly, we proposed two salient features to measure the saliency in pixel-level. These two features are further used to construct an iterative pixel-level enhancement procedure, which can iteratively shift intensity of each pixel according with its defective probability. And then, an original fitting-based classification rule was proposed. Two statistical models are utilized to judge whether each pixel in the given image is defective or not. Finally, the parameter setting was discussed. Our approach includes an iterative enhancement phase and a statistical classification phase, which is fully automatic and training-free.

Chapter 3 proposes an improved AASI approach with golden template picture was proposed for defect detection on curved and highly-reflective surfaces. Firstly, we analyzed the reflection property of highly specular surfaces. And then, a multiple-pairwise reflective observation system was introduced. Multiple-pairwise cameras and diffused lights are fixed in specific positions and angles to capture all defects on the whole curved

surfaces while avoiding shadows and highlights. Finally, the golden template picture (GTP) was introduced to improve the original AASI. The mode intensity is replaced with the intensity of GTP, making the developed AASI-GTP effective for curved surfaces with uneven illumination.

Chapter 4 presents the dataset, experimental setting, experimental results and analyses. Experimental results show that our method generally has better performance than state-of-the-art unsupervised defect detection methods in terms of Precision and F-measure. AASI performs well even for low-contrast defects and small-sized defects with 3×3 pixels, and is robust to uniform illumination variations. In addition, the performance of AASI is the same with flat surfaces coated with different materials, such as plastic, metal and glass, demonstrating its generality. Moreover, the improved AASI with golden template picture exhibits satisfied performance on curved and highly-reflective surfaces. Finally, the computation time was discussed.

Chapter 5 concludes the whole dissertation and introduces future works. An accumulated and aggregated shifting of intensity (AASI) has been proposed for detecting defects on micro 3D textured surfaces and an improved AASI approach with golden template picture has been proposed for detecting defects on curved and highly-reflective surfaces. Experimental results proved the effectiveness of the proposed approaches.

Chapter 2. Accumulated and Aggregated Shifting of Intensity (AASI)

In this chapter, to overcome the drawbacks of conventional works, we propose an unsupervised framework to inspect randomly textured surfaces, especially “uniformly embossed” surfaces, for robust defect detection.

2.1 Micro textured surfaces

In industrial production, embossing is a process for making tiny raised and recessed patterns on surfaces of metal, plastic, or other materials. These micro three-dimensional (3D) structures embossed uniformly on the surface cause slight shadows under illumination, appearing as random textures in their images. From commercial point-of-view, these embossed surfaces have attractive appearances, good hand feeling, and excellent performance in skid resistance. From industrial point-of-view, complex textures on embossed surfaces make weld lines, sink marks, and even defects less noticeable, which improves the appearance quality of products while avoiding the coating, grinding, and other secondary processes. Therefore, uniformly embossed surfaces have been widely used in the world for many products. Defect detection on these surfaces becomes an important and challenging task. For illustration, defect-free and defective examples of embossed surfaces along with enhanced versions processed by the generalized unsharp masking (GUM) [55] are shown in Fig. 2.1. It can be seen that the embossed surface looks uniform, but is actually full of random textures and micro grains caused by uneven distributions of materials. In addition, real-world defects, for example, scratches and stains, may be small and have low contrast. Although defective regions are enhanced by GUM, micro-textures with low contrast on background are also intensified. And then the defect inspection task becomes even more difficult. Because of such characteristics, traditional enhancement algorithms, gray-value-based segmentation algorithms, and gradient based approaches are incapable to detect defects in our scenario. In industrial production line, manual inspection by human beings is still the most popular way to ensure high quality of embossed surfaces. However, manual inspection is time consuming and laborious, which mainly depends on the personal experience and subjective judgment of workers.

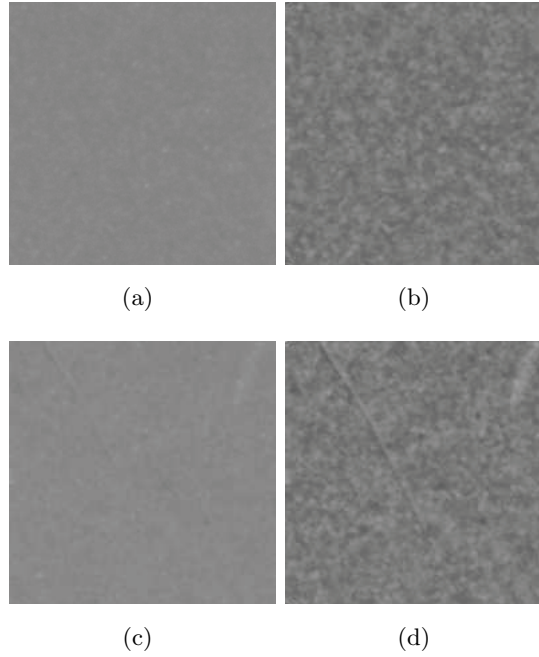


Figure 2.1: Micro 3D textured or uniformly embossed surfaces: (a) defect-free sample, (c) defective sample, (b) and (d) enhanced versions of (a) and (c), respectively.

2.2 Related works

Traditional manual inspection is laborious and time consuming, and depends on the experience of human inspectors, limiting its performance to some extent. Recently, automated visual inspection (AVI) of product surface has been paid increasing attention. In our previous work [56], we proposed a novel defect detection scheme for micro 3D textured surfaces. The framework is shown in Fig. 2.2. As can be seen, the input image is firstly divided into small blocks, and each block is called a die. Then the local orientation code pattern (LOCP) in each die is computed. If the LOCP features of adjacent dies are dissimilar, the latter one will be classified as defective die which contains macro defect. Otherwise, a further inspection of micro defects is conducted by using an intensity incremental outlier detector (IIOD). After comparing all dies with its neighbors, the defect can be. It is notable that unlike traditional definition, the macro and micro defects in this work are defined in a die. If the size of defect in a die is less than half a die, the defect can be called micro defect. Otherwise, it is classified as macro defect.

Die-to-die comparison

As shown in Fig. 2.1., the SHIBO surface is not completely uniform. However, adjacent small regions on surface image should share similar structure characteristics and illumination. So we seek the difference between adjacent regions on the surface image

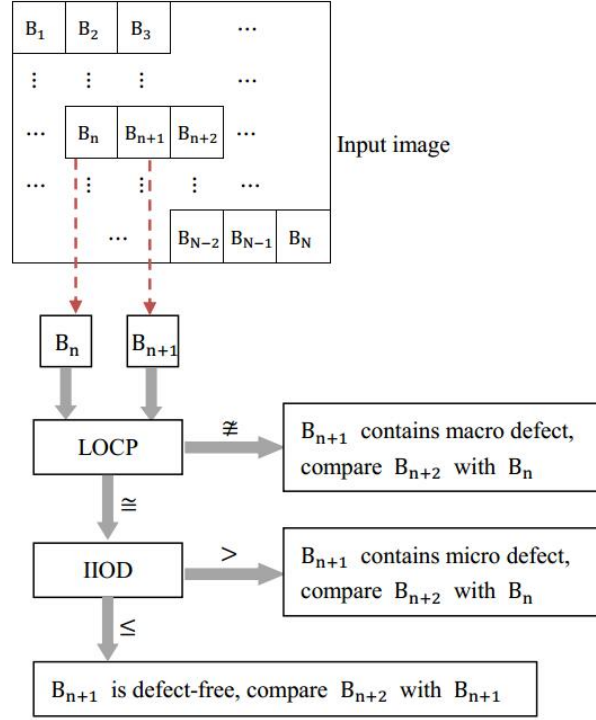


Figure 2.2: Framework of the proposed method.

instead of template comparison. The input image is firstly divided into blocks of the size $s \times s$. The n th block is called the n th ‘die’, and represented as B_n . And then we compare two dies successively. If these dies are similar, they are considered as defect-free. On the contrary, the latter one is classified as defective die. As for the die size s , if s is too large, micro defects may not be detected. If s is too small, the similarity between two dies may be unstable, and defect-free dies may be regarded as defective. To balance the trade-off between accuracy and stability, s is set as 32.

The problem is how to design a robust similarity evaluation scheme for dies on the SHIBO surface. Real defects are different in size and shape. Since our approach aims to detect all defects of different sizes, we firstly propose LOCP to extract texture information, and utilize the histograms of LOCP as similarity measure to detect macro defects. Then the IIOD is proposed to further inspect micro defects. The details will be described next.

LOCP based die-to-die comparison for macro defect detection

In our previous work [57], Orientation Code (OC) was proposed for robust object search. Firstly, the horizontal and vertical derivatives of input image are obtained by Sobel operators as

$$\nabla I_x = \begin{bmatrix} -1 & 0 & +1 \\ -2 & 0 & +2 \\ -1 & 0 & +1 \end{bmatrix} * I \quad (2.1)$$

$$\nabla I_y = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ +1 & +2 & +1 \end{bmatrix} * I \quad (2.2)$$

where ‘ $*$ ’ denotes the convolution operator.

Then the orientation angle can be computed by

$$\theta = \tan^{-1} (\nabla I_y / \nabla I_x) \quad (2.3)$$

After making the range of θ from $[-\pi/2, \pi/2]$ to $[0, 2\pi]$, the OC is defined as

$$OC = \begin{cases} [\theta / \Delta\theta], & |\nabla I_x| + |\nabla I_y| > \Gamma \\ R, & \text{otherwise} \end{cases} \quad (2.4)$$

where $\Delta\theta$ is the quantization width, Γ and R are used to set a large OC value for low-contrast pixels. Here, $\Delta\theta$, Γ , and R are set to $\pi/8$, 10, and 255, respectively.

Since OC is computed in the form of gradient orientation rather than the intensity, it is robust for illumination change and occlusion. However, OC only considers gradient information of single pixel, which contains limited information.

We proposed a novel local feature, called LOCP, which is computed by comparing the OC value of the central pixel with its neighbors, i.e.

$$\delta(OC(g_c), OC(g_p)) = \begin{cases} 1, & OC(g_c) = OC(g_p) \\ 0, & \text{otherwise} \end{cases} \quad (2.5)$$

$$LOCP(g_c) = \sum_{p=1}^8 \delta(g_c, g_p) \quad (2.6)$$

where g_c is the central pixel, and g_p , $p = 1, \dots, 8$, are adjacent pixels around g_c as shown in Fig. 2.3. Compared with OC, LOCP utilize the orientation information in a 3×3 local region to improve accuracy and robustness.

Fig. 2.4 shows LOCP histograms of different dies. From Fig. 2.4 (a) and Fig. 2.4 (b), one can find that defect-free dies of different locations share very similar LOCP histogram profiles. Meanwhile, LOCP histograms of defect-free dies and macro defect contained die are quite different, as shown in Fig. 2.4 (a) and Fig. 2.4 (c). Therefore, macro defect can be located by die-to-die comparison.

To calculate the similarity between two dies, we employ the histogram intersection, which is defined as

$$S(H_n, H_{n+1}) = \sum_{l=1}^L \min(H_n(l), H_{n+1}(l)) \quad (2.7)$$

g_4	g_3	g_2
g_5	g_c	g_1
g_6	g_7	g_8

Figure 2.3: Central pixel g_c and its 8-neighborhood.

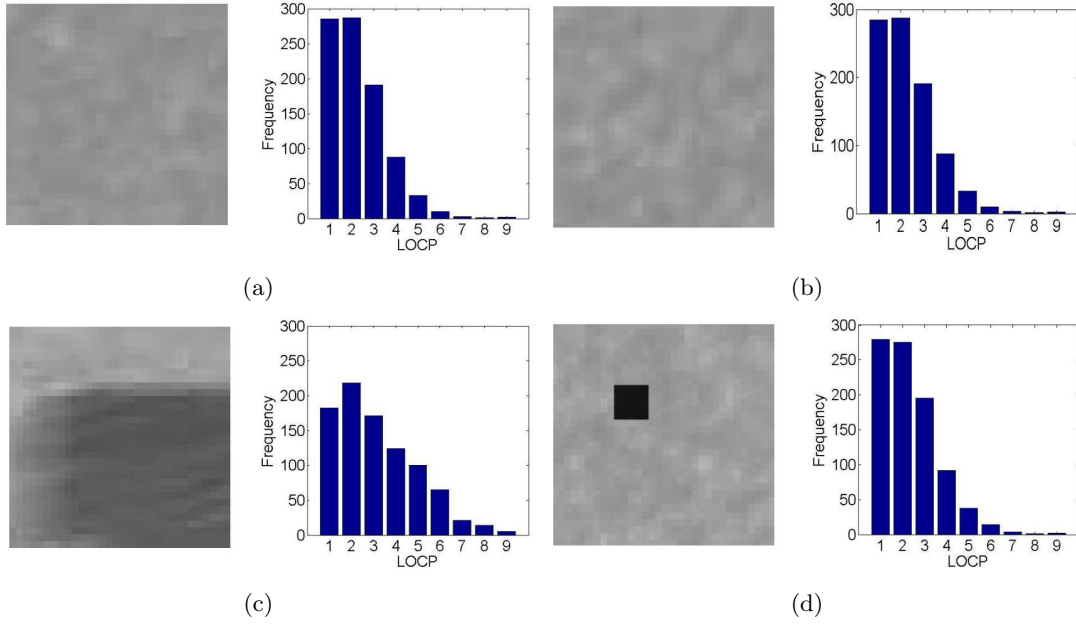


Figure 2.4: LOCP histograms of (a) defect-free die 1; (b) defect-free die 2; (c) die with macro defect; (d) die with micro defect. The die is of size 32×32 pixels.

where H_n and H_{n+1} represent LOCP histograms of die B_n and B_{n+1} , respectively. L is the number of bins in a histogram. If $S(H_n, H_{n+1}) > T_s$, these two dies are similar. T_s is the threshold of similarity, and when T_s is set 0.86, satisfied performance can be obtained in most experiments.

IIOD for micro defect detection

Although LOCP can be used to locate macro defect, it is powerless when the defect is very small. As can be seen from Fig. 2.4 (a) and (d), LOCP histograms of defect-free and defective dies appear very similar in case of micro defect. This is due to the fact that micro defect does not bring significant changes in texture information of a die. Therefore, after the LOCP based die-to-die comparison, if two dies are different, the latter one can be regarded as defective die containing macro defect; and if they are

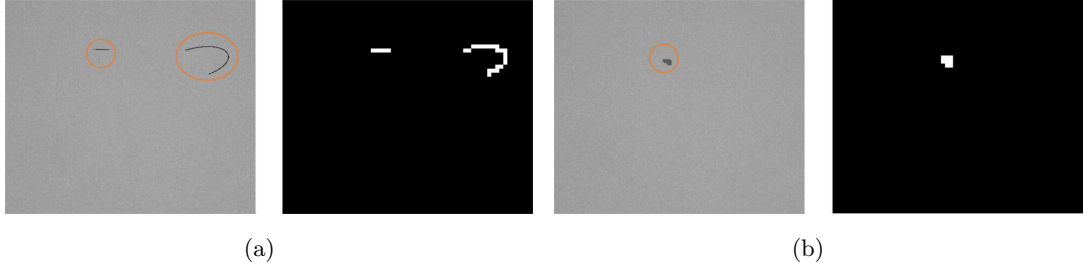


Figure 2.5: Defect detection results of (a) scratch; (b) spot. The left column is the input images of size 1700×2000 pixels, and right column is corresponding detection results.

similar, a further inspection of micro defect is needed.

For the SHIBO surface, pixels in a defect-free die should share similar intensity values, and there should exist intensity difference between background and micro defect. So we propose a detector of intensity increment outliers to inspect micro defect. For a defect-free die, the number of outliers should not be too large. Specifically, B_n is a die with M pixels as $\{x_1, \dots, x_M\}$. The outlier detector is defined as

$$IIOD(x_m) = \begin{cases} 1, & |I(x_m) - I_{med}| > T_I \cdot I_{med} \\ 0, & \text{otherwise} \end{cases} \quad (2.8)$$

where I_{med} is the median intensity value in this die, and T_I is the threshold of intensity increment. As can be seen, IIOD is based on the intensity increment instead of intensity value itself, so it is robust for illumination change.

And then, the number of outliers can be calculated by

$$N_O = \sum_{m=1}^M IIOD(x_m) \quad (2.9)$$

If $N_O > T_N$, B_n can be classified as defective die with micro defect. Otherwise, B_n is defect-free die. T_N is the threshold of outlier number. In the following experiments, we always set $T_I = 0.13$, $T_N = 30$. By repeating above LOCP based die-to-die comparison and IIOD based inspection for the whole image, macro and micro defects on the SHIBO surface can all be detected.

On one hand, the LOCP is developed by binary comparison of local orientation code. The defect detection algorithm then makes a die-to-die comparison of the LOCPs to detect macro defects. On the other hand, the IIOD is designed by checking if the pixels in a local region share similar intensity values or not. The IIOD is finally employed to detect micro defects. This LOCP-IIOD method is able to detect defects with high contrast or large size. However, it is powerless for low-contrast and micro defects.

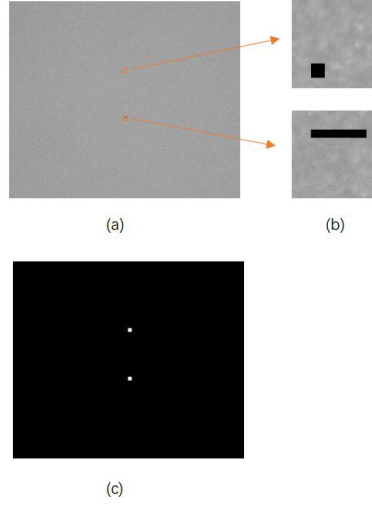


Figure 2.6: Defect detection results of micro defects.

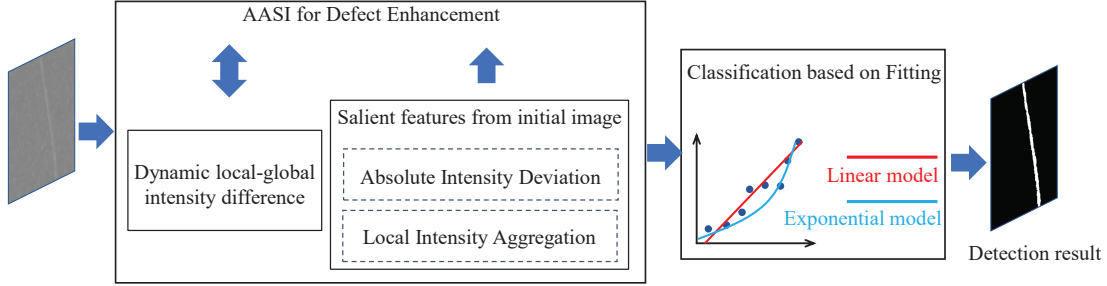


Figure 2.7: Graphical illustration of the proposed approach.

