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Studies on industrial vision inspection methods

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STUDIES ON INDUSTRIAL VISION INSPECTION METHODS

by

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A thesis
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ABSTRACT

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Although vision inspection has been applied to a wide range of industrial applications, inspection accuracy remains a challenging issue due to the complexity involved in industrial inspection. The common method adopted in industry is to use a template image as a reference template to inspect each live image on a pixel-by-pixel basis. In this thesis, a tolerance-based method is studied to replace the template image method. The said tolerance is formed by two indices computed from an image, instead of using the whole image for inspection. To ensure an accurate tolerance zone, a Neural Networks method is used to take into consideration the noise and uncertainties in the parts under inspection. To reduce training time, the Taguchi method is adopted to select a minimum number of the sample images needed for training. Once a tolerance zone is obtained, a live image is inspected against it. If the indices fall inside the tolerance zone, it is deemed as good, otherwise faulty. The inspection accuracy achieved is 94.5%. Three examples are given, one for label inspection and the other two for auto part inspection.

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NOMENCLATURE

AI:	Artificial Intelligence
ANOM:	Analysis of Means
BW:	Black-White
CCD:	Charge Coupled Device
DOE:	Design of Experiments
FFT:	Fast Fourier Transformation
HSV:	Hue-Saturation-Value
NN:	Neural Networks
OA:	Orthogonal Array
OEM:	Original Equipment Manufacturer
RGB:	Red-Green-Blue
ROI:	Region of Interest
S/N:	Signal-to-Noise

CHAPTER 1 INTRODUCTION

1.1 Motivation and Solution

Computer vision, a widely used technology, has been highly developed and adopted in various industrial applications. It has been applied in manufacturing, medicine and aerospace engineering. Especially, computer vision has been playing a crucial role in manufacturing processes [1], such as assembly, measurement, and automated industrial application. Nowadays, it is hard to find a manufacturing plant that does not have some type of machine vision to measure, locate and inspect products.

Vision inspection is one of the areas that attract much attention in computer vision [2, 3]. Researchers have been striving to reduce cost, improve precision and consistency, and shorten inspection time. However, the potential of industrial vision inspection systems has not yet been fully exploited. For example, to date, the vision inspection systems are mainly used as a screening inspection, and the identification and removal of defective products, rather than as a process for continuous improvement of a manufacturing system. The lack of flexibility in the existing industrial vision inspection systems to adapt algorithms to new products and to different industrial applications is the reason for the absence of continuous improvement capabilities.

Currently, when new components are introduced into an existing assembly line, the inspection system requires reprogramming to incorporate the new characteristics of the new components into the inspection algorithms. The same situation will happen when the existing inspection system is introduced into a different industrial application, such as from printing inspection to automobile manufacturing inspection. Often, this process of reconfiguration requires the involvement of the original equipment manufacturer (OEM) of the inspection system to develop new inspection algorithms and adjust the existing inspection system to the new components. The cost of this adjustment period is frequently one of the main obstacles for the appropriate use of inspection systems on the factory floor. Therefore, it is necessary to develop the tools and methodologies that would allow the rapid adaptation of existing inspection systems to new products so that the inspection systems are not rendered obsolete by incremental changes in manufacturing processes.

Over the last two decades, artificial intelligence (AI) methods have been applied to train inspection systems to improve their efficiency and accuracy. The Neural Networks (NN) method is one of the popular AI methods used for image processing. Because of its inherently nonlinear nature, Neural Networks is considered particularly well suited for image processing applications where the classical spatial or frequency methods are not effective. NN-based methods are developed to complement or replace conventional approaches for industrial inspection. Applications of NN-based inspection include quality and process control, document processing, identification and authentication, and medical diagnosis. [4].

The processing efficiency of NN-based vision inspection methods is largely determined by the abstraction level of the input data, which may be classified into three levels, pixel, local feature and object. In the first category, the intensities of individual pixels are provided as the inputs. In the second category, a set of derived, pixel-based features constitutes the inputs. In the last two categories, the properties of individual objects are used as the inputs. In most published works, the input data is either pixel level or feature level, the methods based on which are usually computationally intensive and time consuming.

Though Neural Networks models are different, there is one common aspect, namely, the Neural Networks being used to inspect image as a classifier [5-8]. So the training data must include enough information and has to be pre-processed. The large volume of data means that preprocessing and inspection are time consuming and this has been the biggest obstacle for industrial implementation. Inspection speed and interference of uncertain factors are identified as the main problems of traditional vision inspection system.

In this thesis, a tolerance method is studied. This method combines a statistical method with a Neural Networks method. Different from traditional vision inspection methods, this method is based on two indices of a good image, which are the variances of the rows and columns of the image. Neural Networks are trained using these two indices from a set of sample images. The minimum and maximum values of the two indices form a tolerance zone. To ensure an accurate tolerance zone, Neural Networks is used to take into consideration the noise and uncertainties in the parts under inspection. To improve speed, the Taguchi method is adopted to select a minimum number of the sample images needed for training. When inspecting, the two indices of each image are computed through trained Neural Networks and compared with the tolerance zone. If the indices fall inside the tolerance zone, it is deemed as good, otherwise faulty. Experimental results show that defective items can be effectively detected by examining whether either index falls out of the tolerance zone. In what follows, the details of this method are presented.

1.2 Thesis Outline

This thesis is organized into seven chapters:

Charter 1 is the introduction.

Chapter 2 describes the previous approaches of industrial vision inspection and application of Neural Networks to vision inspection.

In Chapter 3, a tolerance method is studied for industrial vision inspection. Fundamental concepts, algorithms and Neural Networks structure are also provided.

Chapter 4 addresses the practical considerations of industrial vision inspection.

Chapter 5 focuses on optimization of training data.

Chapter 6 presents experiment results.

Chapter 7 summarizes conclusions and discusses future work.

CHAPTER 2 LITERATURE REVIEW

In this chapter, the structure, algorithms and Neural Networks application for industrial vision inspection are reviewed. The drawbacks of traditional methods and improvement goals are discussed.

2.1 Industrial Vision Inspection

Machine vision systems are referred to as automated vision inspection, and those have been applied slowly but surely to a variety of manufacturing applications, all with the goal of improving quality and productivity in manufacturing processes [9]. Machine vision may be described as the acquisition and analysis of vision information. An image is a snap shot of vision information that is composed of many (usually several million) picture elements called pixels. Preprocessing of the pixels allows the vision information to be used for decision making.

Typically, an industrial vision inspection system can be decomposed into a sequence of processing steps [4, 10, 11]: image acquisition to acquire images by a digital camera; image enhancement to improve the quality of the image for subsequent processing; defect recognition to detect defects by comparing the current image with a template image; defect classification to classify a defect type by feature extraction and classification; and decision making to decide if the image should be judged as good or defective. Figure 2.1 illustrates the structure of a typical industrial inspection system. One of the common problems in industrial environment is how to quantify the uncertainties that affect the image fidelity. These uncertainties may be caused by machines dynamics, product variation, and illumination variation.

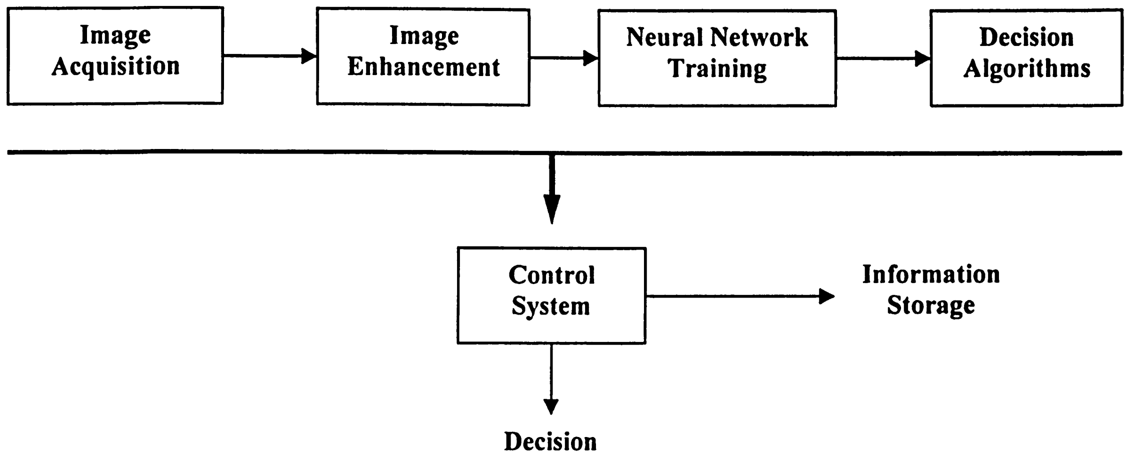


Figure 2.1 Industrial vision inspection system [4]

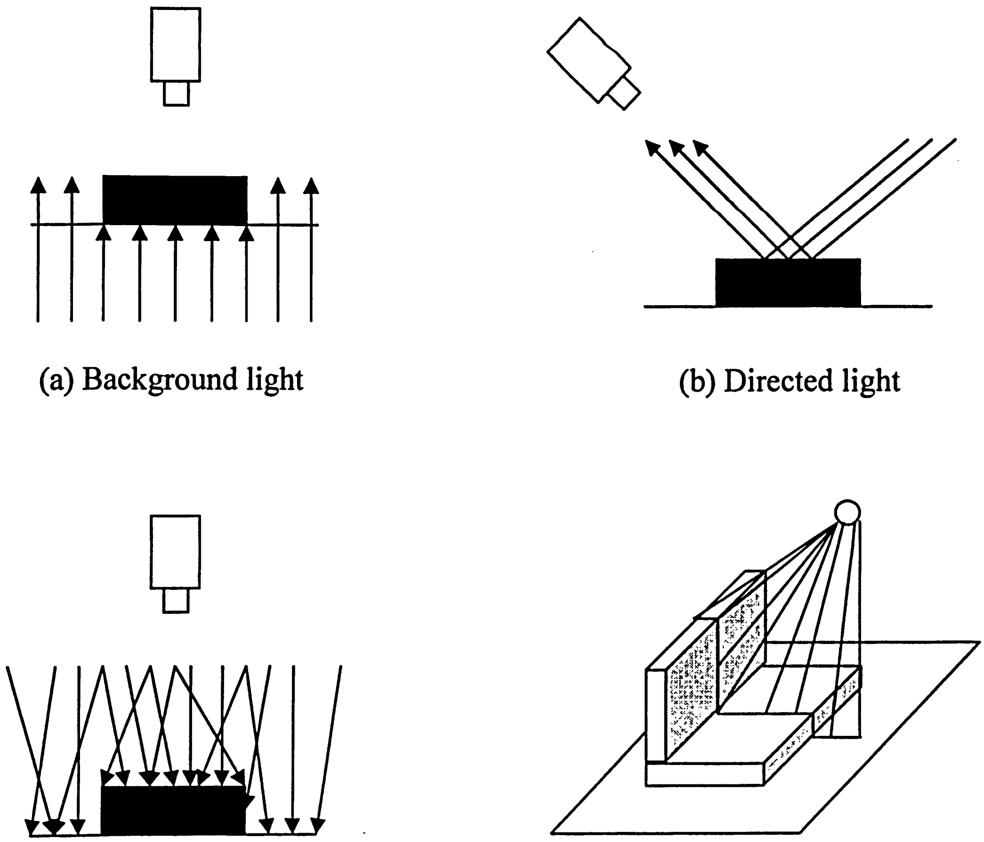
The first component in a generic automated vision inspection station is image acquisition and digitization. Image acquisition is usually done with a camera as the sensor.

One type of image sensor, used in most computer vision systems, is a television camera. The image is focused onto a photoconductive target. At the target, the higher the image intensity in a region, the more charge that is lost at the region. An electron beam is then deflected onto the target magnetically, and this beam makes up the lost charge. The video signal is made up from the beam.

A second type of camera is the digital camera that receives an image via individual sensing elements. Each sensing element records the energy level of reflected light in its geometric domain by the amount of charge generated. The most common type of digital device is the charge coupled device (CCD). The digital camera has the advantage that it is not subject to geometric distortion since there is no electron beam scanning. The digital camera is also less sensitive to noise and overexposure.

Once an image is acquired by a camera, it is sent to an image processor. The functions of the image processor are to digitize the input image from the camera, store the digitized image and implement special purpose functions. The signal is digitized by an analog to digital converter where it is transformed into a matrix of picture elements. Each picture element, called pixel, is a number corresponding to the intensity of light at a particular point in the image. The pixels are stored in the memory where they may be accessed by the various software components.

One of the most critical hardware considerations in an industrial vision inspection system is lighting [30]. It should be noted that there is no such thing as an optimal lighting environment that can be applied to all situations. Lighting is very specific to environment and application. Many different types of lighting can be used. Typical examples include diffuse lighting, background lighting, direct lighting and stripe lighting. Each of these examples is shown in Figure 2.2. An appropriate lighting configuration for a specific industrial vision inspection application must be determined by experimentation. Some applications require changing the lighting environment during processing.



(a) Background light (b) Directed light

(c) Diffuse light (d) Light stripping

Figure 2.2 Lighting environments [4]

Due to the large amount of information contained in each image, it is important to enhance the image prior to processing. Typical enhancements include removal of noise, edge detection and enhancement of contrast. Enhancement may be performed on individual pixels, groups of pixels or the entire image.

One of the crucial and most time-consuming processes in the training phase of vision inspection systems is the selection of inspection features. A feature is usually a prominent or distinctive characteristic that can be extracted from a digital image of a product to be inspected. Ideally, the features used share common characteristics in that they are computationally inexpensive, and simple enough to accommodate new components without major modifications to the actual system.

However, a downside of the feature simplification is that they alone do not provide an error-free classification among inspection parts. In the training phase, the developer of the vision inspection system needs to identify, among known features, a subset of them that provides an adequate level of discrimination between defective and non-defective components. If no subset of features provides the needed discrimination, it is necessary to develop new features to attain the desired level of discrimination. The feature selection process requires a great deal of time and a knowledgeable human developer.

In theory, human inspectors could be utilized to detect missing components. However, in practice, continuous miniaturization and the increasing speed of assembly of these components make human inspection obsolete and the use of industrial vision inspection systems a necessity. However, because of their lack of flexibility, these systems have been used mostly as a way to detect defects rather than to use the information generated by these systems to improve the underlying manufacturing systems. Because of the time it requires, a very important element in achieving this goal is the automation of the selection of the features to use for the inspection.

2.2 Vision Inspection Algorithms of Industrial Vision Inspection System

There are many image processing techniques useful for machine vision inspection. These techniques include area calculation, histogram analysis, boundary following, image subtraction and feature matching [9, 12-14]. The choice of the techniques is primarily based on the types of inspection and application.

Area Calculation

In the area calculation, the region of the image is the portion with the boundary, where the boundary is represented by those pixels that have both black and white neighbors. The application of this technique is to calculate the total number of the black pixels that contain the region and the boundary of the image. An inspection threshold value is predetermined and implemented in the algorithm to distinguish the good parts from the defective ones. The area of good parts should be very close to each other and is always greater than a defective part.

Boundary Following

This procedure must work on a consistent boundary with four-connected neighbors. The boundary is detected clockwise, and the number of the boundary points is accumulated during the entire trace. The number of the boundary points of the test part is then compared with the points of a good part. Based on the difference between the numbers of the boundary points, a good part is distinguished from a defective part. When the difference is within a predetermined range, the part is considered a good part.

Histogram analysis

A gray-level histogram of an image shows the frequency of occurrence of each gray level in the image. The idea behind this technique is that the histograms of the image of all the good parts are similar. The operation of this technique is to calculate the number of pixels for each gray level and compare with the good part. A tolerance is defined in the algorithm to differentiate a defective part from a good part.

Image Subtraction

Image subtraction is the simplest and most direct approach to the inspection problem. This is one of the earliest techniques employed in inspection. The acquired image is compared against the template image. The subtracted image, showing defects, can subsequently be displayed and analyzed. Figure 2.3 shows this direct subtraction process as a logical XOR operation.

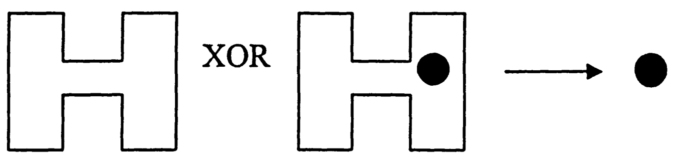


Figure 2.3 Image subtraction [15]

The advantage of this method is easiness to implement. Another advantage is that it allows for verification of the overall defects in the image. But this technique suffers from many practical problems, including registration, color variation, reflectivity variation, lighting sensitivity and other uncertain factors.

Feature Matching

Feature matching is an improved form of image subtraction, in which the extracted features from the object and those defined by the model are compared. The advantage of this matching is that it greatly compresses the data for storage, and at the same time reduces the sensitivity to the input data and enhances the robustness of the system. This matching process is also called template matching.

One of the major limitations of the template matching method is that an enormous number of templates must be used, making the procedure computationally expensive. This problem can be eliminated if the features to be matched are invariant in size, location, and rotation. The disadvantages of this method are that it requires large data storage for the ideal image patterns, and precise registration is necessary for comparison. It is sensitive to illumination and digitization conditions, and the method lacks flexibility. Once the base image is changed, the templates must be withdrawn again. To get the better inspection results, the template optimism usually has to be interfered manually.

2.3 Neural Networks Application of Industrial Vision Inspection System

As one branch of artificial intelligences (AI), the first Neural Networks model was first presented by McCulloch and Pitts in the 1940s [16]. Rosenblatt devised the *perceptron* model in 1962. The model generated much interest because of its ability to solve some simple classification problems. In 1969, Minsky and Papert [16] provided mathematical proofs of the limitations of the perceptron and pointed out its weakness in computation.

The power and usefulness of artificial neural networks have been demonstrated in several applications including speech synthesis, diagnostic problems, medicine, business and finance, robotic control, signal processing, computer vision and many other problems that fall under the category of pattern recognition. For some application areas, neural models show promise in achieving human-like performance over more traditional artificial intelligence techniques.

From the engineering point of view, Neural Networks can be seen as highly parallel dynamical systems that model transformation from inputs to outputs. How the transformation is carried out depends on the Neural Networks model and its way of learning the transformation. The most natural application areas for the Neural Networks are those tasks that require the establishment of an appropriate transformation without analytical modeling. Therefore, it is no wonder that the most successful applications of

Neural Networks can be found in the area of machine vision inspection, where such inputs to outputs transformations dominate the problem.

Much of the current research in Neural Networks is centered on individual network models, whereas in typical industrial applications, a system level of Neural Networks is more desirable. Individual Neural Networks might be seen as components in a broader system, which also contains many other data processing techniques. This kind of use of Neural Networks leads to a hybrid architecture in which some of the processing modules are based on Neural Networks. Then the problem is to decide what benefits Neural Networks may provide for the given industrial application and what kinds of Neural Networks models should be used.

There are at least four main aspects that should be considered in Neural Networks application for vision inspection:

1) <u>Selecting the network learning algorithm</u>

There are two types of learning algorithms of Neural Networks: supervised or unsupervised. If the input and desired output are known, a Neural Networks is said to be under supervised learning. Suppose that a Neural Networks is designed to learn between the following pairs of patterns as shown in Table 2.1. The input patterns are decimal numbers, and the target patterns are given in form of binary values of the decimal numbers:

Table 2.1 Example of supervised Neural Networks

Input Pattern	Target Pattern
01	001
02	010
03	011
04	100

In a Neural Networks model, nodes are connected together to form a network. For supervised learning algorithm, the weights are arbitrarily defined in the first training run. During learning, one of the input patterns is given to the input layer. This pattern is propagated through the network (independent of its structure) to the output layer. The output layer generates an output pattern which is then compared to the target pattern. Depending on the difference between output and target, an error value is computed. This output error indicates the learning effort of network, which can be controlled by the "imaginary supervisor". The greater the computed error value is, the more the weight values will be changed. The weights are updated by a number of iterations so the computed outputs will come closer to the target outputs. The Neural Networks is considered well trained when the difference becomes smaller than a given tolerance.

Neural Networks under unsupervised learning have no such target outputs. It cannot be determined what the result of the learning process will look like. During the learning process, the weight values of such a Neural Networks are "arranged" inside a certain range, depending on given input values. The goal is to group similar units close together in certain areas of the value range. This effect can be used efficiently for pattern classification purposes.

2) Controlling the complexity

When training a network for a given problem, the task of a learning process is to construct a required transformation from the input space to the output space of the network [17]. Any transformation of given inputs to outputs is a function approximation problem. The difficulty is that the training samples might easily lead to multiple possible solutions. In order to obtain useful results, the Neural Networks complexity should be matched with the problem complexity and the number of available training examples.

If the network is too complex, it will perfectly learn the training set while generalizing very poorly. Controlling the complexity is therefore a necessity to ensure good generalization. It is specially a key issue when the training set is small, noisy and even partially incorrect. The practical methods for controlling the model complexity include methods such as early-stopped training, committees of early-stopped networks, weight decay or other regularization methods.

