Title:
Design of CNN-based Visual Inspection System for Flexible PCB

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Introduction:

Quality Inspection in a manufacturing scenario is one of the most important processes to ensure that a product is manufactured well as designed and it has satisfied customer requirements. Therefore, visual inspection, a method of processing with images acquired from camera is most commonly used today due to its benefits of affordability and the ability to produce relatively uniform results. The index derived after the visual inspection used as a basis for ensuring the quality and customer satisfaction of the product, so it is necessary to increase its accuracy, robustness, efficiency and performance speed. Fig. 1 shows the visual inspection system procedure. Essentially, one of the essential steps of a visual inspection is to ensure that it is visually incomplete or free of faults. Thus, human factors, which can intuitively judge a defect are still an important factor in the manufacturing industry. Visual inspection is a minor task that can be solved by humans, but repetitive tasks can cause fatigue in humans and their accumulation can adversely affect the operator's health. Moreover, Human error degrades the robustness of quality inspection and also causes cost problems. Consequently, automated visual inspection systems that perform the process automatically are presented as solutions in many manufacturing scenarios.

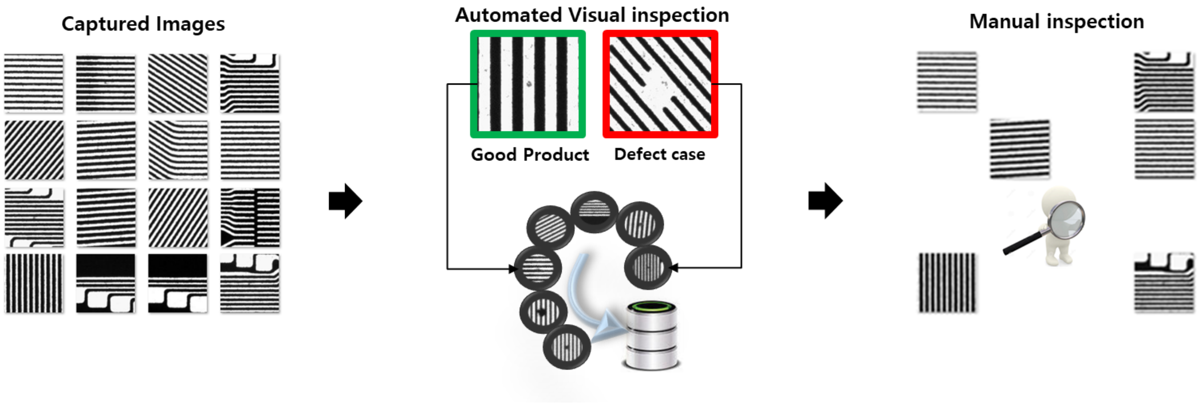

Fig. 1: Visual inspection system procedure.

For obvious types of defects, it is possible to derive the features of images to determine whether they are defective or not, but the problem is the judgment of the defect and good product is ambiguous. Most of this is due to small shape differences in the images. In addition, external factors, such as lighting and camera aging, may interfere with the image quality of the same product. Such an ambiguous image appears to be quite a percentage of the entire visual inspection image. In such cases, opinions may also be divided among highly trained personnel. Fig. 2 shows the image class example. The more types of images that are difficult to define with human eye, the greater the risk to the automated inspection system. But the size of the manufacturing industry is growing, and the image of ambiguity will grow day by day.