2.3 AASI for Defect Enhancement

In order to detect micro defects with low contrast, we proposed a feature enhancement based defect detection framework [58, 59, 60]. The fundamental understanding in our approach are: 1) defects are local anomalies on the surfaces, which are dissimilar to the texture at other locations; 2) defects are infrequent. Therefore, defects can be considered as salient regions and located by modeling visual saliency. A graphical illustration of our approach is shown in Fig. 2.7. We firstly proposed an accumulated and aggregated shifting of intensity (AASI) procedure to iteratively enhance the defect. Two novel features, named absolute intensity deviation and local intensity aggregation, which are associated with the probability of abnormality, are designed to measure the saliency at pixel level. By considering the dynamic property during iteration and the salient features from initial image, AASI can iteratively shift the intensity of each pixel depending on its saliency, i.e., defect probability. The AASI output sequence along iterations of defective pixels follows an exponential function, while that of defect-free pixels can be formalized as a linear function. So the detection process can be regarded as a problem of fitting to

two statistical models.

2.3.1 Basic concept of AASI

As shown by the representative sample in Fig. 2.1 (c), a real-world defect is nearly invisible due to low contrast, an unclear boundary, and various background textures. It is therefore difficult to locate defects by simple intensity thresholding and gradient-based segmentation techniques. To address this issue, this section proposes an AASI procedure to iteratively shift the intensities of all pixels in the image, thus enabling defective pixels to be highlighted by careful design of the shifting mechanism, which discriminates the rate of shifting for potential defective pixels versus defect-free pixels. Potential defective pixels can be shifted more quickly than defect-free ones. After several iterations, the intensity difference between defective and defect-free regions is gradually increased. This leads to defects being highlighted while the defect-free background with complex textures remains basically unchanged.

Let $x[k]$ be the intensity of any pixel at the k th iteration, with $x[0]$ being the initial intensity. An intuitive formulation of AASI is represented as

$$x[k+1] = x[k] + \Delta x[k], \quad (2.10)$$

where $\Delta x[k]$ is the shifting increment at the k th iteration. The incremental intensity $\Delta x[k]$ must be designed in this section and it depends on the specific properties of the current pixel. In order to give some particularity to defective pixels, potential defective pixels are assigned larger values of Δx . Moreover, bright defects are brightened, whereas darker defects are darkened. Thus, all defects can be highlighted with iterations. To this end, we take the following two factors into consideration: the initial property of each pixel in the image and the dynamic property during the shifting. 1) In terms of the initial property in the image, on the one hand, defective pixels of relatively similar intensities spatially appear in clusters or neighbors. On the other hand, intensities of defective pixels are similar to those of some defect-free pixels, but a slight deviation still exists between the intensity of defective pixels and the overall intensity of the whole surface. Based on these two characteristics, the local intensity aggregation and initial absolute intensity deviation are proposed in this section to describe the initial property of each pixel. 2) For the dynamic property of each pixel during the shifting steps, in order to gradually enhance the intensity difference between defective and defect-free pixels, the difference between the intensity of each pixel and the overall intensity of the image is key. This is because the overall background intensity is a robust reference for comparison. After each shifting period, the intensities of all the pixels are updated. It is therefore possible to calculate the local-global intensity difference between each pixel and the overall image, and use it as a guidance for the next step. Because the local-global intensity difference always changes at each iteration, it is referred to as the dynamic local-global intensity difference below.

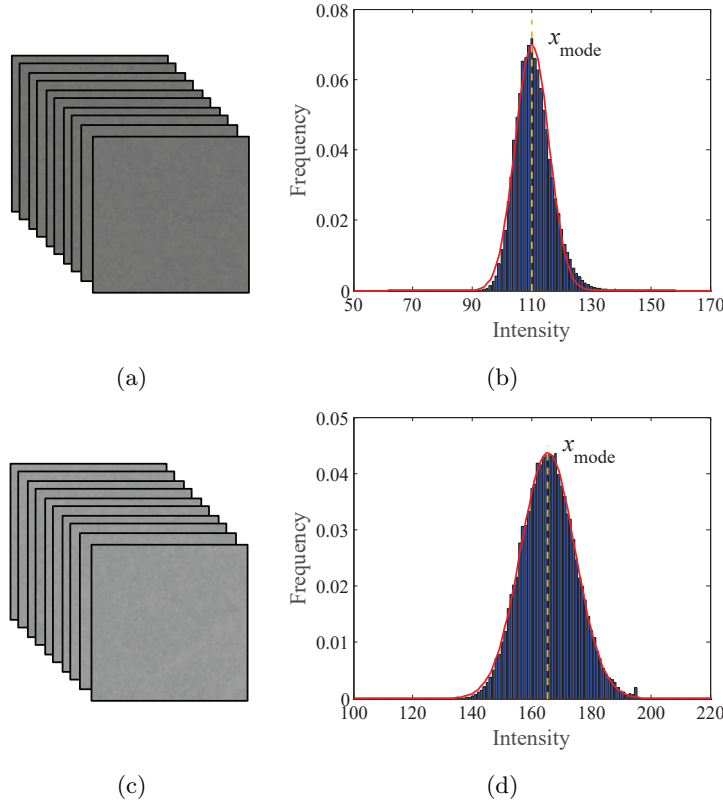


Figure 2.8: Intensity histograms of pixels on micro 3D textured surfaces: (a) 10 defect-free images under dark illumination. (c) 10 defect-free images under bright illumination. (b) and (d) intensity histograms from (a) and (c), respectively.

Formally, we initially define Δx as

$$\Delta x[k] = g \cdot (x[k] - x_{\text{mode}}), \quad (2.11)$$

where g denotes the salient property of each pixel in the initial image, while the term $(x[k] - x_{\text{mode}})$ is the dynamic local-global intensity difference at the k th iteration, with x_{mode} denoting the mode intensity of the initial image.

2.3.2 Dynamic Local-global Intensity Difference

Here we use x_{mode} to represent the overall background intensity for two reasons. Firstly, the intensity on a defect-free surface follows a Gaussian distribution, so the mode intensity equals the mean intensity of the background, that is, $x_{\text{mode}} = \bar{x}$. Secondly, x_{mode} is not changed by a handful of defect or outlying pixels, so it is insensitive to the presence of micro defects. Fig. 2.8 shows the intensity histograms drawn from 20 defect-free samples, and the red curves denote the corresponding results of Gaussian fitting. The fitting curves follow the histograms very closely under different illuminations, indicating that the intensity of micro 3D textured surfaces follow a Gaussian distribution regardless

of illumination, i.e.,

$$x \sim G(\bar{x}, \sigma_x^2), \quad (2.12)$$

where x is the initial intensity, and $\bar{x}$ and σ_x denote its mean and standard deviation, respectively. The intensity at which the probability distribution function (pdf) takes its maximum value is the so-called mode intensity x_{mode} . Local anomalies do not affect the mode intensity, because it is determined by the most frequently occurring intensity value of the pixels. Therefore, x_{mode} is a better measure for representing overall background intensity than $\bar{x}$. Then $x[k] - x_{\text{mode}}$, the intensity difference at the k th iteration, is used to guide the shifting directions. With each iteration, the intensities of all pixels deviate from the background intensity in either directions, of brighter or darker. To shift the intensities of pixels at different rates, another factor of incremental intensity, g , needs to be carefully designed.

2.3.3 Salient Features from Initial Image

Micro 3D textured surfaces can be observed to have nearly uniform appearance in gray level, and defects can be regarded as abnormalities on the surfaces that have relatively high saliency. In other words, higher saliency generally indicates greater defect probability. Therefore, a pixel-level indicator of saliency on the micro 3D textured surface should be investigated. To describe the defect probability of each pixel through pixel-level saliency, we designed two features by use of pixel values and some particular condition in their neighborhood.

Absolute Intensity Deviation

Although pixel intensities vary for an image of micro 3D textured surfaces, which makes defect detection very challenging, their defects still show slight deviation in intensity compared with the background. As above mentioned, the mode intensity x_{mode} is deemed suitable to represent the overall background intensity. By using x_{mode} to represent the overall intensity of background, the absolute intensity deviation between the pixel located at coordinate (i, j) and the overall intensity of the whole image can be calculated by

$$r_{ij} = |x_{ij} - x_{\text{mode}}|. \quad (2.13)$$

To bring the value of absolute intensity deviation into the range $[0, 1]$, the normalized absolute intensity deviation is defined as

$$\hat{r}_{ij} = \frac{r_{ij} - r_{\min}}{r_{\max} - r_{\min}} \quad (2.14)$$

where $r_{\max}$ and $r_{\min}$ indicate the maximum and minimum values of r in the initial image, respectively. Generally, a larger $\hat{r}_{ij}$ indicates higher defect probability. It takes the global information into consideration, and is robust to illumination changes when intensities on the whole surface vary equally.

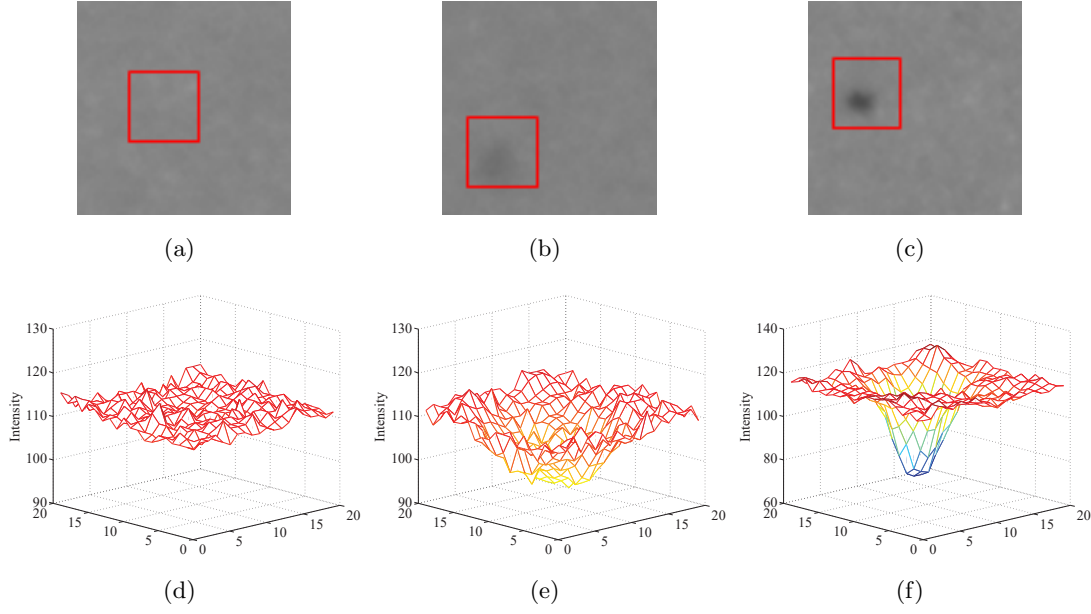


Figure 2.9: Intensity profiles: (a) defect-free surface, (b) low-contrast defect, and (c) high-contrast defect. (d), (e), (f) intensity profiles over a 20×20 region in (a), (b), (c), respectively.

Local Intensity Aggregation

The spatial intensity distributions of defective pixels and background pixels are different. Although the defective pixels usually have similar intensities as some of the defect-free pixels, their aggregation or cluster occurs in any defective region. Namely, defective pixels with relatively similar intensities spatially appear in aggregation and construct pixel groups. Fig. 2.9 visualizes intensities over a 20×20 region in defect-free image, low-contrast defect, and high-contrast defect, respectively. As shown in Fig. 2.9, the defect-free background is nearly uniform, with minor changes in the intensities of adjacent pixels. The intensities of low-contrast defective pixels can be observed to differ from those of the background and are relatively close to those of their neighbors, as shown in Fig. 2.9 (b) and (e). Furthermore, Fig. 2.9 (c) and (f) show that for a defective region with high contrast, intensities are very disparate compared with its background and neighboring pixels aggregate less closely with each other compared with the low-contrast defective region. In summary, the spatial intensity distribution of defects differs from that of defect-free regions.

To quantify such relative intensity aggregation, the following strategy was designed. Given a candidate pixel located at position (i, j) , the intensity difference between the current pixel and any pixel located within a 5×5 neighborhood is evaluated. When the difference is less than the aggregation threshold T_x , the two pixels are considered to be

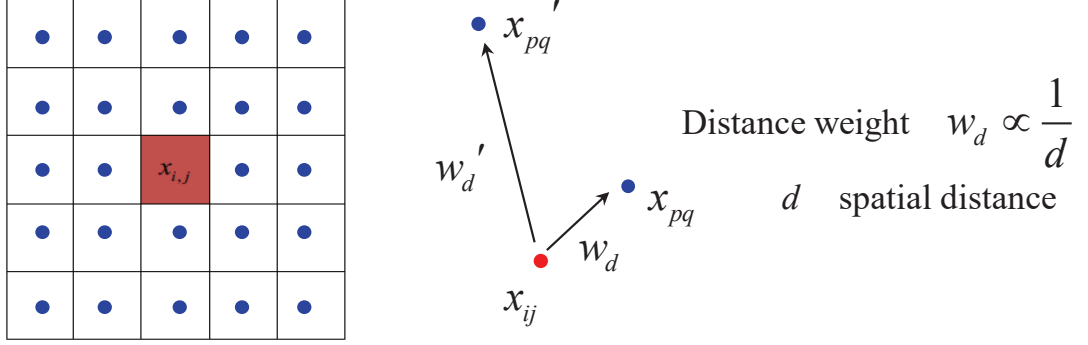


Figure 2.10: Intensity aggregation occurs among neighboring pixels. Pixels positioned closer to the center pixel have greater influence on its intensity aggregation.

aggregated, i.e.,

$$a(x_{ij}, x_{pq}) = \begin{cases} 1, & \text{if } |x_{ij} - x_{pq}| \leq T_x \\ 0, & \text{otherwise} \end{cases}, \quad (2.15)$$

where x_{pq} is one of the neighboring pixels located at point (p, q) . As discussed above, the local intensity aggregation for a defective region is related to its contrast, so we design the threshold T_x adapted to the absolute intensity deviation as

$$T_x = C_T r_{ij}, \quad (2.16)$$

where C_T is a constant coefficient. Because we assume that low-contrast defect pixels aggregate closer than high-contrast ones, a small aggregation threshold is assigned to defect-free regions to reduce mis-classification, a moderate threshold is assigned to a low-contrast defect, and a large threshold is assigned to a high-contrast defect, so that low-contrast and high-contrast defects can all be distinguished from defect-free regions. The remaining problem is to determine a proper value of C_T . As it increases, more defective pixels can be located, but background noise also increases. To address this problem, C_T is empirically set as 0.2 for balancing the detection performance and noises.

Intensity aggregation occurs among neighboring pixels. To represent the intensity aggregation, the relationship between each pixel and its neighboring pixels within a 5×5 region is considered, as shown in Fig. 2.10. For each center pixel, pixels positioned closer to the center pixel naturally have greater influence on its intensity aggregation than those positioned further away.

Based on this intuition, distance weight w_d is defined with a Gaussian kernel [61] as

$$w_d(x_{ij}, x_{pq}) = \Omega_{ij} \cdot \exp\left(\frac{-d(x_{ij}, x_{pq})^2}{2 \times \sigma^2}\right), \quad (2.17)$$

where $d(x_{ij}, x_{pq}) = \sqrt{(i-p)^2 + (j-q)^2}$, σ is the scale parameter set as $\sigma = 3$ in the case of 5×5 neighborhood, and finally Ω_{ij} is a normalization coefficient, which ensures the sum of distance weights from neighboring pixels equals 1, i.e., $\sum_{p,q} w_d(x_{ij}, x_{pq}) = 1$.

Then the local intensity aggregation of pixel located at position (i, j) is calculated as

$$A_{ij} = \sum_{pq} w_d(x_{ij}, x_{pq}) \times a(x_{ij}, x_{pq}), \quad (2.18)$$

where a is utilized to measure the relative intensity aggregation between center pixel and one of its neighboring pixels, and w_d is the distance weight applied to a . A_{ij} describes the degree of intensity aggregation in a 5×5 local region centered at (i, j) . It is calculated from the initial image and is designed to represent defect in terms of spatial intensity distribution. Potential defective pixels have large aggregation values, such that aggregations that are more intense correspond to higher defect probability.

We finally define the salient factor g as the product of the normalized absolute intensity deviation and the local intensity aggregation, i.e.,

$$g = \hat{r} \cdot A, \quad (2.19)$$

where the suffix ij is omitted because of simplicity but one notices that g , $\hat{r}$, and A are all defined for any pixel at the position (i, j) . Because the absolute intensity deviation and local aggregation intensity represent the potential defective pixels from different aspects, both properties should be considered in order to design an effective feature or factor. In addition, because of the random textures on the background, some defect-free pixels have relatively large values of $\hat{r}$ while quite small values of A . The product of these two terms for such kind of pixels is small, thus avoiding mistakenly detecting such background pixels as defects. Therefore, $g = \hat{r} \cdot A$ is a good indicator of defect probability. The value of g always lies within the range of $0 \leq g \leq 1$, and a larger g means higher defect probability.

2.3.4 Overall Framework of AASI

The AASI framework, therefore, shifts the intensities of pixels with different speeds according to their defect probabilities as follows:

$$x[k+1] = x[k] + (\hat{r} \cdot A)(x[k] - x_{\text{mode}}). \quad (2.20)$$

Here we remark that the suffix ij is omitted because of simplicity but the above iteration should be applied to all the pixels.

