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Adaptive Visual Inspection for Assembly Line Parts Verification

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Abstract—**This paper presents an intelligent visual inspection method that addresses the need for improved adaptability of a visual inspection system for parts verification on assembly lines. With the proposed adaptive method, the system is able to adapt to changing inspection tasks and environmental conditions by performing online learning and defect detection simultaneously without requiring excessive offline retraining or retuning. The proposed method consists of three major mechanisms: region localization, online learning, and defect detection. The edge-based geometric pattern-matching technique is used to locate the region of verification (ROV) that contains the subject of inspection within the acquired image. A principal component analysis (PCA) based algorithm is proposed to implement the online learning and defect detection mechanisms. Case studies using field data from a fasteners assembly line are conducted to validate the proposed method.**

Index Terms—**Adaptive visual inspection, online learning, defect detection, principal component analysis, parts assembly.**

I. Introduction

Various visual inspection systems have been applied for quality assurance on parts assembly lines in manufacturing industry. Instead of human inspectors, a visual inspection system can automatically perform parts verification tasks to assure that parts are properly installed and reject improper assemblies. However, most of the existing visual inspection systems are hand-engineered to provide *ad-hoc* solutions to specific inspection tasks under specific environmental conditions [1]–[3]. They normally use a specific template matching algorithm or a feature extraction method. Thus the existing system lacks adaptability with respect to changes of the assembly line. Such changes could be due to:

- Changing products in response to market demands. This requires changing the inspection algorithm of the existing system to deal with new assembly parts.
- Changing environmental conditions, for example, lighting conditions, camera characteristics, and system fixation after a certain period of system operating time. This may render the existing system obsolete, and thus requires adjusting the original inspection algorithm for new environmental conditions.

Since the early 90's, machine learning-based strategies have been proposed to improve the adaptability of visual inspection systems [4], [5]. Unlike the conventional approach that detects defects based on the *a priori* knowledge about the inspected parts, learning-based approaches identify defective cases based on recognition patterns that can be learned from examples using intelligent computing algorithms. As such, the system is flexible to be trained to handle different inspection problems in variable environmental conditions.

Machine learning can be conducted through offline or online processes. In offline learning, all training data are previously obtained and can be accessed repeatedly. In online learning, each case is presented one at a time and training data are collected incrementally. Popular offline learning techniques for visual inspection system include using neural networks and neuro-fuzzy classifiers to perform initial system training, in which recognition patterns are learned from an existing training data. However, a concern often raised by end users is that the performance of the offline learning based system relies heavily on the training data. In many situations it may be difficult or even impossible to collect all representative training samples over a limited period of time.

Recently several researchers have reported their investigations on the application of online learning techniques to develop adaptive visual inspection methods. Those methods attempt to perform learning of inspection patterns during system operating time. Hence, the system does not require an excessive offline training process when it faces the situations of changing inspection task or environmental conditions. For example, Abramovich *et al*. [6] proposed a novel online part inspection method based on a developmental learning architecture that uses the incremental hierarchical discriminant regression (IHDR) tree algorithm. Pena-Cabrera *et al.* [7] utilized the Adaptive Reasoning Theory Map (ARTMAP) neural network, an incremental learning algorithm, to develop an adaptive method for online recognition and classification of pieces in robotic assembly tasks.

Although the aforementioned researches have shown promising results in utilizing online learning techniques to improve the adaptability of visual inspection systems, there is still a lack of more systematic studies with the support of practical experiments. This paper presents preliminary results of a project with an objective to improve the adaptability of a visual inspection system using a learning based approach. An

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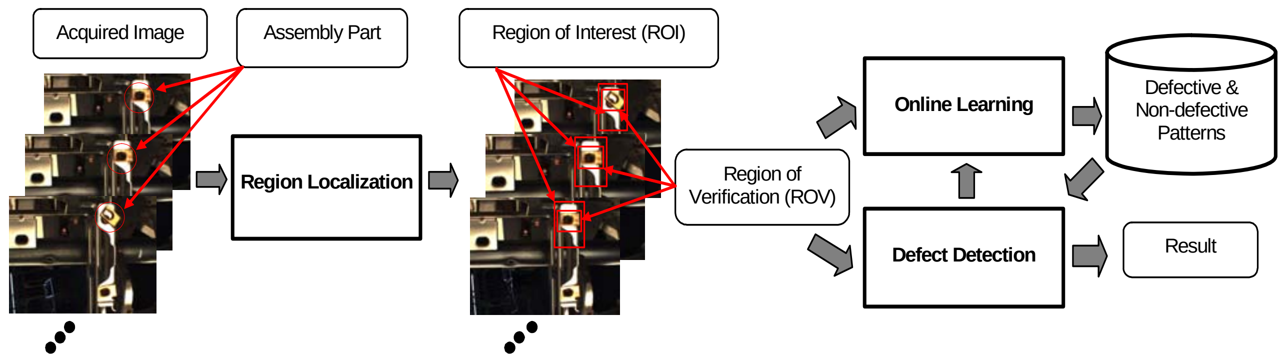


