

An Advanced and Automated Neural Network based Textile Defect Detector

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1. Introduction

All textile industries aim to produce competitive fabrics. The competition enhancement depends mainly on productivity and quality of the fabrics produced by each industry. In the textile sector, there have been an enlarge amount of losses due to faulty fabrics. In the Least Development Countries (LDC) like Bangladesh, whose 25% revenue earning is achieved from textile export, most defects arising in the production process of a textile material are still detected by human inspection. The work of inspectors is very tedious and time consuming. They have to detect small details that can be located in a wide area that is moving through their visual field. The identification rate is about 70%. In addition, the effectiveness of visual inspection decreases quickly with fatigue. Thus, to produce less defective textile for minimizing production cost and time is a vital requirement. Digital image processing techniques have been increasingly applied to textured samples analysis over the last ten years (Ralló et al., 2003). Wastage reduction through accurate and early stage detection of defects in fabrics is also an important aspect of quality improvement. The article in (Meier, 2005) summarized the comparison between human visual inspection and automated inspection. Also, it has been stated in (Stojanovic et al., 2001) that price of textile fabric is reduced by 45% to 65% due to defects. Thus, to reduce error on identifying fabric defects requires more automotive and accurate inspection process. Considering this lacking, this research implements a Textile Defect Detector which uses computer vision methodology with the combination of multi-layer neural networks to identify four classifications of textile defects. Afterwards, a microcontroller based mechanical system is developed to complete the Textile Defect Detector as a real-time control agent that transforms the captured digital image into adjusted resultant output and operates the automated machine (i.e. combination of two leaser beams and production machine), illustrated in Fig. 1.

The main purpose of this chapter is to present an advanced and automatic Textile Defect Detector as a first step for a future complete industrial Quality Information System (QIS) in textile industries of Least Development Countries (LDC). The chapter is organized as follows:

- Section 2 describes relevant previous efforts in the fields, such as textile fabric inspection systems, computer vision and machine learning systems for automated textile defects recognizing, electronic textile (e-textiles) systems etc.
- Section 3 provides the methodology and implementation of the proposed textile defect detectors. Software and hardware system implementation are two major parts. The software system implementation consists the textile image processing and the neural network designing issues. The hardware system consists micro-controller design and implementation issues.
- Section 4 provides the experimental comparison of the proposed implementation on the textile defects detection.
- Finally, Section 5 concludes with some remarks and plausible future research lines.

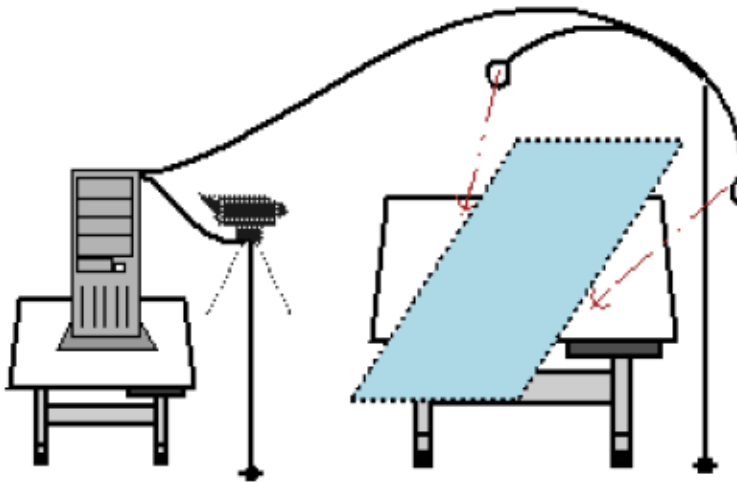


Fig. 1. Real-time Environment of Textile Defect Detector

2. Related work

Machine vision automated inspection system for textile defects has been in the research industry for longtime (Batchelor & Whelan, 1994), (Newman & Jain, 1995). Recognition of patterns independent of position, size, brightness and orientation in the visual field has been the goal of much recent work. However, there is still a lack of work in machine vision automated system for recognizing textile defects using AI. A neural network pattern recognizer was developed in (Zhang et al., 1992).