2.3.5 AASI Behavior

Fig. 2.11 shows the AASI behaviors of defect-free pixels (marked in blue) and two types of defective pixels, i.e., bright ones (marked in yellow) and dark ones (marked in red), where each set of ten pixels are investigated, respectively. Although their original intensities are similar, they follow obviously different tracks by AASI, i.e., the output sequences from the AASI iterations show large differences, where the bright defective

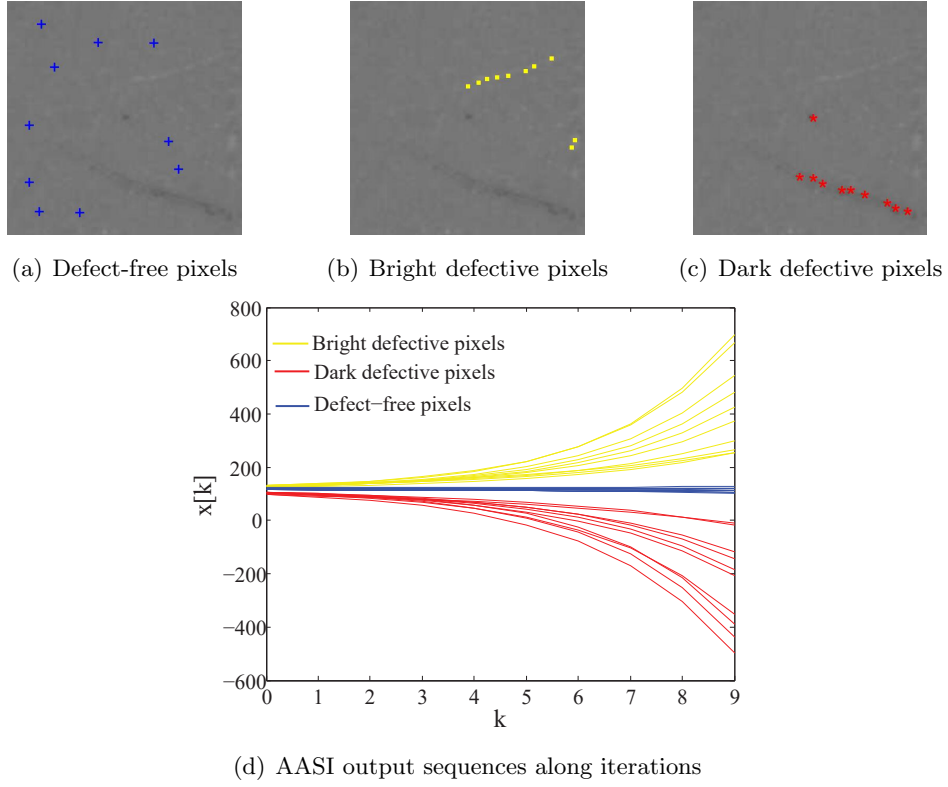


Figure 2.11: Visualization of shifting behavior of AASI procedure. Defective and defect-free pixels run on obviously different tracks by AASI.

pixels move up, dark defective pixels move down, and defect-free pixels remain relatively stable. To visualize the effect of AASI on a whole image, Fig. 2.12 shows several AASI output images at different iterations. Dark defects can be observed to darken, bright ones to brighten, and defect-free pixels to remain basically unchanged, thus highlighting low-contrast defects. Therefore, the original problem is possible to be solved by detecting defects from enhanced images. However, we propose a more robust and efficient way to classify all defective versus defect-free pixels by using statistical fitting models.

2.3.6 Fitting Models in AASI

As explained above, potential defect-free and defective pixels are shifted at different speeds. Although their original intensities may be similar, they follow obviously different tracks by AASI. Therefore, the output sequences from the AASI iterations can be fitted by different models for classification. In particular, we achieve the accurate fitting from statistical point-of-view. We propose two statistical models that use a set of recorded intensities through several iterations, so this method is expected to achieve higher classification performance than simply setting a threshold at a particular iteration.

First, the following relation can be easily obtained by developing Eq. (2.19) and Eq.

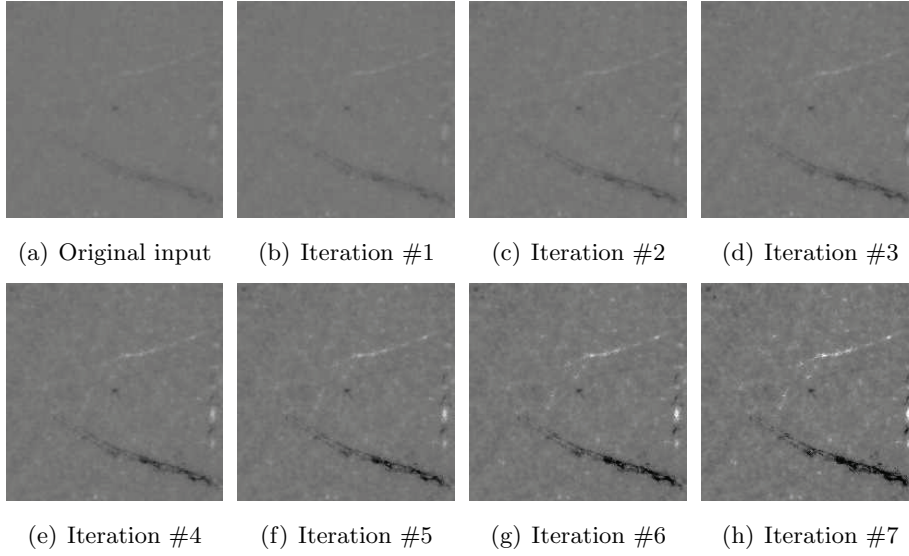


Figure 2.12: AASI outputs at different iterations.

(3.13),

$$x[k] - x[0] = \left[(1+g)^k - 1 \right] \cdot (x[0] - x_{\text{mode}}), \quad (2.21)$$

where $x[k]$ shows an exponential relationship with iteration count k . Using Taylor-series expansion, $(1+g)^k$ can be rewritten as

$$(1+g)^k = 1 + \frac{(\ln(1+g))}{1!}k + \dots + \frac{(\ln(1+g))^n}{n!}k^n + \dots. \quad (2.22)$$

For pixels with low defect probability, the initial salient factor g is always small, i.e., $0 \leq g \ll 1$, so that $(1+g)^k$ can be approximated by

$$(1+g)^k \approx 1 + k \ln(1+g), \quad (2.23)$$

because the decrease of sequence $\frac{(\ln(1+g))^n}{n!}$ is faster than the increase of k^n for small g and k . Substituting Eq. (2.23) into Eq. (2.21), we obtain

$$x[k] - x[0] \approx k \ln(1+g) (x[0] - x_{\text{mode}}). \quad (2.24)$$

This means that $x[k]$ has an approximately linear relationship with k when it is highly probable that the current pixel is defect-free.

In summary, when g is large, it is highly probable that the pixel is defective, and $x[k]$ has an exponential relation with k ; when g is small, there is low probability that the pixel is defective, and $x[k]$ has a linear relation with k in the process of AASI. Based on this consideration, we propose a defective fitting model

$$f_D(k) = a_1 \times b_1^k, \quad (2.25)$$

and a defect-free fitting model

$$f_{DF}(k) = a_2 \times k + b_2, \quad (2.26)$$

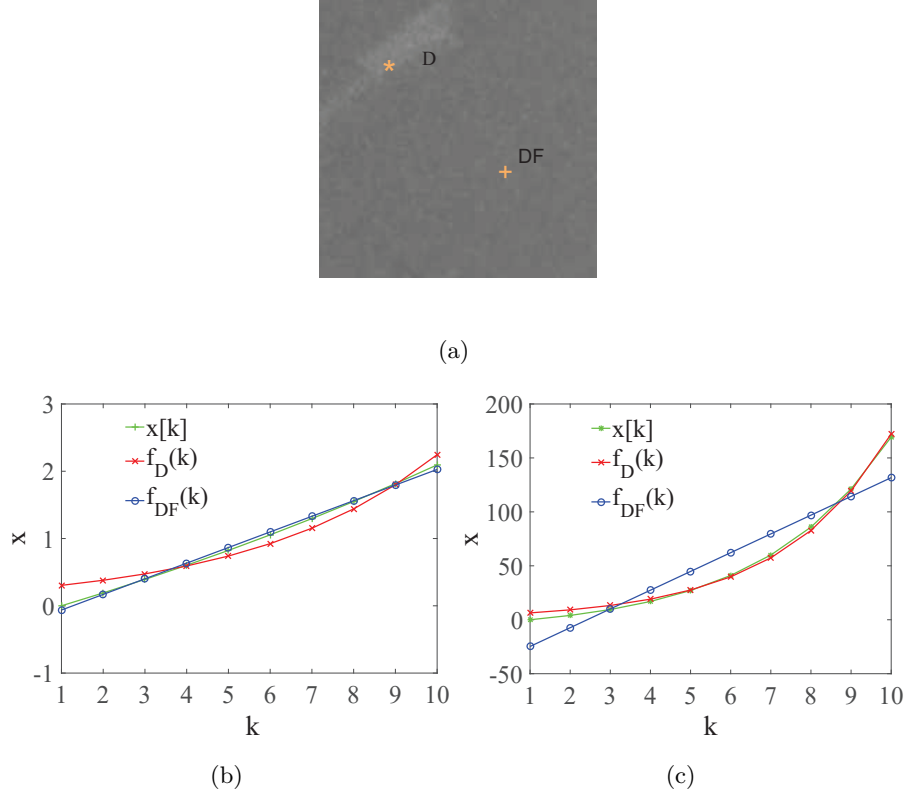


Figure 2.13: Visualization of two fitting models: (a) a defect-free pixel (marked as “DF”) and a defective pixel (marked as “D”). (b) and (c) are the fitting results for shifting tracks of the defect-free pixel and defective pixel in (a), respectively.

where a_1 , b_1 , a_2 , and b_2 are coefficients to be determined through a fitting process. For each pixel, both of the defective and defect-free models must be tried to fit to the output sequence from AASI by use of the least squares estimation (LSE) [62]. Then their residual sum of squares (RSS), which denotes the discrepancy between the outputs and the estimated values of each fitting model, are obtained by

$$E_D [K] = \sum_{k=1}^K (x[k] - f_D(k))^2, \quad (2.27)$$

and

$$E_{DF} [K] = \sum_{k=1}^K (x[k] - f_{DF}(k))^2, \quad (2.28)$$

where K is the iteration limit. By minimizing the RSS value E_D , the parameters a_1 and b_1 in defective fitting model can be obtained, while similarly, a_2 and b_2 are coefficients of the defect-free fitting model when E_{DF} is minimized.

Fig. 2.13 visualizes some fitting results for defective and defect-free pixels. It is evident that the AASI shifting track of a defective pixel is closer to the defective fitting model f_D , so the discrepancy from f_D is smaller than that from f_{DF} . In contrast, the

AASI shifting track of a defect-free pixel has a tighter fit to the defect-free fitting model f_{DF} . Therefore, we propose the ratio of the two minimized RSS values

$$\varepsilon[K] = \frac{E_D}{E_{DF}} = \frac{\sum_{k=1}^K (x[k] - f_D(k))^2}{\sum_{k=1}^K (x[k] - f_{DF}(k))^2} \quad (2.29)$$

for judging whether the pixel is classified to be defective ($\varepsilon \leq T_\varepsilon$) or not ($\varepsilon > T_\varepsilon$), where T_ε is a classification threshold. The pseudocode of the fitting process for classification is presented in Algorithm 1. Fig. 2.14 plots E_D , E_{DF} , and ε along the iterations. As

Algorithm 1 Statistical fitting based classification

Input: AASI output sequence $x[k]$, predefined threshold T_ε .

Output: Classification result.

for each pixel **do**

 fit AASI output sequence by both f_D and f_{DF} ;

 substitute f_D and f_{DF} into Eq. (18) and Eq. (19), respectively;

$\min\{E_D\} \rightarrow \{a_1, b_1\}$, $\min\{E_{DF}\} \rightarrow \{a_2, b_2\}$;

 update f_D and f_{DF} with $\{a_1, b_1\}$ and $\{a_2, b_2\}$, respectively;

 substitute f_D and f_{DF} into Eq. (20);

if $\varepsilon \leq T_\varepsilon$ **then**

 this pixel is classified as defective;

else

 this pixel is classified as defect-free.

end if

end for

can be seen from this figure, since the increased iteration limit leads to the decreased ε and wider gaps between defective and defect-free fitting cases, the ε is preferable for setting reasonable threshold values. In our AASI procedure, the brightness of defective pixels and defect-free pixels are separated after many iterations as shown in Fig. 2.11. However, by utilizing these two fitting models, defective and defect-free pixels may be possibly distinguished by use of a reasonable threshold for classification after only a few iterations, reducing the computational cost. In addition, the proposed classification rules can effectively utilize AASI outputs along all of the iterations up to the iteration limit, so it is more stable and discriminative than any simple thresholding approaches at a particular iteration count.

2.3.7 Morphological Operation

It is notable that our AASI processes and then classifies each pixel independently. However, the human visual system (HVS) tends to understand visual content based on

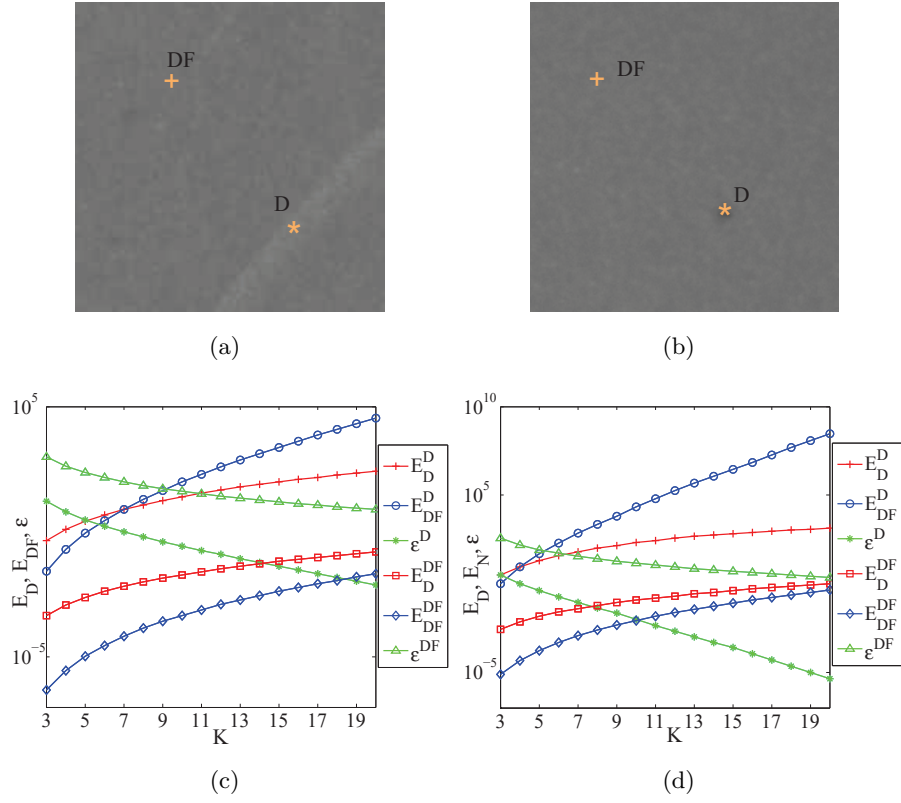
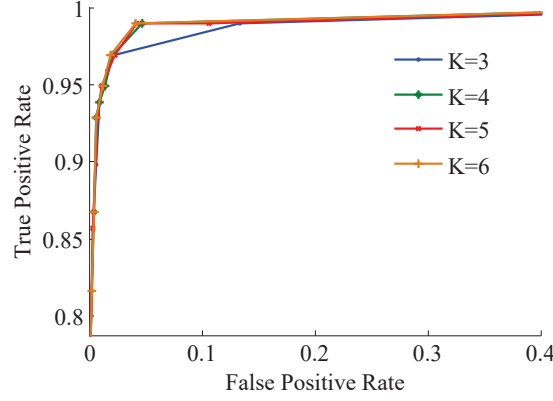


Figure 2.14: Residual values E_D , E_{DF} , and their ratio ϵ along iterations. (a) A defect-free pixel and a defective pixel in a scratch defect. (b) a defect-free pixel and a defective pixel in a spot defect. (c) and (d) show E_D , E_{DF} , and ϵ for the pixels in (a) and (b), respectively, in semi-log plot. In legends, the abbreviations “D” and “DF” represent defect and defect-free, respectively.

local structural primitives [63]. According to the bottom-up mechanisms in the human visual cortex, pixels may be grouped into coherent regions in the early vision stage. That is to say, defect may be understood as a region that contains defective pixels and very small amounts of defect-free pixels by the HVS. So it is common that any defect must be a region having its own size, shape, and position in the real industries. In order to bridge the gap between the pixel-based AASI and the region-based HVS, we utilize the closing morphological operator [64], which is applied to any binary image Y from AASI as

$$Y \cdot M = (Y \oplus M) \ominus M, \quad (2.30)$$

where “ $\oplus$ ” and “ $\ominus$ ” are the dilation and the erosion operator, respectively, and M is a 5×5 mask matrix here. The morphological operator fills the empty spaces inside a local region while preserving the boundary, making the detection results of AASI more consistent with the subjective perception results of the HVS.

Figure 2.15: ROC curves for different iteration limits K .

2.4 Parameter setting

2.4.1 Robustness against Changes in Iteration Limit

In this work, the computational complexity of fitting is related to the iteration limit of AASI. Generally, three points can estimate whether the data comply with a linear distribution or an exponential one. However, due to the effect of noise, three iterations may be insufficient to classify all pixels effectively. To find the optimal K , we plotted the ROC curves for varying iteration limit. As can be seen from Fig. 2.15, ROC curves are very close to each other except the one with $K = 3$. Taking both performance and computation time into consideration, iteration limit is set as $K = 4$ in the following experiments.

2.4.2 Selection of Threshold for Classification

In order to find reasonable values of T_ε , an experiment was conducted on 20 test samples, and the corresponding histograms of ε for defect-free pixels and defective pixels are shown in Fig. 2.16, where the ε values of defective pixels are similarly very small, while that of defect-free pixels are large, indicating that the proposed fitting-based classification rules can classify pixels effectively. However, due to the effects of noise, the histograms of ε of defective and defect-free pixels may be partially overlapped, as shown in Fig. 2.16 (c), resulting in two types of error in the hypothesis test, i.e., false labeling of defect-free pixels as defective and false labeling of defective pixels as defect-free. Therefore, T_ε can be determined by the practical requirement of these two errors. Here we set $T_\varepsilon = 1.2$, which is fixed in the following experiments.