3) Choosing the training data

After the construction of Neural Networks, selected data will be chosen for network training. These training data should contain sufficient information for the task [18].

4) Assessing the performances of the network

To determine how well a network works, the common way is to verify the network with test example sets that were not used during the training process.

2.4 Drawbacks of Traditional industrial vision inspection System

As mentioned before, referential methods, the most popular algorithm used for industrial vision inspection, adopt a comparison either through pixel-based or feature-based method. An ideal image (standard image/template image) or number of ideal images must be saved in the database in advance. To make a final decision, one or more threshold values must be setup. If the difference is out of the threshold value, it means that defect is found. Usually the threshold is set up based on operator's experience or trials.

Also referential methods do not consider uncertain factors like lighting sensitivity, machine dynamics, etc. But all these factors are not avoidable under real industrial environment. Neural Networks are used in some application cases of vision inspection system. But the time consuming problem becomes the biggest obstacle for real industrial implementation. From the viewpoint of industry there are three main difficulties for vision inspection to be used widely:

• Speed: In modern industries, high-speed production line is widely applied. Real time monitoring and inspecting system is required to synchronize with the speed of production line [19].

• Anti-Noise ability: At present, vision inspection systems require controlled environment and precise positioning, and assume everything is in perfect condition. But the real working environment is varied, and improvement should be made to cope with the uncertainties like illumination, etc.

• Flexibility: Industrial vision inspection systems should be flexible and easy to adjust from one product to other new products and from one industry to anther one.

The method studied in this thesis is to deal with these problems.

2.5 Design of Experiments

The Neural Networks requires a sufficient number of training data set to be able to describe the model fully. A too-long learning phase increases the danger of overtraining [20]. Basically, overtraining means that the Neural Networks becomes too familiar with historical data and is less able to generalize and handle new data. If insufficient training data is used, then it causes under training. Thus, the use of different experimental designs is to find the optimum number of training runs needed for a satisfactory training set for a Neural Networks. The key is to obtain the maximum information from a minimum number of data and training runs but still can reach high inspection accuracy. Design of Experiment (DOE) is the way to deal with this problem.

Design of Experiment (DOE) is a structured, organized method that is used to determine the relationship between the different factors (Xs) affecting a process and the output of that process (Y) [21-25]. This method was first developed in the 1920s and 1930, by Sir Ronald A. Fisher, the renowned mathematician and geneticist [25]. DOE involves designing a set of ten to twenty experiments, in which all relevant factors are varied systematically. When the results of these experiments are analyzed, they help to identify optimal conditions, the factors that most influence the results, and those that do not, as well as correlation between these factors.

DOE methods require well-structured data matrices. When applied to a well-structured matrix, analysis of variance delivers accurate results, even when the matrix that is analyzed is quite small. Design of experiments is a useful tool that is applied in industry for product and process design and optimization. Its application leads to an understanding of the complex relationship between the inputs and the outputs. Dr. Genichi Taguchi has developed a method based on "orthogonal array" experiments which gives much reduced "variance" for the experiment with "optimum settings" of control parameters [26]. The "orthogonal array" has been studied widely and is now recognized as a fundamental component in the statistical design of experiments.

Orthogonal arrays (OA) mathematically reduce the number of trials of a full factorial experiment without significantly reducing the effectiveness of the experiments [27-29]. These combinations are chosen to maintain the orthogonality among the various factors, so that there are an equal number of test data points under each level of each factor. The primary use of the orthogonal array is to layout the plan to perform the fractional factorial experiments. There are two basic types of orthogonal arrays, namely two-level orthogonal arrays designated as L4, L8, L12, L16, and L32 OAs and three-level orthogonal arrays L9, L18 and L27 OAs. The number in the array designation indicates the number of rows in the array, corresponding to the number of trials. For example, an L8 OA would consist of eight trials. A two-level, eight-trial orthogonal array (L8 OA) is shown in Table 2.2. There are seven columns in this array, which may have a factor assigned to each.

Table 2.2 L8 Orthogonal array [24]

Trial No.	Column No.						
	1	2	3	4	5	6	7
1	1	1	1	1	1	1	1
2	1	1	1	2	2	2	2
3	1	2	2	1	1	2	2
4	1	2	2	2	2	1	1
5	2	1	2	1	2	1	2
6	2	1	2	2	1	2	1
7	2	2	1	1	2	2	1
8	2	2	1	2	1	1	2

The levels for the trials are designated by '1's and '2's. It can be seen that all columns provide four trials under the first level of the factor and four trials under the second level of the factor. This is one of the features that provide the orthogonality among the factors.

2.6 Summary

In this chapter, the traditional industrial vision inspection system is introduced and followed by the discussions on the drawbacks and improvement goals of the traditional vision inspection method.

It has been identified that the interference of uncertain factors and inspection speed are the main problems of the traditional industrial vision inspection system. The following chapter describes a method under this study to deal with these problems.

CHAPTER 3 METHODOLOGY

In this chapter, the statement of three problems under studied is given. The statistics based Neural Networks method is then introduced and applied to solve the three problems.

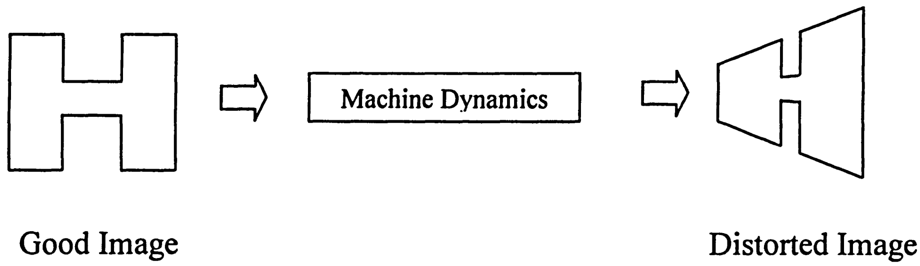
3.1 Problem Statement

There are three problems under study: label printing inspection for printing industry, clips detection for automobile assembly process and casting failure detection for automobile water pump manufacturing. These three problems are representatives of industrial vision inspection problems, the images used for both of training and inspection are affected by industry environment variations and uncertainties, those variations and uncertainties make the Neural Networks training process time-consuming and inaccuracy.

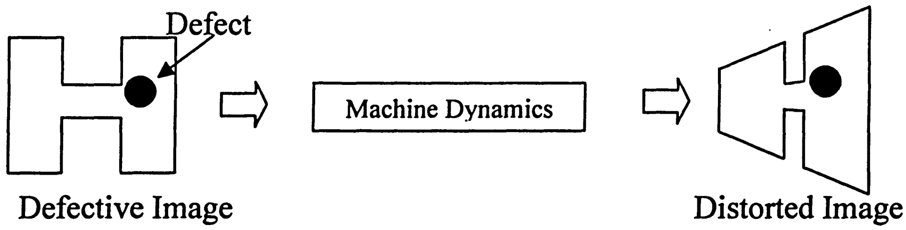
Label printing inspection

The main problem of label printing inspection is to detect defective labels that contain uncertainties including machine dynamics, product variation and illumination variation. Figure 3.1 shows a letter "H" under inspection. Due to machine dynamics, a good letter "H", as shown in Figure 3.1(a), is distorted when captured by a CCD camera. If not treated properly, this letter would be regarded as defective, while in reality the original letter is good.

Therefore, the first task is to filter out the image distortions caused by uncertainties so that the image shown in Figure 3.1(a) will be judged as eligible and that in Figure 3.1(b) as defective. The second task is to set a tolerance for inspection in order to account for the ranges of uncertainties. The proposed algorithm uses a statistical method to define a tolerance zone and uses a Neural Networks method to take systematic uncertainties into consideration.



(a) Distorted image of good image



(b) Distorted image of defective image

Figure 3.1 Distorted images due to machine dynamics [15]

Clips detection

There are a number of variations in clips detection, including the variations of clip position, illumination variation and rotation variation. The images under study were obtained from Van Rob. There are actually quite large differences in the position of the clip within the image between different samples as shown in Figure 3.2. Also the lighting conditions across the samples are not uniform.

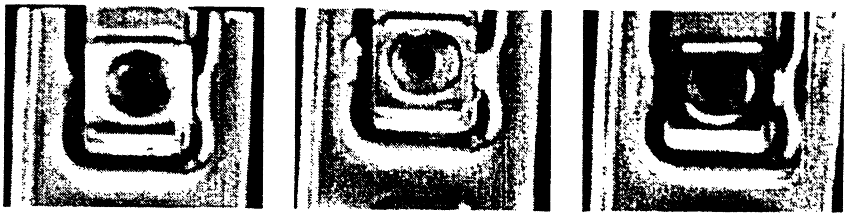


Figure 3.2 Position and illumination variation of clips

Considering all the variations, the main problem of clip detection is to decide what kind of images should be used to train the Neural Networks. Another problem is to decide whether there would be a minimum training set that can be used to reduce the time of training but still can keep high inspection accuracy. To achieve these two goals, the research is made in image processing and image registration to eliminate the noise information. Design of Experiments is used to find a minimum training set.

<u>Casting failure detection</u>

The main goal of casting failure detection is to check the casting failures on the connecting plane of an automobile water pump, like inclusions, porosity (blow holes, pinholes), cold cracking, hot cracking, surface irregularities, and distortion, as shown in Figure 3.3. The images under study were provided by McMaster University. The part is placed on a frame so that the positions in all pictures are exactly the same. How to extract the inspection part from the background and how to detect the tiny defects on the connecting plane and edge are the main tasks.

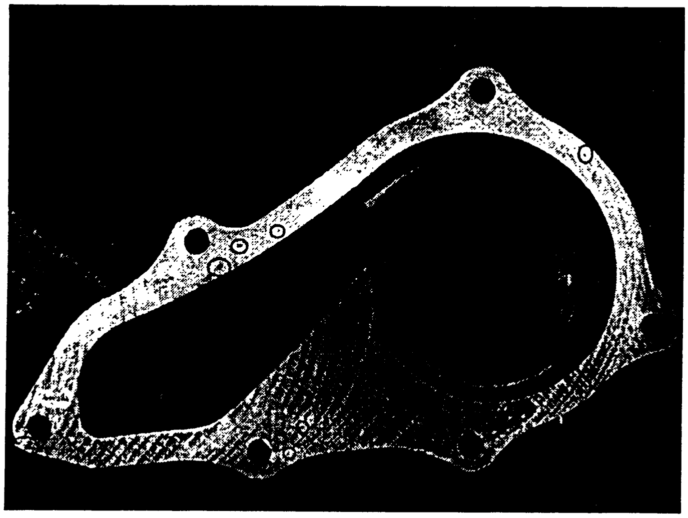


Figure 3.3 Casting failure detection

These three types of inspection problems cannot be solved by the traditional method that compares a live image with a reference image, without considering the effect of noise information and uncertainties containing in the images. Statistics based Neural Networks method is studied to cope with this situation. The method uses only good images to establish a tolerance zone for inspection, and the Neural Networks is used to filter out the industrial environment uncertainties.

3.2 Statistics Method

3.2.1 Live Image, Sample Image and Template Image

There are two main types of images in industrial vision inspection. A live image is the image captured directly from the production line, and a sample image is a live image selected as a reference image. In practice, an inspection image is required to compare to a reference image, called template image in industry. However, there is no true template image due to various factors. A reasonable way is to create a template image based on a number of sample images. In this thesis, an averaging method is adopted to create this image by adding the corresponding pixels of all the good sample images and dividing them by the number of sample images.

3.2.2 Two Indices

The variances of the rows and the columns are selected as two indices. Variance measures the deviation from the mean value; therefore it is selected to establish a tolerance zone that defines an area within which the items under inspection are considered acceptable. The minimum and maximum values of the two indices provide four corner points that can form a rectangular tolerance zone in the 2-D plane. The definitions of row/column numbers and pixel coordinates are given in Figure 3.4.

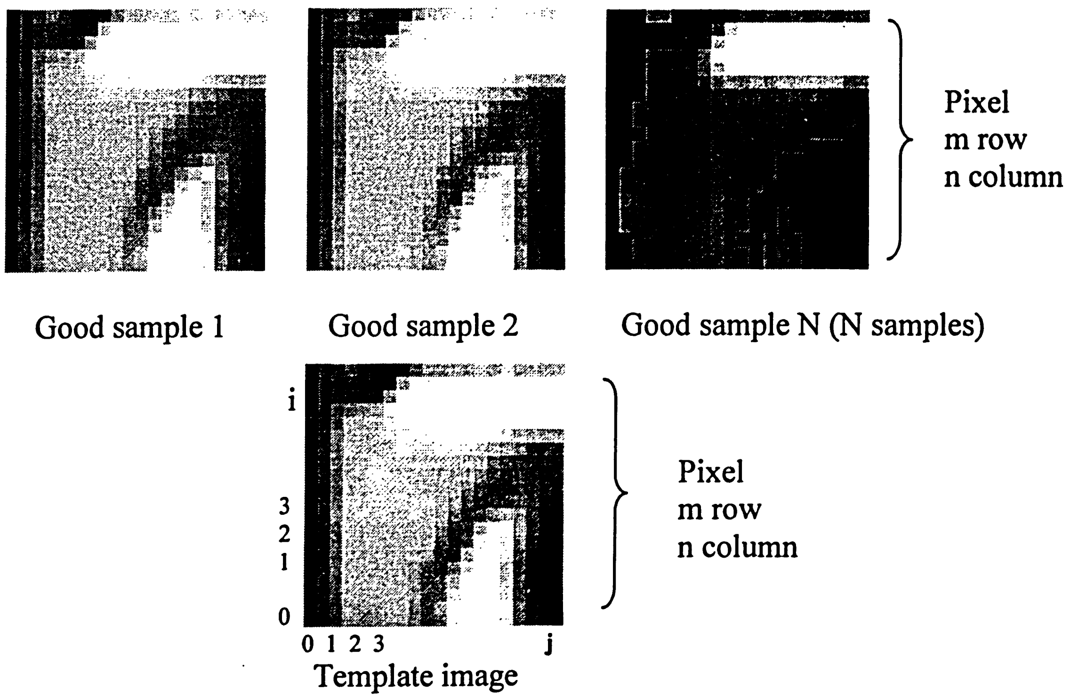


Figure 3.4 Row/Column number and pixel coordinate definition

The template image is created by the averaging method; it is actually a "mean value image". Therefore, for every pixel, the variance is defined as

$$\sigma_{ij}^2 = \frac{1}{N}\sum_{k=1}^{N}(\mathrm{P}_{ij} - \mathrm{S}_{k\_ij})^2 \qquad (3.1)$$

where N is the total number of the good sample images, σ_{ij}^2 denotes the variance of pixel at (i, j), P_{ij} is the gray level of the template image at pixel (i,j), and S_{k_ij} is the gray level of the corresponding pixel in the k_{th} sample image, see Figure 3.4.

The variance for a row is determined as

$$\sigma_{r\_i}^2 = \frac{1}{n}\sum_{j=0}^{n-1}\sigma_{ij}^2 \qquad (3.2)$$

where n is the number of pixels in a row, and $\sigma^2_{r\_i}$ denotes the variance of the i_{th} row. Likewise, the variance for a column is determined as

$$\sigma_{c\_j}^2 = \frac{1}{m}\sum_{i=0}^{m-1}\sigma_{ij}^2 \qquad (3.3)$$

where m is the number of pixels in a column, and $\sigma^2_{c\_i}$ denotes the variance of the j_{th} column.

The minimum and maximum values of the row variance, denoted by $\sigma^2_{r\text{-min}}$ and $\sigma^2_{r\text{-max}}$, respectively, are obtained as

$$\sigma_{r\_min}^2 = \min(\sigma_{r\_0}^2, \sigma_{r\_1}^2, \sigma_{r\_2}^2, \ldots \sigma_{r\_m-1}^2) \quad (3.4a)$$

$$\sigma_{r\_max}^2 = \max(\sigma_{r\_0}^2, \sigma_{r\_1}^2, \sigma_{r\_2}^2, \ldots \sigma_{r\_m-1}^2) \quad (3.4b)$$

The minimum and maximum values of the column variance, denoted by $\sigma^2_{r\text{-min}}$ and $\sigma^2_{r\text{-max}}$, respectively, are obtained as

$$\sigma_{c\_min}^2 = \min(\sigma_{c\_0}^2, \sigma_{c\_1}^2, \sigma_{c\_2}^2, \ldots \sigma_{c\_n-1}^2) \quad (3.5a)$$

$$\sigma_{c\_max}^2 = \min(\sigma_{c\_0}^2, \sigma_{c^2\_1}, \sigma_{c\_2}^2, \ldots \sigma_{c\_n-1}^2) \quad (3.5b)$$

Note that n and m also indicate respectively the number of columns and the number of rows for the image under inspection, and $n\times m$ represents the resolution of the image.

3.2.3 Tolerance Zone

Four indices $\sigma_{r\text{-max}}^2$ ($T_{r\text{-max}}$), $\sigma_{r\text{-min}}^2$ ($T_{r\text{-min}}$), $\sigma_{c\text{-max}}^2$ ($T_{c\text{-max}}$), and $\sigma_{c\text{-min}}^2$ ($T_{c\text{-min}}$) can be used to create a tolerance zone, where $T_{r\text{-max}}$ and $T_{r\text{-min}}$ represent the maximum and minimum row value of the tolerance zone; $T_{c\text{-max}}$ and $T_{c\text{-min}}$ represent the maximum and minimum column value of the tolerance zone. As shown in Figure 3.5, a rectangular tolerance zone is created directly using the four points. If the midpoints of the four points are used instead, a rhomb tolerance zone is created, as shown in Figure 3.6. Therefore, different combinations of the four points can create different shape tolerance zones that may be used to handle different inspection cases.

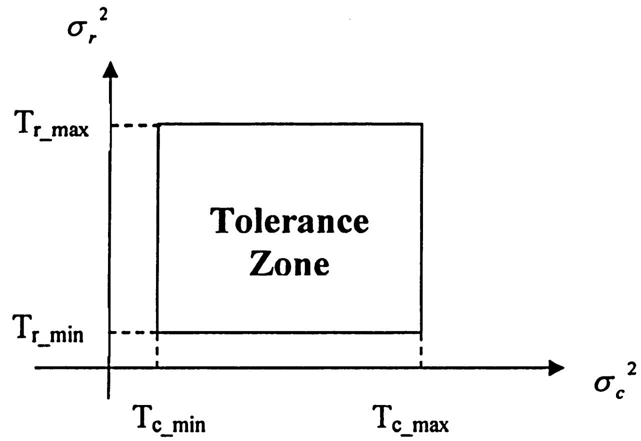


Figure 3.5 Tolerance zone for inspection

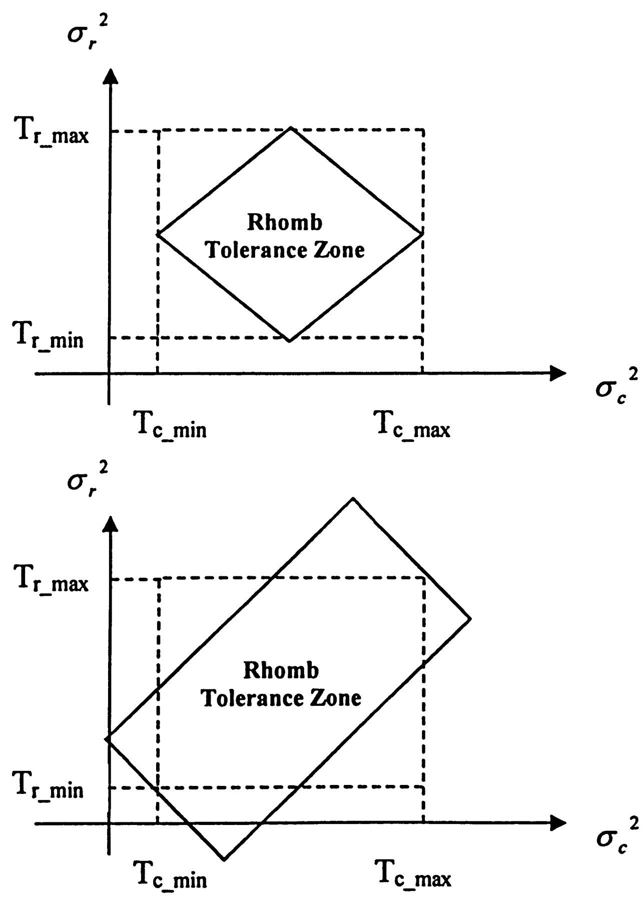


Figure 3.6 Two types of Rhomb tolerance zones

3.3 Statistics Based Neural Networks Method

3.3.1 Structure of Neural Networks

Neural Networks, also known as a parallel distributed processing network, is a computing paradigm that is loosely modeled according to cortical structures of the brain. It consists of interconnected processing elements called nodes or neurons that work together to produce an output function. The output of a Neural Networks relies on the cooperation of the individual neurons within the network to operate.

