A REFERENCE BASED SURFACE DEFECT SEGMENTATION ALGORITHM FOR AUTOMATIC OPTICAL INSPECTION SYSTEM

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A REFERENCE BASED SURFACE DEFECT SEGMENTATION ALGORITHM FOR AUTOMATIC OPTICAL INSPECTION SYSTEM

by

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LIST OF ABBREVIATIONS

AOI	Automatic optical inspection
bACC	Balanced accuracy
CCL	Connected component labelling
CPU	Central processing unit
DBSCAN	Density-based spatial clustering of applications with noises
FFT	Fast Fourier transform
GPU	Graphics processing unit
GRR	Gage repeatability and reproducibility
HDLT	Histogram distance lookup table
IoT	Internet of things
IPP	Intel integrated performance primitives
MCC	Matthew correlation coefficient
MTAD	Multiple template anomaly detection
NCC	Normalized cross-correlation
PCB	Printed circuit board
RID	Registered Image Difference
SDM	Surface defect heat map
ZNCC	Zero-mean normalised cross-correlation

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ALGORITMA SEGMENTASI KECACATAN PERMUKAAN BERASASKAN RUJUKAN UNTUK SISTEM PEMERIKSAAN OPTIK AUTOMATIK

ABSTRAK

Algoritma segmentasi kecacatan permukaan dalam Sistem Pemeriksaan Optik Automatik (AOI) untuk industri pembuatan moden membolehkan kawalan kualiti produk dalam kuantiti yang besar dengan cepat dan mudah dijejaki. Walau bagaimana pun, algoritma kompleks yang tepat memerlukan kuasa pemprosesan yang tinggi, set data pembelajaran yang besar tanpa kesilapan pelabelan. Sebaliknya, algoritma yang mudah tidak sesuai bagi permukaan dengan reka bentuk yang rumit dan permukaan yang berubah-ubah. Kajian ini bertujuan untuk membangunkan algoritma segmentasi dan pengesanan kecacatan permukaan untuk sistem AOI yang memerlukan kuasa pemprosesan yang rendah, set data pembelajaran yang kecil dan mempunyai perintang ralat pelabelan. Strategi Pengesanan Anomali Berbilang Templat (MTAD) digunakan untuk menghuraikan tahap anomali tempatan melalui fungsi jarak yang dikira dari set data pembelajaran. Semua imej set data pembelajaran melalui proses pencahayaan normalisasi, pemadanan, dan penyusunan pada berbilang templat dalam kernel untuk membentuk histogram bagi setiap lokasi piksel. Kemudian, fungsi jarak histogram untuk setiap lokasi dihitung dengan menggunakan kombinasi pseudo-kebarangkalian dan fungsi-fungsi jarak histogram baru pada histogram yang dikelompokkan. Akhirnya, kecacatan permukaan disegmentasikan dari peta haba anomali yang dihasilkan berdasarkan fungsi-fungsi jarak histogram. Hasil kajian menunjukkan bahawa algoritma yang dibangunkan hanya memerlukan set data pembelajaran yang

sekecil 5 sampel sahaja dan mempunyai perintang ralat pelabelan pembelajaran setinggi 50%. Algoritma yang dibangunkan berjaya mencapai ketepatan keseluruhan 90% untuk segmentasi dan ketepatan pengesanan melebihi 90% menggunakan CPU (unit pemprosesan pusat) dalam masa sebenar. Justeru, ia lebih baik berbanding dengan algoritma berdasarkan kelainan imej yang ketepatan segmentasi keseluruhan hanya 65%.

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ABSTRACT

Surface defect segmentation algorithms in Automatic Optical Inspection (AOI) system for modern manufacturing industries provide solutions to quality control with speed, volume and traceability. However, present complex algorithms which are accurate require high processing power using a large size of learning dataset without labelling error. On the other hand, simple algorithms are not suitable for surfaces with complicated designs and variations. This study aims to develop an algorithm for the AOI system to segment and detect surface defects, requiring low processing power and a small number of learning dataset with labelling error resistance. Multiple Templates Anomaly Detection (MTAD) strategy is proposed to describe the local anomaly degree through distance functions computed from learning dataset. The learning dataset images are illumination normalized, registered and stacked across multiple templates in a kernel to form a histogram for each pixel location. Then, the histogram distance function for each location is computed using a pseudo-probability combination of novel histogram distance functions on a clustered histogram. Finally, surface defects are segmented from an anomaly heat map which is generated based on histogram distance functions. Results show that the proposed algorithm required a learning dataset size as small as 5 samples and was resistant to learning labelling error up to 50%. The proposed algorithm achieved an overall segmentation accuracy of 90% and detection accuracy of more than 90% in real-time using CPU (central processing

unit). Thus, it outperformed image difference-based algorithm with overall segmentation accuracy of 65%.

CHAPTER 1

INTRODUCTION

1.1 Study background

Automatic optical inspection (AOI) system is a widely adopted solution to industrial manufacturing quality control (Singh, 2012) and it plays an essential role as industries are stepping into Industrie 4.0 (Kagermann, Wahlster and Helbig, 2013; Hermann, Pentek and Otto, 2016). Despite AOI gaining demand, the idea of an automatic inspection system towards full automation in the industry can be traced back to convention paper in the year of 1957 (Sargrove and Johnston, 1957). Moganti et al. point out several criteria in the industry which favours automatic inspection over manual inspection (Moganti et al., 1996). Some of those points which are as following:

- Relief of human operators.
- Manual inspection is slow, costly, high false call rate, lack in the assurance of high quality.
- High production rate which manual inspection cannot cope.
- Tight tolerance to the point where manual inspection is inadequate.
- The industry has a high-quality requirement where sampling is impractical.