Today's automated fabric inspection systems are based on adaptive neural networks. So instead of going through complex programming routines, the users are able to simply scan a short length of good quality fabric to show the inspection system what to expect. This coupled with specialized computer processors that have the computing power of several hundred Pentium chips makes these systems viable (Dockery, 2001). Three state-of-the-art fabric inspection systems are - BarcoVision's Cyclops, Elbit Vision System's I-Text and Zellweger Uster's Fabriscan. These systems can be criticized on grounds that they all work

under structured environments – a feat that is almost non-existent in list developed countries like Bangladesh.

There are some works in (Ciamberlini et al., 1996) based on the optical fourier transform directly obtained from the fabric with optical devices and a laser beam. Digital image processing techniques have been increasingly applied to textured samples analysis over the last ten years. Several authors have considered defect detection on textile materials. Kang et al. (Kang et al., 1999), (Kang et al., 2001) analyzed fabric samples from the images obtained from transmission and reflection of light to determine its interlacing pattern. Wavelets had been applied to fabric analysis by Jasper et al. (Jasper et al., 1996), (Jasper et al., 1995). Escofet et al. (Escofet et al., 1996), (Escofet et al., 1998) have applied Gabor filters (wavelets) to the automatic segmentation of defects on non-solid fabric images for a wide variety of interlacing patterns. (Millán & Escofet, 1996) introduced Fourier-domain-based angular correlation as a method to recognize similar periodic patterns, even though the defective fabric sample image appeared rotated and scaled. Recognition was achieved when the maximum correlation value of the scaled and rotated power spectra was similar to the autocorrelation of the power spectrum of the pattern fabric sample. If the method above was applied to the spectra presented in Fig.1, the maximum angular correlation value would be considerably lower than the autocorrelation value of the defect free fabric spectrum. Fourier analysis does not provide, in general, enough information to detect and segment local defects.

Electronic textiles (e-textiles) are fabrics with interconnections and electronics woven into them. The electronics consist of both processing and sensing elements, distributed throughout the fabric. (Martin et al., 2004) described the design of a simulation environment for electronic textiles (e-textiles) but having a greater dependence on physical locality of computation. (Ji et al., 2004) analyzed the filter design essentials and proposes two different methods to segment the Gabor filtered multi-channel images. The first method integrates Gabor filters with labeling algorithm for edge detection and object segmentation. The second method uses the K-means clustering with simulated annealing for image segmentation of a stack of Gabor filtered multi-channel images. But the classic Gabor expansion is computationally expensive and since it combines all the space and frequency details of the original signal, it is difficult to take advantage of the gigantic amount of numbers. From the literature it is clear that there exists many systems that can detect Textile defects but hardly affordable by the small industries of the LDC like Bangladesh.

In this research, we propose an automated Textile Defect Detector based on computer vision methodology and adaptive neural networks and that is implemented combining engines of image processing and artificial neural networks in textile industries research arena. In textile sectors, different types of faults are available i.e. hole, scratch, stretch, fly yarn, dirty spot, slab, cracked point, color bleeding etc; if not detected properly these faults can affect the production process massively. The proposed Textile Defect Defector mainly detects four types of faults that are hole, scratch, fresh as no fault and remaining faults as other fault.

3. The automated neural network based textile defect detector

The proposed textile defect recognizer is viewed as a real-time control agent that transforms the captured digital image into adjusted resultant output and operates the automated machine (i.e. combination of two leaser beams and production machine) through the micro-controller. In the proposed system as the recognizer identifies a fault of any type mentioned above, will immediately recognize the type of fault which in return will trigger the laser

beams in order to display the upper offset and the lower offset of the faulty portion. The upper offset and the lower offset implies the 2 inches left and 2 inches right offset of faulty portion. This guided triggered area by the laser beams will indicate the faulty portion that needs to be extracted from the roll. For this the automated system generates a signal to stop the rotation of the stepper motor and cut off the faulty portion. Whenever, the signal is generated the controller circuit stops the movement of the carrying belt and the defective portion of the fabric is removed from the roll. Then after eliminating the defective part again a signal is generated to start the stepper motor and continue the further process. Here, the whole system implementation is done in a very simple way. In addition to this the hardware equipments are so cheap that a LDC like Bangladesh can easily effort it and can make the best use of the scheme.