The most common type of artificial Neural Networks consists of three layers of neurons: a layer of "input" units connected to a layer of "hidden" units, which is in turn connected to a layer of "output" units, as shown in Figure 3.7:

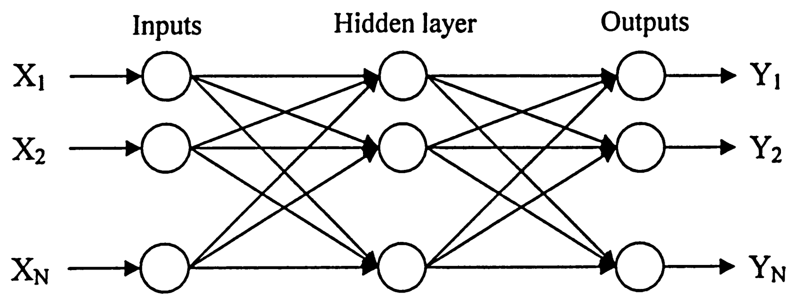


Figure 3.7 A three-layer Neural Networks

- The inputs represent the information fed into the network;
- The activity of each hidden unit is determined by the inputs and the weights on the connections between the inputs and the hidden units;

- The outputs depend on the activity of the hidden units and the weights between the hidden and output units;

3.3.2 Inputs and Outputs

Figure 3.8 shows the Neural Networks structure studied in this thesis, and it is a three-layer model, consisting of input layer, hidden layer, and output layer, with two nodes in each layer.

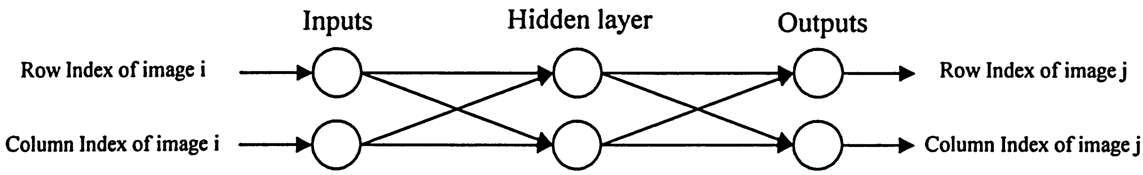


Figure 3.8 Neural Networks structure

In most vision inspection applications, industrial environment uncertainties and product variations are difficult to measure and will affect the inspection accuracy. The method under studied uses supervised learning algorithm, which means inputs and outputs should be given in advance. In this study, the input and output are the average row and column index of a pair of live images, and they are defined as

$$\sigma_{r\_average}{}^2 = \frac{1}{m}\sum_{i=0}^{m-1}\sigma_{r\_i}{}^2 \tag{3.6a}$$

$$\sigma_{c\_average}{}^2 = \frac{1}{n}\sum_{j=0}^{n-1}\sigma_{c\_j}{}^2 \tag{3.6b}$$

where $\sigma^2_{r\text{-average}}$ and $\sigma_{c\_average}^2$ denote the average row and column index of an image, respectively, and $\sigma_{r\text{-}i}^2$ and $\sigma_{c\_j}^2$ denote the variance of the i_{th} row and the j_{th} column, respectively.

3.3.3 Training

The network training is carried out for all the sample images pairs to fully describe the nature function. When the two indices value of the input sample image is transferred into that of the output sample image, the training process of one image pair is considered done. The number of the training pairs can be obtained by:

$$N_{Pairs} = \frac{N(N-1)}{2} \tag{3.7}$$

where N is the number of sample images. The weights between each two layers are obtained after training. As show in Figure 3.8, the structure between inputs and outputs layer which contain weights and hidden layer forms a transfer function TF and it can be regarded as the filter that can filter out the systematic uncertainties to a certain extent.

This industrial vision inspection software was developed by Yi Zhu in 2005 [1]. Figure 3.9 shows the training process and the convergence performance curve.

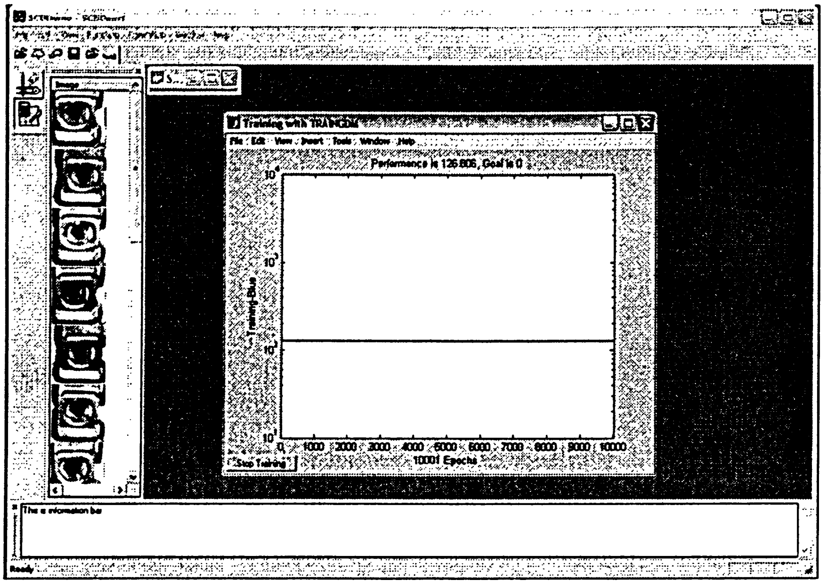


Figure 3.9 Neural Networks training of clips detection

3.3.4 Tolerance Zone

After the transfer function is obtained, the maximum and minimum indices of each sample image are recomputed to filter out the systematic uncertainties. As illustrated in Figure 3.10, $\sigma_{r\text{-}min}^2$, $\sigma_{r\text{-}max}^2$, $\sigma_{c\text{-}min}^2$ and $\sigma_{c\text{-}max}^2$ before filtering are recomputed, which are denoted as $G_{r\text{-}min}$, $G_{r\text{-}max}$, $G_{c\text{-}min}$ and $G_{c\text{-}max}$.

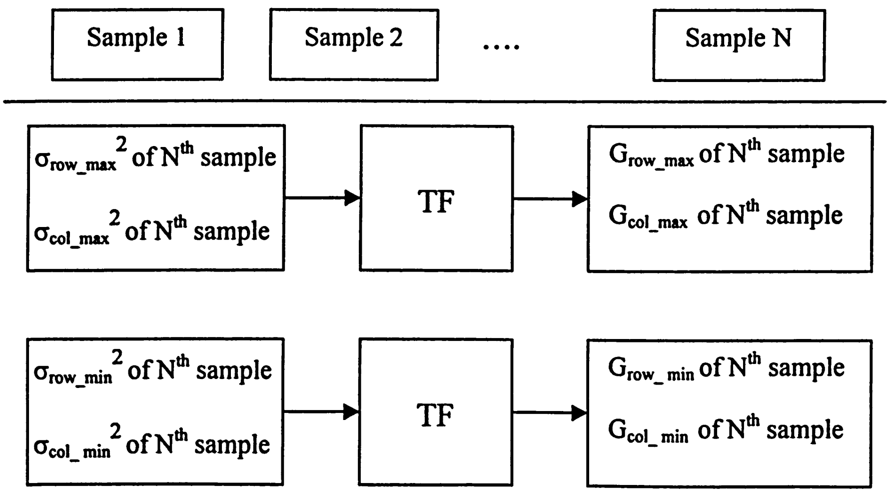


Figure 3.10 Filtering by transfer function

To define a tolerance zone, the global maximum and minimum indices are searched over all the sample images, as defined below

$$T_{r\_max} = \max\{(G_{r\_max})_1, (G_{r\_max})_2, \ldots\ldots, (G_{r\_max})_N\} \quad (3.8a)$$

$$T_{r\_min} = \min\{(G_{r\_min})_1, (G_{r\_min})_2, \ldots\ldots, (G_{r\_min})_N\} \quad (3.8b)$$

where T_{r_min} and T_{r_max} define the eligible row index range. Likewise,

$$T_{c\_max} = \max\{(G_{c\_max})_1, (G_{c\_max})_2, \ldots\ldots, (G_{c\_max})_N\} \quad (3.9a)$$

$$T_{c\_min} = \min\{(G_{c\_min})_1, (G_{c\_min})_2, \ldots\ldots, (G_{c\_min})_N\} \quad (3.9b)$$

where T_{c_min} and T_{c_max} define the eligible column index range. The tolerance zone is then defined by T_{r_max}, T_{r_min}, T_{c_max} and T_{c_min} as shown in Figure 3.5.

3.3.5 Inspection

Once the Neural Networks is well trained and the tolerance zone is created, the inspection can be carried out. As shown in Figure 3.11, the system uncertainties of the maximum and minimum indices of a live image are filtered out by the transfer function TF which gives two points (L_{row_max}, L_{col_max}) and (L_{row_min}, L_{col_min}).

Only when these two points are all located in the tolerance zone, the live image is regarded as good, otherwise it is defective.

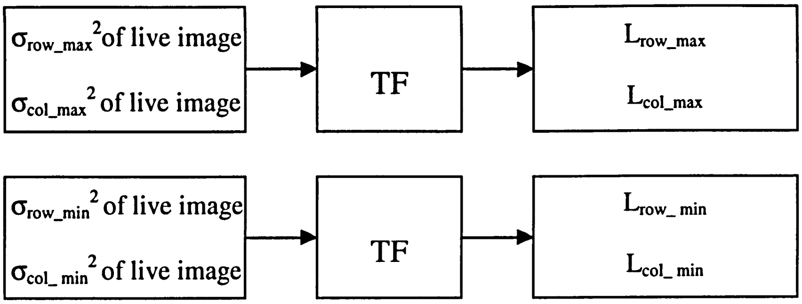


Figure 3.11 Inspection

Figures 3.12 shows an example of inspection, the two points that created the tolerance zone created are (164.776, 171.326) and (13.914, 22.619), red points are the filtered minimum indices of live images, and blue points are filtered maximum indices of live images.

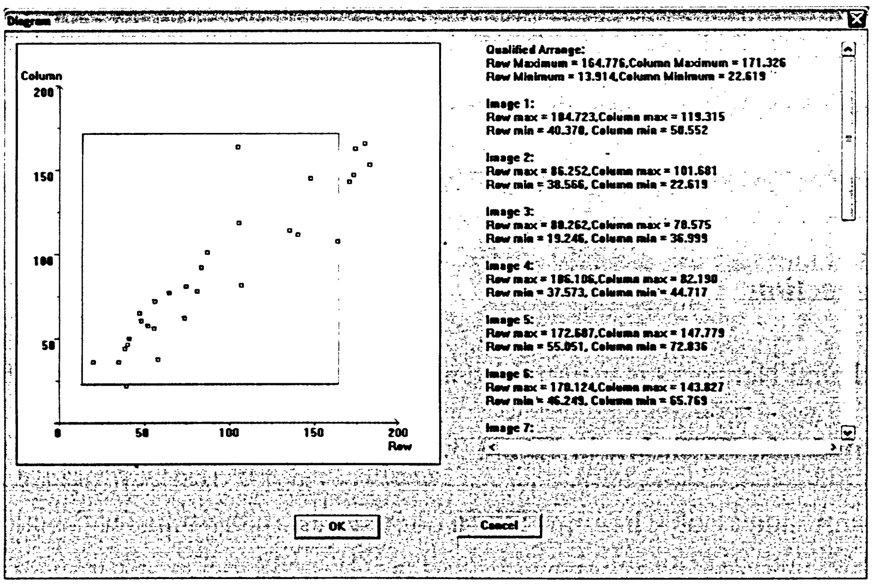


Figure 3.12 Clips detection inspection result

3.4 Summary

In this chapter, the statistics method and statistics based Neural Networks method are discussed in detail. The statistic method is fast but does not consider the uncertain factors. The hybrid method combines the fast speed of the statistic method and the ability of the Neural Networks method to account for the uncertain factors.

CHAPTER 4 PRACTICAL CONSIDERATIONS OF INDUSTRIAL VISION INSPECTION

In this chapter, the practical considerations of the inspection system based on the proposed method are described. This industrial vision inspection system uses good sample images to train a Neural Networks which could filter out the uncertainties. An inspection image is filtered by the Neural Networks first to remove uncertainties and then compared with the tolerance zone.

Three industry examples are presented: label printing inspection for printing industry, clip detection for automobile assembly process and casting failure detection for automobile water pump manufacturing.

4.1 Image Processing

Image processing is one of the important steps in industrial vision inspection, which is to improve the quality of the image for subsequent steps. Factors that influence the quality of the images include background, illumination, and human interferences.

Lighting is an important part of any industrial inspection system. By careful selection of a light source and its positioning, the effectiveness of inspection can be improved. It is more cost effective and better engineering practice to capture a good image at source, rather than spend a lot of efforts to clean it up later. For example, threshold is a simple image processing technique, and is only reliable if there is a high contrast between the regions to be divided. Figure 4.1 and 4.2 illustrate an application where screws are being inspected for size. Image processing is greatly simplified when a high-contrast image is obtained by backlighting, rather than a multiple grey-scale image from front lighting.

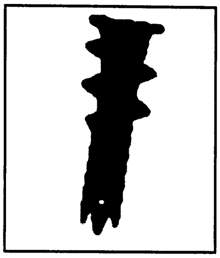


Figure 4.1 Silhouette of screw obtained by back-lighting [30]

Figure 4.2 Silhouette of screw obtained by front-lighting [30]

Images for inspection obtained directly from the product line contain both useful and useless information. Useful information is the main part of an inspection process. Useless information is also defined as noise factor that affects the inspection accuracy. For different image acquisition methods and lighting conditions, different types and quantities of noise will be obtained. The useful information is defined as Region of Interest (ROI) that contains the main inspection zone. Figure 4.3 shows the example of ROI in label printing inspection. The images under study were supplied by Rotoflex.

(a) the original image (b) ROI of image

Figure 4.3 Label printing inspection [15]

Figure 4.4 shows the ROI in the clip detection on a cross-bar assembly process. The clips inside the red rectangular boxes are the main targets of inspection, which is the ROI.

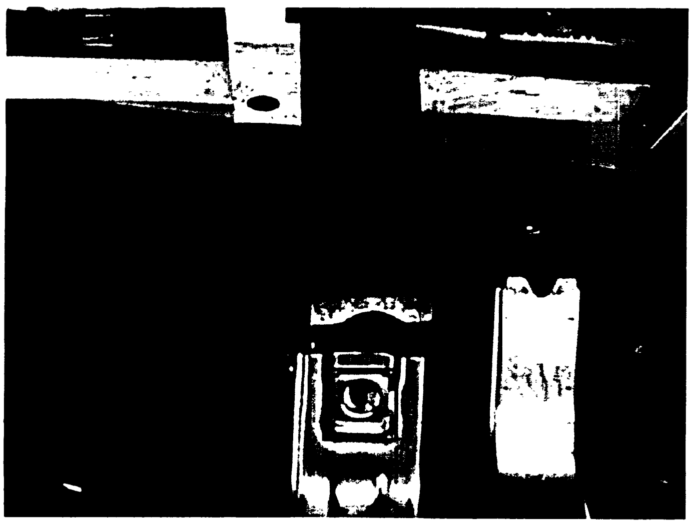
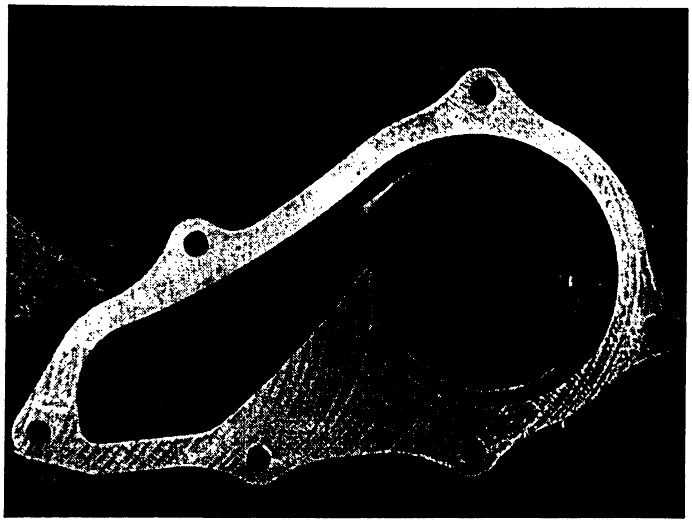
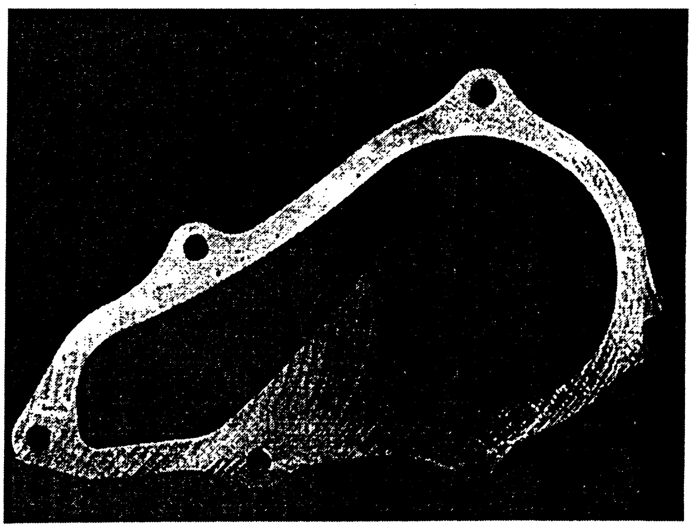


Figure 4.4 Clips detection

Figure 4.5 shows the ROI in the casting model inspection. The main goal of this inspection is to check the casting failures on the connecting plane of an automobile water pump, like inclusions, porosity (blow holes, pinholes), cold cracking, hot cracking, surface irregularities, and distortion, as mentioned before. Figure 4.5 (a) is the original image that contains considerable background noise information, Figure 4.5 (b) is the image after pre-processing that contains only useful information.



(a) Image with both useful and useless information



(b) Image with only useful information

Figure 4.5 Casting failure inspection

4.1.1 Fixed Crop Zone

For clip detection, a cross-car beam contains clips at various points across its surface, and these clips must be present at the required locations and properly seated in the beam. In inspection, the part is moving fast in front of the camera. Pictures with the clip present and missing are shown in Figures 4.6 and 4.7.

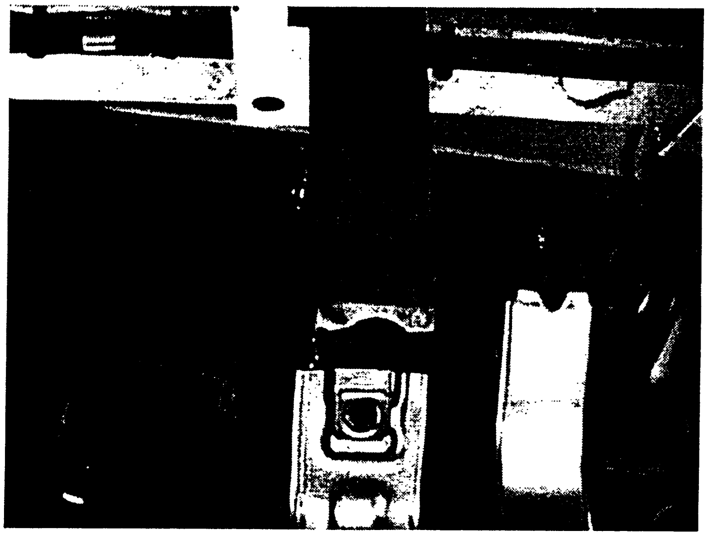


Figure 4.6 Clip present

Figure 4.7 Clip missing

Since these images are not registered, there are quite large differences in the positions of the clips within the images between different samples as shown in Figure 4.8.

The lack of alignment poses a problem for any method that tries to directly compare two images, e.g., for comparison against a template image. One method could be to compensate for this by locating the appropriate sub-image for comparison, but this problem is almost as difficult as finding the clip itself.