Following the footstep of technology advancement, the severity of the criteria pointed out by Moganti et al. has increased to a point where manual inspection becomes impractical and inefficient in a modern manufacturing setting. On top of that, internet of things (IoT) for production monitoring, full quality assurance coverage and total traceability (Segura Velandia et al., 2016) leads to increasing demands for AOI system in modern manufacturing industries. The combining factors of increasing industrial diversity which adopts AOI system and increasing manufactured product complexity demands inspection algorithms to be very robust, reliable and efficient (Sindagi and Srivastava, 2015; Gaidhane, Hote and Singh, 2018).

In recent years, machine learning research for surface defect detection algorithms and studies of deep learning application in the AOI system are gaining popularity. As machine learning algorithms are data-intensive (Sordo and Zeng, 2005; Figueroa et al., 2012), data availability determines their practicality in different use cases. Although IoT application in manufacturing industries increased data accessibility in big data environment (Lee et al., 2013), surface defects image data for a certain product can be highly limited due to cost and availability (Ren, Hung and Tan, 2018). On top of that, algorithm speed, computation cost, data labelling and use model are common challenges in machine learning application in surface defect detection.

Situation visited above has motivated this study to develop an efficient referential-based algorithm to bridge the gap between the ideal application of machine learning-based inspection algorithm and reality. In 1.2, the problem statement of this study is formally elaborated while this study's objectives are stated in 1.3. The significant and scope of this study is evaluated in 1.5 and 1.4. Finally, an overview of this thesis is given in 1.6.

1.2 Problem statement

The gap between state-of-art surface defect inspection algorithms for AOI system and an ideal referential-based surface defect inspection algorithm expected from the manufacturing industry remains. The industry expects an ideal algorithm which can segment surface defect efficiently: low computation cost, low inspection duration, low memory usage and high accuracy. Moreover, it is robust to be applied to any surface inspection problems on any product design with any vision system. Aside from the algorithm's performance, its user experience is as important. Although the user experience depends on the software design, the ideal algorithm must have the capability to conform to the design: very little algorithm parameters, scalable to any learning or inspection database size, high tolerance to human error, stable, deterministic and intuitive.

Segmentation capability is one of the research gaps observed from recent studies, including deep learning algorithms. These studies lack segmentation capability, despite being robust and accurate in detection. Secondly, resistant to human labelling error is missing from many referential-based algorithms. Their accuracy is dependent on learning accurately labelled data which is significantly harder to produce for segmentation problem. Besides, they need a large amount of data. The need for large and accurately labelled data results in high computation cost and very unfriendly user experience. Consequently, these gaps cost both AOI system providers and users in many forms: algorithm setup time, downtime, production time, hardware cost and maintenance cost.

This study addresses the research gaps of requiring high processing power, learning dataset size and quality in surface defect segmentation problem by proposing a reference-based surface defect segmentation algorithm for AOI system.

1.3 Study objective

The main objective of this study is to develop an algorithm for the AOI system to do surface defect segmentation using little requirement on processing power, learning dataset size and quality. The main study objective can be broken down into three aims signifying different milestones of this study:

1. Design a fast learning – inspection flow to be implemented in the software.

2. Derive an unsupervised, repeatable, scalable and learning error-resistant method to determine high anomaly regions from multiple good templates for surface defect segmentation.
3. Develop a software module and test the proposed algorithm's segmentation accuracy.

1.4 Study scope

This study's focus can be summarized into four important aspects: *algorithm development*, *surface defect segmentation*, *AOI system* and *quantitative analysis*. *Algorithm development* defines the action and outcome of this study where *surface defect segmentation* explains the function of the algorithm. Ultimately, an *AOI system* is a tool where the outcome of the research will be reflected on.

In this study, *algorithm development* includes formulation on theory and mathematic behind and deployment on the field. Despite it is a machine vision-related algorithm, the combination and specification of a vision system is not the focus of the study. Evaluation of various aspect of the algorithm is part of the process to validate the effectiveness of the proposed algorithm.

Surface defect segmentation defines the type of defect and function of the algorithm this study focuses on. Surface defect includes all deviations observable from a surface exceeding design's variation tolerance of a product regardless of its impact on the product's functionality directly or indirectly. The type of product in this study is limited to manufactured product from modern manufacturing sites which uses *AOI systems* as their quality assurance solution. The developed algorithm in this study focuses on defect segmentation rather than defect detection, under the criteria listed in 1.3. As defect detection ability is closely related to segmentation, it will be touched by this study concisely but briefly.

AOI systems define the scope of the tool where the proposed algorithm is applied. *AOI system* is a subset of automatic visual inspection system which uses visible light as a source of illumination for visual inspection. Shorter wavelength light like X-ray and longer wavelength like infra-red visual inspection is not in the scope of this study.

Quantitative analysis defines the scope of the data analysis presented in this study. Each objective or aim presented in Section 1.3 is measured, identified, and analyzed within a quantifiable scope. Table 1.1 presents a list of measurable aims and their respective quantifiable scopes defined in this study. Although the segmentation's quality is analyzed visually in this study, the analysis is always relatable to the segmentation's quality metric measured.