Fig. 1: Adaptive Visual Inspection Method

adaptive method based on online learning concept is proposed in this preliminary work.

II. Adaptive Visual Inspection Method

An adaptive visual inspection method requires that the system is capable of detecting defective cases within certain tolerance while learning recognition patterns at the same time. As illustrated in Fig. 1, the adaptive visual inspection method consists of three major mechanisms:

1) *Region Localization Mechanism* locates the region of interest (ROI) and the corresponding region of verification (ROV) containing the inspection subject within the acquired image.
2) *Online Learning Mechanism* incorporates the freshly located ROV into the system knowledge base if the ROV is identified as a new non-defective pattern.
3) *Defect Detection Mechanism* verifies whether the ROV appears as a defective case using the existing non-defective patterns from the knowledge base that is constantly updated by the learning mechanism.

A. Region Localization

Region localization is required so that the amount of data processing can be reduced. In the proposed method, the region of interest (ROI) within a given image contains two sub-regions, as shown in Fig. 2:

- Region of Verification (ROV): It must include the inspection subject, that is, the assembly part being inspected. Appearance verification of this region may indicate part missing or improper installation.

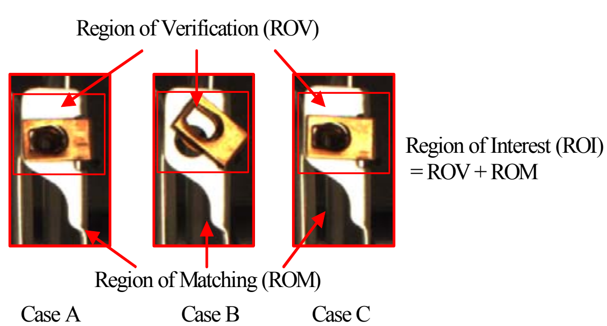


Fig. 2: Defining Region of Interest (ROI)

- Region of Matching (ROM): This region contains features that are invariant to both non-defective and defective cases. Therefore, the appearance pattern of this region can be used as a matching reference/template to locate the ROI and the corresponding ROV.

Region of verification (ROV) holds the key to the performance of online learning and recognition. Efficient and effective identification of ROV is provided by the ROM. It can be defined manually during the system setting up and tuning stage.

An edge-based pattern-matching technique is employed in the region localization mechanism. Instead of comparing pixels of the whole image, an edge based technique compares edge pixels with the template. It offers several advantages over the pixel-to-pixel correlation method. For example, it offers reliable pattern identification when part of an object is obstructed, as long as about 60% of its edges remain visible. Because only edge information is used, this technique can rotate and scale edge data to find an object, regardless of its orientation or size. In addition, this technique can provide good results with a greater tolerance of lighting variations. In this research, the region localization mechanism is implemented using an edge-based geometric pattern-matching module (i.e., Geometric Model Finder) in Matrox® Imaging Library, a commercial software provided by Matrox® Imaging Inc. More background on this module can be obtained in [8].

B. Online Learning and Defect Detection

In the proposed adaptive visual inspection method, the principal component analysis (PCA) technique is used to implement the online learning and defect detecting mechanisms. Principal component analysis (PCA) involves a mathematical procedure that allows optimal representation of images with a reduced order of basis functions called eigenpictures. The eigenpictures are generated from a set of training images. The projection of an image onto the subspace of eigenpictures is a more efficient representation of the image. Many works on image recognition and feature extraction have adopted the idea of the PCA based image representation/decomposition [9].