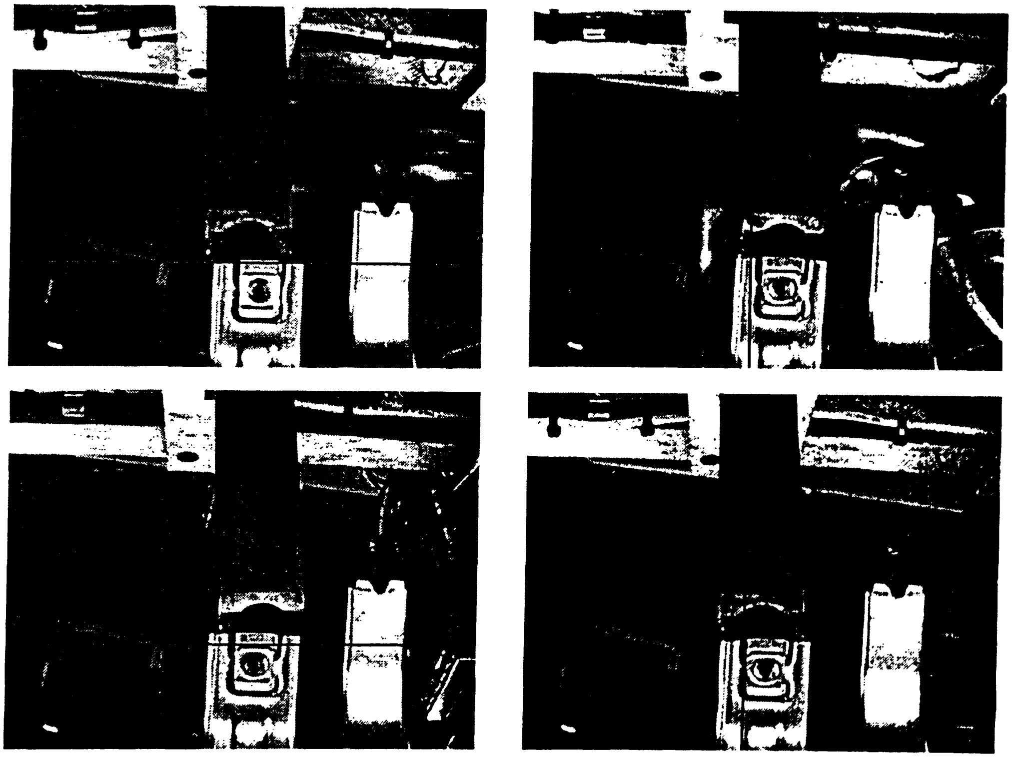


Figure 4.8 Position variation of clips

To find the ROI from the raw image, one of the easiest ways is cropping the images with a fixed zone that could contain all the position variations of clips in all sample images. Figure 4.9 shows the images after cropping.

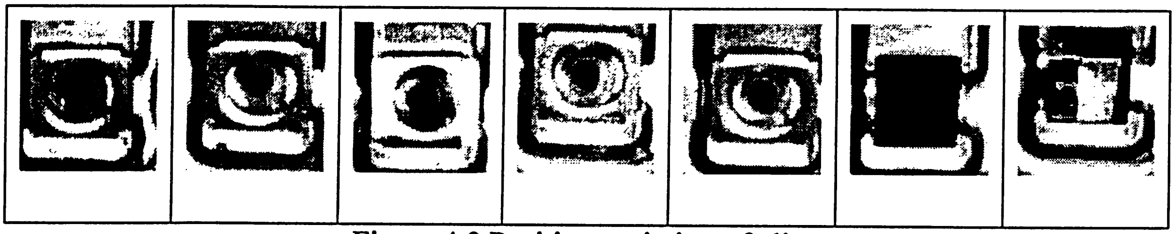


Figure 4.9 Position variation of clips

4.1.2 Colour Filter

The RGB colour model is an additive model in which red, green, and blue are combined in various ways to reproduce other colors [31]. These three colors should not be confused with the primary pigments of red, blue, and yellow, known in the art world as 'primary colors'.

When working with a picture of an inspection part, changing one colour to another seems like a trivial bitmap manipulation. But a single image can have thousands of colors (unique RGB triples). For example, the original picture shown in Figure 4.10 has 109,014 colours in it, while the clip contains over 3,600 colors in Figure 4.11.

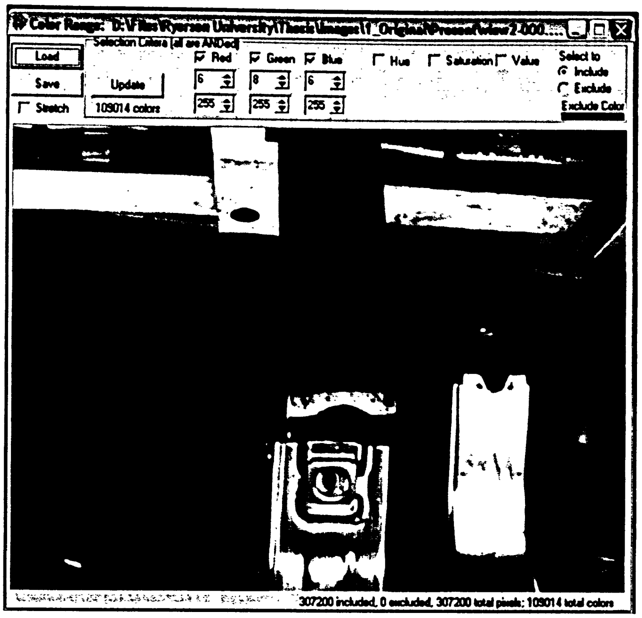


Figure 4.10 Colour information of original image

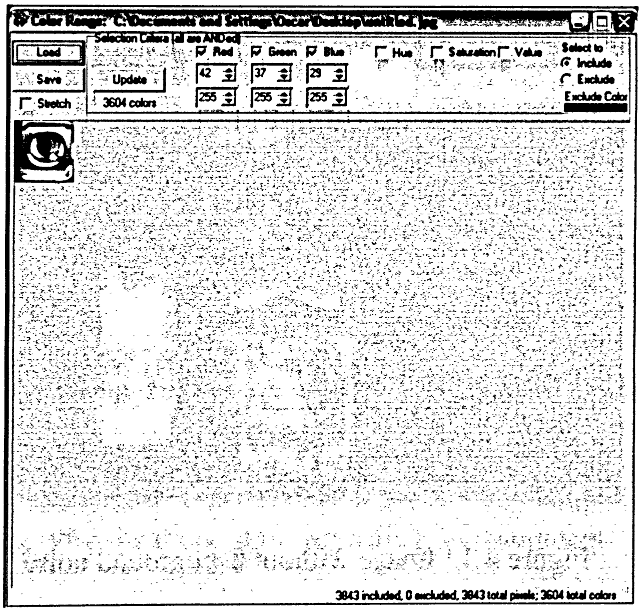


Figure 4.11 Colour information of clip only

Instead of selecting a single R-G-B triple, often a small colour cube with a range of R-G-B values can be selected for change. In addition to working with RGB colour space, other color spaces, such as HSV (Hue-Saturation-Value), are useful. With HSV color space, a Hue of 0 degrees is red, 60 is yellow, 120 is green, 180 is cyan, 240 is blue and 300 degrees is magenta. Saturation and value range from 0 to 255. The "dark yellow" pixels are rejected above by only selecting "Values" above 128.

By setting appropriate excluding colour (black is chosen for above example) and value for R-G-B, most of background information could be filtered out. The result is shown in Figure 4.12, by excluding red color intensity from 6 to 120, the most part of background noise information is wiped off.

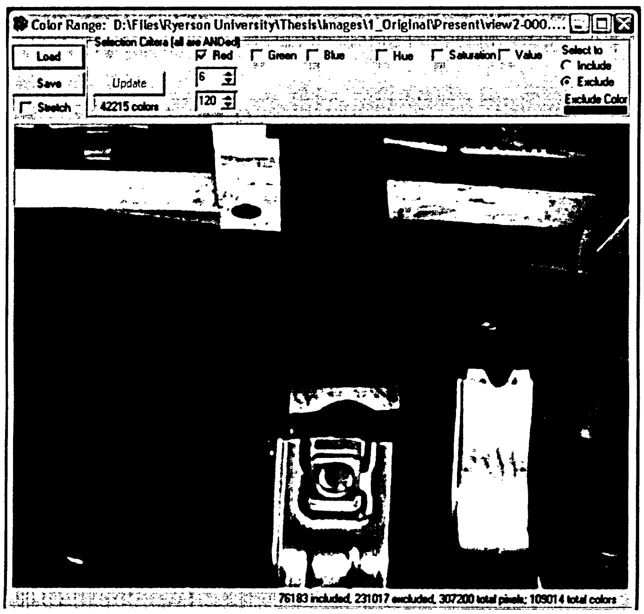


Figure 4.12 Image without background noise

4.1.3 Mask Matrix

Another way to extract the inspection zone is to merge the raw image with a mask matrix. A mask matrix is created by using a good sample image. This method is only applicable to parts that are installed on a frame when taking photos by a camera. For the casting failure detection, the model is placed on a frame so that the positions of the model in all pictures are exactly same.

The images under study are grayscale. Grayscale images intended for visual display are typically stored with 8 bits per sampled pixel, which allows 256 intensities (i.e., shades of gray) to be recorded, typically on a non-linear scale. The accuracy provided by this format is very convenient for programming. Figure 4.13 shows part of the original image and its original grayscale value matrix.

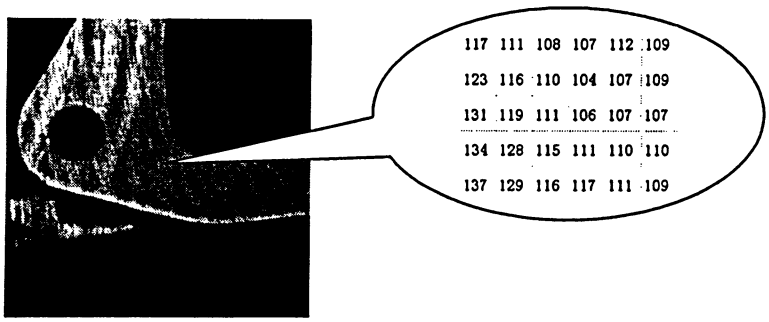


Figure 4.13 Original image and its grayscale value matrix

MATLAB Image Processing Toolbox is used to create a mask matrix which provides a comprehensive set of reference-standard algorithms and graphical tools for image processing, analysis, visualization, and algorithm development. Steps are given as follows:

Firstly, load the image into MATLAB as a matrix, and the image is shown in Figure 4.14.

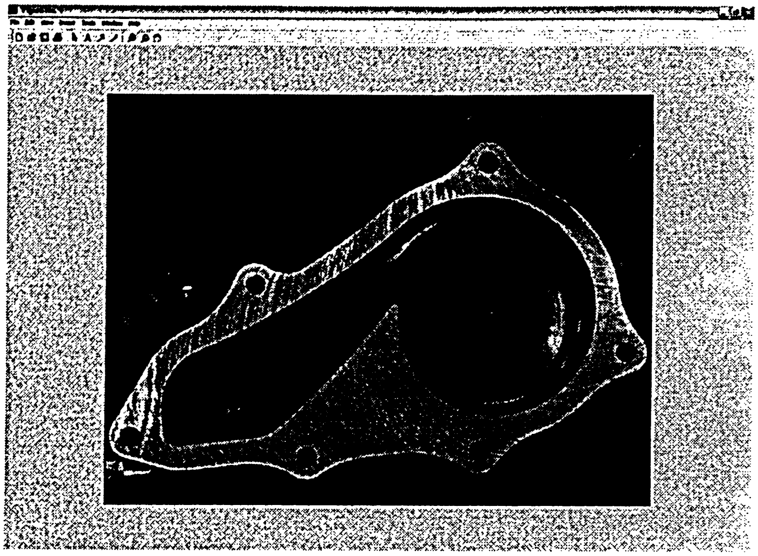


Figure 4.14 Loading image into MATLAB

Second step is finding the threshold grayscale value of each pixel. The pixel with grayscale value below the threshold value is set to be "0", which is the black area as shown in Figure 4.15. Oppositely, the pixel with grayscale value above the threshold value is set to be "255", which is the white area. The image is converted to a black-white format after this step, as shown in Figure 4.15. Figure 4.16 shows part of the BW image and its grayscale value matrix.

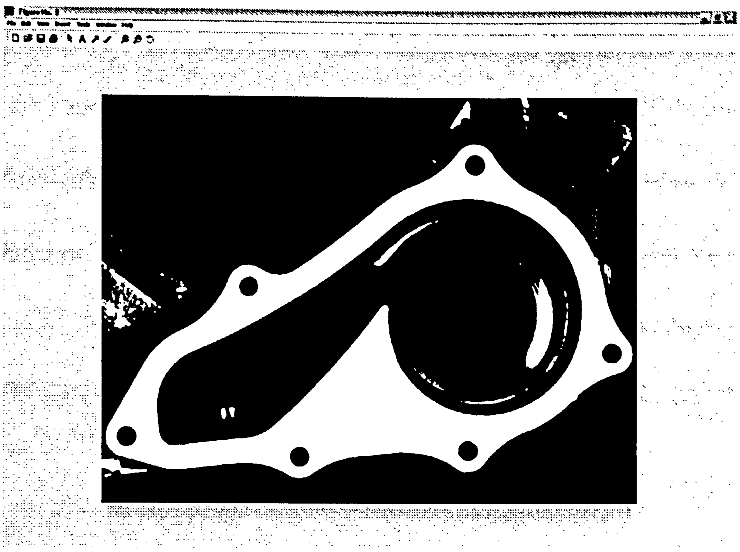


Figure 4.15 Black & White image

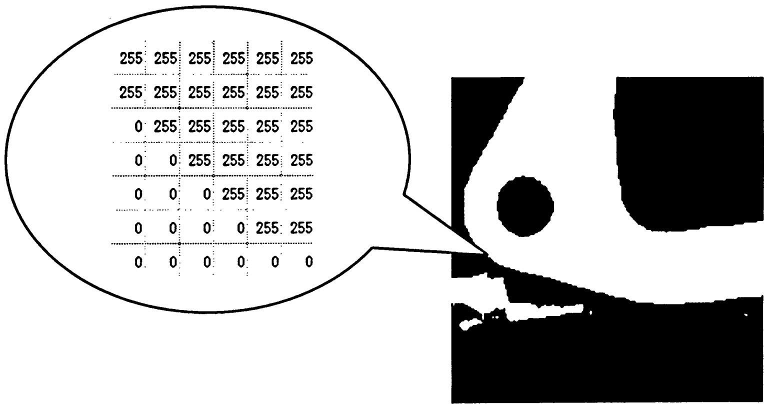


Figure 4.16 B&W image and its grayscale value matrix

The B&W image contains the main inspection zone along with many noise zones that have grayscale values also higher than the threshold value. To get rid of the noise, an area calculation is applied to the image. As shown in Figure 4.15, each area calculation is the accumulation of the white pixels.

After obtaining all the areas of the white zones including main inspection part and noise information zones, the maximum one is kept, as it is the main inspection part, to form the mask matrix. The values of others noise information pixels are artificially set to be "0". The obtained mask is shown in Figure 4.17. The live images are merged with the mask matrix to extract the inspection zone, as shown in Figure 4.18.

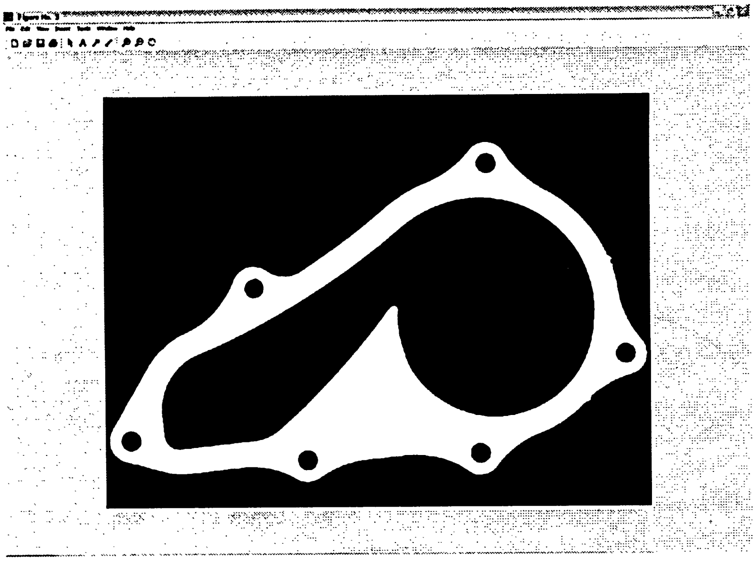


Figure 4.17 Mask matrix for casting failure detection

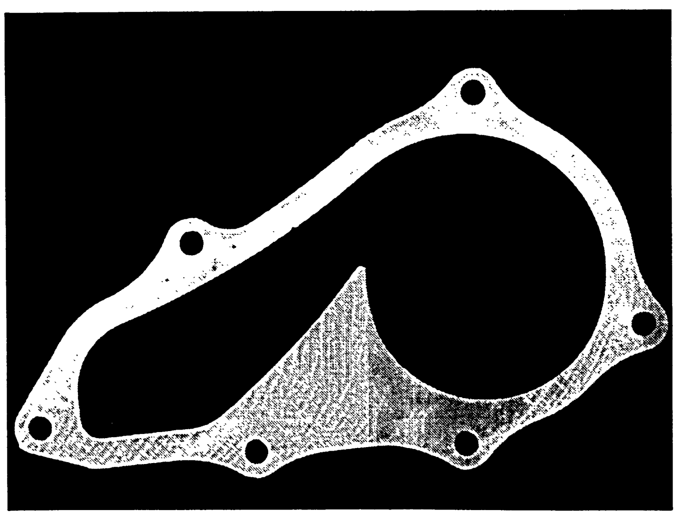


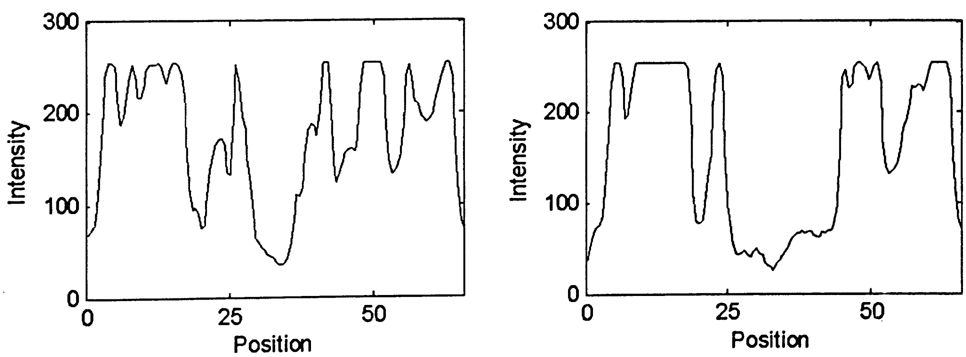
Figure 4.18 Live image after merged with mask matrix

4.1.4 Fast Fourier Transformation

A simple approach to solving the clips detection problem is via a line profile. To use this technique, a horizontal or vertical line is placed over the clip at some point. Ideally, this line should cross the clip at the same point in each test. The intensity values of the pixels along the line can then be used to form a histogram or another one-dimensional representation. Usually, this would be done with a greyscale image.

The graph can then be characterized in different ways, such as locating maxima or minima, determining various moments, etc. The goal would be to choose a few variables whose values strongly correspond to either presence or absence of the clip. See Figure 4.19 for a demonstration of the technique, a horizontal line profile is used.

Present and missing clips with line path superimposed

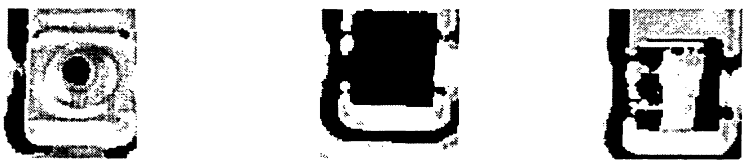


Resulting line profiles

Figure 4.19 Line profile of clips detection

The Fast Fourier Transform is an important image processing tool which is used to decompose an image into its sine and cosine components. The output of the transformation represents the image in frequency domain, while the input image is in spatial domain.

FFT is one practicable way for clip detection. It can solve the problem of position change of the clips. In the present analysis, there are only three situations to be identified: clip present, clip missing and clip missing but with a robot arm in the hole, as shown in Figure 4.20.



Clip present Clip Missing Clip missing with Robot arm

Figure 4.20 Three types of images

Using a horizontal line over the clip at same point on these three situations, Figure 4.21 shows the spectrum of each situation. Clearly, the FFT of line profiles can be used to determine if the clip is present, even though the position of the clip is changed, and the difference of base frequencies between missing and present is distinct.

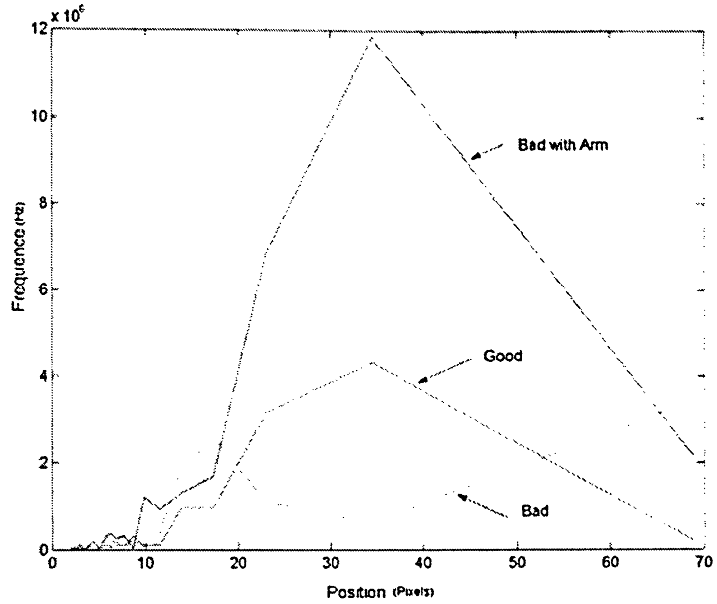


Figure 4.21 Fast Fourier Transform of three type images

The obvious drawback of this approach is that it can only determine if the clip is present or missing. Other features, such as determining the angle of the clip, cannot be determined easily using line profiles (although it could be done if several line profiles were made). The technique is also quite sensitive to changes in position of the clips, which are common in this problem.