Table 1.1: Aims and their respective quantifiable scopes defined for the study.

Aims	Quantifiable Scope
Small learning dataset size	As low as 5 samples
High labelling error in learning	Up to 50% of error percentage
Fast speed	Less than $500ms$

1.5 Study significance

This study of proposing surface defect segmentation algorithm which has characteristic discussed in 1.3 is very important in the advancement of AOI technology towards lesser human intervention. Proposed algorithm impacts directly on the robustness of use case and the challenge of data availability in surface defect segmentation problem. Moreover, the proposed algorithm can provide current existing AOI systems robust, accurate and reliable referential-based surface defect segmentation algorithm without extra demands on hardware.

In terms of research, the proposed algorithm provides a flexible concept for other surface defect segmentation algorithms in future works. Furthermore, the proposed algorithm provides a solution to defect region labelling problem in the application of deep learning algorithms which is lacking especially in AOI systems.

1.6 Thesis overview

This thesis has six chapters in total. Each chapter is organized and briefly introduced as follows.

CHAPTER 1 introduces the background of this study and leads to the problem encountered which motivates this study. The aim and scope are outlined in the Study objective and Study scope to clarify the direction and boundary of this study. Study significance at 1.5 addresses the importance and impact of the outcome of this study.

CHAPTER 2 reviews previous literature and studies related to this study. By categorizing algorithms into PCB-semiconductor inspection and texture inspection, various surface defect detection and segmentation algorithms are reviewed. At the end of this chapter, an overview of the proposed algorithm is given.

CHAPTER 3 gives an in-depth concept and formulation of the proposed algorithm. The chapter is organized according to the proposed algorithm's workflow. Starting from learning flow to inspection flow, all related algorithms and their theories, equations and implementation to the flow are given in details. Novel algorithms which this study introduces consisted of characteristic studies in addition to theories and equations. This chapter gives an important foundation to study's experiment or deployment methodology in the subsequent chapter.

CHAPTER 4 describes the implementation of the proposed algorithm. Vision system design and computer specification are given as an experimental setup for this study. Then, software and its implementation of the proposed algorithm from the previous chapter is outlined. Data collected for algorithm evaluation is introduced in this chapter. Lastly, the algorithm evaluation strategy is given.

CHAPTER 5 is the result and discussion chapter for this study. Segmentation result from the proposed algorithm is studied according to criteria stated in Study objective: accuracy, learning sample size and labelling error. For each analysis, the proposed algorithm is reviewed against the objective of this study. Then, the repeatability of the proposed algorithm is evaluated. Moreover, the comparison between the proposed algorithm and another algorithm is done and discussed. A summary of the study's finding is given at the end of this chapter.

CHAPTER 6 concludes this study with a summary of findings and its contribution. Future works and other applications are suggested at the end of this chapter.

CHAPTER 2

LITERATURE REVIEW

This chapter reviews literature works related to surface defect segmentation and detection in the AOI system. Surface defect inspection in AOI system can generally be separated into two large categories: printed circuit board (PCB) inspection (Moganti et al., 1996), semiconductor inspection (Huang and Pan, 2015) and texture inspection. PCB inspection involves inspection on either bare PCB or assembled PCB. Bare PCB are PCB without electronic components while assembled PCB is PCB after electronic component placement in either pre-reflow or post-reflow condition. On the other hand, semiconductor inspection involves inspection on a wafer, liquid display, solar cell, and light-emitting diodes (LED) (Tsai and C. H. Yang, 2005). Last but not least, texture inspection involves inspection on a textured surface like textile (Yan, Paynabar and Shi, 2015; Li and Zhang, 2016), ceramic (Karimi and Asemani, 2014; Hanzaei, Afshar and Barazandeh, 2017), metal (Tsai and Tseng, 1999; Tsai and Lin, 2002), wood (Silvén, Niskanen and Kauppinen, 2003), and stone (Liu and MacGregor, 2006; Yoon, Lee and Liu, 2013).

The works of literature for PCB inspection algorithms, semiconductor inspection algorithms and texture inspection algorithms can be further categorized differently according to the methodology for clarity (Moganti et al., 1996; Xie, 2008; Huang and Pan, 2015). The reason for differences in algorithms categories probably due to differences in surface characteristic. However, for the sake of simplicity, this study combines PCB inspection algorithms and semiconductor inspection algorithms under the same branch of category. For PCB inspection algorithms and semiconductor inspection algorithms, there are two categories: referential and non-referential (Moganti et al., 1996; Huang and Pan, 2015). On the other hand, texture inspection algorithms can be categorized into four categories: statistical, structural, filter-based and model-based (Xie, 2008; Ren, Hung and Tan, 2018).

2.1 PCB and semiconductor inspection algorithms

In this section, previous works of literature related to PCB and semiconductor surface defect detection or segmentation algorithms are reviewed. As suggested by Moganti et al. and foretold previously, these algorithms can be grouped into referential, non-referential, and hybrid (Moganti et al., 1996). However, over years of advancement in algorithm research, the scope and definition of these groups have changed accordingly.