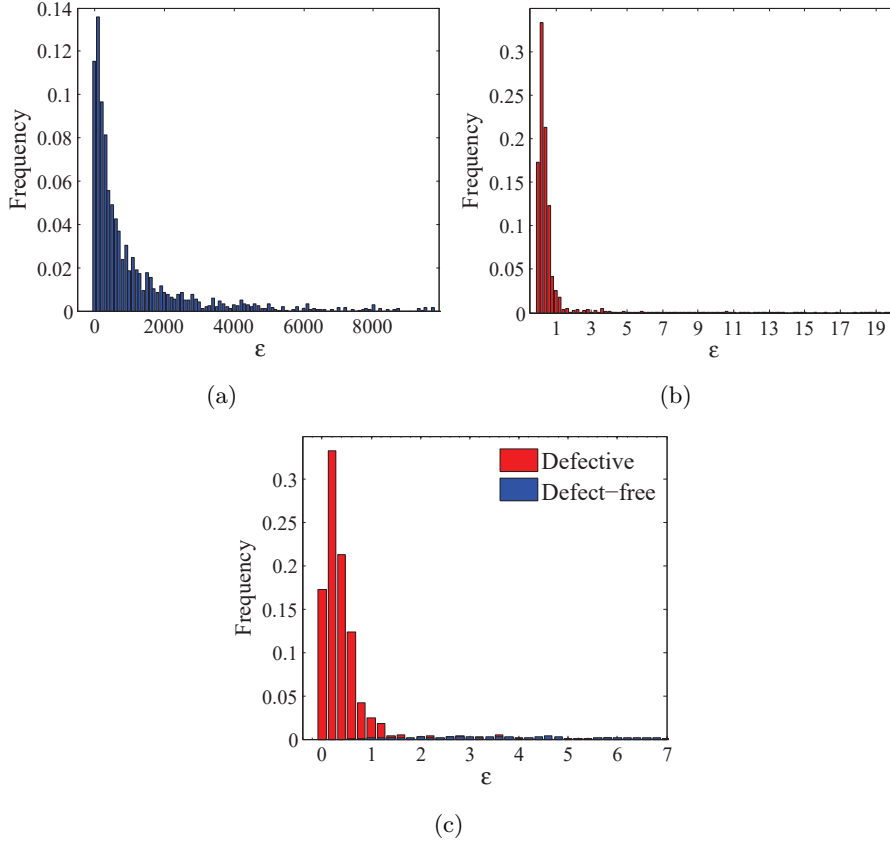


Figure 2.16: Histograms of ε for (a) defect-free pixels, and (b) defective pixels. (c) Partial enlargement of ε histograms with respect to defect-free and defective pixels.

2.4.3 Discussion about Threshold for Aggregation

As discussed above, with C_T increases, more defective pixels can be located, but the background noise is also enhanced. C_T is empirically set as 0.2 for balancing the detection performance and noises. In order to solve this problem more reasonably, we need theoretical derivation as a guidance. From the intensity distribution of defect-free background, it becomes possible to theoretically estimate the value of C_T . By substituting Eq. (3.12) into Eq. (2.15), we obtain

$$a(x_{ij}, x_{pq}) = \begin{cases} 1, & \text{if } \left| \frac{x_{ij} - x_{p,q}}{x_{ij} - x_{\text{mode}}} \right| \leq C_T \\ 0, & \text{otherwise} \end{cases}. \quad (2.31)$$

For defect-free background, the intensity follows Gaussian distribution, i.e., $x \sim G(\bar{x}, \sigma_x^2)$, and the mode intensity equals to the mean intensity, i.e., $x_{\text{mode}} = \bar{x}$. Therefore, $x - x_{\text{mode}} \sim G(0, \sigma_x^2)$, and the intensity difference of any two pixels follows Gaussian distribution with expected value 0 and variance $2\sigma_x^2$, i.e., $x_{ij} - x_{pq} \sim G(0, 2\sigma_x^2)$, where (i, j) and (p, q) are arbitrary coordinates of pixels, and $(i, j) \neq (p, q)$. In addition, it can be calculated that the covariance of $x_{ij} - x_{pq}$ and $x - x_{\text{mode}}$ equals to zero, i.e.,

$\text{cov}(x_{ij} - x_{pq}, x - x_{\text{mode}}) = 0$, so these two normal variables are independent. According to the property of Cauchy distribution, if two independent random variables obey Gaussian distribution with expected value 0, their ratio follows a Cauchy distribution, therefore,

$$\eta = \frac{x_{ij} - x_{pq}}{x - x_{\text{mode}}} \sim \text{Cauchy}(0, \sqrt{2}). \quad (2.32)$$

Then the probability of defect-free pixels possessing the intensity aggregation can be calculated by utilizing the pdf of a Cauchy distribution as

$$P_E = P(|\eta| \leq C_T | \text{defect-free}) = \int_{-C_T}^{C_T} p_c(\eta; 0, \sqrt{2}) d\eta, \quad (2.33)$$

where $p_c(\eta; 0, \sqrt{2}) = \frac{1}{\sqrt{2}\pi(1+\eta^2/2)}$.

The local intensity aggregation is the property of potential defective pixels. Therefore, P_E indicates the probability of defect-free pixels being falsely labeled as defective in our AASI procedure. With the practical request of this error loss, a reasonable threshold C_T can be obtained by

$$C_T = \sqrt{2} \tan\left(\frac{\pi}{2} P_E\right). \quad (2.34)$$

2.5 Summary

In this chapter, an accumulated and aggregated shifting of intensity (AASI) based framework was proposed to solve the problem of detecting defects on micro 3D textured surfaces. Firstly, we proposed two salient features to measure the saliency in pixel-level. These two features are further used to construct an iterative pixel-level enhancement procedure, which can iteratively shift intensity of each pixel according with its defective probability. And then, an original fitting-based classification rule was proposed. Two statistical models are utilized to judge whether each pixel in the given image is defective or not. Finally, the parameter setting was discussed. Our approach includes an iterative enhancement phase and a statistical classification phase, which is fully automatic and training-free.

From the viewpoint of pattern recognition, the goal of this method is to discover low-contrast defective patterns from micro 3D textured background. To achieve this goal, the proposed AASI procedure mainly consists of salient feature extraction, pixel-level image processing, and statistical-models-based pixel classification. The procedure follows a typical pattern recognition framework and provides novel concepts for the unique target of defect detection.

Chapter 3. AASI with Golden Template Picture (AASI-GTP)

In Chapter 2, the AASI method was proposed for defect detection on micro 3D textured surfaces. It is noting that here micro-3D is utilized to describe the geometrical property of textures embossed on the flat surface. In other words, AASI is proposed for flat surfaces embossed with random textures. However, real-world products usually have 3D shape, which are covered with curved surfaces. In this Chapter, we proposed an inspection framework for highly-reflective and curved surfaces. The flowchart is shown in Fig. 3.1. A multiple-pairwise reflective observation system is employed to capture all defects on the curved surface. The curved surface is divided into several nearly-flat parts based on the curvature radius. An illumination solution is then utilized to make defects visible on the nearly-flat surface. Then a set of images will be captured by multiple pairs of camera and light source, in which the shadows and highlights are eliminated. Finally, a novel procedure, called AASI-GTP, was developed to detect defects from those captured images. By utilizing golden template image, AASI-GTP can handle uneven background and illumination.

3.1 Changeling of defect detection on highly-reflective and curved surfaces

Inspecting objects with highly-reflective and curved surface are typical tasks of surface quality inspection in many industrial production processes. Tian *et al.* [65] presented-review of the surface measurement methods characterized by using active vision and light scattering techniques and then proposed a new integrative method for multi-parameter surface measurement. Zhang *et al.* [66] presented a vision system to automatize the detection and classification of surface defects due to the grinding and polishing processes. Sun *et al.* [67] proposed a real-time imaging and detection system for weld defects in steel tubes. Jia *et al.* [68] presented a real-time visual inspection system that uses support vector machine to automatically learn complicated defect patterns. Omar *et al.* [69] presented a system capable of selfadjusting its painting booth operation for an automotive fuel tank production, based on the defects detected by a real time inspection system. Norifumi *et al.* [70] presented a new method based on an optics model for highly

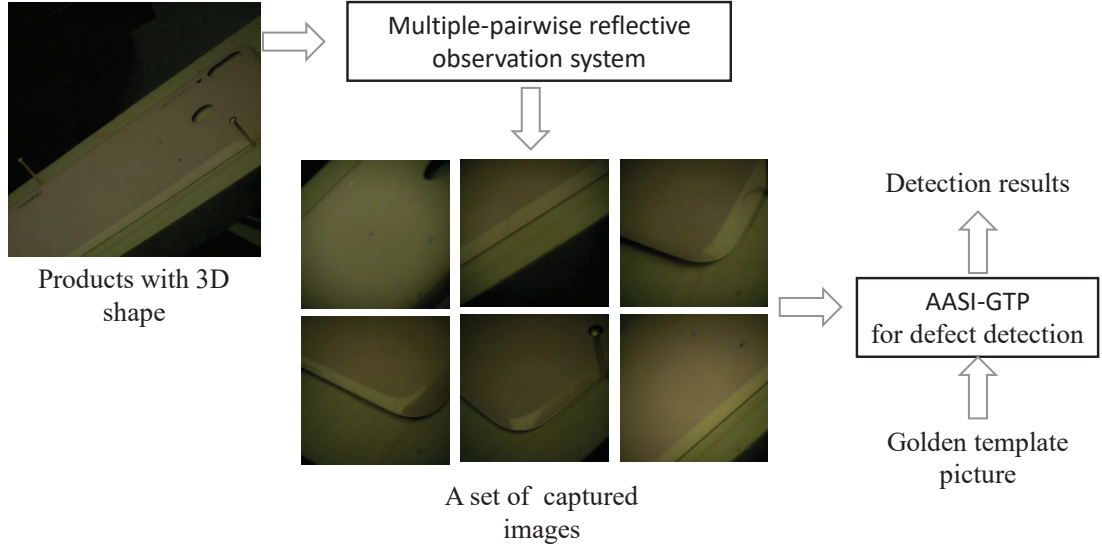


Figure 3.1: The workflow for defect detection on highly-reflective and curved surfaces.

reliable surface inspection of industrial parts.

There exist three particularly challenges for defect detection on highly-reflective and curved surfaces.

- **Uneven intensity:** curve surface has varied topography, making the intensity changed on the surface, as shown in Fig. 3.2 (a).
- **Masked defects:** there may exist highlighted regions on the surface, which will hidden the defects, as shown in Fig. 3.2 (b).
- **Sensitive to illumination direction:** defects on the highly-reflective and curved surface with very weak diffuse reflection are too sensitive to illumination direction to form recognizable information. The reason is that curve surface topography is complex and defect properties such as shape, direction, and location are complex and various.

3.2 Illumination solution for defect detection on highly-reflective plane

In this section, the reflection property of highly-reflective surface are first discussed. And then a novel illumination solution is investigated to capture defects on highly-reflective surfaces.

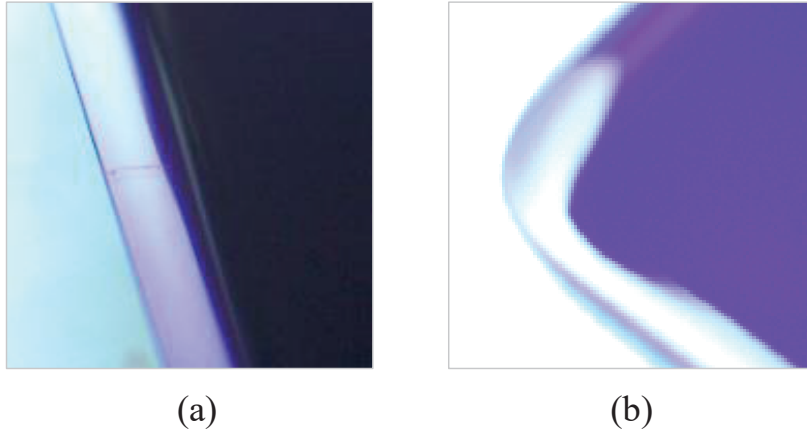


Figure 3.2: Typical examples of these challenges: (a) uneven intensity at the edge, and (b) highlights around the corner, which may make defects hidden.

3.2.1 Reflection Analysis on highly-reflective surface

Fig. 3.3 shows three typical cases of reflection on the surface [71].

- **Specular reflection:** it is also known as mirror reflection, in which each incident ray is reflected at the same angle to the surface normal as the incident ray, but on the opposing side of the surface normal in the plane formed by incident and reflected rays.
- **Diffuse reflection:** the ray incident on the surface is scattered at many angles rather than at just one angle as in the case of specular reflection.
- **Specular reflection reflected two or more times:** it occurs in the case of material smaller in size than the wavelength of the incident ray.

On the highly-reflective surface, there mainly exists specular reflection. The diffuse reflection on it is very weak. Here we only consider the influence of specular reflection.

3.2.2 Illumination solution for defect detection

As shown in Fig. 3.4 (a), each incident ray on the highly-reflective plane is reflected at the same angle to the plane normal as the incident ray. Therefore, by choosing a proper angle and pose configuration of camera, the plane can be captured as a very bright image. However, the direction of reflected ray may be changed if there exist defects on the plane, as shown in Fig. 3.4 (b). This is due to the fact that the topography of defective region is changed. Motivated by this phenomena, a illumination solution for defect detection on the highly-reflective plane is designed. The camera is fixed at the same angle to the plane normal as the incident ray, but on the opposing side of the

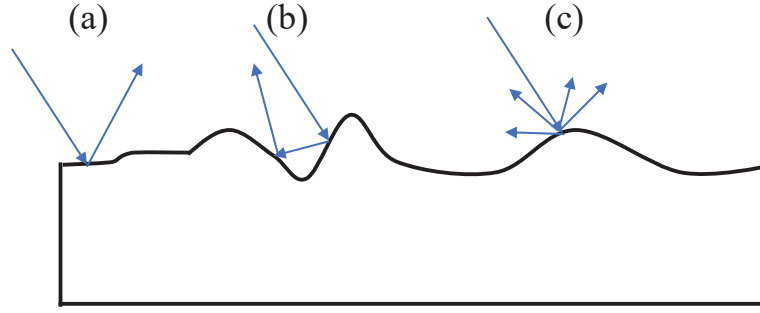


Figure 3.3: Typical cases of reflection on the surface: (a) specular reflection, (b) diffuse reflection, and (c) specular reflection reflected two or more times.

surface normal in the plane. Under such condition, the reflection ray from defective region is distinctly different from defect-free region. Defect-free region in the captured image will be very bright, while the defect will be dark, making the defect highlighted.

3.3 Multiple-pairwise reflective observation system

As discussed above, the proper illumination and observation directions is helpful for visualizing defects on the highly-reflective plane. However, for a curved surface, topography is varied, so that it is impossible to observe a 3D-shaped product from one direction. In addition, it is difficult to make all defects visible under illumination with one direction. Strong specular reflection may make defects covered in highlighted regions, and weak diffuse reflection may lead defects having low contrast with defect-free region. In order to capture all defects on a curved surface, a multiple-pairwise reflective observation system is proposed in this section, as shown in Fig. 3.5.

- The curved surface is regarded as combination of several planar surfaces according to the curvature radius of the surface.
- Multiple light sources and cameras are utilized to capture a set of images, respectively. Each nearly planar surface is illuminated and viewed by a separate pair of light source and camera. By selecting proper directions and pose configuration, all defects can be observed while the shadows are eliminated in target region.
- Diffusion plate is utilized to transmit rays from light source to target region, making all reflected rays reach the camera.

3.3.1 The mathematical model

G. Rosati *et al.* [73] proposed a mathematical model to calculate the maximum size of the inspected area as a function of the curvature of the surface and of system

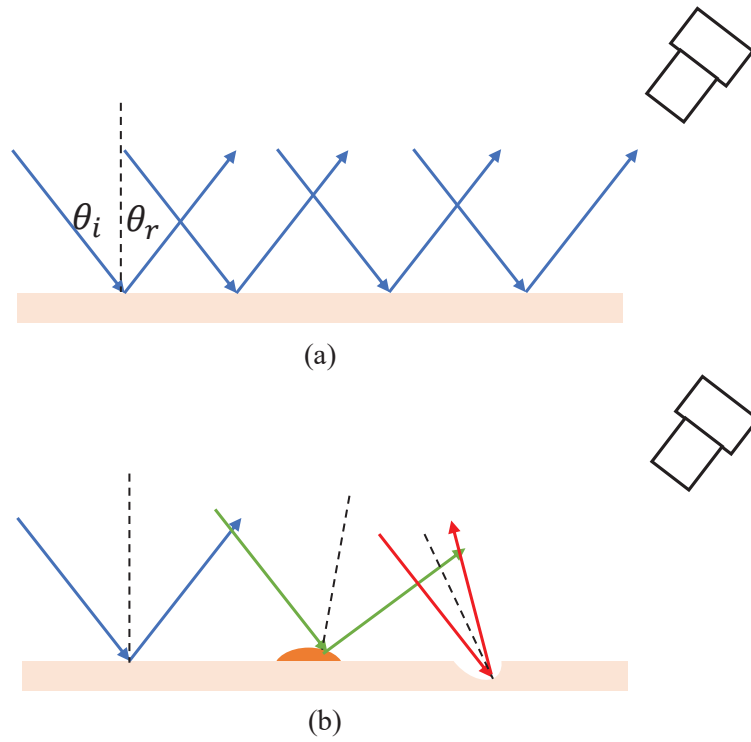


Figure 3.4: Specular reflection on the highly-reflectively plane: (a) defect-free surface, (b) surface with defects.

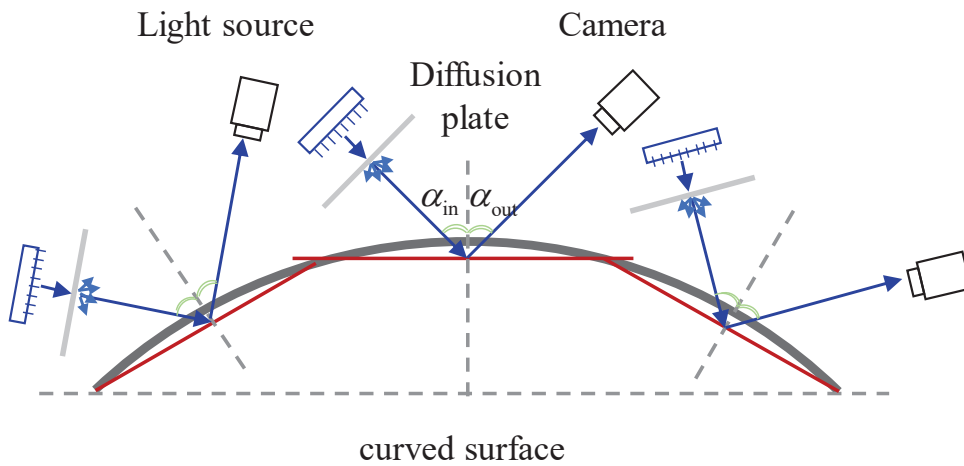


Figure 3.5: Multiple-pairwise reflective observation system.

parameters. For this purpose, a cylindrical object is considered. Fig. 3.6 shows the layout of observation system. The light source, which is not shown in this figure, will be placed behind the diffusion plate. The diffusion plate is assumed to make the diffused light reflection, while the inspected object with highly-reflective surface is assumed to make a perfect specular reflection.