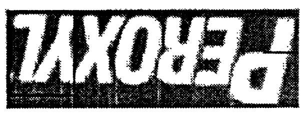
4.2 Image Registration

Image registration is the process of establishing point-by-point correspondence between two images of a scene. This process is needed in various computer vision applications, such as stereo depth perception, motion analysis, change detection, object localization, object recognition, and image fusion. Image registration is a crucial step in all image analysis.

A two point-based registration method is adopted [15] for image registration. This method is based on computing the center positions of two identical objects images, such as letters or a zone with a distinctive character. Two corresponding lines can be identified on both base image and registration image that can be used to register both in position and orientation.

Step 1: Zone Selection

Select two registration zones and find the center of each zone of the base image and sample image. Figure 4.22(a) shows a base image for registration in which two areas are picked. Figure 4.22(b) shows an image to be registered, in which two corresponding areas are also picked.



(a) Base Image

(b) Image to Be Registered

Figure 4.22 Two-Point registration

Step 2: Position Registration

Two registration lines can be formed for both the base image and registration image by linking the two pairs of center points. The two images can be registered in the right position using the two midpoints of the registration lines, see Figure 4.23. Figure 4.24

shows a registration example of a clip, image No.2-535 is registered based on image No.2-018.

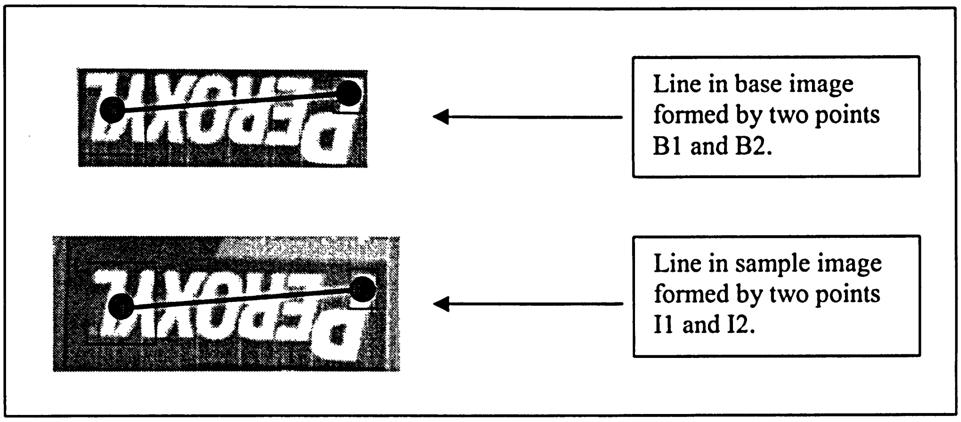


Figure 4.23 Position registration

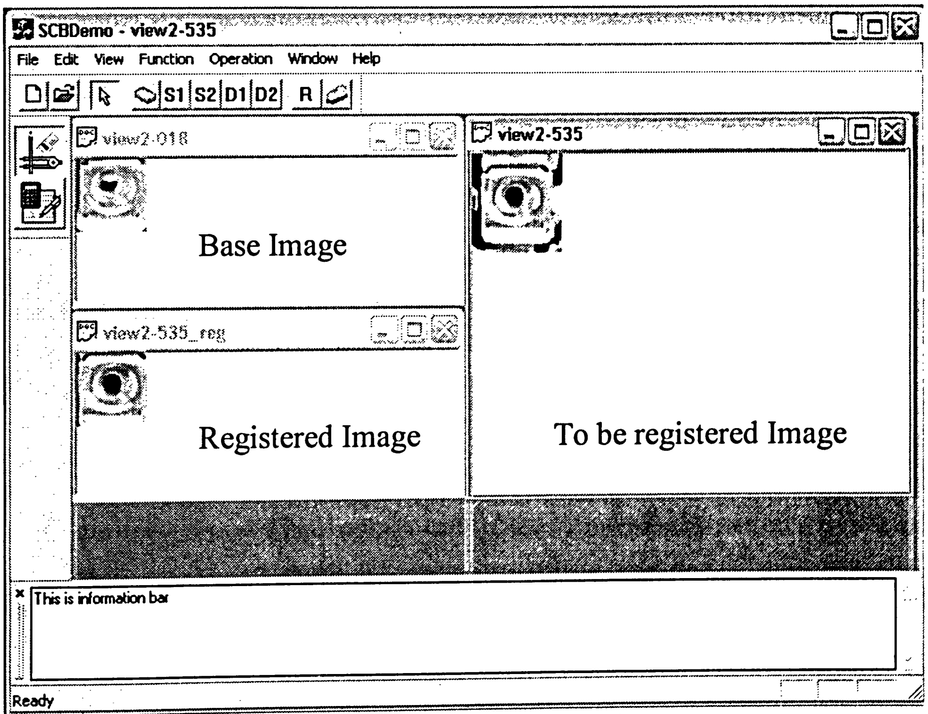


Figure 4.24 Image registration

4.3 Summary

In this chapter, the practical considerations for industrial vision inspection are discussed which focus on image processing and image registration. Image processing and image registration are two important steps to reduce the noise effect before the images are used for Neural Networks training and inspection.

CHAPTER 5 OPTIMIZATION OF TRAINING DATA

In this chapter, optimization of training data is discussed. To adequately describe an engineering problem, a large number of training data are needed to train the Neural Networks. However, this will be very time consuming. The best solution is to find the minimum number of training data.

5.1 Taguchi Method

Too-long learning phase increases the danger of over-training [5]. Basically, over-training means that the Neural Networks becomes too familiar with historical data and is less able to generalize and handle new data [5]. If sufficient training data is not used, then it causes under-training. The use of design of experiments is to find the minimum number of training data needed for a satisfactory training set for a Neural Networks. The key is to obtain sufficient information from a minimum number of data to carry out training with high inspection accuracy. The Taguchi method provides such a solution.

An important component of The Taguchi method is the categorization of factors into two major categories: control factors and noise factors [24, 32]. Noise factors are those either not under the perfect control of the management or controlled only through substantial effort and cost. The control factors are controllable variables or managerial decision factors. During the robust design phase of Taguchi's method, the relative importance of each control factor on the performance is identified. By finding the best parameter settings, the selected alternative is improved or optimized, in the sense that the performance is satisfactory even under uncertainty in the manufacturing environment. Ideally, parameter settings are sought that minimize the variation of the performance characteristics around its mean and adjust this mean to the target value.

For industrial vision inspection, considering the noise factors (industrial environmental variations and product variations), the Taguchi method helps to choose the best training data. After analyzing all the images taken from the product line, there are four kinds of noise factors, as shown in Figure 5.1 and Figure 5.2, including illumination, horizontal and vertical position variations, rotation and robot arm when clip is missing. Only the images where clip is present are used to train the Neural Networks; thus, the robot arm noise is not considered.

Figure 5.1 Position and robot arm noise factor

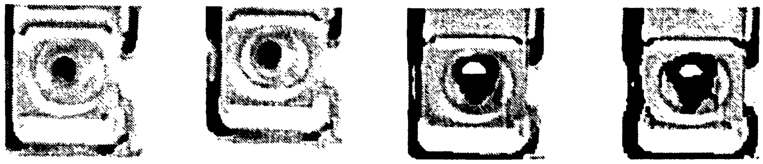


Figure 5.2 Illumination variation

Three levels are defined for each factor. Table 5.1 lists the noise factors and levels. For illumination, there are bright, medium and dark levels. The horizontal variation has the left, center and right levels. Vertical variation has the upper, center and lower levels. Rotation variation has clockwise, center and counter-clockwise levels.

Table 5.1 Noise factors and levels

Factors			**Levels**		
A	Illumination		Bright	Medium	Dark
B	Position	Horizontal	Left (5 pixels to the left edge)	Center	Right (5 pixels to the right edge)
C		Vertical	Upper (5 pixels to the up edge)	Center	Lower (5 pixels to the down edge)
D		Rotation	Clockwise (5 degree)	Center	Counter Clockwise (5 degree)

5.2 Orthogonal Array

Assuming there are no interactions between these factors, a standard L_9 orthogonal array can be obtained based on these four factors and their three levels, as shown in Table 5.2. By using this L_9 orthogonal array, the experiments trial run is reduced from 81 to 9. Each trial run represents one kind of image, such as trial run No.1. This is the image that has the clip located at up-left in the fixed zone and its illumination is bright. Training and inspection is based on these nine kinds of image set. First, nine sample images for each case are chosen to train the Neural Networks; then another fifteen selected live images are used to test the inspection accuracy.

Table 5.2 L_9 Orthogonal array

Trial Runs	Noise Factors			
	A	B	C	D
1	1 Bright	1Left	1 Upper	1 CW
2	1 Bright	2 Center	2 Center	2 Center
3	1 Bright	3 Right	3 Lower	3 CCW
4	2 Medium	1 Left	2 Center	3 CCW
5	2 Medium	2 Center	3 Lower	1 CW
6	2 Medium	3 Right	1 Upper	2 Center
7	3 Dark	1 Left	3 Lower	2 Center
8	3 Dark	2 Center	1 Upper	3 CCW
9	3 Dark	3 Right	2 Center	1 CW

An example is shown in Figure 5.3, the nine sample images with its clip located at the center-left with a bright illumination are used to train the Neural Networks, and another selected fifteen live images are used to test the accuracy of the inspection. The overall error inspection, positive faults and negative faults are calculated. Positive fault means that the clip is present but the inspection system shows that it is missing. Negative fault means that the clip is missing but the Neural Networks system shows that it is present. Obviously, negative fault can not be accepted.

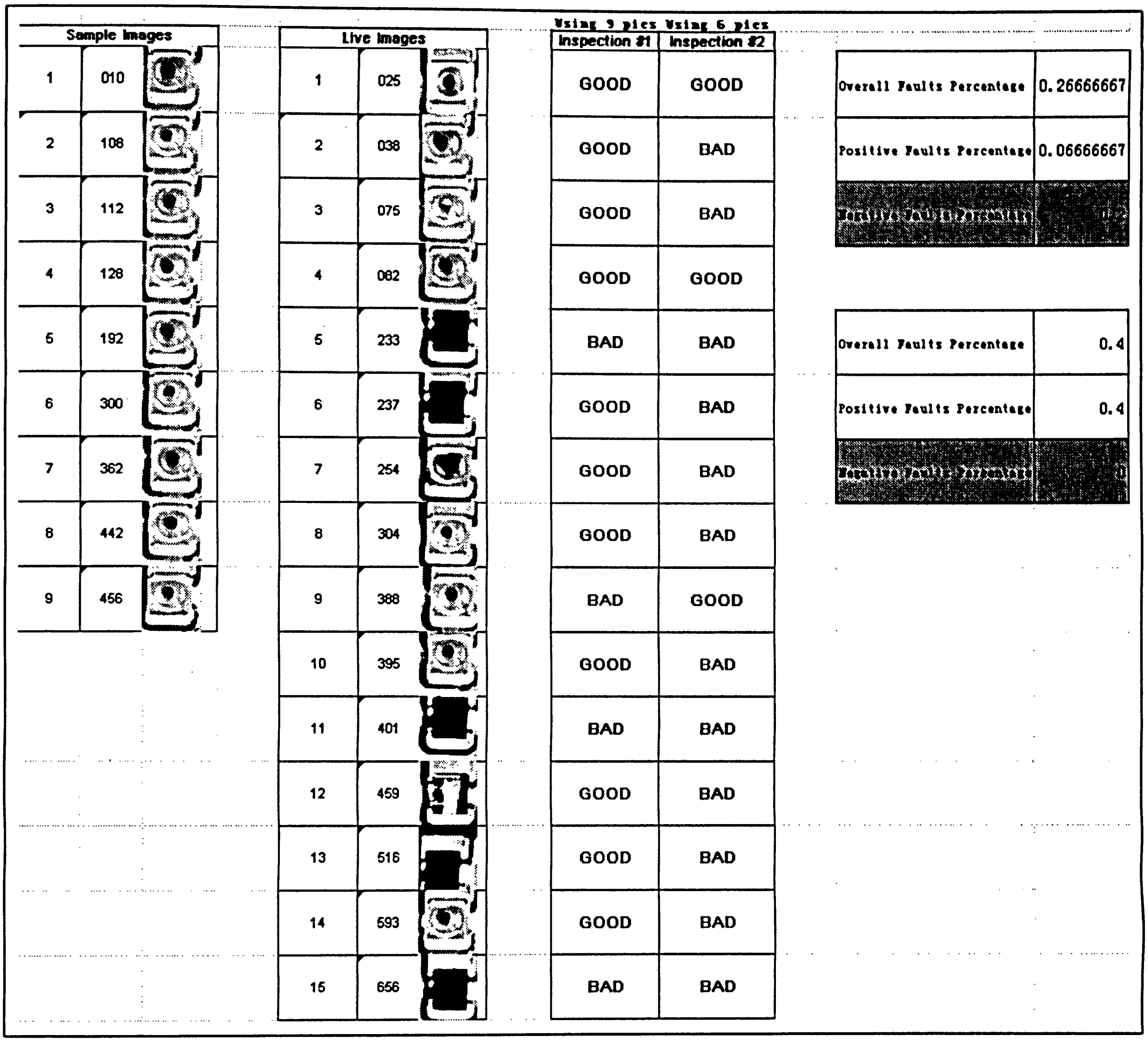


Figure 5.3 One orthogonal array test

5.2.1 Calculation of S/N ratio for each trial run

In each trial run, the number of wrong inspection over the total number of images is defined as the overall error inspection:

$$EI_i = \frac{N_{wi}}{N_{total}} \tag{5.1}$$

Where EI_i is the overall error inspection for i_{th} run, N_{wi} is the number of wrong inspection including positive faults and negative faults, N_{total} is the total number of images being inspected, which is fifteen in this study.

The S/N ratio for each experiment was then calculated as:

$$S/N = -10\log_{10}(EI_i) \tag{5.2}$$

Table 5.3 below lists the calculation results and S/N ratios for each experiment

Table 5.3 S/N ratios for each experiment

	A	B	C	D	EI	S/N
1	1	1	1	1	0.400	3.9794
2	1	2	2	2	0.267	5.7398
3	1	3	3	3	0.600	2.2185
4	2	1	2	3	0.600	2.2185
5	2	2	3	1	0.533	2.7303
6	2	3	1	2	0.533	2.7303
7	3	1	3	2	0.333	4.7716
8	3	2	1	3	0.533	2.7303
9	3	3	2	1	0.600	2.2185

5.2.2 ANOM Results

An analysis of means (ANOM) table was created, see Table 5.4. An ANOM table shows the effect of the S/N ratio on each factor for each level.

Let $\bar{y}_{ij}$ be the observed S/N ratio when a factor A is at level i, and a factor B is at level j.

Thus, the average sample mean when factor A is at level i is:

$$\bar{y}_{i\bullet} = \frac{1}{J}\left(\sum_{j=1}^{J} \bar{y}_{ij}\right) \tag{5.3}$$

Then, the average sample mean when factor B is at level j is:

$$\bar{y}_{\bullet j} = \frac{1}{I}\left(\sum_{i=1}^{I} \bar{y}_{ij}\right) \tag{5.4}$$

In the above equation, i is the number of times level i occurs for factor A, and J is the number of times level j occurs for factor B.

Table 5.4 ANOM table

Factor	Levels		
	1	**2**	**3**
A	3.9792	2.5597	3.2401
B	3.6565	3.7335	2.3891
C	3.1467	3.3923	3.2401
D	2.9761	4.4139	2.3891

These effects are also shown in Figure 5.4.

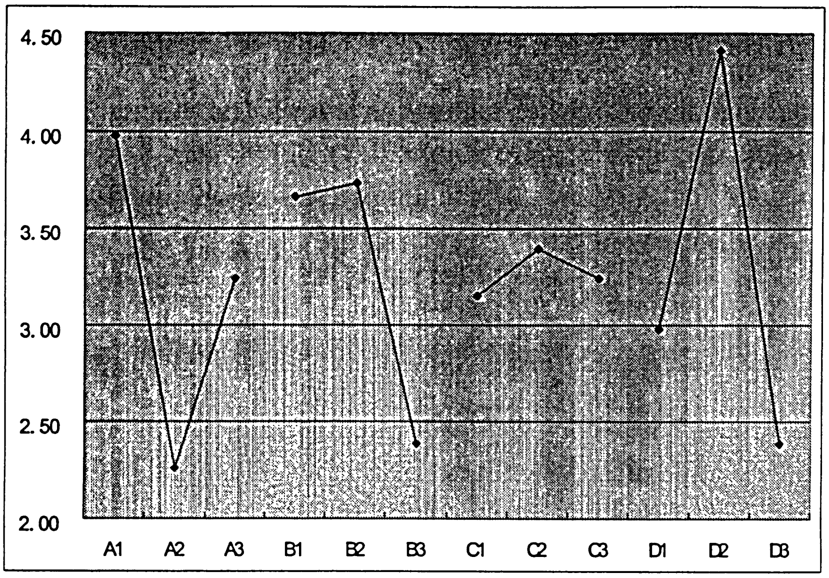


Figure 5.4 Plots of factor effects

As mentioned before, the combination of the different level for four factors is one sort of image; therefore, an importance sequence of the nine sorts of images can be obtained by adding the corresponding level of each ANOM value from each factor, as shown in Table 5.5. Because the rotation variation (factor D) is within 2 degree and only appeared in a few images, therefore, only factor A, B, and C are computed.

Table 5.5 Sequence of nine sorts of images

	A	B	C	Sum of ANOM	Importance Sequence
1	1	1	1	10.7824	2
2	1	2	2	11.1049	1
3	1	3	3	9.6084	5
4	2	1	2	9.6084	6
5	2	2	3	9.5333	8
6	2	3	1	8.0955	9
7	3	1	3	10.1368	3
8	3	2	1	10.1202	4
9	3	3	2	9.0215	7

5.3 Minimum Training Set

For each trial run that has a 9-sample-image training set, the test results show both positive and negative faults. A tighter tolerance zone should be created to reduce the negative faults. One way to create a tighter tolerance zone is to change the quantity of the sample images for Neural Networks training. More experiments are carried out to obverse the variation of accuracy when changing the number of images for training.

Figure 5.5 shows an experiment when using only two images to train the Neural Networks. The tolerance zone is so tight that a lot of positive faults appeared. As shown in Figure 5.6, ten out of eleven images are wrong detected.

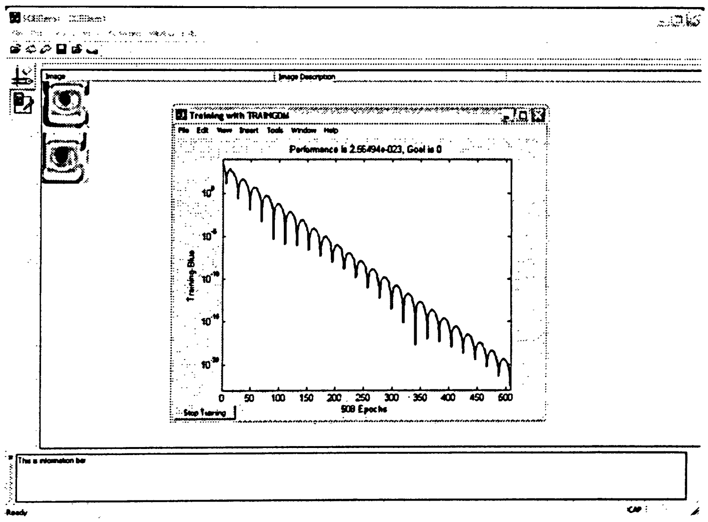


Figure 5.5 Trained by two sample images

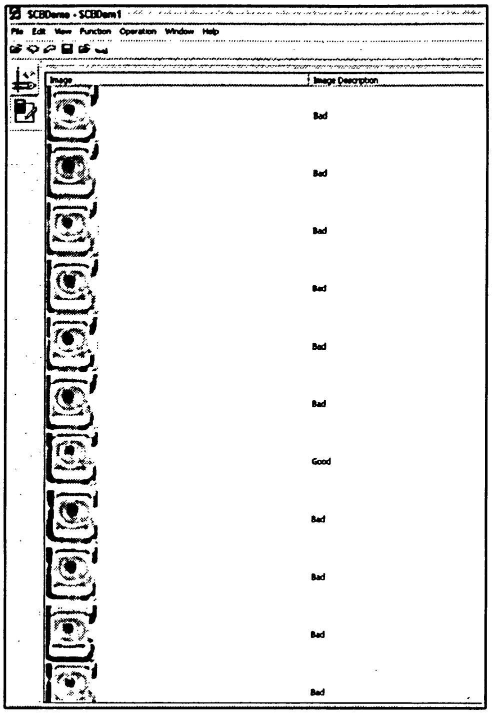


Figure 5.6 Inspection result of Neural Networks trained by two images

Figure 5.7 shows an experiment when using twelve images to train the Neural Networks. The tolerance zone is so loose that a lot of negative faults have appeared. As shown in Figure 5.8, all twelve images are wrong detected.

