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AUTOMATED QUALITY INSPECTION OF FABRICS – A BAYESIAN APPROACH

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ABSTRACT

Industrial inspection is one of the crucial factors to ensure quality of product before they reach the market. Significant attention of the researchers has been being drawn by automated textile inspection systems in order to replace manual inspection, which is time consuming and not accurate enough. Automated textile inspection systems mainly involve two challenging problems, one of which is defect classification. The inspection of real fabric defects is particularly challenging due to the large number of fabric defect classes. It is reported that the price of fabric is reduced by 45%-65% due to the presence of defects, which results in the emergence of intelligent inspection systems to ensure the high quality of products. This paper mainly focuses on detecting various kinds of defects that might be present in a given fabric sample based on the computer vision of the fabric. We apply the maximum a posteriori (MAP) rule in Bayesian algorithm to find the best match of the input image with the sample. We present a possibly appropriate set of geometric features in order to address the problem of Bayesian algorithm based textile defect classification.

KEYWORDS: Bayesian Algorithm, Computer Vision, Maximum A Posteriori (MAP) Estimation

INTRODUCTION

The importance of quality control in industrial production is increasing day by day. Textile industry is not an exception in this regard. The accuracy of manual inspection is not enough due to fatigue and tediousness. Moreover, it is time consuming. High quality cannot be maintained with manual inspection. The solution to the problem of manual inspection is automated, i.e. machine-vision-based textile inspection system. Automated textile inspection systems have been drawing a lot of attention of the researchers of many countries for more than a decade. Automated textile inspection systems mainly involve two challenging problems, namely defect detection and defect classification.

A lot of research has been done addressing the problem of defect detection, but the amount of research done to solve the classification problem is inadequate. Defect classification involves multiple problem areas, since classification process is composed of several steps. Scene analysis and feature selection is one of the important steps of classification process. Inadequate scene analysis results in an inappropriate feature set.

Selection of an inappropriate set of features increases the complexities of the subsequent steps and makes the classification task harder. Selecting an appropriate set of features to solve a classification problem is very difficult. In an appropriate feature set, the discriminatory qualities of the features are high and the number of features is small. Moreover, an appropriate set of features takes into account the difficulties lying in the feature extraction process and also result in acceptable performance.

FABRIC DEFECTS

Fabric texture refers to the feel of the fabric. It is smooth, rough, soft, velvety, silky, lustrous, and so on. The different textures of the fabric depend upon the types of weaves used. Textures are given to all types of fabrics, cotton, silk, wool, leather, and also to linen. The objective of the proposed work is to identify whether the fabric is defective or not. The various types of defects detected during quality controls are broadly classified as follows.