In PCA, for a given set of training images, each w by h pixel image is represented by a vector of size $w \times h$,

$x_k = [p_1; p_2; ...; p_{w \times h}]$. The eigenpictures U can be obtained by solving the following equation:

$$U^T (X - \mu)(X - \mu)^T U = \Lambda \quad (1)$$

where matrix $X = [x_1, x_2, ..., x_k, ..., x_K]$ denotes the set of training images, vector $\mu = [\mu_1; \mu_2; ...; \mu_{wxh}]$ is the mean of the training images, and Λ is a diagonal matrix of eigenvalues $diag(\lambda_1, \lambda_2, ..., \lambda_K)$. Corresponding to first l largest eigenvalues $(\lambda_1, \lambda_2, ..., \lambda_l)$, l major eigenpictures are selected to form a subspace of eigenpictures U_l. By projecting onto the subspace of U_l, the set of training images X and a newly acquired image x can be represented by their projection coefficients $U_l^T (X - \mu)$ and $U_l^T (x - \mu)$, respectively. Those coefficients can be used to reconstruct their original images.

The image reconstruction error measures the difference between the original and the reconstructed images. The reconstruction errors can be used to detect abnormality or novelty [10]–[12]. Assuming that all training images are normal cases, the reconstruction errors of the training images follow a normal distribution with a mean value m and a standard deviation σ. This hypothesis has been validated in the case studies of this research, as described later in Section III. For a newly acquired image x, the reconstruction error can be calculated as:

$$\|r\| = \|x - y\| \quad (2)$$

where x is the original image and y is the reconstructed image based on the projection coefficients, i.e., $y = U_l a + \mu$, $a = U_l^T (x - \mu)$. By choosing a certain confidence interval α (e.g., 99.74% confidence interval translates to $\alpha = 3$ for a normal distribution), the image is considered as an abnormal case if its reconstruction error $\|r\|$ is not in the range of $\{m - \alpha\sigma, m + \alpha\sigma\}$. The values of $m - \alpha\sigma$ and $m + \alpha\sigma$ are the lower and upper thresholds for determining normal cases, respectively.

Conventionally, the PCA technique is used in offline learning mode that requires all the training data to be available in beforehand. Thus, it is unsuitable to applications that demand online updates to the PCA model. This paper presents an algorithm to build and update the PCA model incrementally to incorporate new training patterns. As illustrated in Fig.3, a PCA model is constructed using non-defective data patterns during the model development phase and employed to detect defective cases in the model execution phase. During the model development phase, inspection results are verified by a human operator to identify false negative cases. A false negative case refers to a false classification of defective case, which means an actual non-defective case is classified as a defective case by the existing PCA model. Consequently, the false negative case is used as a new non-defective pattern to re-train the existing PCA model. Thus, the online learning mechanism updates the PCA model only when a false negative case is identified and added into the training set. Once the counts of false negative cases have reached steady state after a certain period time, the PCA model is considered stabilized and then the model execution phase begins. The PCA based online learning and defect detection mechanisms are described as follows:

- *Model Development Phase*
  Both online learning and defect detection mechanisms contribute to the construction of a PCA model. In this paper, the PCA model is denoted by *MP*, which retains the generated eigenpictures U_l and the mean of training images μ. It also retains the mean value m and the standard deviation σ of the reconstruction errors on the training set containing the false negative cases that represent non-defective patterns. In particular, the model development phase consists of four steps:

  1) *Model Initialization*
     1.a) Initialize a PCA model with $x(1)$, the ROV

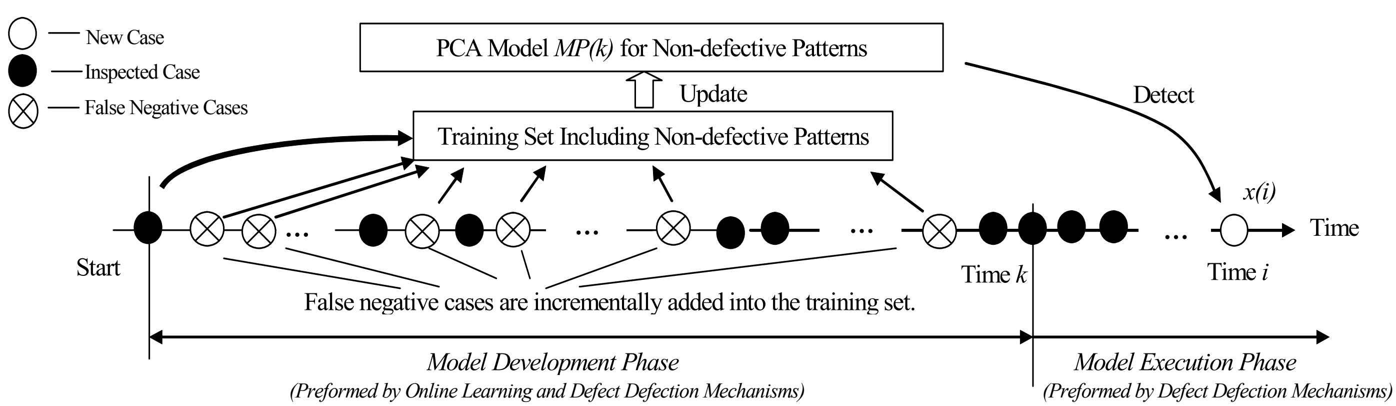


Fig. 3: The PCA Based Algorithm for Online Learning/Defect Detection Mechanisms

defined in the first image, which represents the first non-defective pattern of the inspected assembly part, i.e., $MP(i)$ at $i = 1$:

$$\{U_l(i) = 0_{1x(w*h)}, \mu(i) = x(i), m(i) = 0, \sigma(i) = 0\}$$

1.b) Add $x(1)$ into the training set, in which new non-defective patterns will be incrementally added when they are identified during the model development phase.

2) *Defect Detection*

2.a) For $i > 1$, compute the projection coefficients of the ROV from a newly acquired image $x(i)$. Reconstruct the image of the ROV and then calculate the reconstruction error, based on the current existing PCA model $MP(i-1)$, by using (2).

2.b) Conclude on whether the newly acquired image appears as a defective case according to the corresponding upper and lower thresholds of non-defective patterns.

3) *Inspection Result Verification*

3.a) Verify the inspection result obtained from 2.b) by a human operator. Update the false negative counts $Cfn(i)$.

3.b) If $x(i)$ is identified as a false negative case , add $x(i)$ into the training set, then go to step 4). Otherwise, return to step 2) to process the next acquired image/ROV.

4) *Model Update*

Build a new PCA model $MP(i)$ based on the updated training set by using (1). Return to step 2) to process the next acquired image/ROV.

- *Model Execution Phase*
  The model development phase can be considered completed when the counts of false negative cases $Cfn(i)$ have reached plateau. Subsequently, the PCA model can be used to detect defective cases without requiring further updating. In the model execution phase, the defect detection mechanism inspects each newly acquired image/ROV based on the PCA model that has been built in the model development phase, by using (2).

III. CASE STUDY

For case studies, field data are collected from an existing fastener inspection system for a truck cross-car beam assembly. The visual inspection system examines a total of 46 metal clips inserted by assembly robots for their proper installation. The existing system works well after excessive amount of manual tuning. Improving the system adaptability to changes has been a top priority. Fig. 4 shows examples of two types of clips on the cross-car beam assembly.

In order to simulate an online operation, the proposed adaptive method was applied to a dataset of images that were acquired sequentially in 24 hours. Experimental results are promising; indicating the potential of the proposed method to offer adaptability in a visual inspection system. Figure 5 shows the experimental results of inspecting Clip 1 as shown in Fig. 4. The dataset for this type of clips includes 1595 non-defective cases and 4 defective cases. The observations from the experiment are summarized as follows:

- In the model development phase, the proposed adaptive method was able to update the PCA model each time when a false negative case was identified. As shown in Fig.5 (a), there were 34 cases whose reconstruction errors were