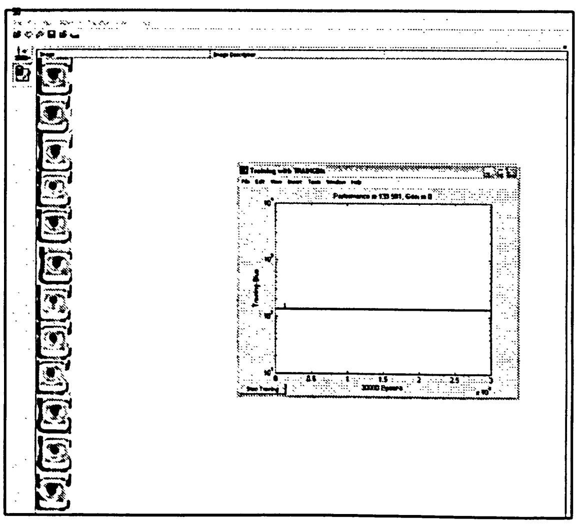


Figure 5.7 Trained by twelve sample images

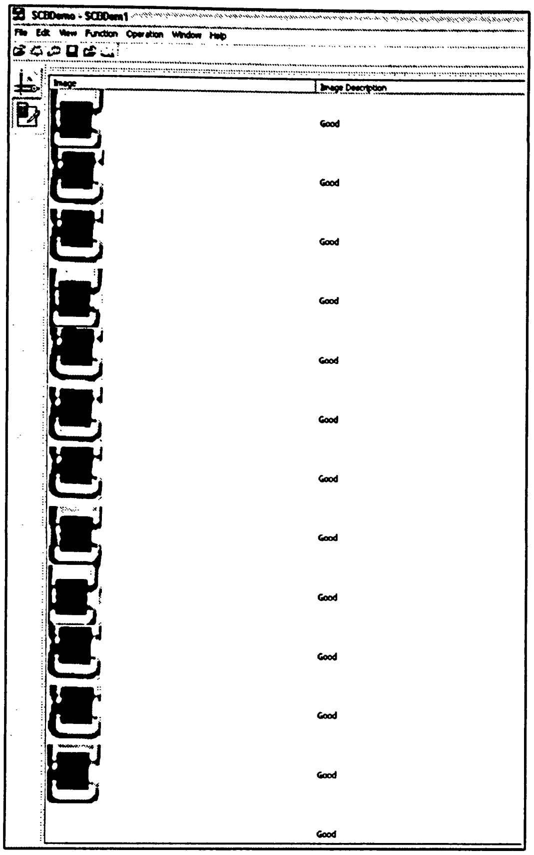


Figure 5.8 Inspection result of Neural Networks trained by twelve images

Table 5.6 shows the variation of accuracy under different number of training images, a total of 194 images (including 59 defective images) are used to test the accuracy for each training set:

Table 5.6 Inspection accuracy base on different training set

No.	Number of Training images	Positive Faults	Negative Faults	Inspection Accuracy
1	2	113	0	41.8%
2	4	37	0	82.5%
3	6	13	0	93.3%
4	8	9	7	91.8%
5	10	5	27	83.5%
6	12	5	38	77.8%

As shown in Table 5.6, when only two images are used to train the Neural Networks, there are 113 out of 135 positive faults and no negative faults, and the inspection accuracy is only 41.8%. When training set increases from 2 to 12, positive faults decrease from 113 to 5 out of 135, but negative faults increase from 0 to 38 out of 59. As mentioned before, negative faults can not be accepted. Comparing the six-image training set with eight-image training set, the inspection accuracy are all higher than 90%, but eight-image training set will cause 7 negative faults. Hence six-image training set should be considered to be the final decision.

Now, another decision has to be made as to which three images will be reduced while using only six sample images according to the importance sequence. Finally, six from 135 images were chosen as the best minimum training set. 440 (including 381 good and 59 bad) live images are chosen to test the Neural Networks system. The accuracy achieved was 94.5%, 24 images were detected wrong, which were all positive faults. The inspection results are shown in the following chapter.

5.4 Summary

In this chapter, the Taguchi method is used to find the minimum training data set. A four factor, three-level L_9 orthogonal array is used to reduce the experiment trials. From the experimental results, a six-sample-image training set is chosen to train the Neural Networks.

CHAPTER 6 EXPERIMENTAL VERIFICATION

To verify the accuracy of the industrial vision inspection system, a large number of experiments are carried out on the three industry problems mentioned in Chapter 3. The system is tested using both good images and defective images.

6.1 Label Printing Inspection

14 images (shown in Figure 6.1) were used for the Neural Networks training, and 58 images were used for inspection tests, among which 19 are with defects. Figure 6.2 (a) to (f) shows the inspection results of 58 images. The arrow signs in Figure 6.2 (b) and (e) point out the false inspections.

From the test results, it can be seen that 18 defect images are detected as defective. There is one positive fault, as shown in Figure 6.3 (a). And there is one negative fault because the defect portion is tiny and located in the black background area, as shown in Figure 6.3(b). In total, there are 2 inspection faults out of 58, and the accuracy is around 96%.

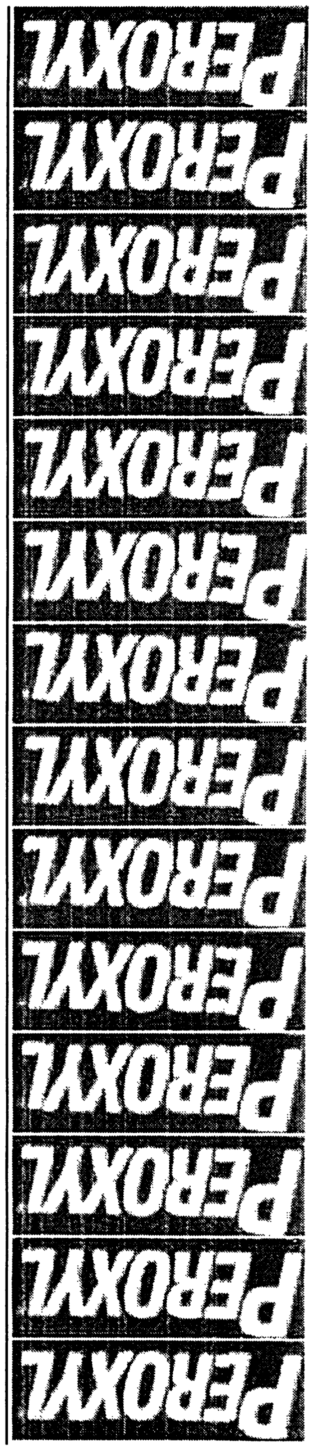


Figure 6.1 Sample images for training

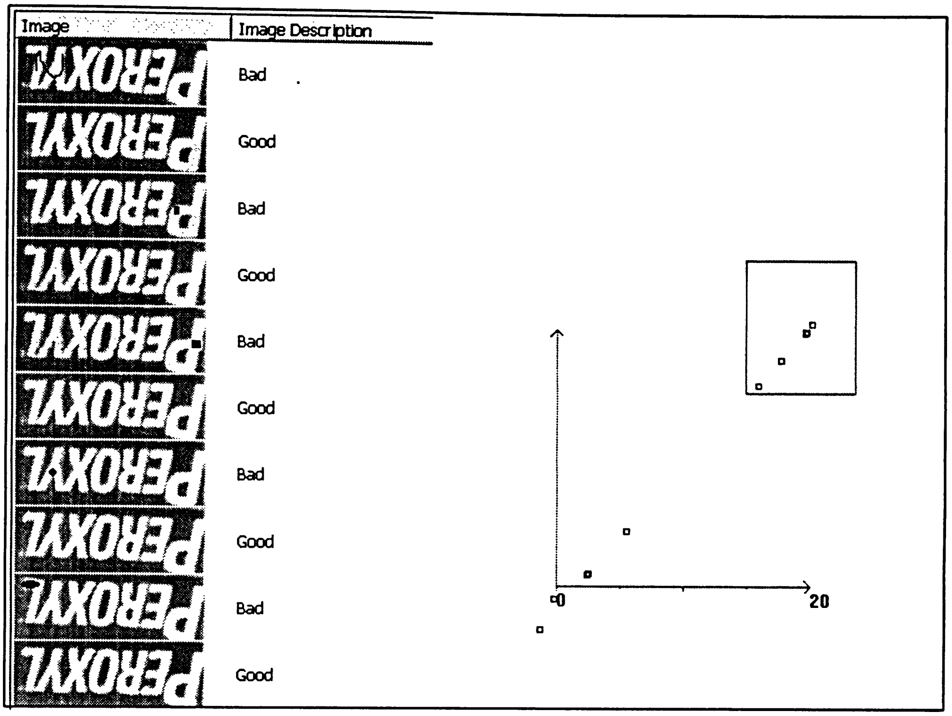


Figure 6.2 (a) Inspection of 1st set of 10 images

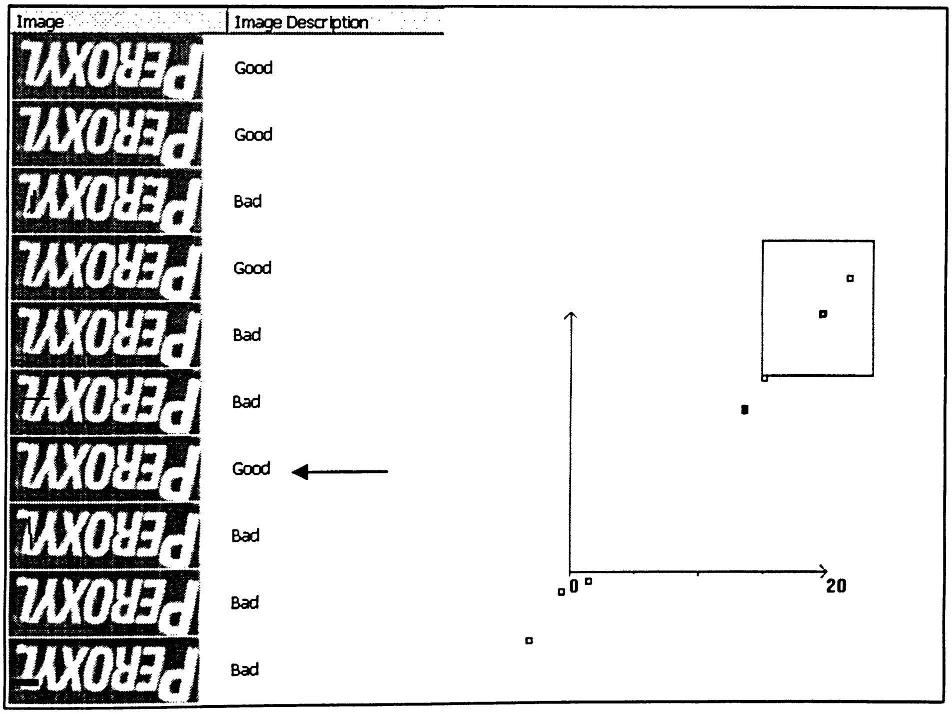


Figure 6.2 (b) Inspection of 2nd set of 10 images

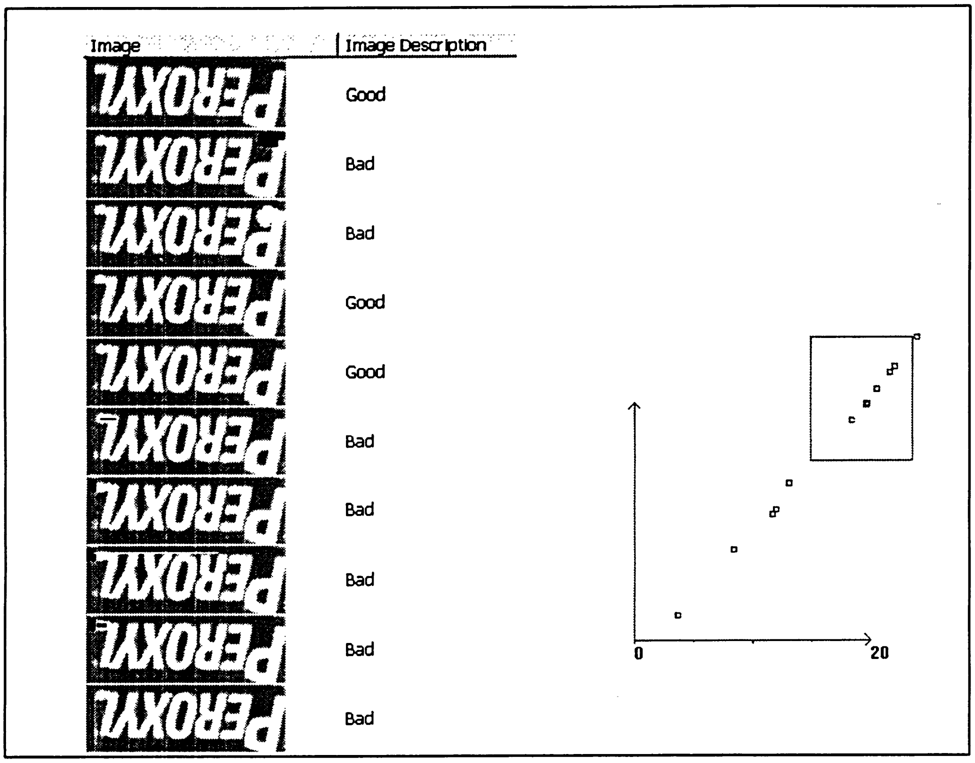


Figure 6.2(c) Inspection of 3rd set of 10 images.

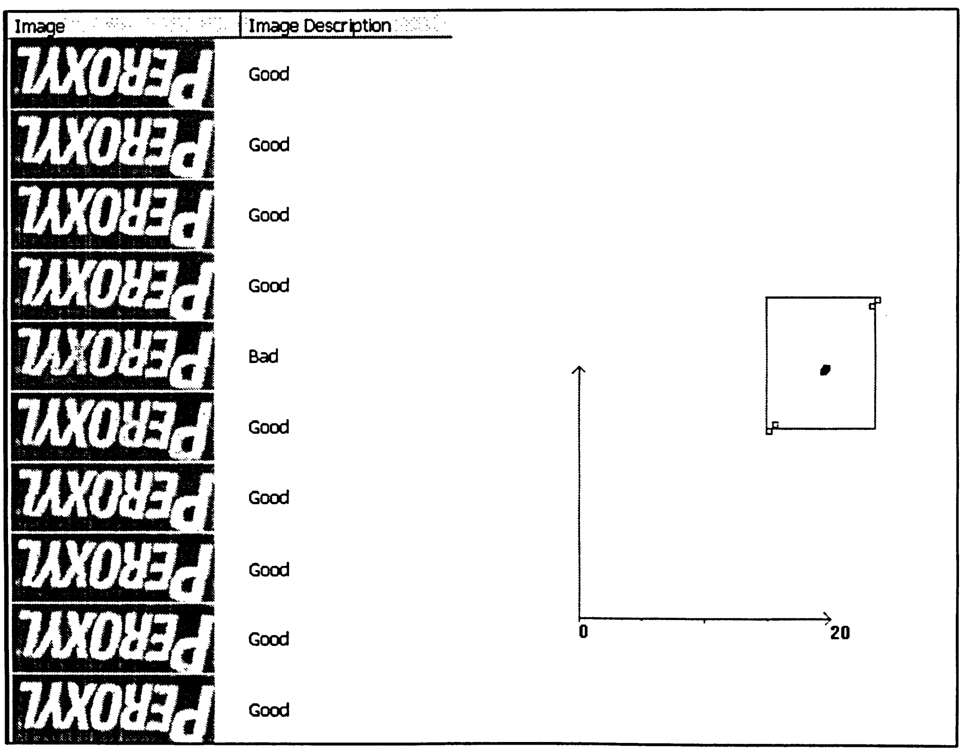


Figure 6.2 (d) Inspection of 4th set of 10 images

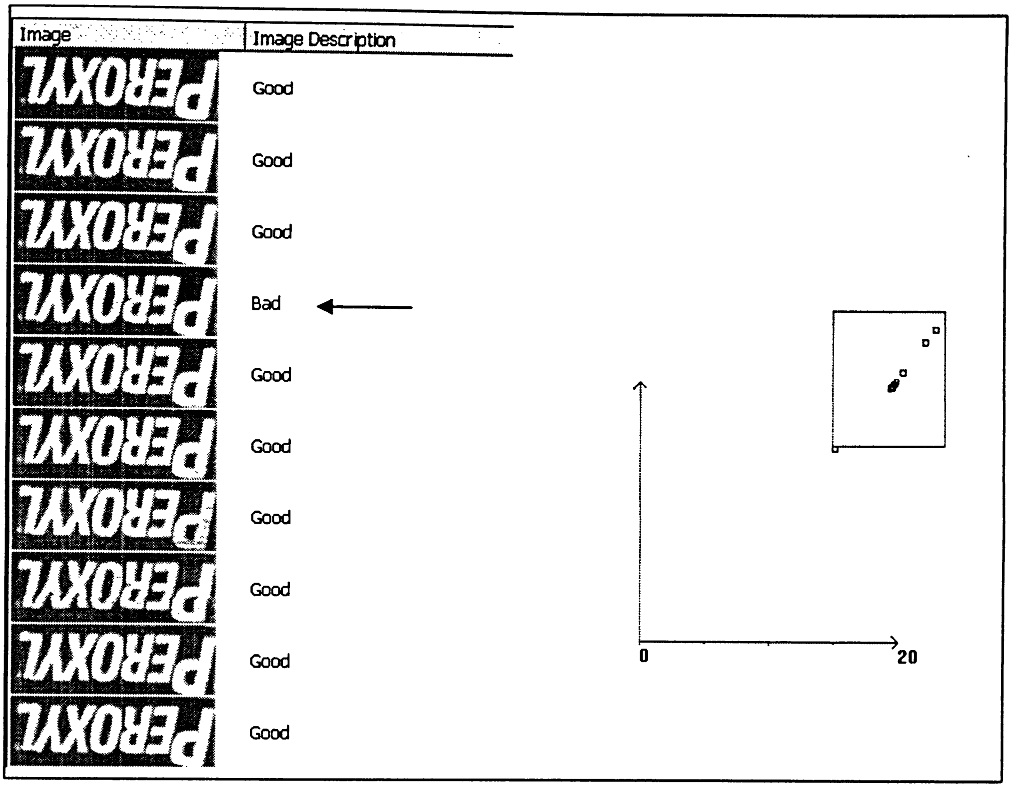


Figure 6.2 (e) Inspection of 5^{th} set of 10 images

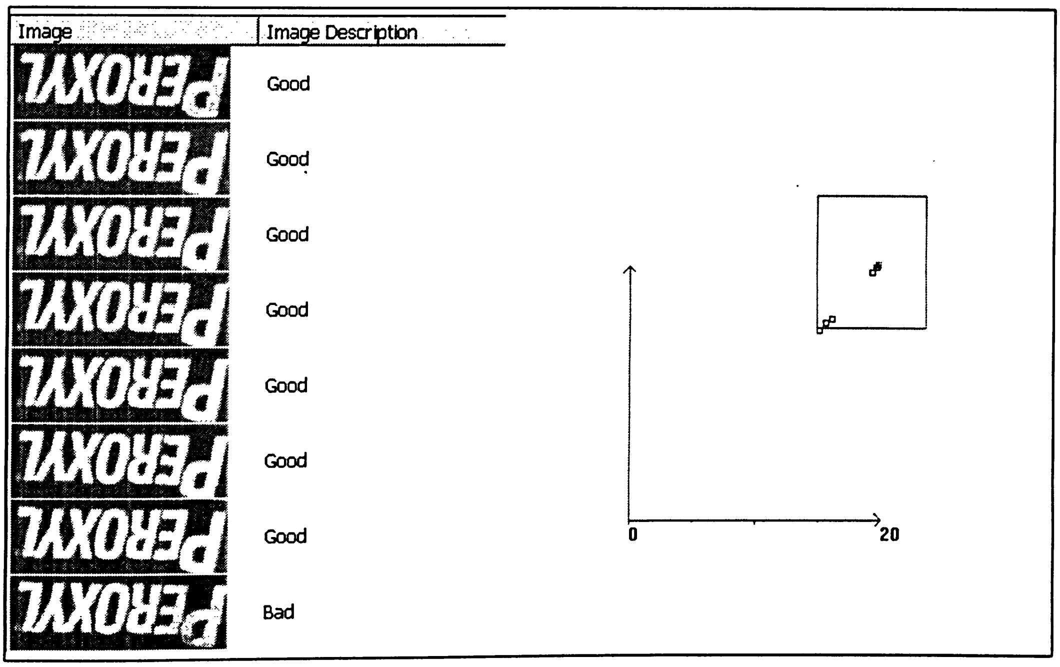


Figure 6.2 (f) Inspection of 6^{th} set of 8 images

Figure 6.2 Label printing inspection result

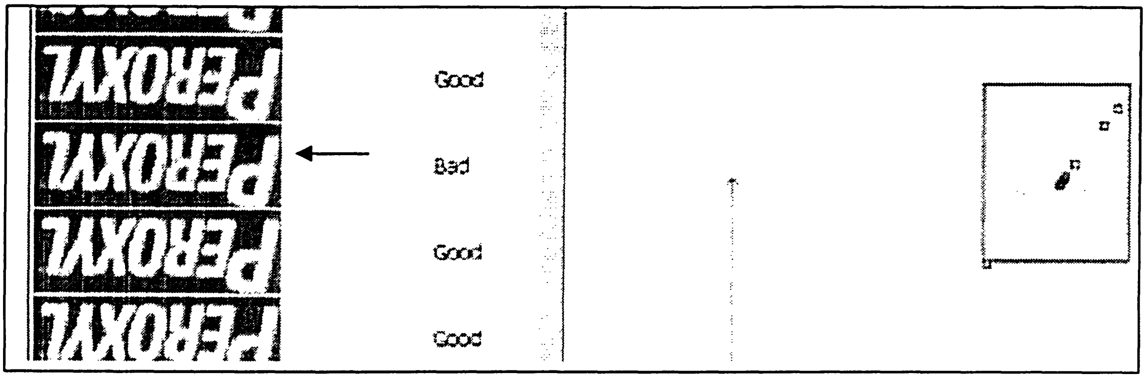


Figure 6.3 (a) positive fault

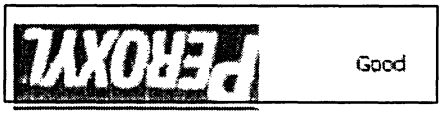


Figure 6.3 (b) negative fault

Figure 6.3 Two wrong detections

6.2 Clips Detection

The use of the Taguchi method effectively reduces the quantity of sample images to six images that are used for the Neural Networks training. 440 images were used for inspection tests, among which 59 are defective without clips on the beam.