The methodology that the whole system consists of two major parts - software and the microcontroller based hardware implementation. The major steps required to implement the Textile Defect Detector is depicted in Fig. 2.

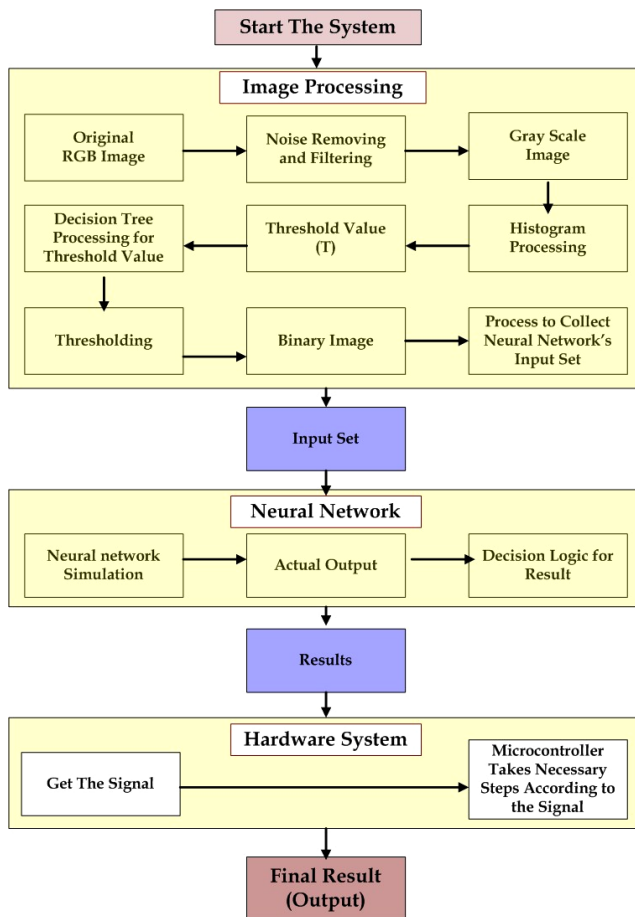


Fig. 2. Major components of the Textile Defect Detector

3.1 The software system

The software system can be a competitive model for recognizing textile defects in real world. Base on the research, the software system design is also separated into two additional parts. The first part focuses on the processing of the images to prepare to feed into the neural network. The second part is about building a neural network that best performs on the criteria to sort out the textile defects. Whenever, the software, detects a fault of any type mentioned above, sends/ triggers a signal to the hardware system.

3.1.1 Processing textile image for the neural network input

At first the images of the fabric is captured by digital camera in RGB format (Fig.3 and Fig.5) and passes the image through serial port to the computer. Then, noise is removed using standard techniques and an adaptive median filter algorithm has been used as spatial filtering for minimizing time complexity and maximizing performance (Gonzalez et al., 2005) to converts digital (RGB) images to grayscale images (left in Fig. 4). A decision tree is constructed based on the histogram of the image in hand to convert the gray scale image in a binary representation. As we know from the problem description that there are different types of textile fabrics and also different types of defects in textile industries hence different threshold values to different pattern of faults there is no way to generalize threshold value (T) from one image for all types of fabrics. Notice this phenomenon in histograms illustrated in Fig. 3 (The identified threshold value T, should be greater then 120 and less than 170) and Fig. 5 (The identified threshold value T, should be greater then 155 and less then 200). A local threshold was used based on decision tree, which was constricted using set of 200 image histograms of fabric data. Illustration of the decision tree is provided in Fig. 6.

After restoration local thresholding technique (decision tree processing) is used in order to convert grayscale image into binary image (right in Fig. 4). Finally, this binary image is used to calculate the following attributes.

- The area of the faulty portion: calculates the total defected area of an image.
- Number of objects: uses image segmentation to calculate the number of labels in an image.