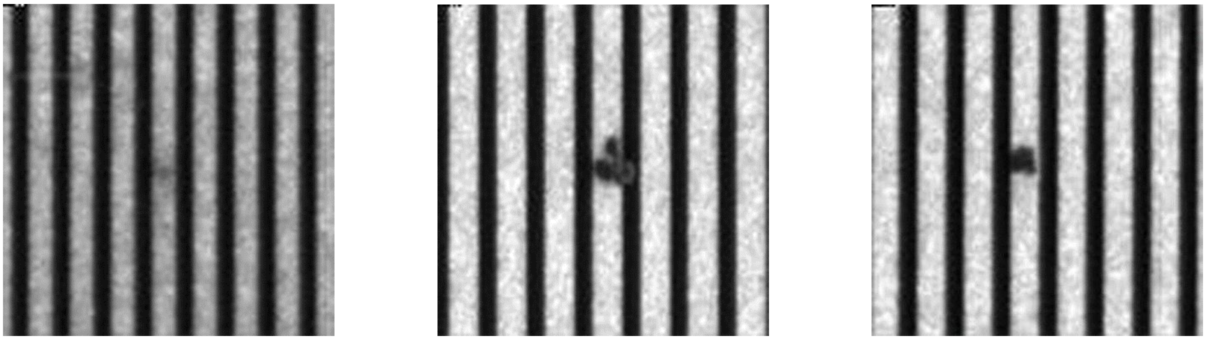

Fig. 2: Image class example, from left to right: (a) good product case, (b) Good product on dust case (actually, good product), (c) defect case.

The purpose of the automatic inspection system is to divide the Defect Area from the background and classify it into predefined categories of faults. In an environment that controlled by stable conditions, a simple Thresholding technique may suffice to distinguish faults when only a predefined category of defect occurs. More sophisticated defect classification techniques are required if the manufacturing level is low, if new techniques are introduced, and if the image capture conditions are not controlled.

Approach	**Method**
Statistical	Histogram properties
	Local binary pattern
	Autocorrelation
Structural	Edge Features
	Skeleton representation
	Morphological operations
Filter based	Spatial domain filtering
	Joint spatial frequency
Model based	Random field models
	Texem model

Tab. 1: Four Categories of defect classification techniques.

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Xie [4], Neogi [2] introduced defect classification techniques in four main categories, primarily statistics, structure, filter based and model based. Tab.1 shows the four categories of defect classification techniques. All four categories of techniques are those that summarize manually given image data into optimal representations. Pernkopf [3] introduced the feature incoding technique to carry out stabilization studies when selecting different categories of defects. Jiang et al [1] demonstrated the appropriateness of the filter-based formula for surface analysis. While these methods have produced satisfactory results for generally known issues, not be applied to new problems or to problems in other sets. This is because these manually conducted defect classification techniques have their own characteristics to respond only to manually defined feature extracts. Its manual costs not be ignored because it has to be redesigned each time a new type of defect occurs. Considering these points, this paper proposes a CNN (Convolutional Neural Networks) based inspection system to overcome the difficulties in manually defining categories of emerging faults. CNN consists of a random initial set of filters, whose goal is to learn the best filter for a given issue. CNN produces meaningful results from minimum interaction with humans, using well-divided raw data and minimal effort to give the answers to each image. This paper will set up an automated visual inspection system and introduce the process of its design and learning parameters.

Main Section:

Generally referred to as the design of the CNN model, the method of configuring the Hyper-parameter, as opposed to the neuron parameters learned during transport. The hyper parameter is manually preselected and significantly affects the performance of the CNN model. Major parameters are the number of neurons, the number of layers, activation function, running rate, and the drop-out. In case of CNN, additional hyper-parameters like filter size needed. The purpose of this paper is to derive learning models from an appropriate combination of hyper parameters. The automated visual inspection system proposed in this paper consists of four main sections: input, preprocessing, training & validation, and management. Fig. 3 shows the proposed framework.