Figure 6.5 shows inspection results. In Figure 6.5(a), (b), and (c), the arrow signs point out the false inspections which are all positive faults. Figure 6.5(d) and (e) show the inspection results of all 59 defective images, there are no negative faults. In total, there are 24 positive faults out of 440 images; the accuracy is around 94.5%. The results show that the tolerance zone created by 6 sample images chosen after using the Taguchi method can contain all the variations including position, rotation, illumination and robot arm when clips are missing.

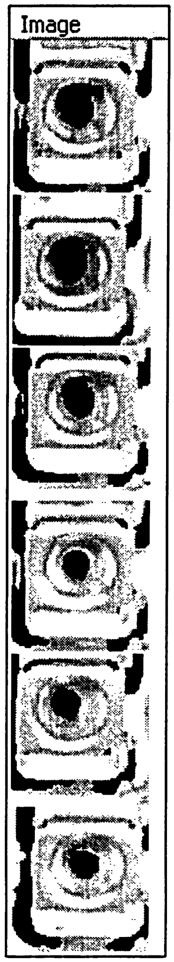


Figure 6.4 Six sample images

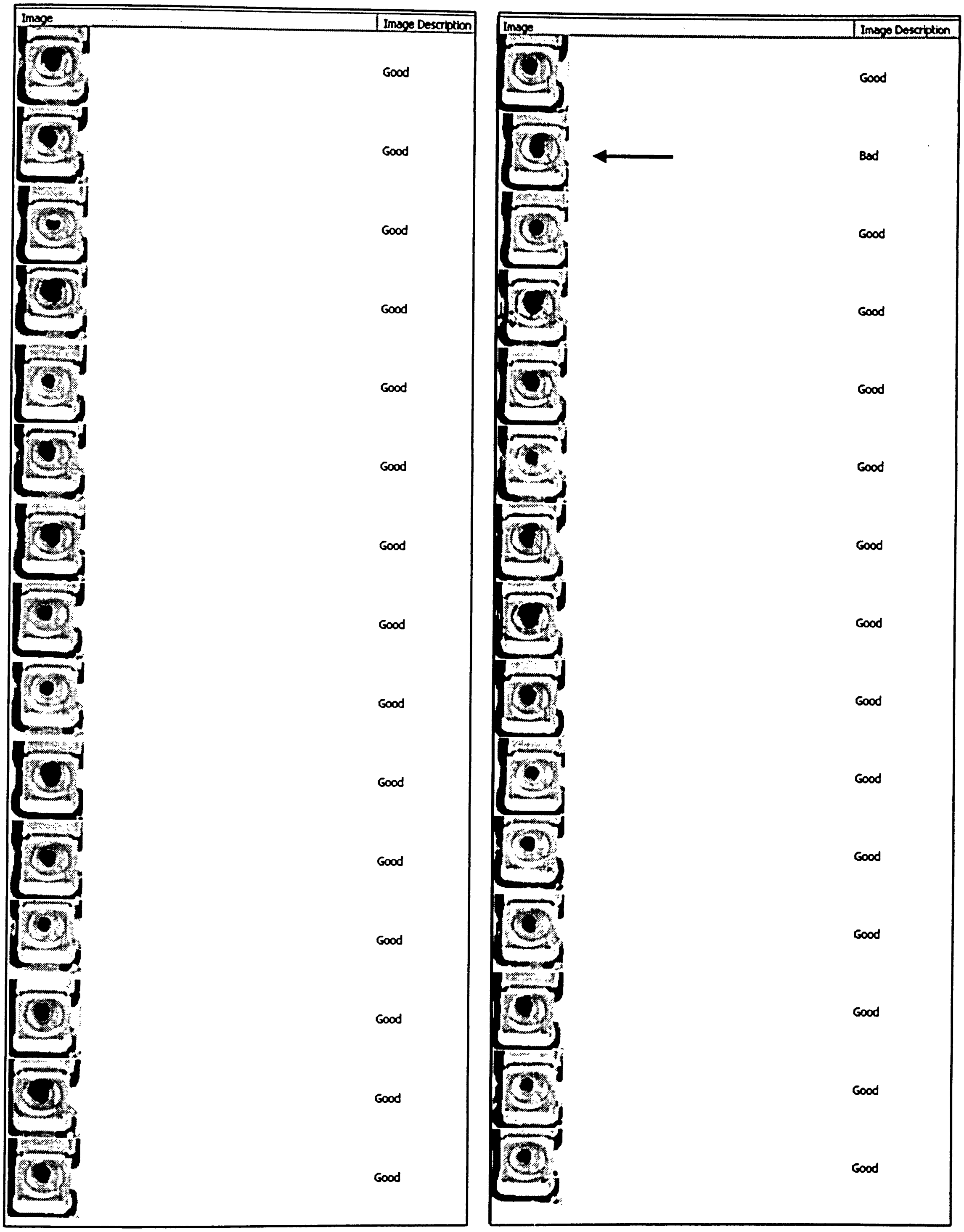


Figure 6.5 (a) Inspection of 1st and 2nd sets

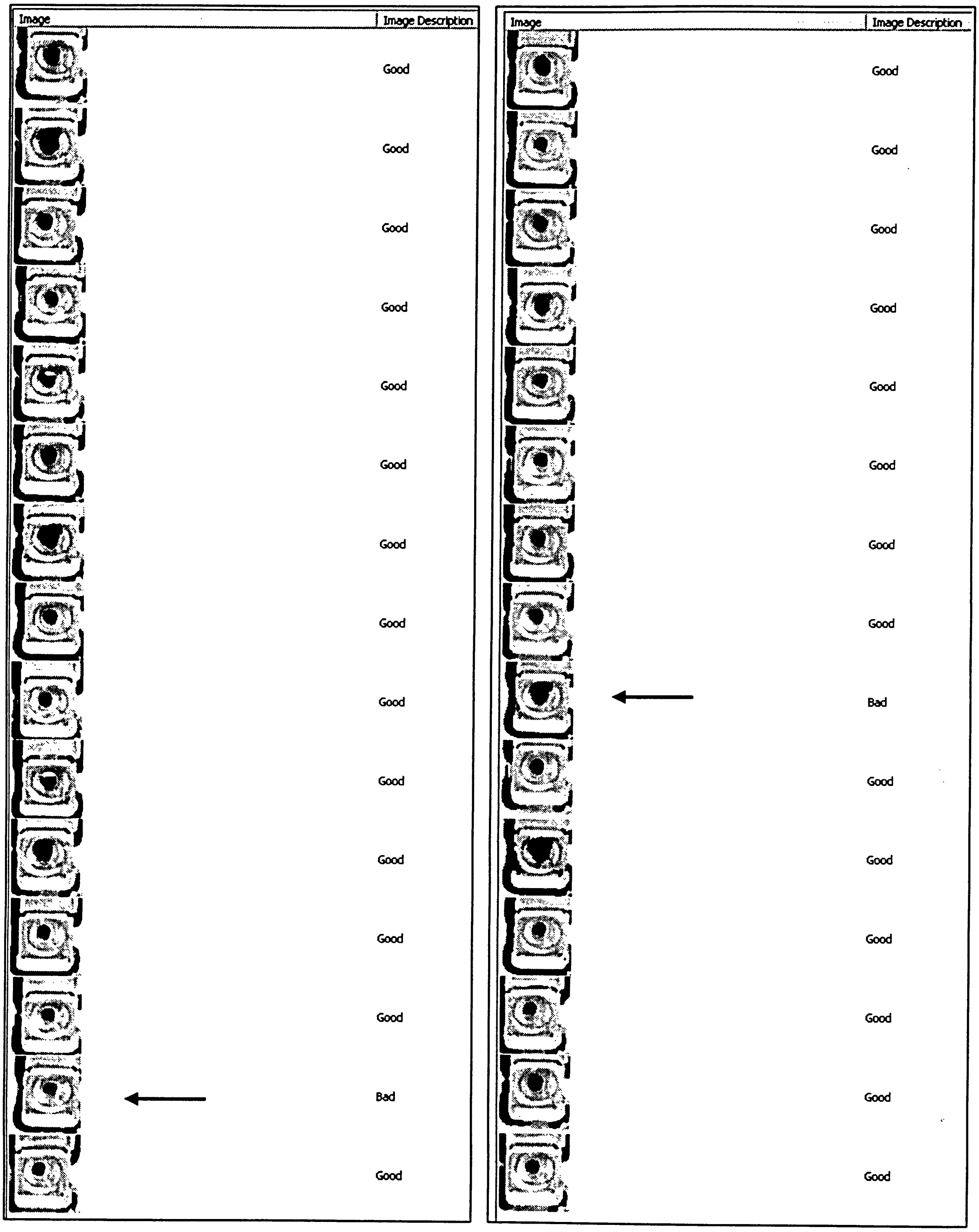


Figure 6.5 (b) Inspection of 3rd and 4th sets

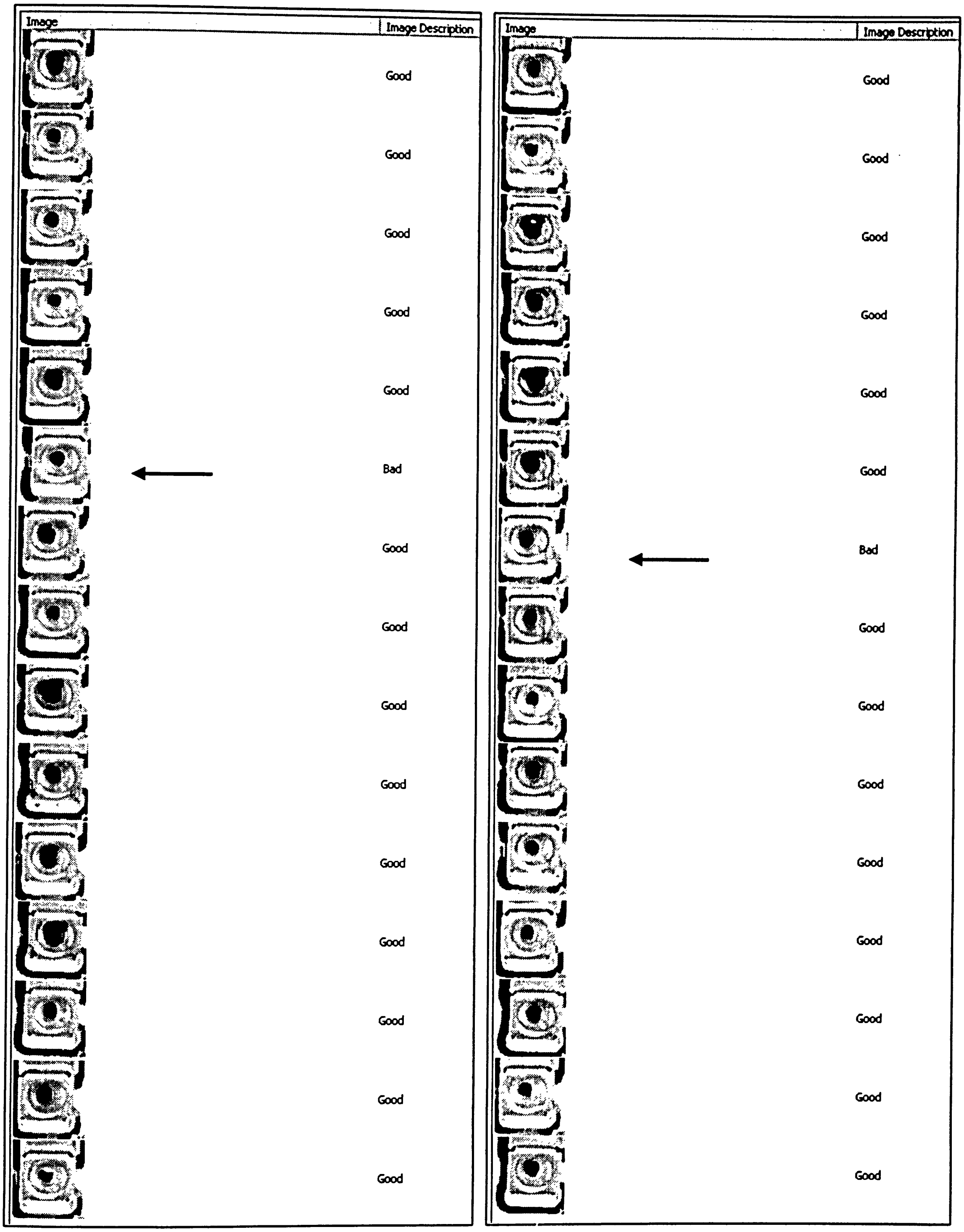


Figure 6.5 (c) Inspection of 5th and 6th sets

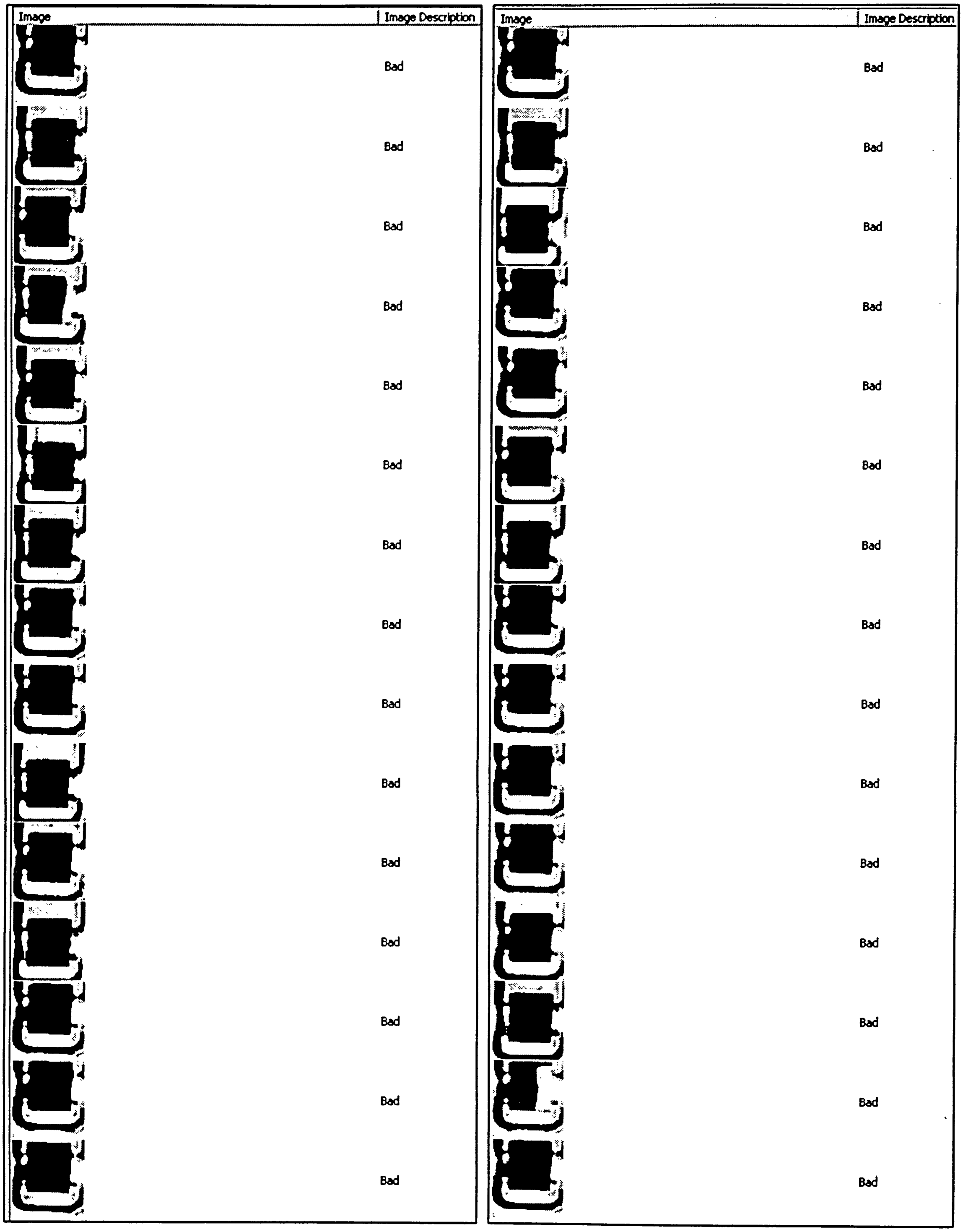
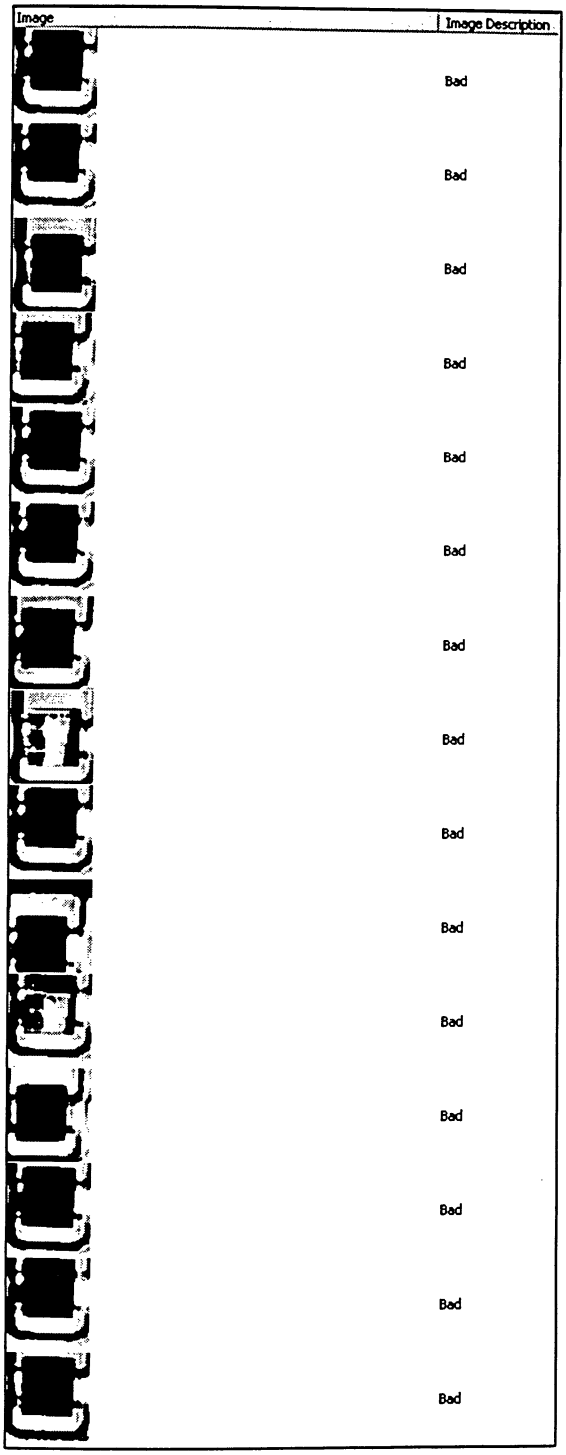


Figure 6.5 (d) Inspection of 7^{th} and 8^{th} sets



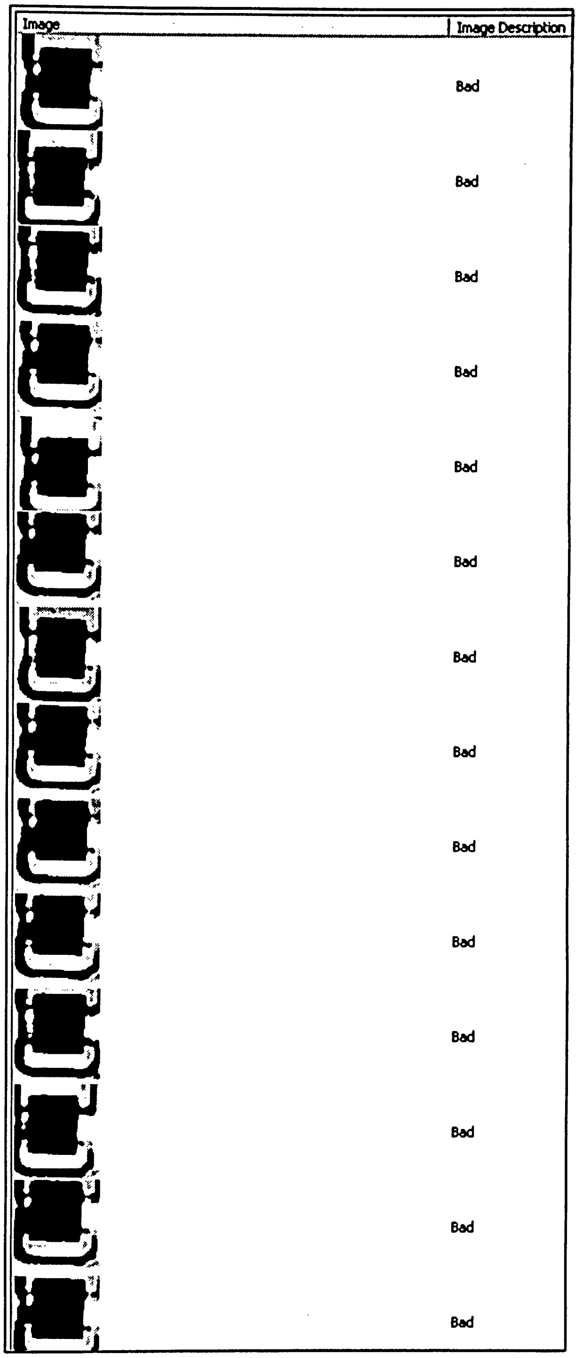


Figure 6.5 (e) Inspection of 9^{th} and 10^{th} sets

Figure 6.5 Clips detection inspection result

6.3 Casting Failure Inspection

Only thirteen images are obtained from the water pump product line. Four good sample images are used for Neural Networks training, and the other nine defective images are used for testing. The good sample images are shown in Figure 6.6. Figure 6.7 shows the inspection results of nine defective images. Although there is no false inspection, it is necessary to test the network with more live images in the future.