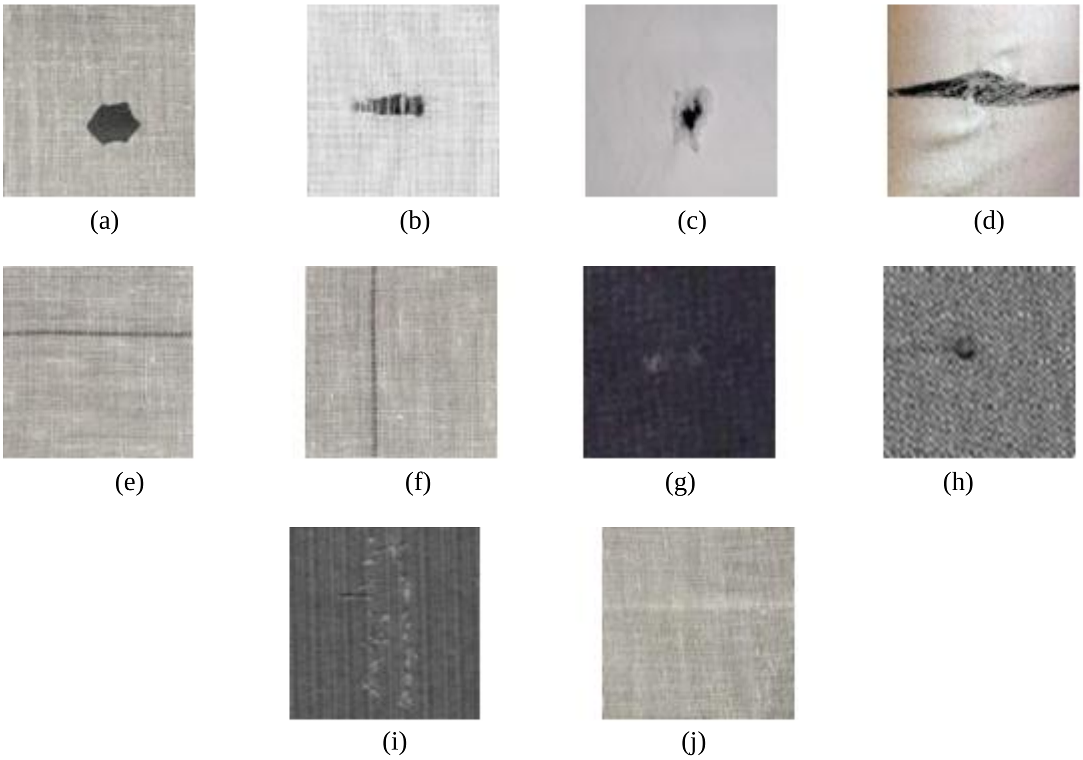

Figure 1: Fabric Defect Samples
(a) Broken Ends (b) Gout (c) Hole (d) Oil Stains (e) Missing Yarn (Horizontal) (f) Missing Yarn (Vertical) (g) Color Yarn (h) Knot (i) Scratch (j) Variation of Yarn

- **Broken Ends:** This defect is caused by a bunch of broken ends woven in the fabric.
- **Gout:** A gout is a foreign matter usually lint or waste accidentally woven into the fabric.
- **Hole:** The occurrence of hole, cut or tear.
- **Oil or Other Stain:** These are spot defects of oil, rust, grease or other stains found in the fabric.
- **Missing Yarn:** It appears as a thin striped shade of the color of fabric. It is usually long. It is of two types, namely vertical and horizontal.
- **Color Yarn:** It appears in a shape, close to a small rectangle of one color, on a fabric of another color.
- **Knots:** Occurs when broken threads are pieced together by improper knotting.

PROPOSED METHODS

The main motive of the proposed method is to develop an economical automated fabric defect detection considering the reduction in labor cost and associated benefits. The development of fully automated web inspection system requires robust and efficient fabric defect detection algorithms. Numerous techniques have been developed to detect fabric defects and the purpose of this paper is to propose a better method when compared to other techniques.

At first the images of the fabric is captured by digital camera in RGB format and passes the image through serial port to the computer. Then, noise is removed using standard techniques. RGB images are then converted to grayscale images to converts digital (RGB) images to grayscale images. Then the following features are calculated.

- **The Area of the Faulty Portion:** Calculates the total defected area of a image.
- **Number of Objects:** Uses image segmentation to calculate the number of labels in an image.
- **Shape Factor:** Distinguishes a circular image form a noncircular image. Shape factor uses the area of a circle to identify the circular portions of the fault.

These three attributes are used as input sets to Bayesian image analysis in order to recognize expected defects.

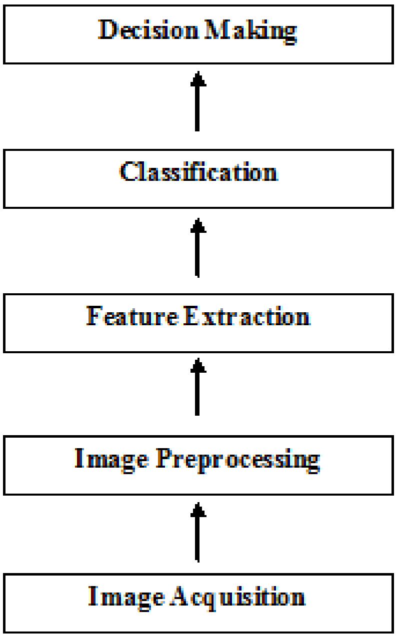

Figure 2: Steps Involved in Development of the Automated Inspection System

BAYESIAN IMAGE ANALYSIS

The Bayesian approach provides the means to incorporate prior knowledge in data analysis. Bayesian analysis revolves around the posterior probability, which summarizes the degree of one's certainty concerning a given situation. Bayes's law states that the posterior probability is proportional to the product of the likelihood and the prior probability. The likelihood encompasses the information contained in the new data. The prior expresses the degree of certainty concerning the situation before the data are taken.

Although the posterior probability completely describes the state of certainty about any possible image, it is often necessary to select a single image as the 'result' or reconstruction. A typical choice is that image that maximizes the posterior probability, which is called the MAP estimate.