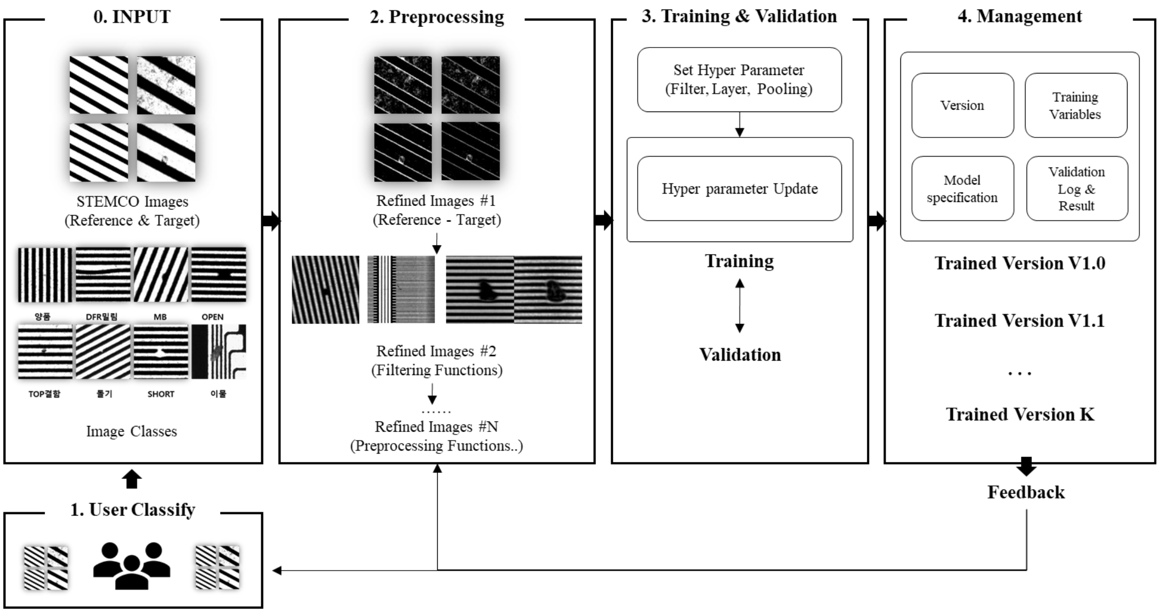

Fig. 3: CNN based visual inspection system framework.

First, he inputs section sorts classes of pairs of references to the image and Target. Its classification is divided into eight defect classes, each having a size of 128 * 128 pixels and is composed of 1,000 images per class. The Image is enhanced to 32 * 32 group images using grid segmentation, and once again by rotation and mirroring. The reason for this is to increase the volume of learning data and to facilitate learning. These grouped raw images are modified in the refine section, a layer that highlights the features throughout a certain filtering process.

In preprocessing section, reference images are used to determine differences from design purposes. The purpose of this section is to reduce the influence of Background on CNN learning. The images that effectively exclude the background will be included in the training set and will be studied accordingly. In the Training & Validation section, learning and validation is carried out and calculate the learning rate. To carry out this framework, hyper-parameter experiments consist of four groups. In this paper, each of the four groups of running speed, validation speed and performance will be measured and its effectiveness calculated. Tab. 2 shows the proposed experiment groups.

	LV1	**LV2**	**LV3**	**LV4**
Layer #1	Conv(3*3) x 6	Conv(3*3) x 16 Conv(3*3) x 16	Conv(3*3) x 16 Conv(3*3) x 16 **Padding(2)**	**Conv(3*3) x 32** **Conv(3*3) x 32**
Pooling	Max pooling (2)			
Layer #2	Conv(3*3) x 16	Conv(3*3) x 32 Conv(3*3) x 32	Conv(3*3) x 32 Conv(3*3) x 32 **Padding(2)**	**Conv(3*3) x 64** **Conv(3*3) x 64**
Pooling	Max pooling (2)			
Layer #3	Conv(3*3) x 128	Conv(3*3) x 256 Conv(3*3) x 256	Conv(3*3) x 256 Conv(3*3) x 256	**Conv(3*3) x 512** **Conv(3*3) x 512**
Fully connected 2048 **Fully connected 96** **Softmax**				

Tab. 2: Experiment Groups.

Conclusion:

Fast and reliable automatic visual inspections are one of the main challenges in manufacturing scenarios. However, automated visual inspections in existing industries require a large human resource to passively define the extraction of defect types of features, and tend to depend on each individual defect characteristic. Thus, if new types of defects are detected, or if the conditions of the inspection environments are not evenly controlled, it could disrupt the stable inspection. This paper proposes an automated visual inspection system based on the Convolutional neural network (CNN), which reduces human resource factor and enables a faster automated visual inspection when new types of defects are detected. In this paper, we measure the performance of the Hyper-parameter configuration and derive an effective combination. This could apply not only to flexible PCB but also to the field of visual inspection.

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