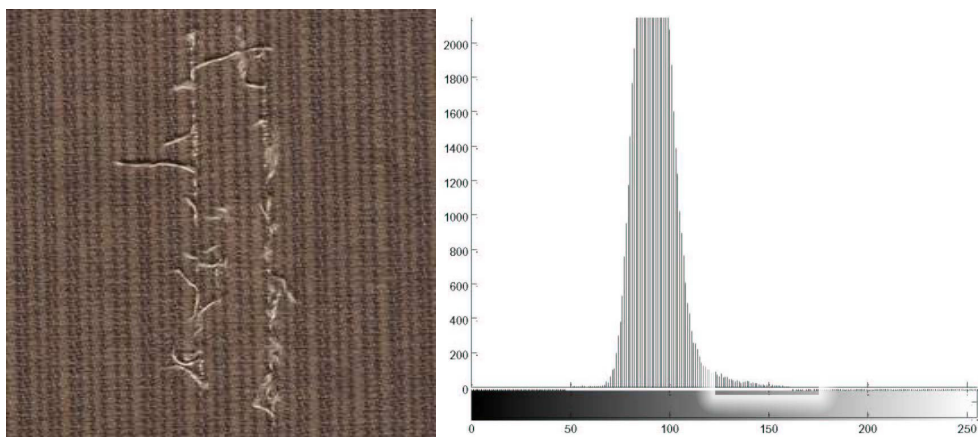


Fig. 3. Original faulty scratch fabric image and histogram representation

- 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 attributes are used as input sets to adapt the neural network through training set in order to recognize expected defects. An example of neural network input set is presented in Table 1.