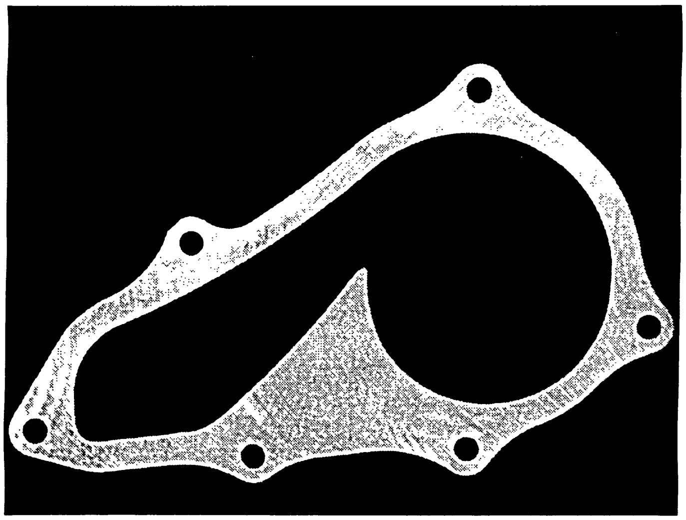


Figure 6.6 (a) sample image #1

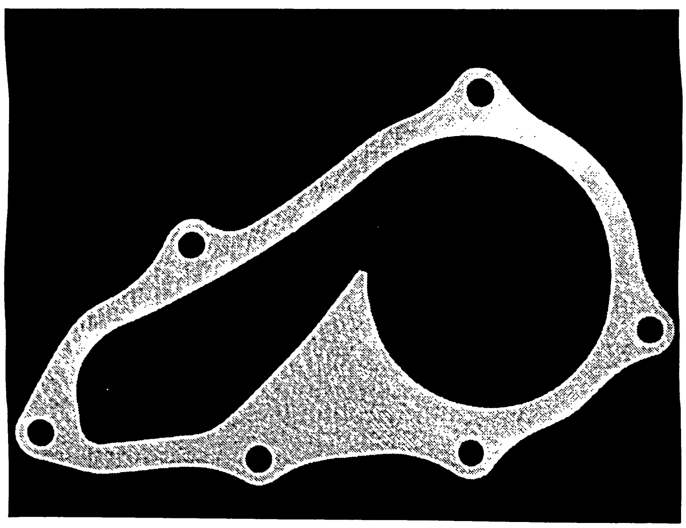


Figure 6.6 (b) sample image #2

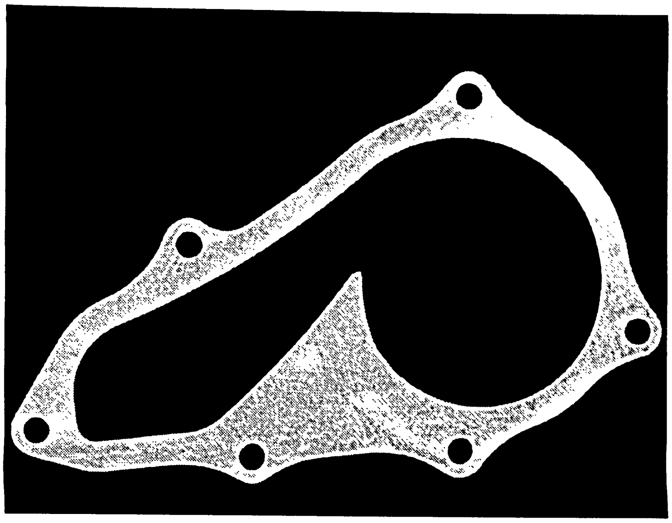


Figure 6.6 (c) sample image #3

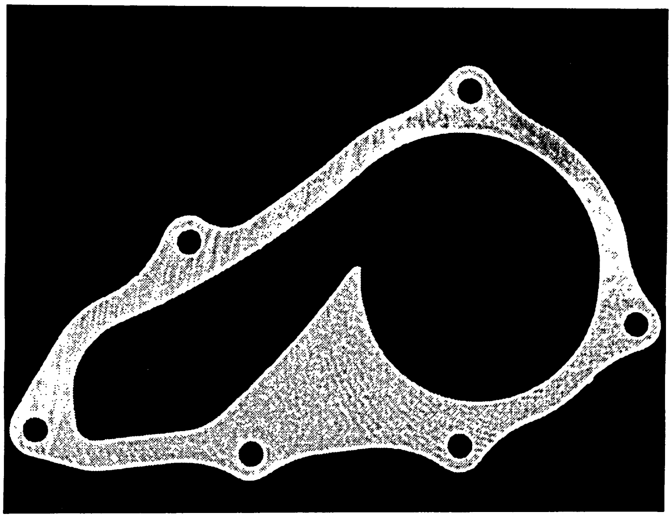


Figure 6.6 (d) sample image #4

Figure 6.6 Four sample images of casting failure detection

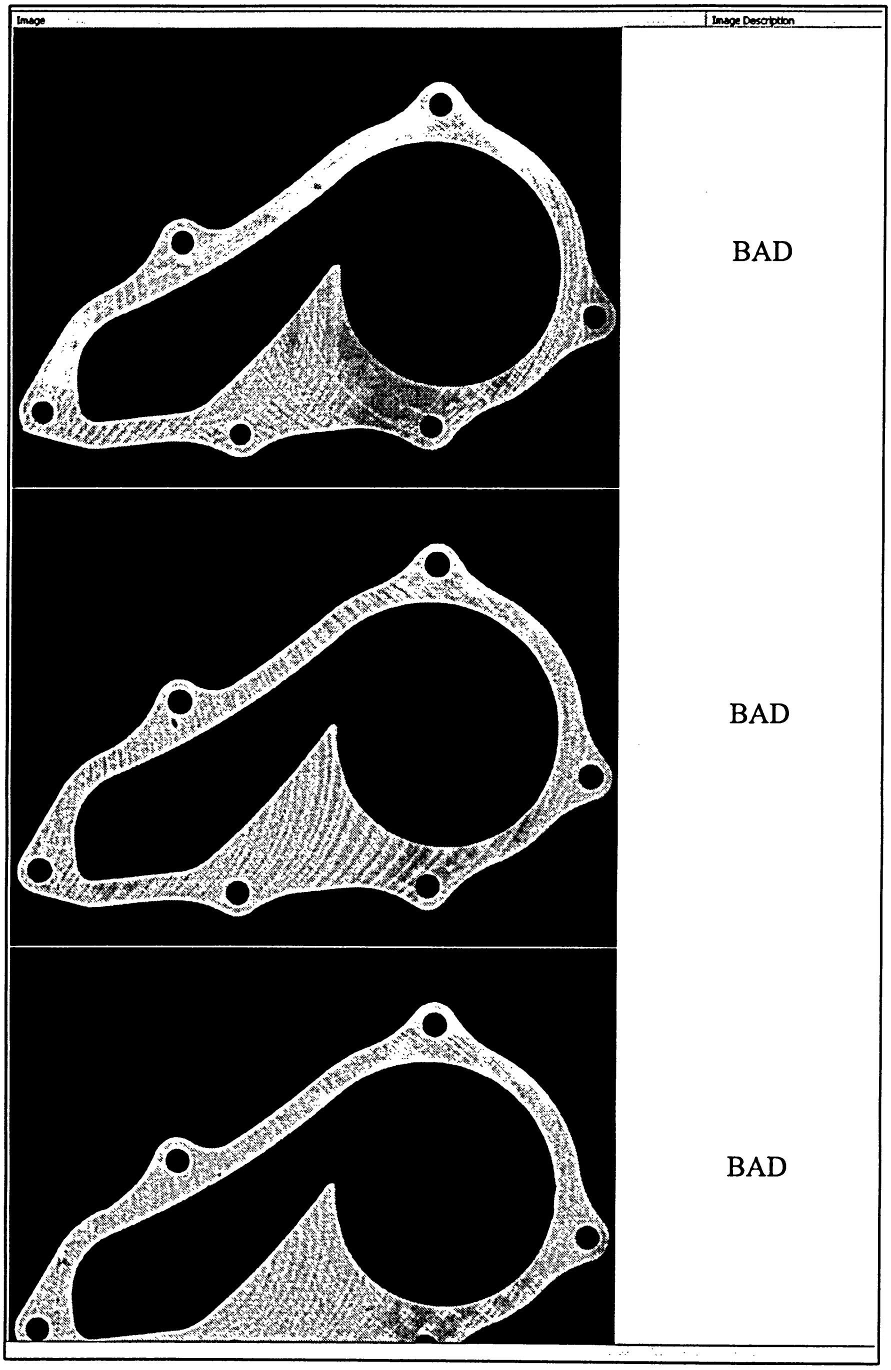


Figure 6.7 (a) Inspection of 1st set of 3 images

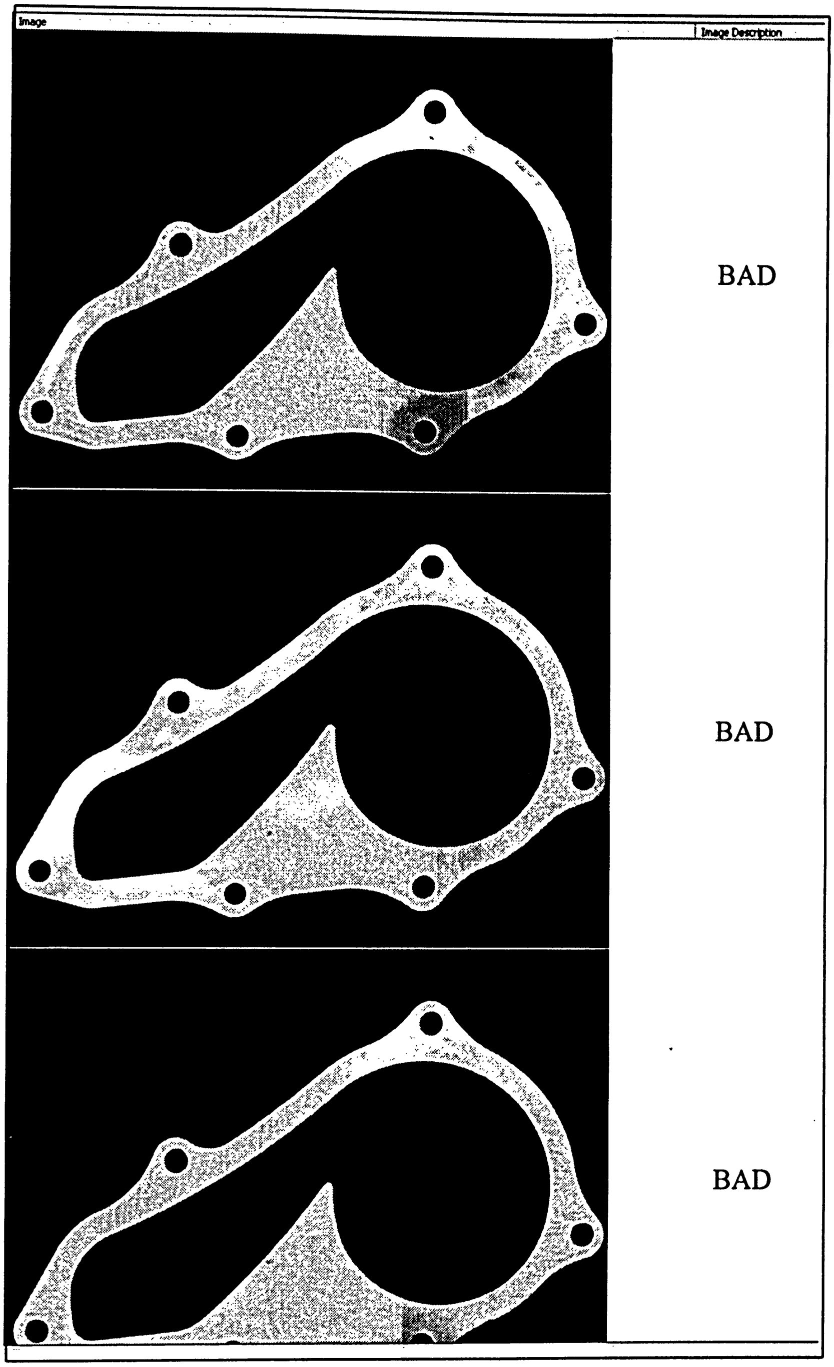


Figure 6.7 (b) Inspection of 2nd set of 3 images

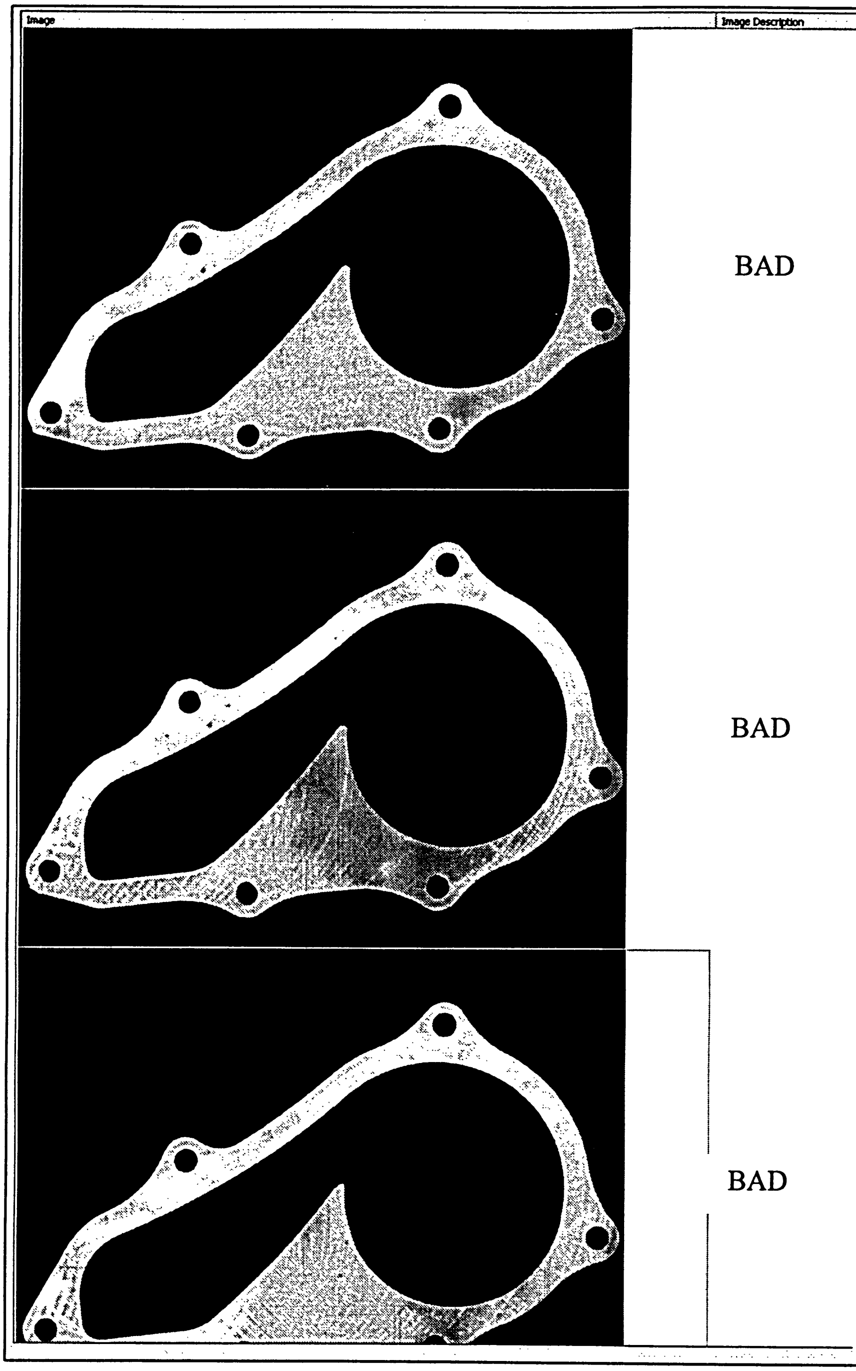


Figure 6.7 (c) Inspection of 3rd set of 3 images

Figure 6.7 Casting failure inspection result

CHAPTER 7 CONCLUSIONS AND FUTURE WORK

In this thesis, a hybrid method is studied. This method combines a statistical method with a Neural Networks method. Neural Networks are trained using two indices from a set of sample images. The inspection system has been implemented and verified on both label printing and auto part manufacturing process. According to the results, the inspection accuracy was around 95%.

7.1 Contributions

The contributions of this thesis are listed below:

1. Reduction of noise information

As mentioned in the beginning of the thesis, industry environmental variations and product variations are two problems that should be solved to improve inspection accuracy.

To remove the background noise information and to extract the inspection part from the raw images of clips detection, a fixed crop zone is developed. The position and rotation variations can be encircled inside the fixed crop zone. This method is applicable to products to be inspected with a simple shape.

The mask matrix is implemented to solve the problem for the products to be inspected if they have a complicated shape and their edge is hard to detect. A mask matrix is established based on a sample image and containing only "0" and "255", which is black and white in grayscale. The white area is the mask of inspection part. For casting failure detections, the connecting plane of a water pump to be inspected can be exactly extracted from a raw image by merging it with the mask matrix. This method is applicable to products which are installed on a frame when taking photos by a camera.

2. Minimum Training Set

The Taguchi method is used to find the minimum training set in clips detection with diverse and abundant images. The variation is classified into four noise factors, and three levels are defined for each factor.

A four-factor, three-level L_9 orthogonal array is used to cope with reducing the number of trials without significantly reducing the effectiveness of the experiments. After analyzing the experimental results, an importance sequence is obtained that helps to decide which sort of image should be chosen to form a minimum training set. Finally, a six-image training set is chosen for network training, and the inspection accuracy is 94.5% without negative faults.

7.2 Future Work

Although the simulation results show that the industrial vision inspection system can obtain good performance and high accuracy, some future work is suggested as follows:

1) More testing should be done based on other industries and live images.

2) To improve the accuracy and reduce the positive faults, a better sample image choosing method should be developed.

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