For referential algorithms, they involved more than a database of good samples (Moganti et al., 1996) or golden template (Xie and Guan, 2000; Shankar and Zhong, 2005). Any learning-based algorithm for PCB and semiconductor inspection which requires the algorithm to refer a model during an inspection are referential algorithm in this research. This includes defect detection algorithm based on reference image through pattern recognition (Bartlett et al., 1988; Park and Tou, 2002; Tsai and Yang, 2005; Sun, Sun and Surgenor, 2009), features extraction based on neural network (Neubauer, 1997; Kim et al., 1998; Acciani, Brunetti and Fornarelli, 2006; Luo, 2007; Ong, Samad and Ratnam, 2008; Lin, 2009), and image comparison based on image processing (Singh, 2012; Yuan, Wu and Peng, 2015), normalized cross-correlation (Tsai, Lin and Chen, 2003; Crispin and Rankov, 2007), wavelet transform (Ibrahim and Al-attas, 2005; Lin, 2009), eigenvalue (Tsai and R. H. Yang, 2005), rule-based (Shankar and Zhong, 2006) and principal component analysis (Sun, Sun and Surgenor, 2009).

For the past ten years, a novel approach using shift-tolerant dissimilarity measure uses optical flow field to calculate the degree of difference between a reference and a test image is cited in multiple works of literature. It was proposed by Tsai et al., suggesting an optical flow field as a superior approach to the conventional template matching method. (Tsai, Chiang and Tsai, 2012). The proposed approach has tolerance to misalignment and local variation. However, it does not have multiple template capability to justify good template from a population.

An ICA basis images-based defect segmentation for solar modules is proposed. It is a referential algorithm involving a learning and detection stage. A set of defect-free solar cell sub-images are used to find a set of independent basis image using ICA. Then, these learned basis images are used to reconstructed solar cell sub-images under inspection using a linear combination method. Reconstruction error is used to justify if a solar cell sub-image is defective (Tsai, Wu and Chiu, 2013).

Tsai et al. proposed a method based on Haar-like feature extraction and a new clustering technique for solar cell defect detection. Defect-free images are used as a training sample for a binary-tree clustering method which partitions these images into tens of groups. For each partition levels, the cluster with the worst uniformity based on PCA is separated into two clusters using Fuzzy C-means. During an inspection, the distance from a test point to each cluster's centroid is evaluated to deduce the evidence of a defect (Tsai et al., 2015).

Two studies on defect detection on OLED panel are published by Sindagi et al. and Son in the same year. Sindagi et al. proposed a novel approach based on local inlier-outlier ratios and modified LBP using a simple set of features. Local inlier-outlier ratios complement modified LBP well as local inlier-outlier ratios often catch micro defects where modified LBP missed (Sindagi and Srivastava, 2015). On the other hand, Son proposed defect detection method on OLED panel using Fisher information distance of local Gaussian distributions between reference and test image

(Son, 2015). Both proposed algorithms are referential but very different in nature. The approach by Sindagi et al. is based on machine learning classifier while approach by Son is based on information distance.

Kong et al. proposed a surface defect segmentation method through a three-step framework. First, a template image is selected from a set of template images automatically using bag-of-words models based on corners and feature representations. Then, a robust image registration method based on the approximate maximum clique method is used to align the test image with the template. Lastly, an illumination invariant image comparison based on the edge is used to segment surface defect. This method can achieve high detection rate provided all three steps are carried out excellently (Kong, Yang and Chen, 2017). However, this study uses only one template which is often not enough to describe the norm of a product.

Gaidhane et al. proposed an efficient similarity measure approach to detect a surface defect on PCB which is reportedly well tolerated to local variations and misalignment (Gaidhane, Hote and Singh, 2018). It uses the rank of a symmetric matrix derived from companion matrices between reference and inspection image. The rank is found to be distinctively large for defective images. The proposed similarity measure is computationally efficient, responsive to defect and yet robust enough to ignore local variation. Although it is an improvement over other similarity measures, on-the-spot computation of rank is still a burden to inspection speed.

Non-referential approaches to PCB and semiconductor-related surface defect detection or segmentation problems born from the idea called design-rule verification. Image processing methods, ROI specific thresholding and parameter tuning, encoding techniques are common examples of approaches with design-rule verification in mind

(Moganti and Ercal, 1995). However, not all non-referential approaches are based on design-rule verification (Tsai and Luo, 2011).

In the last decade, a non-referential defect detection method based on mean shift technique is applied on multi-crystalline solar wafer surfaces. Due heterogenous texture resulted from random grain structure, any homogenous texture inspection algorithm nor referential algorithm will not work. Hence, the mean shift technique which moves data points to a mode based on kernel density estimator is applied to detect a high variation of edge directions as defective (Tsai and Luo, 2011). However, this method is currently limited to multi-crystalline structures.

In a study to detect three parallel lines in solar panel end face, multiple linear regression method is applied. This method is non-referential. Many image processing techniques are applied in real-time to extract edge points of these lines before applying multiple simple linear regression. Regressed lines are compared to specification to justify if it is defective (Lin et al., 2014). The proposed algorithm is very fast and simple but lack of robustness as the algorithm is designed to tackle a specific problem.

The AOI system industry has been using non-referential approaches for PCB and semiconductor-related surface defect detection and segmentation problem for more than a decade (Moganti and Ercal, 1995). This is because non-referential approaches are simple, fast and predictable. However, non-referential approaches are limited in their use-case. Despite robust referential approaches are introduced over the years, there are still gaps in describe multiple templates efficiently, labelling error and speed.