Area	Number of Objects	Shape Factor
76700	1	0.77389

Table 1. Neural network input set

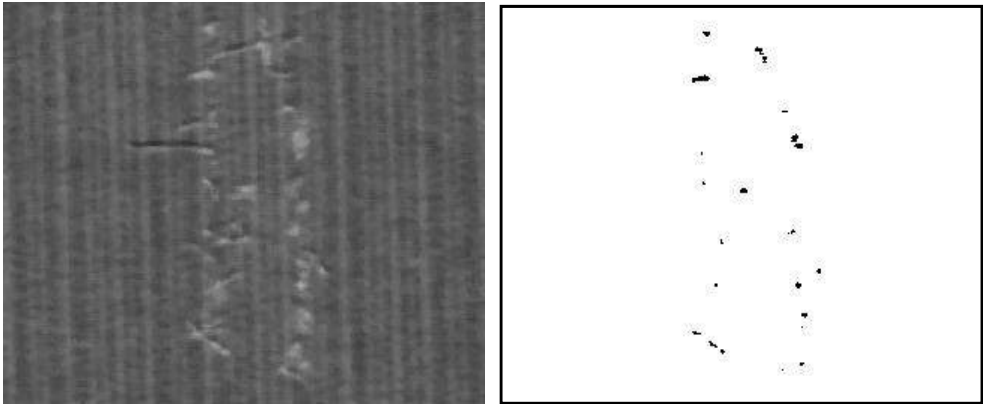


Fig. 4. Faulty scratch grayscale (left) and binary (right) fabric images

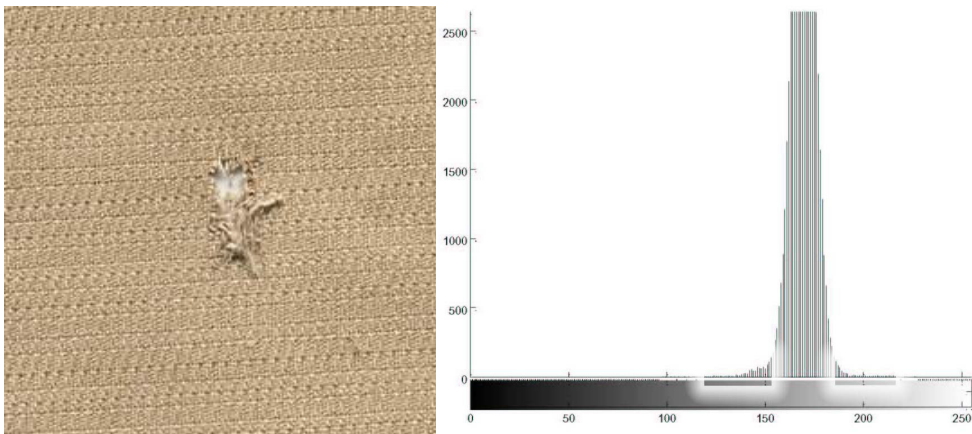


Fig. 5. Original faulty hole fabric image and the histogram representation

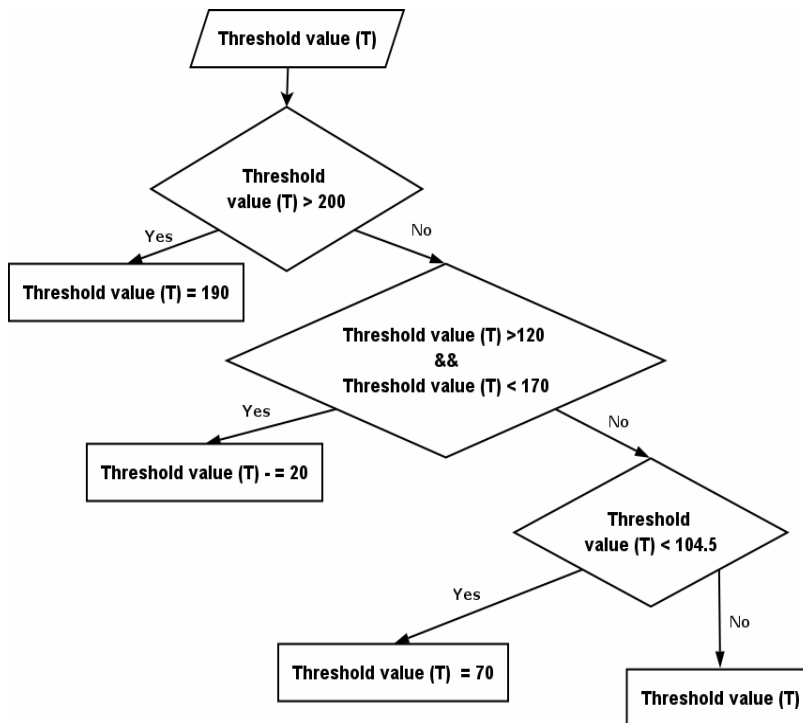


Fig. 6. Decision Tree for Threshold Value (T) to convert from gray to binary

3.1.2 Suitable neural network

In search of a fully connected multi-layer neural network that will sort out the defected textiles, we start with a two layer neural network (Fig. 7). Our neural network contains one hidden of 44 neurons and one output layer of 4 neurons.

The neurons in the output layer is delegated as 1st neuron of the output layer is to Hole type fault, 2nd neuron of the output layer is to Scratch type fault, 3rd neuron of the output layer is to Other type of fault and 4th neuron of the output layer is for No fault (not defected fabric). The output range of the each neuron is in the range of [0 ~ 1] as we use log-sigmoid threshold function to calculate the final out put of the neurons. Although during the training we try to reach the following for the target output $[[1\ 0\ 0\ 0], [0\ 1\ 0\ 0], [0\ 0\ 1\ 0], [0\ 0\ 0\ 1]]$ consecutively for Hole type defects, Scratch type defects, Other type defects and No defects, the final output from the output layer is determined using the winner- take-all method.

To determine the number of optimal neurons in the hidden layer was the tricky part, we start with 20 neurons in the hidden layer and test the performance of the neural network on the basis of a fixed test set, and then we increase the number of neurons one by one and till 60, the number of neurons in the hidden layer is chosen based on the best performance. The error curve is illustrated in Fig. 8.