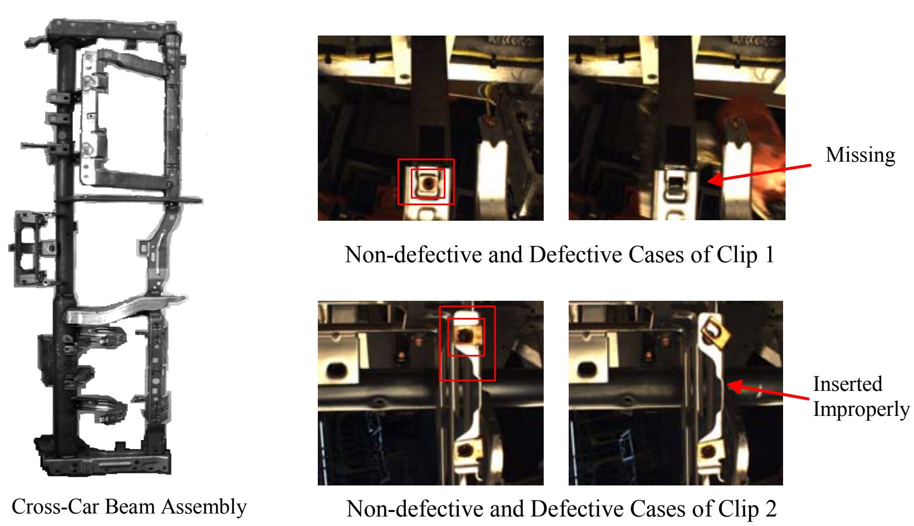
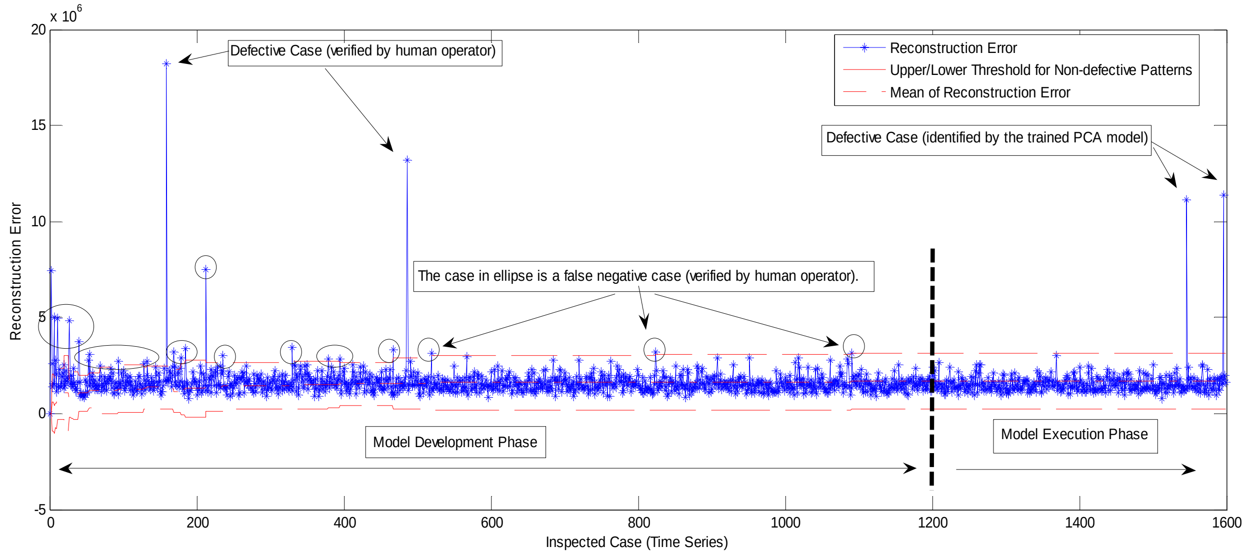
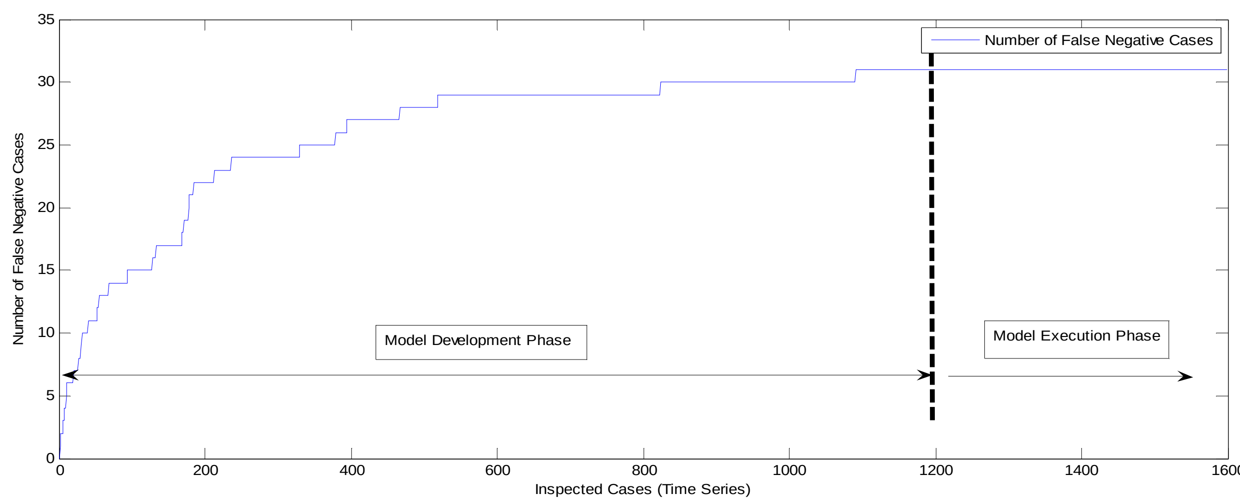