2.2 Texture inspection algorithms

For the past 20 years, many textural surface defect inspection algorithms are reviewed in different works of literature for different surfaces (Xie, 2008; Gajanan, 2014; Karimi and Asemani, 2014; Mishra and Shukla, 2014). From a publication by Xie, textural surface defect inspection algorithm can be categorized into four different approaches: statistical, structural, filter-based and model-based. Statistical approach and filter-based approach are popular approaches toward texture inspection problem (Xie, 2008). A statistical approach uses the local spatial distribution of pixel grey values as a measurement to textural characteristic. Examples of statistical measure for textural analysis are histogram statistics, co-occurrence matrices, auto-correlation, local binary patterns (LBP), eigenvalue (Tsai et al., 2012), entropy (Tsai and Lin, 2002; Susan and Sharma, 2017) and rotation invariant measure of local variance (RIMLV) operator (Hanzaei, Afshar and Barazandeh, 2017). A filter-based approach applies filter banks on an image and computes the energy of the filter response. It can be done in the spatial domain, frequency domain or both. Global texture removal through discrete Fourier transform (DFT) to highlight non-textural defects on textural background have been a method used by several works of research (Tsai and Hsieh, 1999; Chan and Pang, 2000; Tsai and Huang, 2003; Kuo et al., 2018). Gabor filter is windowed Fourier transform using Gaussian function to introduce spatial dependency into Fourier analysis. It is a staple part of methods proposed in several works of research. Mirmahdavi et al. use optimal Gabor filter to extract features for Gaussian Mixture Model (GMM) modelling as a defect detection method on a randomly textured surface (Mirmahdavi et al., 2015). Another study uses composite differential evolution (CoDE) to optimize the parameters of Gabor filters to achieve optimal feature extraction of fabric defects (Tong, Wong and Kwong, 2016). In a study by Li et al., Gabor filter is used to enhance features' contrast on fabric before defect detection using Pulse coupled neural network (PCNN) (Li and Zhang, 2016).

Recently, an unsupervised texture defect detection which does not require user input is proposed by Susan and Sharma. They use Gaussian mixture entropy model as regularity index which is computed locally from texture patches through a sliding window. Outliers are detected by exceeding three standard deviations. The proposed algorithm does not require manual input and achieves high accuracies (Susan and Sharma, 2017). However, future works need to be done to extend this idea to PCB and semiconductor inspection.

With the recent advancement in deep learning research, a deep learning-based surface defect segmentation algorithm published very recently by Ren et al. based on convolution using trained classier. The classifier is trained with small patches from images using transfer learning. This study uses Decaf as their transfer learning model. Classification of small patches from inspecting image provides predications based on trained classifier for pixel-wise segmentation. This method can improve segmentation accuracy of three defect type (Ren, Hung and Tan, 2018). Studying result from this study, segmentation quality of the proposed algorithm is closer to localization than segmentation. Moreover, it needs speed improvement to be applicable for real-time inspection.

An unsupervised deep learning approach on a textured surface is proposed recently. It uses defect-free samples for model training, and it can detect and localize defects. The approach is done by reconstructing image patches with convolutional denoising autoencoder networks at different Gaussian pyramid levels. Defect detection is based on reconstruction residual of the training patches at different resolution channels (Mei, Yang and Yin, 2018).

Similarly, Li, Zhao and Pan have the same idea of using denoising autoencoder and detection based on reconstruction residual. By using Fisher criterion-based stacked denoising autoencoder (FSCDA), fabric textures are classified into defective and non-defective categories. Segmentation is achieved through applying a threshold on residual between the reconstructed image and defective patch (Li, Zhao and Pan, 2017).

In another deep learning related literature, Racki, Tomazevic and Skocaj investigated the performance of surface defect segmentation and classification using a compact CNN architecture. Unlike many works which rely on pre-trained CNN network, proposed CNN architecture does not rely on a pre-trained network. They can achieve segmentation accuracy on par with state-of-art algorithms using small and coarsely labelled learning data set (Racki, Tomazevic and Skocaj, 2018). This study has suggested a better use model of deep learning-based defect segmentation algorithm with capability of coarse labelling.

Recently, Qiu et al. proposed a highly efficient deep-learning-based method as a textural surface defect segmentation algorithm in an AOI system (Qiu, Wu and Yu, 2019). Their method consisted of three stages: segmentation, detection, matting. In the segmentation stage, pixel-wise prediction of the defective region is done using a lightweight fully convolutional network (FCN). Then, predicted defective regions are corrected in stage 2 and refined in stage 3 using a guided filter. Despite achieving 99% of segmentation accuracy, the method is not suitable for a structural or a designed object. Moreover, the work of literature does not mention about resistance to a labelling error.

As a conclusion, texture inspection algorithms proposed are mostly inapplicable for PCB or semiconductor inspection. This is because texture inspection algorithms focused on surface texture instead of a designed pattern on a surface. Nevertheless, literature about texture inspection algorithms gave an overview of current state-of-art approaches which inspires this study.