Let O' be the leftmost illuminated point on the transverse section on the cylinder, as shown in Fig. 3.6. This point will be irradiated by the leftmost point of the diffusion plate (point D), from which a light ray will be generated toward O' and then reflected by the object toward to the focus of the camera. According to the optical geometry laws, the incident and the reflected rays will form the same angle with the normal to the object surface in O' . The y coordinate of point O' can be denoted as

$$-y_{O'} = \tan \beta \cdot [H + R \cdot (1 - \cos \alpha)] = R \sin \alpha, \quad (3.1)$$

where R is the radius of the cylinder, H is the distance between the focus of the camera and the object. And the angle α and β are the ones shown in the bottom scheme of Fig. 3.6. By rearranging Eq. 3.3, we can obtain an explicit expression of angle β as a function of H , R , and angle α , i.e.,

$$\beta = \arctan \left[\frac{R \sin \alpha}{h + R \cdot (1 - \cos \alpha)} \right]. \quad (3.2)$$

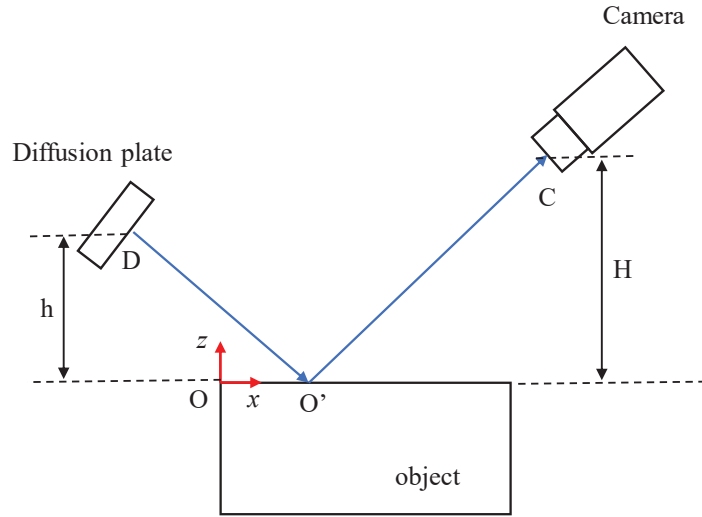
Therefore, for a given position of the diffusion plate, we can calculate the width of the diffusion plate which allows to illuminate a desired portion of the cylinder (α) by

$$L = 2 \{ R \sin \alpha + [H + R \cdot (1 - \cos \alpha)] \cdot \tan (\beta + 2\alpha) \}. \quad (3.3)$$

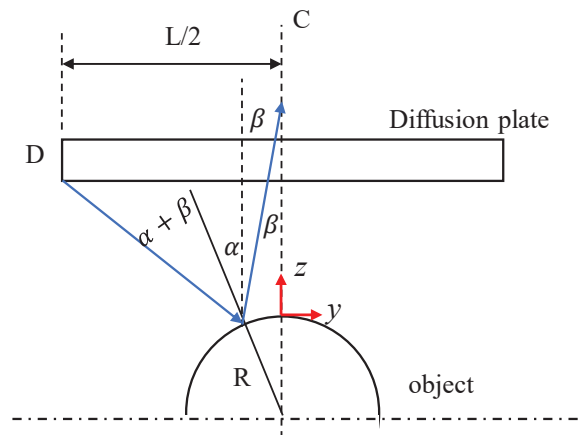
In other words, we obtain the explicit expression of diffusion plate width L as a function of object radius R and inspection angle 2α , at a given height of the camera (denoted as H) and of the diffusion plate (denoted as h).

3.3.2 The 3D layout of observation system

We investigate the 3D layout of observation system for a cellphone surface as an example. According to the curvature radius of the cellphone, its surface can be divided into three types: flat surface, edges, and corners. Since corner has complex curvature radius, it can be further divided into three parts, as shown in Fig. 3.8. Each parts of cellphone surface is separately observed by a pair of illumination and camera. A sketch map of imaging system is shown in Fig. 3.7. As can be seen from Fig. 3.7, the space coordinate systems of whole imaging system, product, camera, and illumination, are designed respectively. A corner of the product is set as the origin of the public coordinate system, marked as "O". And the central points of product, camera, and illumination are marked as "P", "I", and "C", respectively. Their coordinates in space for different types of surfaces from cellphone are listed in Table 3.1. In addition, Table 3.2 shows



(a)



(b)

Figure 3.6: The mathematical model of observation system: (a) xoz plane view, and (b) yoz plane view.

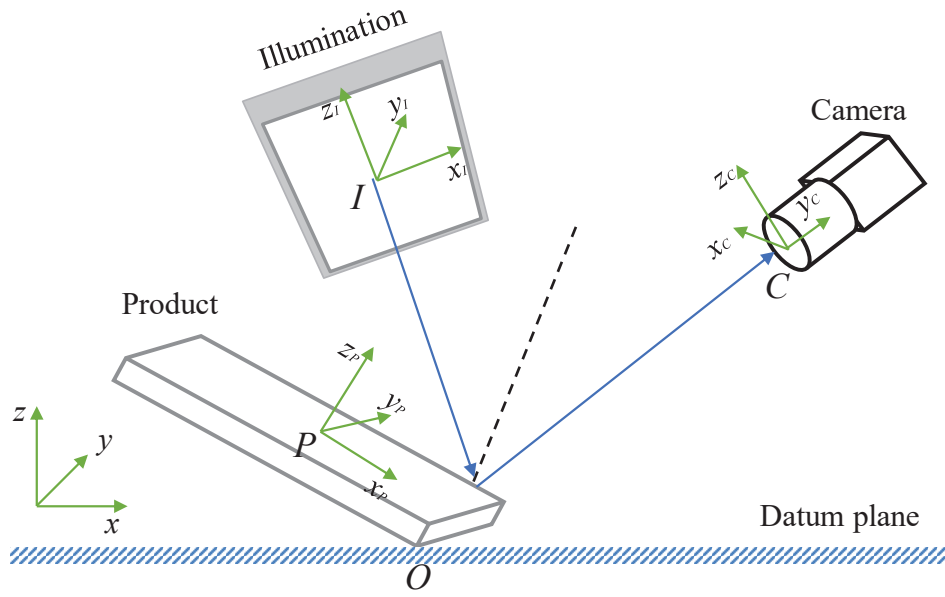


Figure 3.7: The sketch map of imaging system.

their angles with public coordinate systems. Based on these numerical information, a transformation matrix between coordinate systems can be calculated. Finally, we can obtain the 3D layouts of observation system for the overall cellphone surface, as shown from Fig. 3.9 to Fig. 3.13. The position, angle, and pose of elements varied with different types of surfaces. Some captured images are shown in Fig. 3.14. As can be seen from Fig. 3.14, the target region is brighter than other parts. Defects in target region are visible. In addition, shadows and highlights are eliminated, reducing the difficulty of defect detection.

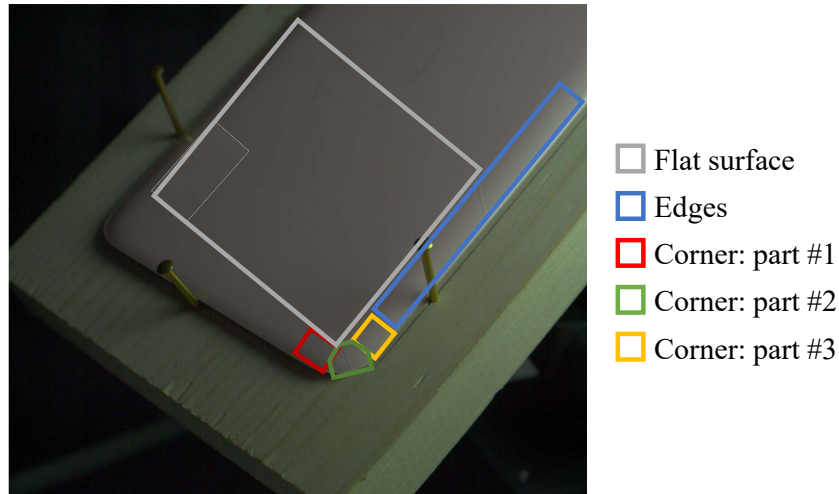


Figure 3.8: The cellphone surface can be divided based on its curvature radius into five parts: flat surface, edge, corner 1, corner 2, and corner 3.

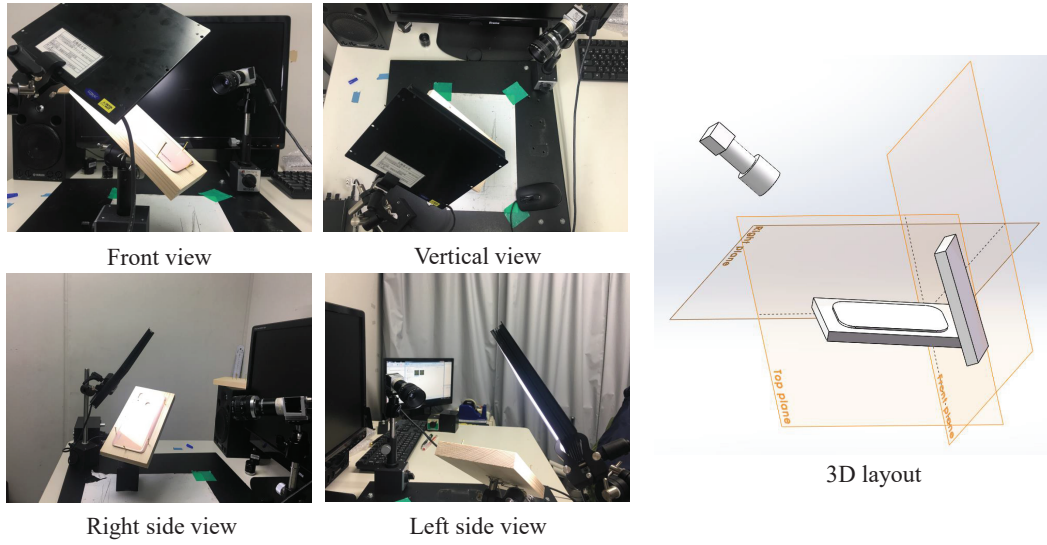


Figure 3.9: The 3D layout of observation system for flat surface.

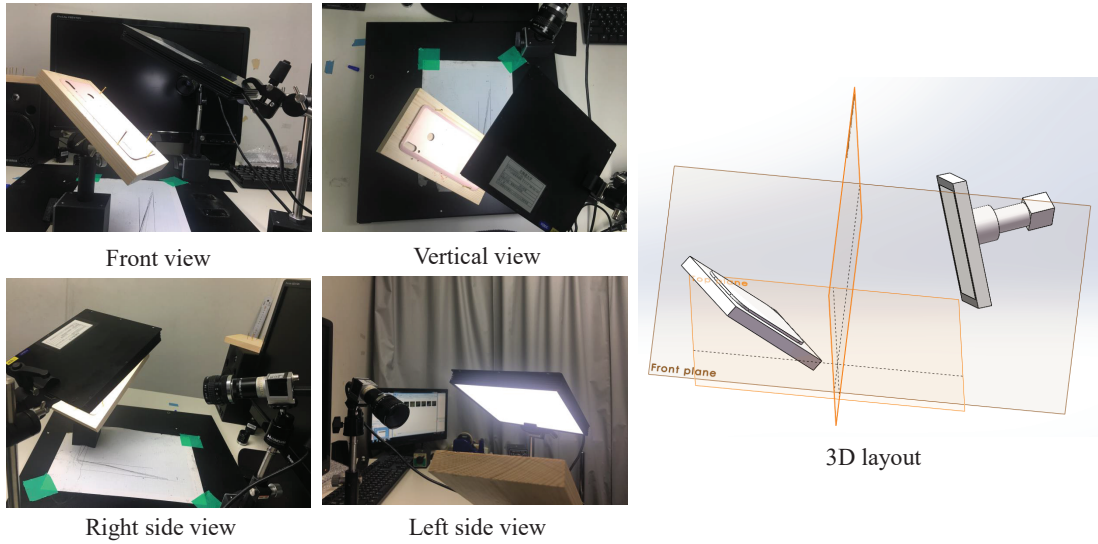


Figure 3.10: The 3D layout of observation system for edge.

Table 3.1: Coordinates of central point in space

Types	Product	Camera	Illumination
Flat surface	$(-3.3, 8.4, 5.4)$	$(13.4, 26.2, 13)$	$(-6.6, 4.3, 17.3)$
Edge	$(-4.5, 8.7, 5.4)$	$(9.5, 24.6, 13)$	$(11.3, 7.6, 15)$
Corner #1	$(-10.2, 1.6, 5.4)$	$(8.8, 21.3, 12.5)$	$(-7.3, 15.5, 11)$
Corner #2	$(-10.2, 1.6, 5.4)$	$(10.4, 23.3, 12.5)$	$(10.5, 3.2, 14.8)$
Corner #3	$(-10.2, 1.6, 5.4)$	$(14, 20.2, 12)$	$(13, 11.7, 10)$

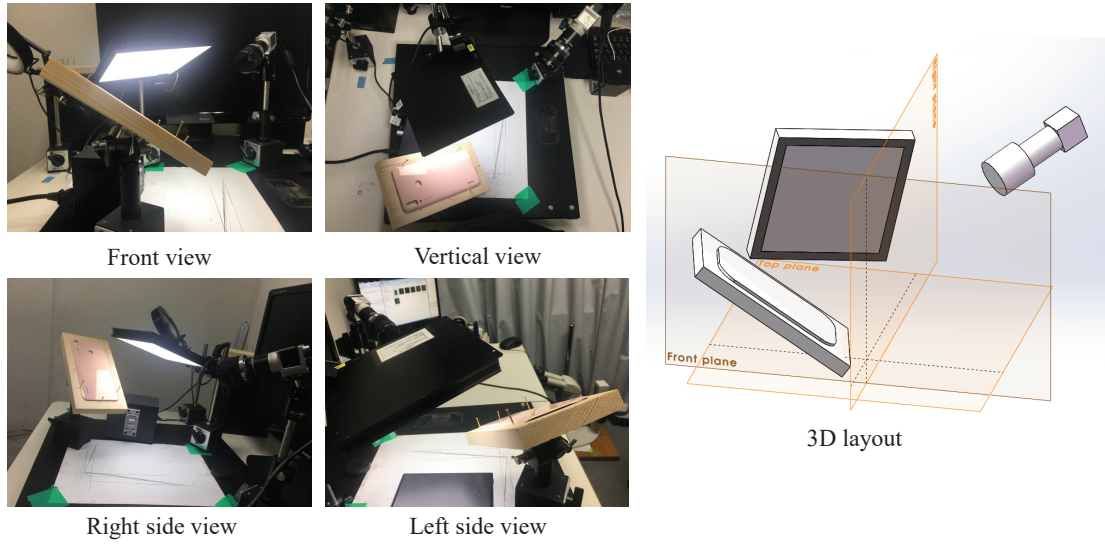


Figure 3.11: The 3D layout of observation system for part #1 of corner.

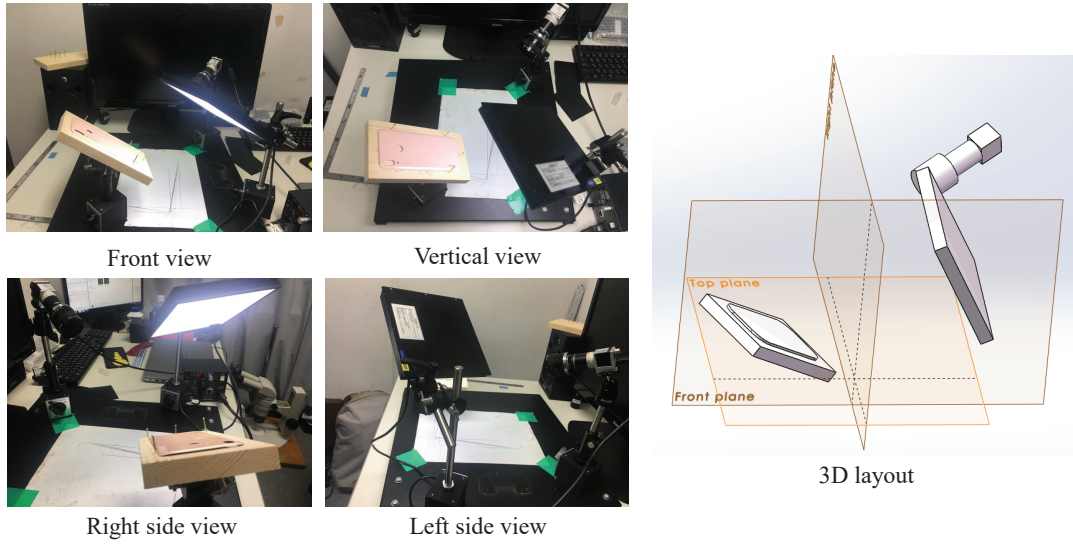


Figure 3.12: The 3D layout of observation system for part #2 of corner.

Table 3.2: Angles with public coordinate surfaces

Types	Product	Camera	Illumination
Flat surface	$(37^\circ, 82^\circ, 123^\circ)$	$(11^\circ, 87^\circ, 80^\circ)$	$(54^\circ, 36^\circ, 88^\circ)$
Edge	$(37^\circ, 82^\circ, 54^\circ)$	$(20^\circ, 70^\circ, 81^\circ)$	$(24^\circ, 79^\circ, 114^\circ)$
Corner #1	$(37^\circ, 99^\circ, 58^\circ)$	$(22^\circ, 73^\circ, 99^\circ)$	$(14^\circ, 48^\circ, 57^\circ)$
Corner #2	$(37^\circ, 99^\circ, 58^\circ)$	$(22^\circ, 70^\circ, 102^\circ)$	$(36^\circ, 92^\circ, 57^\circ)$
Corner #3	$(37^\circ, 99^\circ, 58^\circ)$	$(25^\circ, 65^\circ, 81^\circ)$	$(75^\circ, 81^\circ, 156^\circ)$

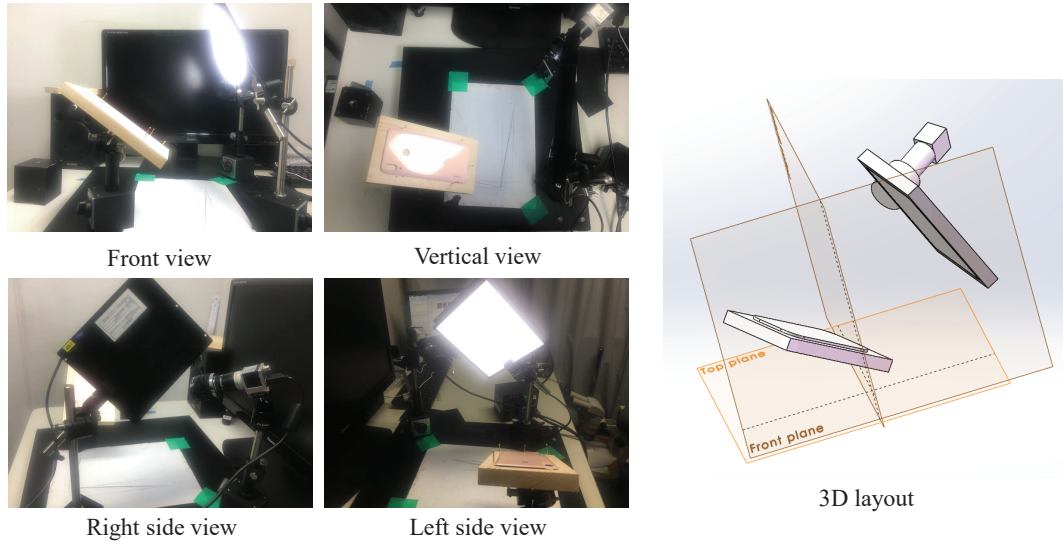


Figure 3.13: The 3D layout of observation system for part #3 of corner.