The normalization sets the scale for the probability density function:

$$\int p(x)dx = 1$$

where the integral is over all possible values of *x*. This normalization simply states that some value of *x* is certain to occur. The transformation property of density functions guarantees that the integrated probability over any interval in *u* is identical to that over the corresponding interval in *x*.

$$p(u) = p(x)\left|\frac{dx}{du}\right|$$

Present state of certainty is characterized by the probability density function $p(x)$. We perform an experiment and take some data d. Bayes's law is given as:

$$p(x/d) = \frac{p(d/x)\,p(x)}{p(d)}$$

We call $p(x|d)$ the posterior probability density function, or simply the posterior, because it effectively follows the experiment. It is the conditional probability of x given the new data d. The probability $p(x)$ is called the prior because it represents the state of knowledge before the experiment. The quantity $p(d|x)$ is the likelihood, which expresses the probability of the data d given any particular x. Bayes's law provides the means for updating our knowledge, expressed in terms of a probability density function, in light of some new information, similarly expressed.

When any answer other than the correct one incurs the same increased cost, the obvious estimate is the value of x at the maximum of the posterior probability density function:

$$\hat{x} = argmax\, p(x/d)$$

This choice is the well-known maximum *a posteriori* (MAP) estimator.

RESULTS

Experimental results are used to verify the proposed approach. In this experiment, five defect models and their corresponding real samples are used to examine this approach.