2.3 Study Gap

The gaps which this study would like to address can be summarized into four different capability gaps:

- Multiple templates capability
- Learning labelling error resistance capability
- Segmentation capability
- Textural and non-textural application capability

For the first gap, the multiple templates capability is the ability to capture textural and non-textural feature variances across multiple templates through learning. Many previously proposed reference-based methods rely only on a single template. Among those methods are golden template (Xie and Guan, 2000), neural network feature extraction (Lin, 2009), image comparison (Yuan, Wu and Peng, 2015), normalized cross-correlation (Crispin and Rankov, 2007), wavelet transform (Lin, 2009), eigenvalue (Tsai and R. H. Yang, 2005), rule-based (Shankar and Zhong, 2006), modified local binary patterns (LBP) (Sindagi and Srivastava, 2015; Son, 2015), symmetric matrix rank (Gaidhane, Hote and Singh, 2018) and mixture model entropy (Susan and Sharma, 2017). Even though methods like optical flow field (Tsai, Chiang and Tsai, 2012) and small patches deep learning (Mei, Yang and Yin, 2018; Racki, Tomazevic and Skocaj, 2018) learn using multiple templates, they cannot capture non-textural feature variances.

For the second gap, the learning labelling error resistance capability is the ability to tolerate labelling error in learning. All proposed reference-based method which reviewed in this study assumed all templates are correctly labelled. Hence, they did not mention the effect of the learning labelling error.

For the third gap, the segmentation capability is the ability to segment defect accurately. Methods like principal component analysis (Sun, Sun and Surgenor, 2009) and clustering Haar-like features (Tsai et al., 2015) can only detect defects without segmentation. Meanwhile, other methods like ICA basis images-based (Tsai, Wu and Chiu, 2013), three-steps-framework (Kong, Yang and Chen, 2017; Qiu, Wu and Yu, 2019) and autoencoder (Li, Zhao and Pan, 2017) segment defect as an intermediate result for defect detection. Hence, their segmentation accuracies are not mentioned. The small patches deep learning method is the only method in which segmentation accuracies is coarsely mentioned.

For the fourth gap, the textural and non-textural application capability is the ability to apply a method on both textural and non-textural surfaces. This study finds that all methods are only applicable in either textural or non-textural surfaces, except for golden template method, symmetric matrix rank and autoencoder.

Table 2.1 summarizes the works of literature and their capability gaps according to the categories: multiple templates capability (MT), learning labelling error resistance capability (ER), segmentation capability, and textural and non-textural application capability (T&NT). The segmentation capability category is split into two categories: segmentation as an intermediate result (SIR) and segmentation accuracy (SA) because there are many methods have segmentation as an intermediate result without mentioning its accuracy. In column MT, ER, SIR and SA, a method is marked under each category column if it has the capability (Y) or it does not have the capability (N) for the category. In column T&NT, a method is marked as textural only (T), non-textural only (NT) or both (B).

Table 2.1: Algorithm methods from various works of literature and their gaps according to capability categories: multiple templates (MT), learning labelling error resistance (ER), segmentation as an intermediate result (SIR), segmentation accuracy (SA), and textural and non-textural application (T&NT). For column MT, ER, SIR and SA, "Y" is capable and "N" is incapable. For column T&NT, "T" is textural only, "NT" is non-textural only and "B" is both.

Method	MT	ER	SIR	SA	T&NT
Golden Template	N	N	N	N	B
Neural Network Feature Extraction	N	N	Y	N	NT
Image Comparison	N	N	Y	N	T
Normalized Cross-Correlation	N	N	N	N	NT
Wavelet Transform	N	N	Y	N	NT
Eigenvalue	N	N	Y	N	NT
Rule-based	N	N	Y	N	NT
Principal Component Analysis	Y	N	N	N	NT
Optical Flow Field	Y	N	Y	N	NT
ICA Basis Images-based	Y	N	Y	N	T
Clustering Haar-like Features	Y	N	N	N	T
Modified LBP	N	N	Y	N	T
Three-Steps-Framework	Y	N	Y	N	NT
Three-Steps-Framework (Deep Learning)	Y	N	Y	N	T
Symmetric Matrix Rank	N	N	Y	N	B
Mixture Model Entropy	N	N	Y	N	T
Small Patches Deep Learning	Y	N	Y	Y	T
Autoencoder	Y	N	Y	N	B

CHAPTER 3

THEORY

3.1 Proposed Algorithm

This study proposes an efficient surface defect segmentation algorithm using anomalies detection method based on multiple templates. The proposed algorithm uses a coarsely aligned image through registration to compare with an established norm from a group of learning samples. The proposed algorithm uses good sample images and does not require labelling on the learning images, achieving a semi-unsupervised learning capability. Figure 3.1 illustrates an overview learning-inspection framework of the proposed algorithm. The overview and in-depth explanations are given in the following sections.