Table 3.3: The system parameters of the cellphone surface imaging.

Element	Parameter
Pixel pitch (um)	5.5×5.5
Focal length (mm)	25
Resolution (mm/pixel)	29
Illumination intensity (W)	130
Number of Illumination and camera	16
Die size (pixel)	300×300
Die number	51

Table 3.3 shows the parameters of imaging system for the cellphone surface inspection. As can be seen from Table 3.3, 16 groups of camera and illumination are utilized to capture all defects on the cellphone surface. The captured images are divided into 51 dies. All dies have the size of 300×300 pixels and the resolution of 29 mm/pixel. The intensity of a die is gradually changed. The remaining task is conducting defect detection on these dies.

3.4 AASI-GTP for defect detection

Since the intensity of curved surfaces shows big difference, the original AASI is powerless for such surfaces. In this section, the golden template picture is introduced to remove the intensity unevenness of defect-free background. The so called “golden template picture” can be regarded as a defect-free template captured under the same illumination condition as defective samples.

Follow the image formation theory [72, 73], an test image x can be separated into

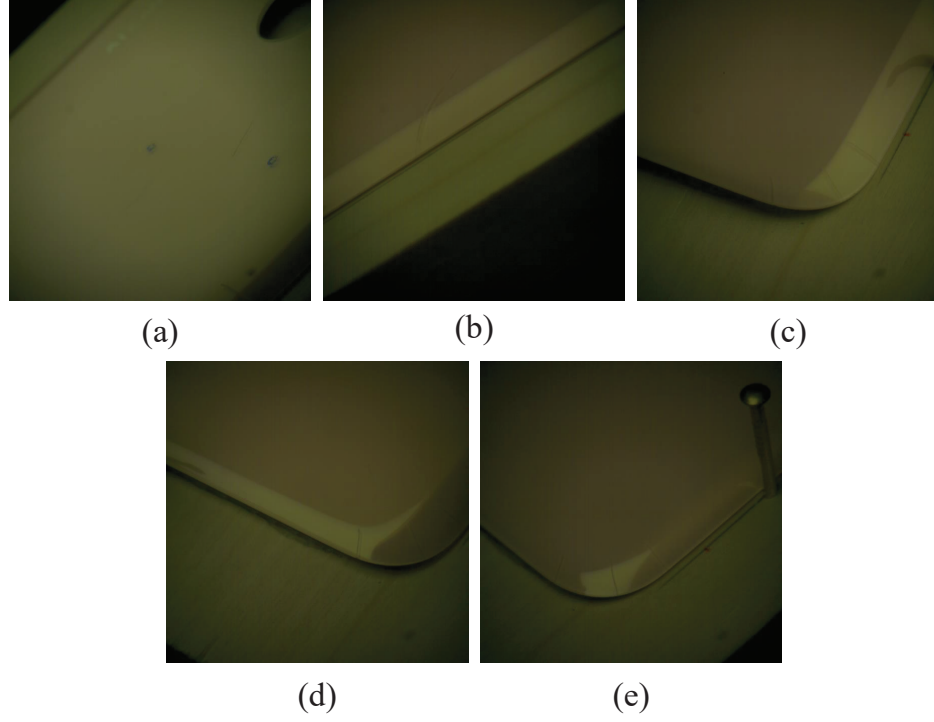


Figure 3.14: Captured images of (a) flat surface, (b) edge, (c) part #1 of corner, (d) part #2 of corner, (e) part #3 of corner.

two sub-images as

$$x = L \cdot R, \quad (3.4)$$

where

- L is the illumination image, which depends on the light source;
- R is the reflectance image, which is related to the characteristic of surface.

Since the golden template picture GTP is captured under the same condition with x , it can be similarly expressed as

$$\text{GTP} = L_{\text{GTP}} \cdot R_{\text{GTP}}, \quad (3.5)$$

where

- L_{GTP} is the illumination image of golden template picture, and $L_{\text{GTP}} = L$;
- R_{GTP} is the reflectance image of golden template picture.

Thus the difference between test image x and golden template picture GTP can be calculated as

$$|x - \text{GTP}| = L \cdot |R - R_{\text{GTP}}|, \quad (3.6)$$

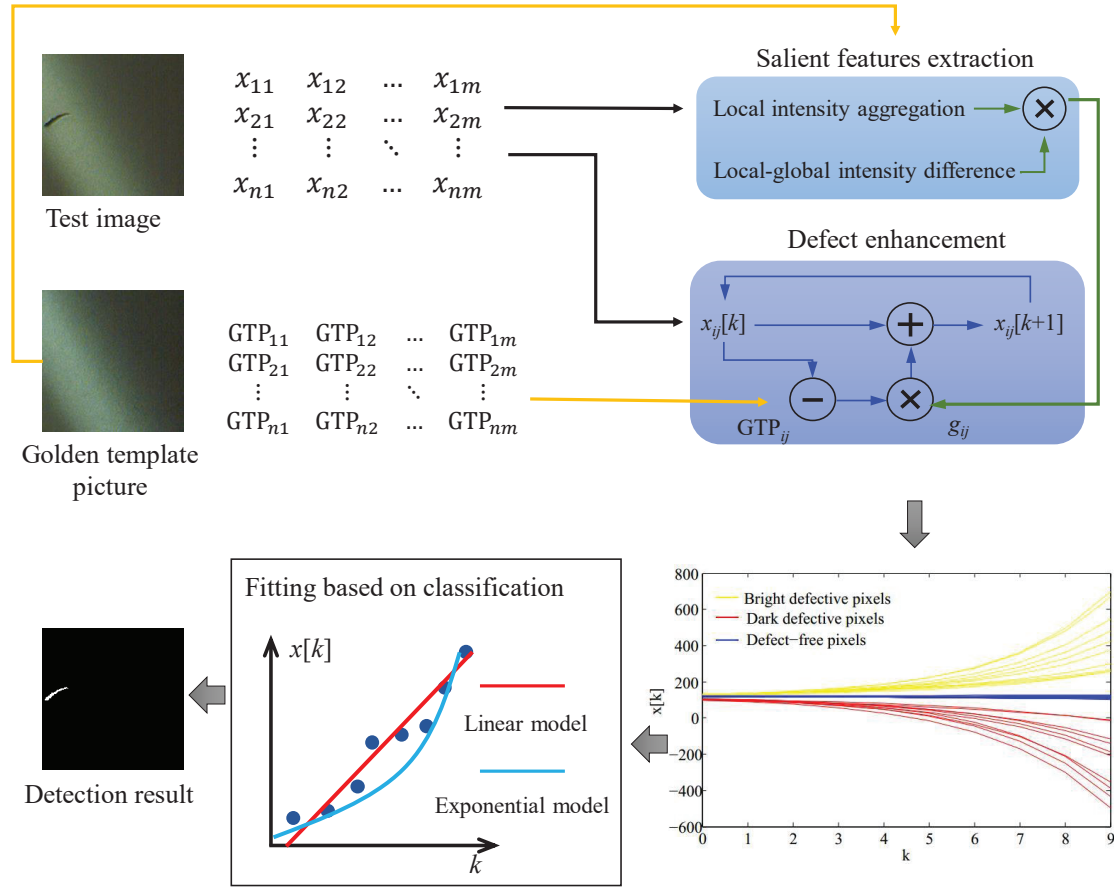


Figure 3.15: Graphical illustration of the proposed AASI-GTP method for defect detection.

where $|R - R_{GTP}|$ is depending on the characteristic difference between the test sample and golden template. Since test sample and golden template share the same 3D shape, textures, and surface materials, the only difference is there may be defects on the sample surface. The value of $|x - GTP|$ is close to zero for defect-free pixels, while that of defective pixels may be large. So $|x - GTP|$ can be related to defective probability.

From another perspective, the value of $|x - GTP|$ is close to zero for defect-free pixels, so GTP can be regarded as the background intensity, i.e., the intensity of defect-free pixels. It is notable that GTP is not a single value, but an image of the same size as the test image. The mode intensity in AASI can not represent the intensity of defect-free background if the intensity shows unevenness on the background. By introducing GTP instead of mode intensity, the original AASI procedure can be improved as follows.

Firstly, the absolute intensity deviation between the pixel located at coordinate (i, j) and the background intensity can be calculated by

$$r'_{ij} = |x_{ij} - GTP_{ij}|. \quad (3.7)$$

To bring the value of absolute intensity deviation into the range $[0, 1]$, the normalized absolute intensity deviation is defined as

$$\hat{r}'_{ij} = \frac{r'_{ij} - r'_{\min}}{r'_{\max} - r'_{\min}} \quad (3.8)$$

where $r'_{\max}$ and $r'_{\min}$ indicate the maximum and minimum values of r' in the initial image, respectively. Generally, a larger $\hat{r}'_{ij}$ indicates higher defect probability. And then, the local intensity aggregation of pixel located at position (i, j) is calculated as

$$A_{ij} = \sum_{pq} w_d(x_{ij}, x_{pq}) \times a'(x_{ij}, x_{pq}), \quad (3.9)$$

$$a'(x_{ij}, x_{pq}) = \begin{cases} 1, & \text{if } |x_{ij} - x_{pq}| \leq T_x \\ 0, & \text{otherwise} \end{cases}, \quad (3.10)$$

where x_{pq} , w_d , and T_x are one of neighboring pixels, distance weight, and aggregation threshold, respectively.

The distance weight w_d is defined with a Gaussian kernel [61] as

$$w_d(x_{ij}, x_{pq}) = \Omega_{ij} \cdot \exp\left(\frac{-d(x_{ij}, x_{pq})^2}{2 \times \sigma^2}\right), \quad (3.11)$$

where $d(x_{ij}, x_{pq}) = \sqrt{(i-p)^2 + (j-q)^2}$, σ is the scale parameter set as $\sigma = 3$ in the case of 5×5 neighborhood, and finally Ω_{ij} is a normalization coefficient, which ensures the sum of distance weights from neighboring pixels equals 1, i.e., $\sum_{p,q} w_d(x_{ij}, x_{pq}) = 1$.

As discussed above, the local intensity aggregation for a defective region is related to its contrast, so the threshold T_x is adapted to the absolute intensity deviation as

$$T_x = C_T r'_{ij}, \quad (3.12)$$

where C_T is a constant coefficient. As it increases, more defective pixels can be located, but background noise also increases. To address this problem, C_T is empirically set as 0.2 for balancing the detection performance and noises.

Finally, the shifting framework of AASI with golden template image (AASI-GTP) is defined as

$$x[k+1] = x[k] + (\hat{r}' \cdot A)(x[k] - x_{\text{mode}}). \quad (3.13)$$

Here the suffix ij is omitted for simplicity.

A graphical illustration of AASI-GTP is shown in Fig. 3.15. Two salient features, local-global intensity deviation and local intensity aggregation, are firstly calculated based on the test image and golden template to measure the saliency at the pixel level. These two features and the golden template image are further used to construct iterative enhancement procedure, which iteratively shifts the intensity of each pixel depending on

its saliency, i.e., defect probability. The output sequence along iterations of defective pixels follows an exponential function, while that of defect-free pixels can be formalized as a linear function. So the detection result can be obtained through fitting to two statistical models. By employing the golden template image to represent the intensities of defect-free pixels, AASI-GTP is expected to detect defects on curved and highly-reflective surfaces.

3.5 Summary

In this chapter, an improved AASI approach with golden template picture was proposed for defect detection on curved and highly-reflective surfaces. Firstly, we analyzed the reflection property of highly-reflective surfaces and investigated an illumination solution to make defects visible on highly-reflective plane. And then, a multiple-pairwise reflective observation system was introduced. Multiple-pairwise cameras and diffused lights are fixed in specific positions and directions to capture all defects on the whole curved surfaces while avoiding shadows and highlights. A set of images were obtained. Finally, the golden template picture (GTP) was introduced to detect defects from these images. The mode intensity is replaced with the intensity of GTP, making the developed AASI-GTP effective for curved surfaces with uneven illumination.

Chapter 4. Experimental Evaluation

4.1 Dataset

4.1.1 Micro 3D textured surfaces

The dataset is from real-world industrial products, which consists of 165 test images captured under three different illumination conditions. All test images have the size of 200×200 pixels and the resolution of 29 pixel/mm, of which 80% are defective, and another 20% are defect-free, as shown in Fig. 4.1. The whole dataset can be downloaded at <https://hce.ist.hokudai.ac.jp/cloud/index.php/s/kRbF25pNd0mKzeX>.

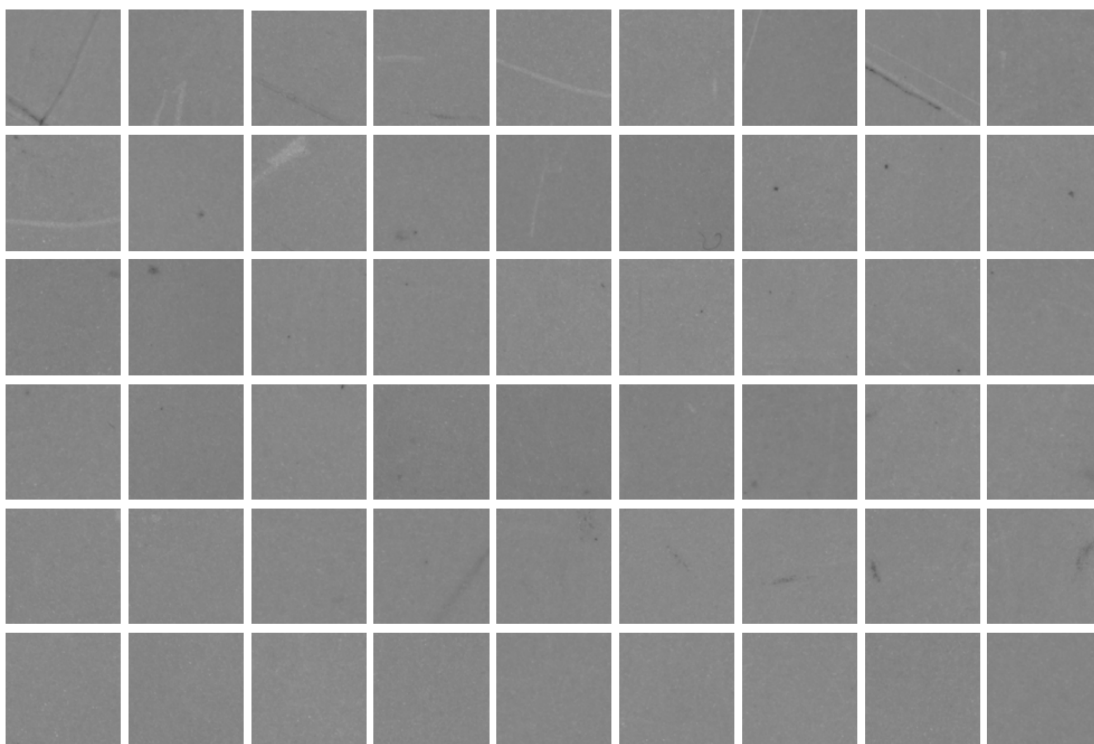


Figure 4.1: Test images of 3D micfo textured surfaces captured from real-world industrial products under normal illumination.

Defects on embossed surfaces have various shapes, sizes and contrasts. Fig. 4.2 shows five representative examples:

- scratches usually occur as long, thin lines;

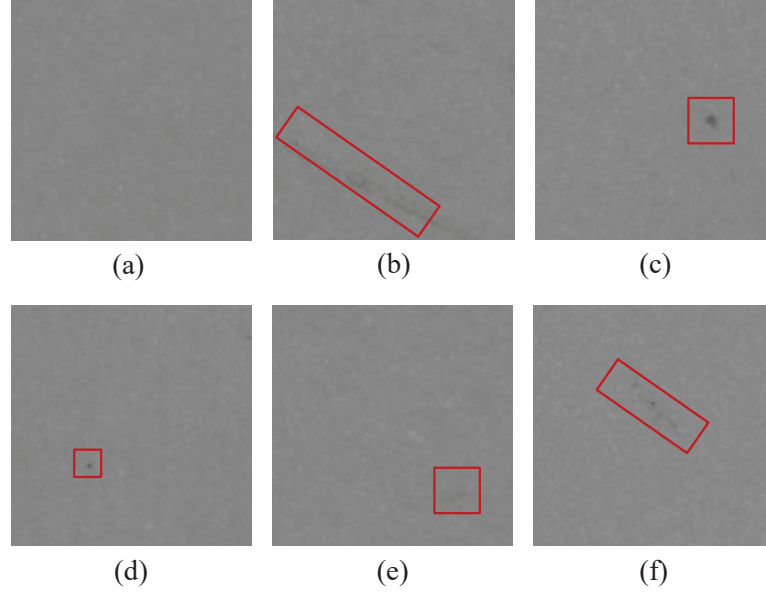


Figure 4.2: Representative types of defect on 3D micro textured surfaces: (a) defect-free sample, (b) scratch defect, (c) spot defect, (d) micro defect, (e) low-contrast defect, and (f) diffused defect.

- spots are continuous, lumped, and nearly circular or square in shape;
- micro defects are very small in size (less than 5×5 pixels) and are easily confused with inherent grains on the embossed surfaces;
- low-contrast defects have intensities that are very close to their surroundings and unclear boundaries;
- diffused defects often occur as near disposed discontinuities.

In addition, for each test image, the pixel-level ground truth is manually marked by using “1” to denote defective pixels and “0” to denote defect-free pixels.

4.1.2 Metal-coated surfaces

The metal-coated dataset is also from real-world industrial products. There are three sets of products, as shown in Fig. 4.3. Each set includes several samples, and among them one is defective, and others are defect-free. The ID number amount of each sample is shown in Table 4.1.

