Intelligent Segmentation of Industrial Component Images

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Abstract*- *An application of machine vision, incorporating neural networks, which aims to fully automate real-time inspection in component identification process, is described. The current methodology adopted comprises two distinct stages - the segmentation of the component from the background content of the image, and the segmentation of suspect defect areas inside the region itself. In the first stage, preprocessing and enhancement, segmentation techniques have been employed to adaptively and accurately segment the region from a given image. The second processing stage utilizes a feature extraction and classification further Back propagation network which is trained on a test set of image data previously segmented by a conventional adaptive threshold method. It is shown that the two techniques can be combined to fully segment images.

Index Terms - ***Automated inspection, Back propagation neural networks, image segmentation***

I. INTRODUCTION

All industries aim to produce competitive goods. This is possible if these goods conquer the consumer and maintain their profit. The competition enhancement depends mainly on productivity and quality. With the advances in electronic technologies, much can be done to improve productivity by using automation as an integral part of manufacturing systems. The primary benefits of automation are reduction in organization time, improvement on equipment utilization, better processing and reduction in manual intervention. Industrial quality control is designed to ensure that defective products do not reach the customer.

For this reason, it forms essential information for the whole industrial process, with influence from the design to logistic planning, as well as on manufacturing. Moreover, the quality control must be automated too. Therefore, automatic quality control has become one of the major business strategies and perhaps the most important way to achieve success in a highly competitive world market. The classification of defective components from qualified ones constitutes a fundamental issue of the mechanical industry for both economical and productive reasons.

Component inspection is widely used in industry to examine any type of components for possible flaws or defects such as cracks, porosity, lack of fusion and solid inclusions.

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Increasingly, real time systems, featuring the use of Digital cameras, are being used which allows for on-line inspection of critical components in industrial applications. This enables any faults that are present to be quickly rectified without serious capital loss. Such real time systems have also enabled the concept of on-line digital inspection to become a reality, where image processing can be used to enhance image quality to aid the manual inspection procedure.

The current advances in computer processing power and the advent of relatively inexpensive dedicated digital image processors will result in the increased speed and sophistication, but reduced cost, of such systems. In addition to the relatively simple operation of image enhancement, sophisticated image analysis for digital component image is a widely studied research field, with much recent research being directed at fully automated inspection systems [I-5].

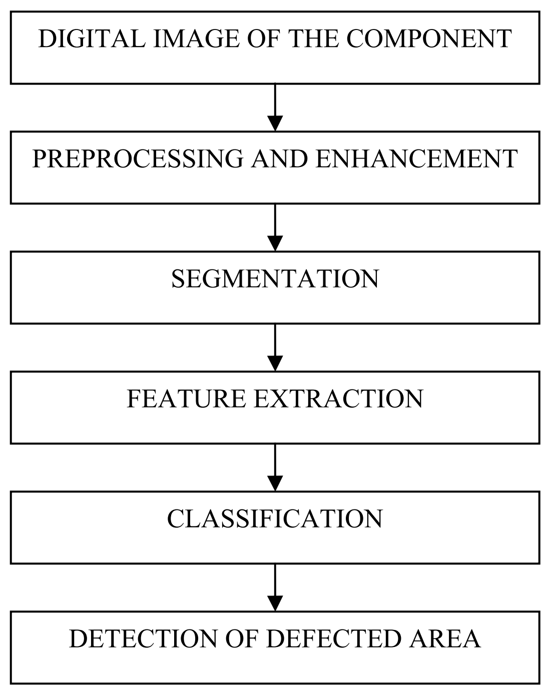

Figure.1 Overview of intelligent defect detection

Such systems aim to eliminate the variability in inspection cycles in which human observers are currently used. In such cases the outcome of the manual inspection of a component is subject to factors such as operator fatigue and experience poor

component in digital component image. Haralick et al. have suggested 14 texture features such as angular second moment (ASM), contrast(CON), correlation (COR), variance(V AR), inverse difference moment (IDM), sum average(SA), sum variance(SV), difference variance (DV), entropy (ENT), sum entropy (SENT), difference entropy (DENT), information measures of correlation (IMC1, IMC2), maximal correlation coefficient(MCC)

V. CLASSIFICATION

Classification of objects is an important area of research and of practical applications in a variety of fields, including pattern recognition and artificial intelligence, medicine, statistics and vision analysis. Classifier design can be performed with labeled or unlabeled data.

Neural networks (NN) can learn various tasks from training examples; classify phenomena, and model nonlinear relationships. However, the primary features that are of concern in the design of the network are problem specific. Despite the availability of some guidelines, it would be helpful to have a computational procedure in this aspect, especially for the optimum design of an NN. The gradient descent algorithms have reported difficulties in learning the topology of the networks whose weights they optimize.