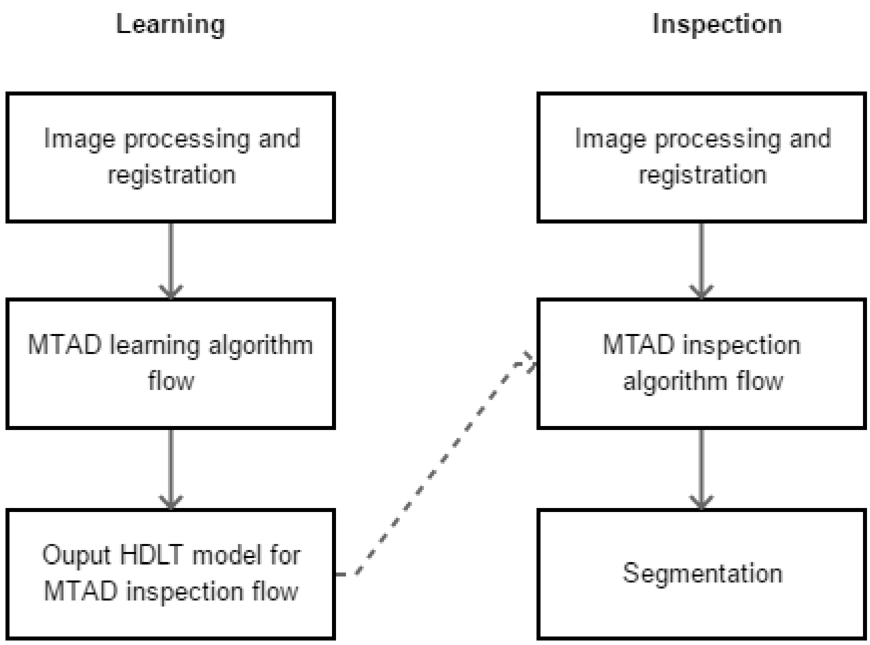

Figure 3.1: Overall proposed algorithm flow consisting learning and inspection algorithm flow.

The overviewing concept of the proposed algorithm is presented in Section 3.2, to give a clear picture of the inner working of the proposed algorithm. Then, the common image processing algorithm applied to images before anomalies detection method proposed is described in Section 3.3. The proposed algorithm's detailed formulation is explained in two main algorithm flows: learning in Section 3.4 and inspection in Section 3.5 as illustrated in Figure 3.1. For each algorithm flow, the algorithms and their theories are presented further in their respective sections. While some algorithms used are already well established, some algorithms are uniquely derived for this study.

3.2 Concept

Multiple templates anomaly detection (MTAD) consists of a chain of algorithms connected by a common input-output interface: image. Hence, instead of being an algorithm by itself, the proposed MTAD is a method or strategy with a specific purpose in place: anomaly region detection. The concept of MTAD method proposed in this study can be understood as finding the anomaly degree of a registered inspection image's region based on an established corresponding region's norm using corresponding multiple local regions from a set of registered learning templates. The term "registered image" in this study refers images which are aligned using any image registration algorithm. The image registration algorithm used for this study is described in Section 3.3.1.

The use model for the MTAD method can be described in two major flows: learning and inspection. It resembles a standard machine learning use model that consists of both learning and prediction (inspection). Despite the similarity in structure, MTAD differs conceptually from usual machine learning. While both supervised and unsupervised machine learning aimed to generate learning models to describe the decision boundary between labelled or unlabeled classes, MTAD does not aim to establish a decision boundary. Instead, MTAD aims to establish a norm (learning model) based on historical data (learning samples) to describe the anomaly degree or difference from the established norm in a local region. Hence, unlike usual supervised learning and unsupervised learning, MTAD does not require labelling on learning samples nor does it has classified output. From another perspective, MTAD breaks defect segmentation problem into a binary classification problem for each region or pixel.

MTAD's concept bears similarity to algorithms proposed in several publications (Tsai and C. H. Yang, 2005; Tsai, Chiang and Tsai, 2012; Kong, Yang and Chen, 2017). This method proposed a way to describe the norm from multiple registered samples effectively and efficiently.

3.3 Image processing and registration

This section describes common image processing algorithms applied in this study before learning or inspection of proposed MTAD method. Other than base template image which specifies the first cropped general pattern of a component, all learning and inspection images are registered and processed in the same manner. The algorithm flow where these algorithms are applied is depicted in Figure 3.2.

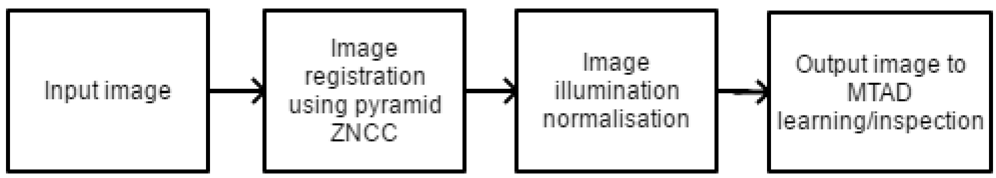

Figure 3.2: Image processing and registration algorithm flow.

3.3.1 Pyramid ZNCC image registration

Normalized cross-correlation (NCC) is a well-known and widely used template matching algorithm (Xie and Guan, 2000; Debella-Gilo and Kääb, 2011; Tsai, Chiang and Tsai, 2012). It is often referred to as the two-dimensional Pearson product-moment correlation coefficient. The equation for NCC is given in Equation (3.1).

$$\mathrm{NCC}(S,T)=\sqrt{\frac{\sum_{x,y}T(x,y)\cdot S(x,y)}{\sum_{x,y}T(x,y)^2\cdot\sum_{x,y}S(x,y)^2}} \tag{3.1}$$

However, the brightness of templates and images are often different in image processing applications. Hence, the brightness of template and image are normalized through subtracting both template and image with their respective mean. This yields the zero-mean normalized cross-correlation (ZNCC) used in this study. ZNCC equation is given by Equation (3.2).