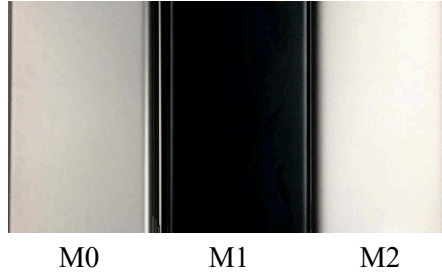


Figure 4.3: Metal-coated surfaces with three sets.

Table 4.1: The ID number of metal-coated surfaces

Set	Amount	Number
M0	3	M-00-00, M-00-01, M-00-02
M1	5	M-01-00, M-01-01, M-01-02, M-01-03, M-01-04
M2	6	M-02-00, M-02-01, M-02-02, M-02-03, M-02-04, M-02-05

4.1.3 Glass-like surfaces

The glass-like dataset were captured from 22 industrial products, which have different colors and shapes, as shown in Fig. 4.4. These products were divided into six sets according to their models, and each set includes several samples. Among them one is defective, and others are defect-free. The ID number and amount of each sample is shown in Table 4.2.

4.2 Analysis measurements

To evaluate the performance quantitatively, three widely used measures [74] are utilized, which are defined as

$$\text{Precision} = \frac{TP}{TP + FP}, \quad (4.1)$$

$$\text{Recall} = \frac{TP}{TP + FN}, \quad (4.2)$$

$$\text{F-measure} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}, \quad (4.3)$$

where

- TP is the number of true positive pixels in detection result;
- FP is the number of false positive pixels in detection result;
- FN is the number of false negative pixels in detection result.

True positive, *false positive*, *true negative* and *false negative* are four possible outcomes in an instance. Since our target is defect detection, we define defective pixels as

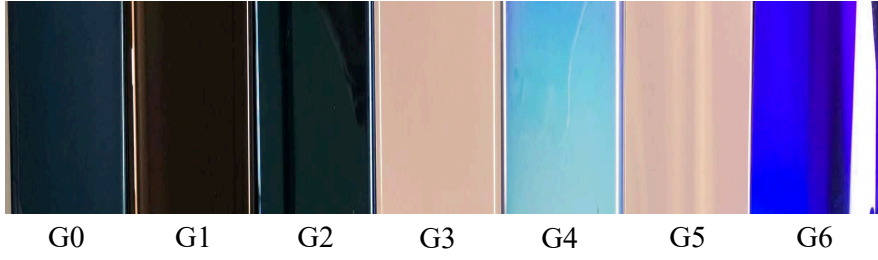


Figure 4.4: Glass-like surfaces with six sets.

Table 4.2: The ID number of glass-like surfaces

Set	Amount	Number
G0	3	G-00-00, G-00-01, G-00-02
G1	2	G-01-00, G-01-01
G2	2	G-02-00, G-02-01
G3	4	G-03-00, G-03-01, G-03-02, G-03-03
G4	3	G-04-00, G-04-01, G-04-02
G5	3	G-05-00, G-05-01, G-05-02
G6	2	G-06-00, G-06-01

positive pixels, and defect-free pixels as negative pixels. If the pixel is defective and it will be classified as defective, it is counted as a true positive; if it is classified as defect-free, it is counted as a false negative. If the pixel is defect-free and it will be classified as defect-free, it is counted as a true negative; if it is classified as defective, it is counted as a false positive. Fig. 4.5 shows an abridged general view of the analysis measurements: *Precision* and *Recall*. Through Fig. 4.5, *Precision* can be seen as a measure of exactness for defect detection and *Recall* can be seen as a measure of completeness of detection. The F-measure indicator comprehensively considers recall and precision. Larger F-measure indicates higher performance.

4.3 Experimental results

4.3.1 Performance on micro 3D textured surfaces

The proposed AASI is compared with existing unsupervised methods, including anisotropic diffusion model [43] and phase only transform (PHOT) algorithm [30]. Typical detection results by these methods are shown in Fig. 4.6. From top to bottom we have the test images, the ground truths, the results of Diffusion [43], PHOT [30], AASI, and AASI with the morphological operator (AASIM). One can found that PHOT can not achieve good performance in detecting scratches, as listed in Fig. 4.6 (a) and (b). Because PHOT utilizes a two-dimensional DFT to transform inputs, which has a behavior to remove one-dimensional defects. As shown in Fig. 4.6 (b), diffusion model is

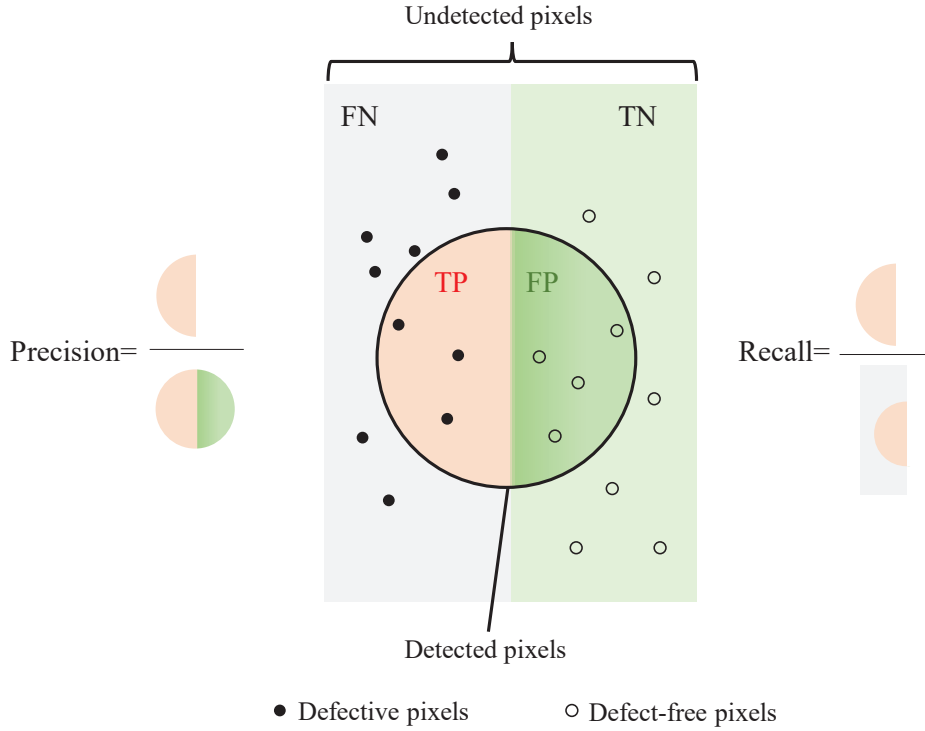


Figure 4.5: Abridged general view of the analysis measurements.

somewhat weaker for low-contrast scratch, because it smooths low-gradient pixels within a small region, making the intensity of scratch similar to that of adjacent defect-free region. In addition, diffusion model has an expansion effect on defects to some degree, because of its inherent diffusion principles. That is to say, defect-free regions adjacent to defective regions are easily misclassified. One can see from Fig. 4.6 (h), diffused defect is regarded as continuous abnormality in Diffusion model. Compared to these methods, the proposed AASI and AASIM, iterative procedures with pixel-level saliency enhancement, are more accurate and able to detect defects with different shapes, sizes, and contrasts. In addition, the morphological operator fills “holes” inside defects while preserving boundaries, which could further enhance the performance of AASI.

The quantitative evaluation results in pixel level are shown in Table 4.3. The overall results on 150 samples are reported in the last row. And the best records are marked in bold. On one hand, AASI shows a clear advantage over Diffusion and PHOT in terms of Precision, demonstrating the accuracy of it. This is due to the fact that defect-free pixels are rarely misclassified by our AASI procedure. On the other hand, AASI does not show high Recall values because of its pixel-by-pixel classification behavior, which gives rise to holes inside detection results. By employing the “closing” morphological operator to bridge the gap between the pixel-level AASI and the region-level HVS, AASIM improves the performance in terms of Recall, while inheriting the strengths of AASI in terms of Precision. Taking both of Precision and Recall into consideration, AASIM outperforms

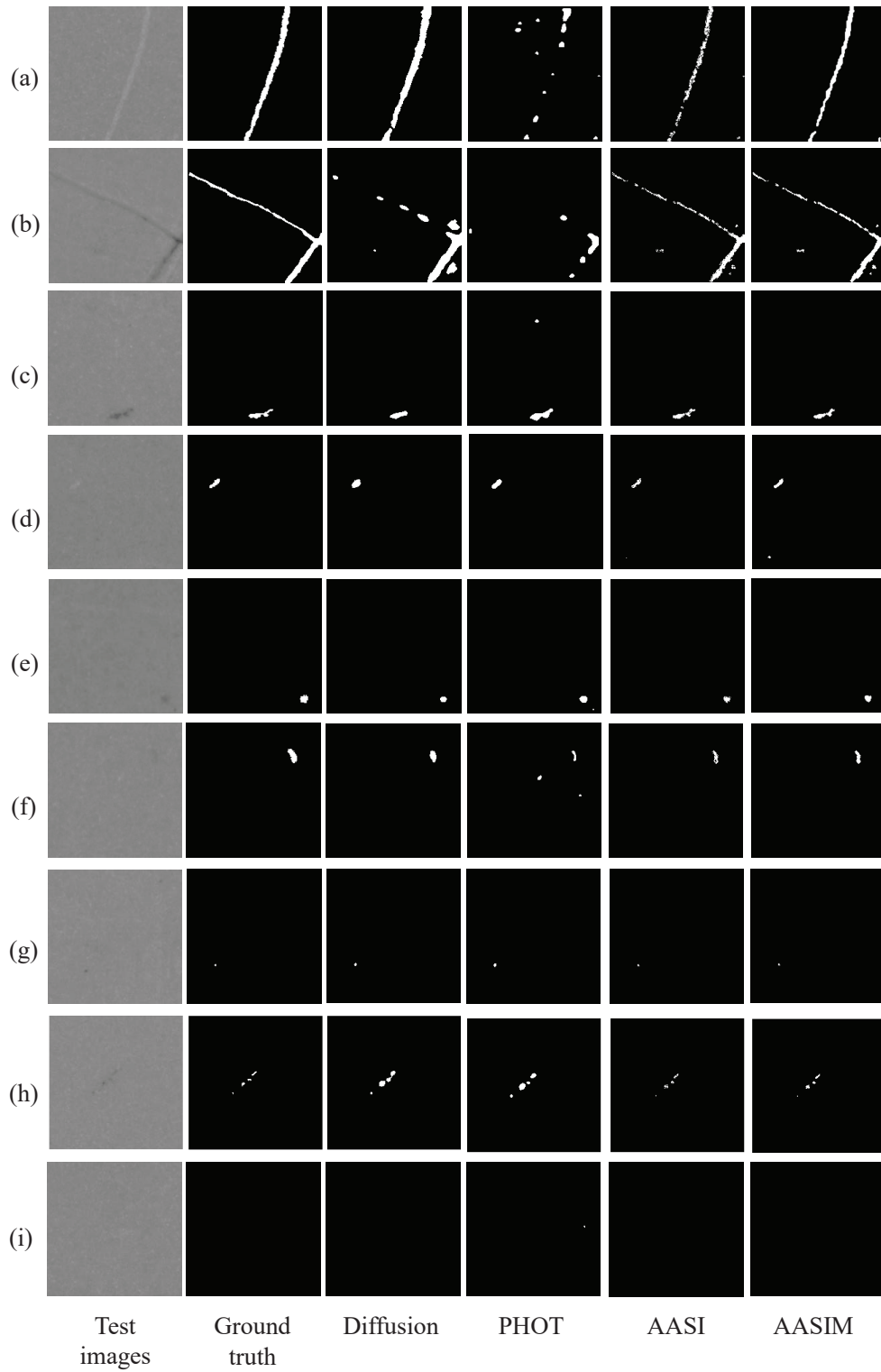


Figure 4.6: Detection of defects with different shapes, sizes, and contrasts. From left to right: (a) and (b) two scratches, (c) and (d) two spots, (e) and (f) two low-contrast defects, (g) micro defect, (h) diffused defect, and (i) defect-free sample.

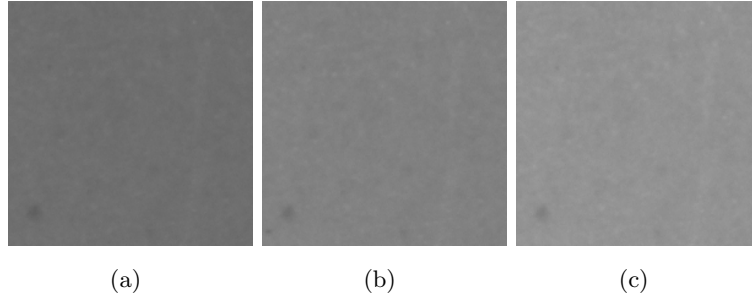


Figure 4.7: Example of test images captured from the same sample under three typical conditions of uniform illumination in the factory: (a) dark, (b) normal, and (c) bright.

Table 4.3: Overall performance comparison for defect detection in pixel level

Samples	Precision				Recall				F-measure			
	Diffusion	PHOT	AASI	AASIM	Diffusion	PHOT	AASI	AASIM	Diffusion	PHOT	AASI	AASIM
(a)	0.7827	0.7093	0.9957	0.9638	0.9606	0.2492	0.4265	0.6874	0.8626	0.3689	0.5971	0.8024
(b)	0.5613	0.7851	0.8198	0.8103	0.6457	0.2537	0.5769	0.6397	0.6006	0.3802	0.6772	0.7149
(c)	0.7235	0.5836	0.8618	0.8297	0.6872	0.9111	0.7318	0.7597	0.7049	0.7114	0.7915	0.7932
(d)	0.6423	0.7069	0.9724	0.8693	0.8061	0.8367	0.7141	0.8164	0.7149	0.7664	0.8235	0.8420
(e)	0.9157	0.8017	0.9924	0.9755	0.7103	0.9065	0.5989	0.7102	0.8000	0.8509	0.7469	0.8221
(f)	0.7274	0.7030	0.9767	0.9761	0.8422	0.4834	0.5854	0.7718	0.7806	0.5729	0.7320	0.8620
(g)	0.8571	0.5882	0.8571	0.8571	0.8367	0.9892	0.8367	0.8367	0.8468	0.7377	0.8468	0.8468
(h)	0.3312	0.3314	0.8882	0.8167	0.9444	0.9630	0.6556	0.7852	0.4904	0.4931	0.7544	0.8006
Overall	0.7680	0.6693	0.9355	0.9076	0.8032	0.6762	0.6150	0.7577	0.7852	0.6727	0.7421	0.8259

the other methods in terms of F-measure. We therefore draw the conclusion that the proposed AASI framework achieves state-of-the-art performance.

4.3.2 Robustness against Illumination Change

The illumination conditions of real factories are complex and capricious. So the robustness to illumination change is very important in evaluating industrial applicability of defect detection approach. To evaluate the robustness of AASI against uniform illumination change, we conducted further experiments on 90 images, which are generated from 30 products by capturing them from real-world products under three typical conditions of uniform illumination in the factory: dark, normal, and bright. Fig. 4.7 shows example of test images captured from the same product under different illumination conditions. The experimental results are listed in Table 4.4. From (a) to (h) are AASI performances on corresponding samples shown in Fig. 4.6. The overall results on 30 products are reported in the last row. It is notable that the parameters used in AASI are the same for all illumination conditions. One can conclude from Table 4.4 that the proposed AASI achieves similar performances for the three illumination conditions. This is due to the fact that the proposed saliency features are robust against uniform illumination change. Moreover, the proposed classification rule based on the two types of fitting models utilizes the shifting tracks in the AASI procedure, which is also free from

Table 4.4: Performance of the proposed method for three conditions of uniform illumination in pixel level

Samples	Precision			Recall			F-measure		
	Dark	Normal	Bright	Dark	Normal	Bright	Dark	Normal	Bright
(a)	0.9785	0.9638	0.9059	0.6146	0.6874	0.6078	0.7550	0.8024	0.7275
(b)	0.7727	0.8103	0.7629	0.6883	0.6397	0.6668	0.7281	0.7149	0.7116
(c)	0.7989	0.8297	0.7813	0.7765	0.7597	0.7227	0.7875	0.7932	0.7509
(d)	0.8871	0.8693	0.8179	0.7612	0.8164	0.8534	0.8193	0.8420	0.8353
(e)	0.9839	0.9755	0.9600	0.6355	0.7102	0.6729	0.7722	0.8221	0.7912
(f)	0.9725	0.9761	0.9468	0.7604	0.7718	0.7863	0.8535	0.8620	0.8591
(g)	0.8123	0.8571	0.8314	0.7852	0.8367	0.7515	0.7985	0.8468	0.7894
(h)	0.7877	0.8167	0.7362	0.7619	0.7852	0.7222	0.7746	0.8006	0.7291
Overall	0.8824	0.8998	0.8492	0.7351	0.7559	0.7323	0.7976	0.8210	0.7794

Table 4.5: Performance for three conditions of uniform illumination in image level

Illumination	Detection rate (%)	False alarm rate (%)
Dark	98	1
Normal	98	1
Bright	98	1

the influence of initial intensities. The quantitative evaluation results in image level are shown in Table 4.5. As can be seen from Table 4.5, our method obtained 98% detection rate under three kinds of illuminations, i.e., 98% defects could be detected. And the false alarm rate is 1%, i.e., 1% detected defects are defect-free sample.

In general, AASI is considered as robust to uniform illumination change. It can detect defects taken under different illumination conditions without changing the classification parameter.

4.3.3 Performance on flat surfaces coated with metal or glass

In order to demonstrate the generalisation ability of the proposed method, AASIM is further applied on metal surfaces and glass-like surfaces. Fig. 4.8 shows several representative detection results. From top to down are test images, ground truth, and detection results, respectively. As can be seen from Fig. 4.8 (a) and (b), diffused defect and spot defect on metal surfaces were successfully inspected. In addition, micro defect and low-contrast defect on glass-like surfaces were also roughly inspected, as shown in Fig. 4.8 (d) and (e). Overall, AASI shows effective performance not only on micro 3D surfaces, but also on metal-coated and glass-like surfaces.