Artificial Neural Networks (ANNs) are networks of interconnected simple units that are based on a simplified model of the brain. ANNs are useful learning tools by being able to compute results quickly interpolating data well. There are two main types of ANNs, feed forward networks and recurrent networks. Perceptrons is a special case of feed forward networks with only input and output nodes. Three main Perceptron learning algorithms are covered: mistake bound Perceptron algorithm, Perceptron training rule and the Delta rule.

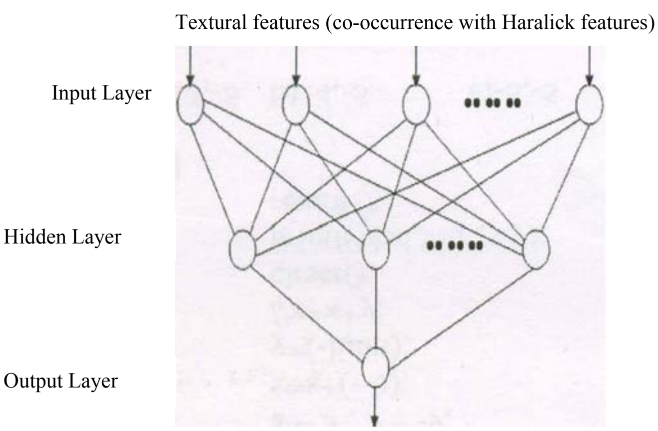

Figure 2. Artificial Neural Networks (ANNs)

The delta rule uses gradient descent, which makes it easy to compute what changes are needed to optimize the network. The backpropagation-learning algorithm is widely used for multi-layer feed forward network. This uses gradient descent as well. Bayesian learning is based on statistics and knowledge of prior statistics to classify or predict. Bayes Theorem is central to Bayesian learning. Some of the key terms are defined below:

Artificial Neural Networks: (ANN)

These networks allow for learning using highly parallel series of simple units and are suited for data that is noisy and vector based.

Backpropagation - A learning algorithm for multi-layered feed forward networks that uses the sigmoid function.
Hidden layer - The set of nodes that are not input or output units.
Learning rate - A value greater than 0 but less than 1, this is used so that the weights on the links do not change to quickly, or the ANN might never converge onto the optimal solution.
Linearly separable function - A function where if plotted in a n-dimensional plane, the negative and positive examples of the function can be totally separated using a straight plane across the space.
Multi-layer Feed Forward Networks - A network with at least one unit that is not output or, input, where the direction of data flow is in only one direction.
Perceptrons - A network with no units that are output or input, where the direction of data flow is in only one direction.
Supervised Learning - All learning algorithms where the known targets are used to adjust the network. **Target -** The expected output of the input. This is used to calculate the error.
Threshold function - The function to decide whether a unit should fire or not. Typically 1 for exceeding the threshold and 0 or -1 otherwise.
Units / Nodes - simple elements of a ANN, they take in input from other nodes or training data, sum up the data and applies a threshold function to decide what output to send.
Weighted links - Connects units together, conceptually shows the strength of the bond between two units

The classifier employed in this paper three-layer backpropagation neural network. The backpropagation neural network optimizes the net for correct responses to the training input data set. More than one hidden layer may be beneficial for some applications, but one hidden layer is sufficient if enough hidden neurons are used (Werbos, 1974; Rumelhart et al. 1986; Herz et al. 1991).

BACKPROPAGATION ALGORITHM

The backpropagation algorithm can be implemented in two different modes: on-line mode and batch mode. In the on-line mode the error function is calculated after the presentation of each input pattern and the error signal is propagated back through the network modifying the weights before the presentation of the next pattern. This error function is usually the Mean Square Error (MSE) of the difference between the desired and the actual responses of the network over all the output units. Then the new weights remain fixed and a new pattern is presented to the network and this process continuous until all the patterns have been presented to the network. The presentation of all the patterns is usually called one epoch or single iteration. In practice many epochs are needed before the error becomes acceptably small.

A great advantage of our method is that structural information can be extracted without knowledge of the localization of the individual defect region contained in a cluster. In the experiments we have compared the classification capability of the combined method with that of statistical descriptors based on co-occurrence matrices of the whole image. The experiments showed in this method have better classification performance than that of statistical descriptors computed from the co-occurrence matrices of the whole image. The goal of the experimental study was to demonstrate that the performance of the classical co-occurrence approach to texture feature extraction can be greatly improved by performing the computation of the co-occurrence matrices. Consequently, we did not focus on techniques for automated feature selection and on the optimization of the classifier design. Finally, the detection system can automatically detect defective regions on a component image and alert the industry person to these regions.

VI REFERENCES

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