$$\mathrm{ZNCC}(S,T)=\sqrt{\frac{\sum_{x,y}(T(x,y)-\mu_T)\cdot(S(x,y)-\mu_S)}{\sum_{x,y}(T(x,y)-\mu_T)^2\cdot\sum_{x,y}(S(x,y)-\mu_S)^2}} \tag{3.2}$$

ZNCC by itself is not rotation-invariant. Moreover, brute forces matching without rotation-invariant and scale-invariant takes up a huge amount of computation. Many studies suggested methods to not only improve ZNCC processing speed (Briechle and Hanebeck, 2001; Chen et al., 2013) but to enhance ZNCC by adding rotation-invariant and scale-invariant (Sassanapitak and Kaewtrakulpong, 2009). This study uses rotation-invariant ZNCC with fast Fourier transform (FFT) through the implementation of an image pyramid. Both image pyramid and FFT are presented following in brief.

An image pyramid is a multi-scale representation of an image through subsampling and smoothing. Figure 3.3 is an example of an image pyramid. This technique is used to estimate an image's rotation and translation through ZNCC at a lower resolution level before moving up to a higher resolution level. When moving up from lower resolution level to higher resolution level, three-dimensional search space (x, y, θ) for rotational and translation registration is reduced according to lower resolution's finding. This image registration optimization technique is used in different studies to speed up image registration problem (Thévenaz, Ruttimann and Unser, 1998; Gonzalez and Woods, 2008; Kim et al., 2009).

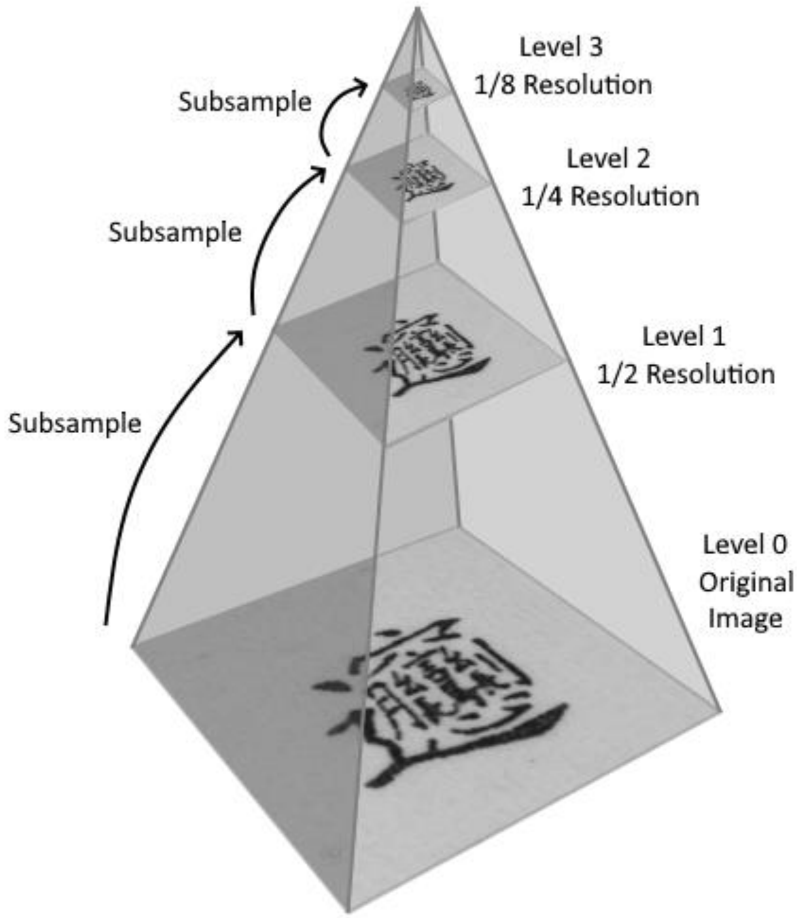

Figure 3.3: Representation of image pyramid with four levels.

ZNCC with FFT is a well-established method which utilizes multiplication in an image's frequency domain corresponding to the convolution in the image's spatial domain (Gonzalez and Woods, 2008). This relationship is explained in convolution theorem in Equation (3.3) and Equation (3.4) where $\mathcal{F}$ is Fourier transform operator, asterisk sign is convolution operator, dot sign is multiplication operator, T and S are template and image respectively. This technique does not require convolution through window sliding of a kernel throughout an image. Hence, it is faster than conventional ZNCC.

$$\mathcal{F}\{T * S\} = \mathcal{F}\{T\} \cdot \mathcal{F}\{S\} \tag{3.3}$$

$$hence,$$

$$T * S = \mathcal{F}^{-1}\big\{\mathcal{F}\{T\} \cdot \mathcal{F}\{S\}\big\} \tag{3.4}$$

Application of pyramid ZNCC in this study is to provide image registration for MTAD method proposed for surface defect segmentation. As it is not part of the proposed algorithm, it can be replaced by any state-of-art image registration algorithm. However, for this study, pyramid ZNCC will be used as it is well-established, available in existing libraries, and simple. While it is not as accurate and robust as many image registration algorithms, it is enough for the MTAD method proposed to segment defective region without false rejects due to misalignment.

3.3.2 Illumination normalization

Illumination normalized images are images which brightness are corrected to improve its visual quality. The objective of using an image normalization algorithm is to effectively create a norm of image regions without biased by differences in illumination. This study assumes there is no significant illumination gradient under an