Table 4.6 list the quantitative evaluation results in terms of Precision, Recall, and F-measure. As can be seen from Table 4.6, the proposed AASIM exhibits similar performance on metal and glass-like surfaces as on micro 3D textured surfaces. This is due to the fact that AASI does not utilize any 3D geometrical properties of background tex-

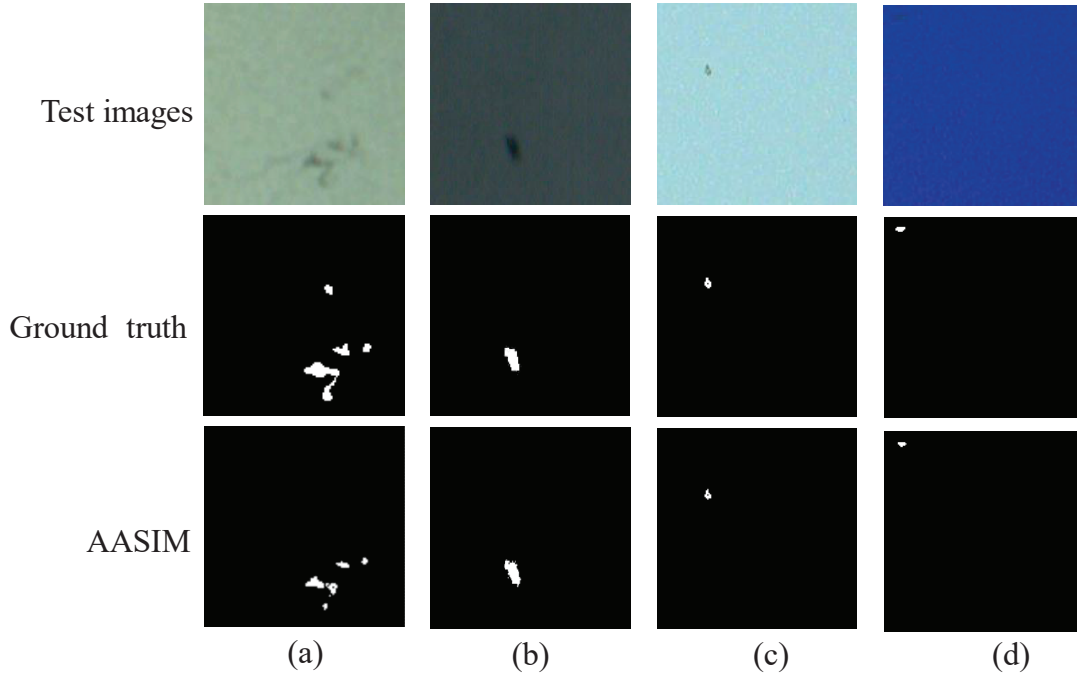


Figure 4.8: Detection of defects on flat surfaces. From left to right: (a) diffused defect and (b) spot defect on metal-coated surfaces, (c) micro defect and (d) low-contrast defect.

Table 4.6: Performance on flat surfaces coated with metal or glass

Samples	Precision	Recall	F-measure
(a)	0.7914	0.5331	0.7370
(b)	0.9828	0.7125	0.8261
(c)	0.9565	0.8148	0.8800
(d)	0.8014	0.6385	0.7092

tures. The saliency-guided enhancement and statistical fitting-based classification also work well for flatten textures. So AASI is also effective for flat-textured and non-textured surfaces, such as metal-coated and glass-like surfaces.

4.3.4 Performance on curved surfaces

The proposed AASI is powerless for curved surfaces because shadows and highlights usually exist on it. Here we utilize the improved AASI with golden template picture to detect defects on curved and highly-reflectively surfaces. Experimental results on curved metal surfaces are shown in Fig. 4.9 and Table 4.7. As can be seen from Fig. 4.9, although the intensity on the defect-free region exists big difference, defects can be successfully detected, and the detection results are highly consistent with the results of

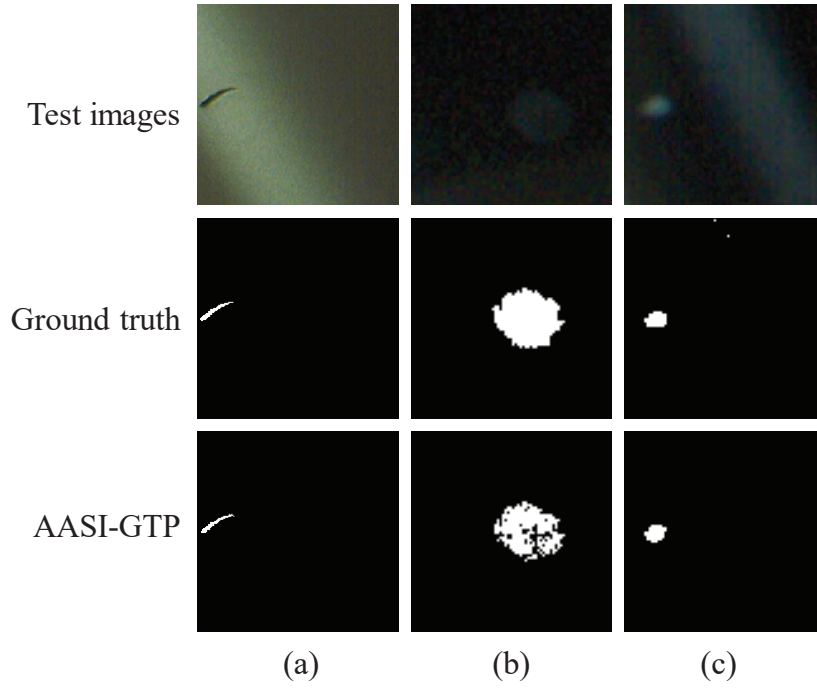


Figure 4.9: Detection of defects on curved metal surfaces.

Table 4.7: Performance on curved surfaces coated with metal

Samples	Precision	Recall	F-measure
(a)	0.9478	0.8934	0.9198
(b)	0.8707	0.7769	0.8211
(c)	0.9298	0.8983	0.9138

manual labeling.

The proposed AASI-GTP was further applied on curved glass-like surfaces. Fig. 4.10 shows representative experimental results. As can be seen from Fig. 4.10, defects can be roughly detected even if the background has uneven intensity, gradient colors, and clear textures. The corresponding values of Precision, Recall, and F-measure is listed in Table 4.8. AASI-GTP achieved high Precision values, which inheriting the strength of AASI. However, the Recall values are not very high. Defects in the highlighted background may be missed, which is needed improvement in the future.

Table 4.8: Performance on curved surfaces coated with glass

Measure	(a)	(b)	(c)	(d)	(e)
Precision	0.9609	0.9750	0.8167	0.8261	0.9724
Recall	0.6173	0.6507	0.7613	0.5352	0.7076
F-measure	0.7517	0.7800	0.7881	0.6494	0.8191

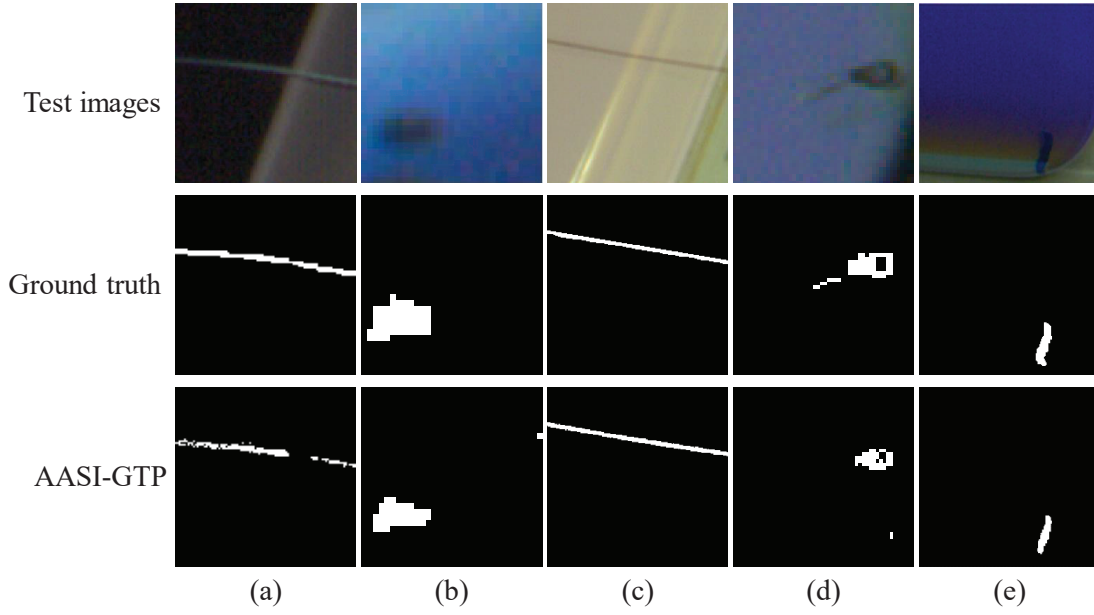


Figure 4.10: Detection of defects on curved glass surfaces.

4.4 Computational cost

Computational complexity is often considered as an important indicator of the practicability of defect detection methods. Our approach was firstly implemented by MATLAB R2010b on a PC with Intel i7 processor and 8 GB RAM. The average processing time for one test image with 200×200 pixels is 0.1525s. The proposed method was reprogrammed in C++ and the running time was increased to 0.06s per image.

4.5 Summary

In the chapter, the dataset and experimental setting were firstly introduced. All test images are from real-world industrial products. Secondly, we applied the proposed AASI on micro 3D textured surfaces for defect detection. Experimental results show that our approach generally has better performance than state-of-the-art unsupervised defect detection methods in terms of Precision and F-measure. AASI performs well even for low-contrast defects and small-sized defects with 3×3 pixels, and is robust to uniform illumination variations. Morphological operator “closing” can further enhance its performance. In addition, AASI shows similarly performance on flat surfaces coated with different materials, such as plastic, metal and glass, demonstrating its generality. Thirdly, the improved AASI with golden template picture was utilized to inspect curved and highly-reflective surfaces. Golden template picture is helpful for eliminating unevenness of intensity on curved surfaces. Experimental results on metal-coated and glass-like surfaces demonstrates its effectiveness. Finally, the computation time was discussed.

Chapter 5. Conclusions and future works

5.1 Conclusions

Aiming at defecting defects on micro 3D textured surfaces and on curved and highly-reflective surfaces, an accumulated and aggregated shifting of intensity (AASI) and an improved AASI approach with golden template picture (AASI-GTP) have been proposed, respectively. Defects are regarded as abnormalities on surfaces, which can be measured by the pixel-level saliency. The proposed AASI is therefore based on two saliency features, i.e. absolute intensity deviation and local intensity aggregation, which are associated with the probability of abnormality. The AASI adopts an iterative mechanism to enhance the defects from background. By considering the dynamic property during iteration and the salient features from initial image, AASI iteratively shift the intensity of each pixel depending on its saliency, i.e., defect probability. The AASI output sequence along iterations of defective pixels follows an exponential function, while that of defect-free pixels can be formalized as a linear function. So the detection process can be regarded as a problem of fitting to two statistical models. The proposed AASI-GTP is based on a multiple-pairwise reflective observation system which fixes multiple-pairwise cameras and diffused lights in specific positions and angles to capture all defects on the whole curved surfaces while avoiding shadows and highlights. Unlike AASI using mode intensity to represent the overall brightness of product surface, a golden template picture (GTP) is introduced to represent the pixel-wise brightness of the surface in AASI-GTP. By replacing mode intensity in AASI with GTP, the AASI-GTP is constructed for detecting defects on curved and highly-reflective surfaces.

To validate the performance of the proposed AASI, a dataset is collected from real-world industrial products. The dataset consists of 165 test images captured under three different illumination conditions. All test images have the size of 200×200 pixels and the resolution of 29 pixel/mm, of which 80% are defective, and another 20% are defect-free. Defects on embossed surfaces have various shapes, sizes and contrasts. Experimental results on AASI show that it outperforms state-of-the-art unsupervised defect detection methods in terms of Precision and F-measure. It performs well even for low-contrast defects and small-sized defects with 3×3 pixels, and is robust to uniform illumination variations. The AASI model provides a new way, i.e. saliency-guided shifting of intensity, for detecting low-contrast objects on complex background of random textures. To validate the performance of the proposed AASI-GTP, a dataset is also collected from

real-world industrial products. The dataset consists of images taken from both metal-coated surfaces and glass-like surfaces. The images of metal-coated surfaces are taken from three sets of products, and the images of glass-like surfaces are taken from six sets of products which have different colors and shapes. Experimental results on AASI-GTP show that, defects on metal-coated surfaces and glass-like surfaces, which are on curved surfaces with reflection, can be well detected because of the multiple-pairwise reflective observation system which provides information of every point on the surface. Even curved surface with high reflectance, AASI-GTP can also find out defective pixels, because the reflectance problem can be avoided by using the introduced golden template picture.

In general, the proposed AASI and AASI-GTP not only solve the problems of defecting defects on micro 3D textured surfaces and on curved and highly-reflective surfaces, respectively, but also provides insights for solving similar scientific problems. The AASI provides various insights for similar problems which need to detect weak signals from highly-noised environment. The ideas of both saliency feature extraction and iterative enhancement are helpful for find out weak signal (i.e. low-contrast defects in our scenario) from highly-noised environment (i.e. micro 3D textured surfaces in our scenario). Meanwhile, the idea of AASI-GTP also provides some insights for similar problems which need to acquire complete information and remove the influence of structured noises. The idea behind the proposed multiple-pairwise reflective observation system is able to obtain complete information (i.e. every points on a curved surface in our scenario), and the idea behind the golden template picture is able to remove the influence of structured noises (i.e. reflectance in our scenario).

5.2 Future Works

Although the proposed AASI and AASI-GTP solve the problems of defecting defects on micro 3D textured surfaces and on curved and highly-reflective surfaces, respectively. There are several important directions for further improving the performance from either acceleration point-of-view, algorithm point-of-view, and observation system point-of-view:

- **Acceleration point-of-view:** First, the AASI and AASI-GTP models are currently implemented by software for sequential processing on CPU, which heavily limits the processing speed of the algorithm. Although the current processing speed is bearable, it is better to consider more on further acceleration for increasing industrial efficiency. In the future, one important research direction is to implement AASI and AASI-GTP models by parallel programming on multi-thread processors, such as GPU or FPGA.
- **Algorithm point-of-view:** Second, the AASI and AASI-GTP models are designed for micro textured surfaces. Some products uses large textures to obtain

beautiful appearance. The AASI and AASI-GTP models are not suitable for these large textured surfaces. In future works, it is a promising research topic to extend AASI to more general application scenarios, such as large textured surfaces.

- **Observation system point-of-view:** Third, the observation system utilized several pairs of camera and light source, which increases the cost of imaging and the computation time. Reducing the number of camera and light source by designing proper diffusion plate is one of directions in the future. In addition, a further investigation of other imaging techniques, such as polarized light imaging and schematic of hyperspectral imaging, is needed for capturing more clear defects.

Acknowledgements

I have been studying and doing research at Hokkaido University for more than three years. Looking back on the entire course of my PhD, I want to appreciate the help and encouragement from many people.

First and foremost, I would like to thank my supervisor, Prof. Shun'ichi Kaneko, for his guidance and support all the time. Working with him is a great experience. Prof. Kaneko led me to enter the world of image processing and pattern recognition. He taught me how to summarize the core issues from complex engineering phenomena, helped me to analysis problems, and guided me how to solve those problems. Whenever I encountered difficulties, he always encouraged me, told me not to be afraid of challenges and to love my research. He not only spent long time guiding my research and dissertation, but also cared about my daily life, my physical and mental health with great patience. Without his kindly guidance and help, this wonderful journey would not have been possible.

I would like to express my appreciation to Prof. Yuh Yamashita and Prof. Takayuki Tanaka. Their insightful advices and valuable comments have helped me a lot to complete the dissertation and prepare the presentation. Prof. Tanaka also guided me and discussed with me about my research at weekly-general meetings. I learned a lot from his important suggestions which are sincerely appreciated.

Thanks to Mr. Hirokazu Asano at Kamakura Koki Co., Ltd. and Dr. Takashi Kusaka at Hokkaido University for their suggestions and discussions. Thanks to all the professors in the Graduate School of Information Science & Technology, Hokkaido University, for their guidance and help throughout the past three years. I also owe my thanks to Ms. Miki Kikkawa and Ms. Masae Michinaka for their endless support on both of my research and my daily life.

It is an honor to work with many brilliant members in HCE Laboratory. Thanks to Dr. Wenjun Zhou, my tutor, who gave me a lot of help especially when I first arrived. Thanks to Mr. Asahi Matsuda, Ms. Saori Miyajima, Mr. Kotaro Hashimoto. I learnt a lot from them through the discussions. Thanks to my friends, Mr. Sheng Xiang, Ms. Ying Tian, and Mr. Ren Hongyuan, for their daily help and company. Thanks a lot for these wonderful days with you.

Finally, I would like to thank my parents and my husband for their unconditional support and understanding over the years!

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Appendix A Publications lists

A.1 Journal Papers

1. Y. Yan, S. Kaneko, and H. Asano, “Accumulated and aggregated shifting of intensity for defect detection on micro 3D textured surfaces”, Pattern Recognition, vol. 98, pp. 107057, 2020.

A.2 International Conferences

1. Y. Yan and S. Kaneko, “Unsupervised accumulated aggregation shifting for robust defect detection in real industry”, in: the 15th International Conference on Quality Control by Artificial Vision (QCAV), 2019, pp. 30-35.
2. Y. Yan, S. Xiang, H. Asano, and S. Kaneko, “Accumulated aggregation shifting based on feature enhancement for defect detection on 3D textured low-contrast surfaces,” in: the 24th International Conference on Pattern Recognition (ICPR), 2018, pp. 2965-2970.
3. Y. Yan, S. Xiang, H. Asano, and S. Kaneko, “Robust defect detection on 3D textured low-contrast surfaces using accumulated aggregation shifting model,” in: the 12th France-Japan and 10th Europe-Asia Congress on Mechatronics, 2018, pp. 110-115.

A.3 Domestic Conferences

1. Y. Yan, S. Xiang, H. Asano, and S. Kaneko, “Accumulated aggregation shifting and its application to robust defect detection on SHIBO surfaces in real industry,” in: Precision Engineering Society Fall Conference 2018, September 5-7, 2018, Hakodate, Japan.
2. Y. Yan, S. Xiang, S. Kaneko, and H. Asano, “Accumulated aggregation shift for salient feature enhancement to detect defects in 3-D textured low-contrast surfaces,” in: Vision Engineering Workshop 2017, December 7-8, 2017, Yokohama, Japan.
3. Y. Yan, S. Kaneko, and H. Asano, “Intensity increment outliers detector and local orientation code pattern for robust defect detection in background of SHIBO surfaces,” in: Vision Engineering Workshop 2017, June 7-9, 2017, Yokohama, Japan.

A.4 Related Papers

1. Y. Yan, S. Du, H. Zhang, and Y. Ma, “When spatial distribution unites with spatial contrast: an effective blind image assessment model”, IET Image Processing, vol. 10, no. 12, pp. 1017-1028, 2016.
2. Y. Yan, S. Du, H. Zhang, and Y. Ma, “Learning the histogram sequences of generalized local ternary patterns for blind image quality assessment,” in: International Conference on Graphic and Image Processing (ICGIP), 2015.