Fig. 4: Examples of Clips on Cross-Car Beam Assembly



(a) Reconstruction Errors vs. Inspection Cases



(b) Counts of False Negative Cases vs. Inspection Cases

Fig. 5: An Experimental Result for Inspection of Clip in Case Study

beyond the thresholds for non-defective patterns. Manual verification confirmed 2 defective cases and hence 32 false negative cases. These 32 false negative cases were incrementally incorporated into the PCA model for updates. As illustrated in Fig. 5 (b), after processing a total of 1200 case images, there appeared no new false negative case. Therefore, the model development phase was considered completed at that point.

- In the model execution phase, the trained PCA model efficiently identified all defective cases without generating false negative cases. In this experiment, the PCA model retained four major eigenpictures corresponding to the four largest eigenvalues that contributed 70% of total of eigenvalues. Figure 6 shows the distribution of reconstruction errors for non-defective cases using the trained PCA model. It validates our hypothesis of a normal

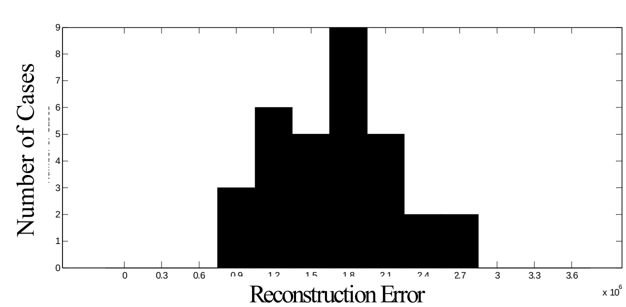


Fig.6: Distribution of Reconstruction Errors

distribution with a mean value of $m = 1.68 \times 10^6$ and a standard deviation of $\sigma = 4.88 \times 10^5$. The 99.74% confidence interval with $\alpha = 3$ was used to define the thresholds.

In order to show that the proposed adaptive method was able to achieve a similar performance for different types of clips under different environmental conditions, we generated results on two different datasets that were acquired for inspecting two types of clips from two different periods. In the two periods, the lighting conditions and camera settings were different. The experimental results showed that the proposed method had similar performances for the two different datasets.

IV. Conclusion

This paper presents an adaptive visual inspection method that addresses the need for improved adaptability of a visual inspection system for assembly line parts verification. The proposed adaptive method is developed based on an online learning concept that attempts to perform simultaneous online learning and defect detection during the system's operating time. As such, the system is flexible to handle new inspection task and the changed environmental conditions without requiring excessive retraining and retuning.

The proposed adaptive method consists of three major mechanisms, including region localization, online learning, and defect detection. (*i*) The region localization mechanism utilizes the edge-based pattern matching technique to locate the region of verification for the inspected assembly part within each acquired image. (*ii*) The online learning and defect detection mechanisms are implemented based on the principal component analysis (PCA) technique. In the model development phase, the online learning and defect detection mechanisms work together to incorporate the identified false negative cases as new non-defective patterns into the PCA based model. In the model execution phase, the defect detection mechanism can efficiently identify defective cases by employing the PCA model that is built in the model development phase.

Although this research is still in its preliminary stage, the experimental results showed that the proposed adaptive method was promising in achieving the objective of this research. Future work of this research will focus on further development which includes (*a*) validating the proposed method with a greater range of data reflecting variations in both inspection tasks and environmental conditions; (*b*) investigating alternative online learning approaches that can incorporate and identify different types of defective patterns. The expected outcome of this research will be beneficial to the application of intelligent visual inspection in the manufacturing industry.

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