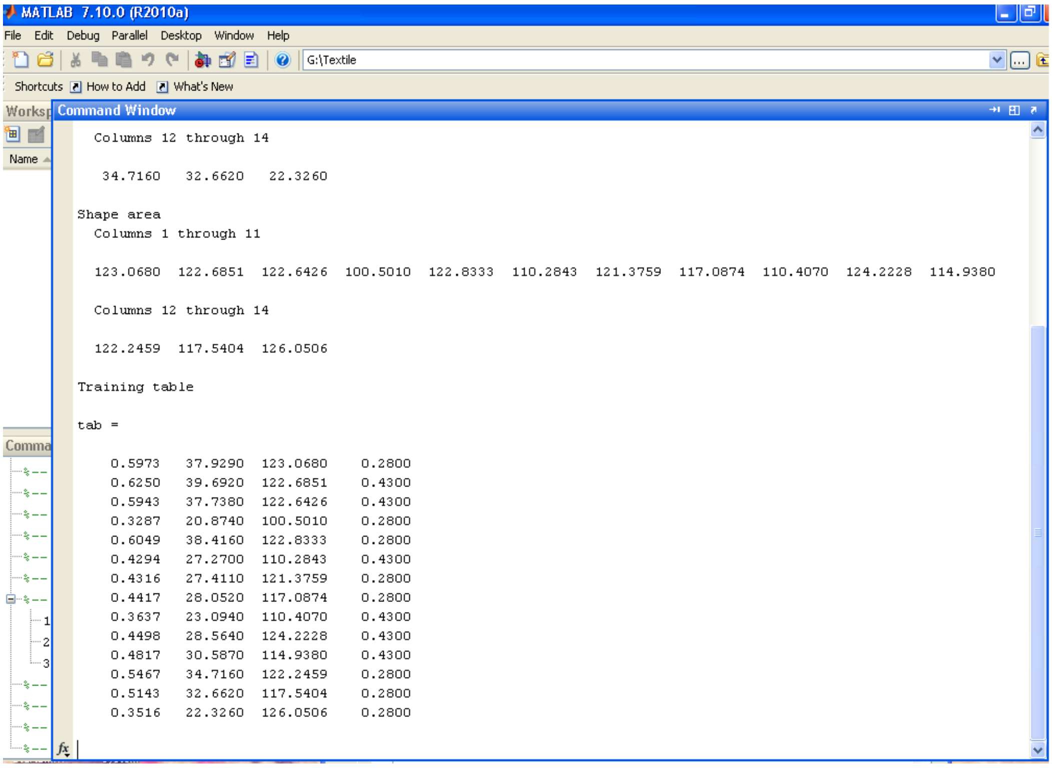

Figure 3: Prior Probability Table Formed Using Bayesian Image Analysis

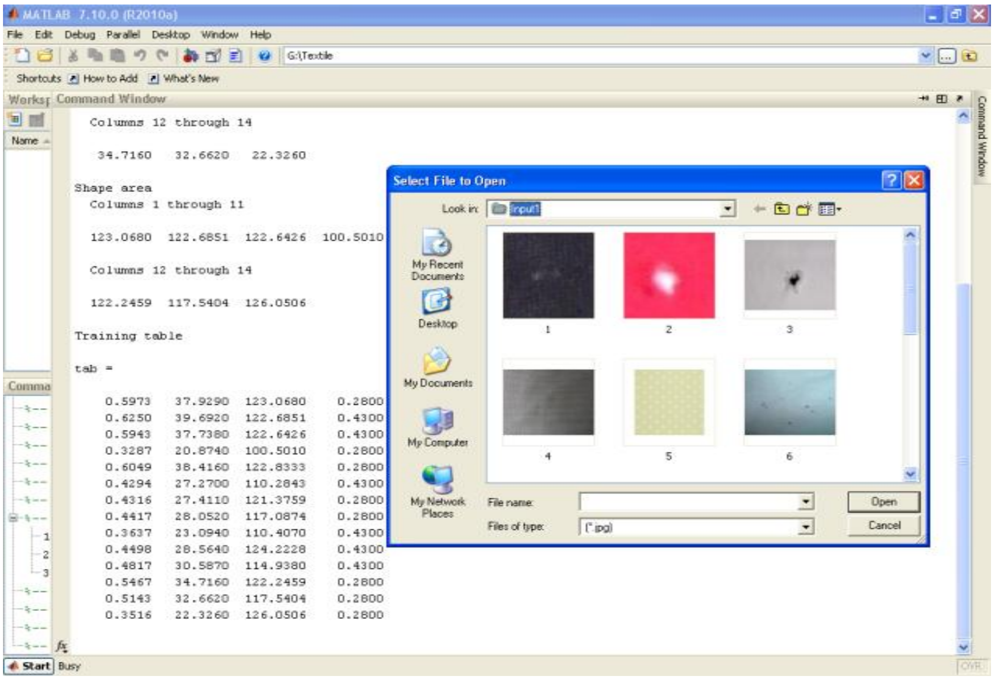

Figure 4: Input Image is given to the System

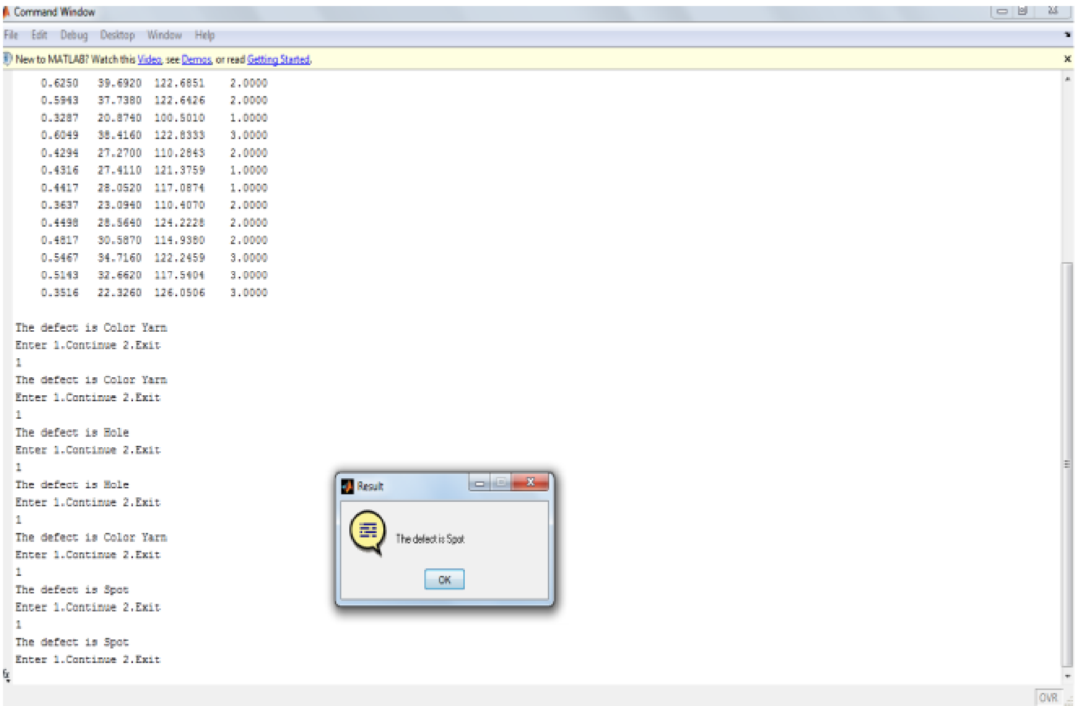

Figure 5: Identification of Fault in the Fabric

CONCLUSIONS AND FUTURE WORK

The manual textile quality control usually goes over the human eye inspection. Notoriously, human visual inspection is tedious, tiring and fatiguing task, involving observation, attention and experience to detect correctly the fault occurrence. The accuracy of human visual inspection declines with dull jobs and endless routines. Sometimes slow, expensive and erratic inspection is the result. Therefore, the automated inspection system protects both: the man and the quality. Here, it has been demonstrated that Automated Industrial Inspection System Using Image Processing is capable of detecting fabrics' defects with more accuracy and efficiency.

Further the research can be enhanced for more number of defects and increased number of sample image data.

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