The parameters used in the neural network can be summarized as:

- Training data set contains 200 images; 50 from each class.
- Test data set contains 20 images; 5 from each class

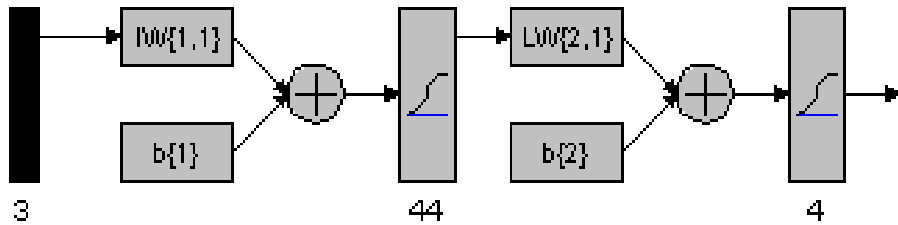


Fig. 7. Design of Feed Forward Back propagation Neural Network

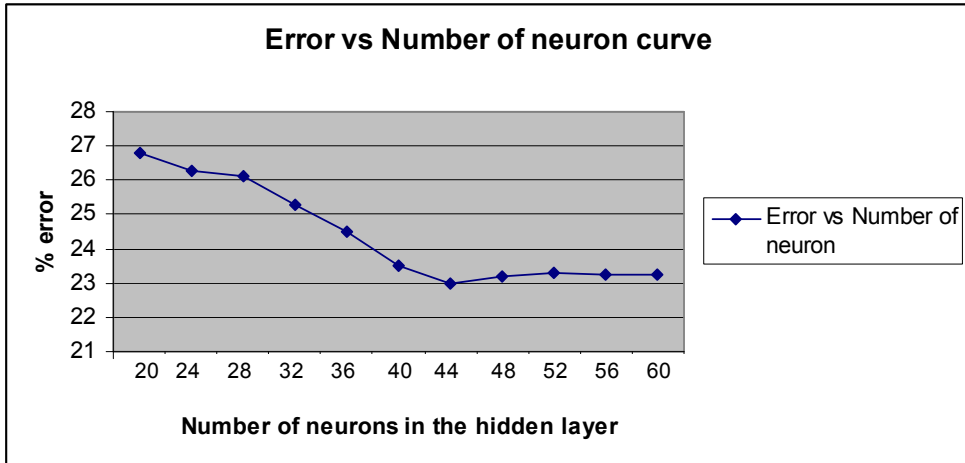


Fig. 8. Performance (in % error) curve on the neuron number in the hidden layer

- The transfer function is Log Sigmoid.
- Performance function used is mean square error
- Widrow-Hoff algorithm is used as learning function (Hagan et al., 2002) with a learning rate of 0.01.
- To train the network resilient back propagation algorithm (Riedmiller and Braun, 1993), (Neural Network Toolbox, 2004) is used. Weights and biases are randomly initialized. Initial delta is set to 0.05 and the maximum value for delta is set to 50, the decay in delta is set to 0.2.
- Training time or total iteration allowed for the neural networks to train is set to infinity, as we know it is a conversable problem. And we have the next parameter to work as stopping criterion

Disparity or maximum error in the actual output and network output is set to 10^{-5} . After calculating input set, neural network simulates the input set and recognizes defect of image as an actual output. From the resultant output, the software system can release final result by the help of decision logic. So, the software system is a simple engine based on computer vision methodology and neural networks in textile industries sector. Efficiency is one of the key points of this system as a result all the algorithms applied on the system is aggressively tested by time and space complexity. The system will successfully minimize inspection time than other manual or automated inspection based system.

3.2 The hardware system

The hardware system is capable to detect the upper offset and the lower offset of the faulty portion. The upper offset and the lower offset implies the 2 inches left and 2 inches right offset of faulty portion and needs to be extracted from the fabric roll. After cutting the desired portions of fabric, the detector resumes its operation.

Microcontroller Implementation: In order to program the microcontroller, PICProg is used to burn the program into the PIC16F84A. It is pic basic program, which uses the serial port of the computer and a simple circuit. The code for the PIC was written and saves as *.asm file. Then PicBasic Pro 2.45 was used to convert it into an *.hex file and after that using PICProg the hex file was written into the PIC. The outlet of the microcontroller is exposed in Fig.9 and Fig. 10.

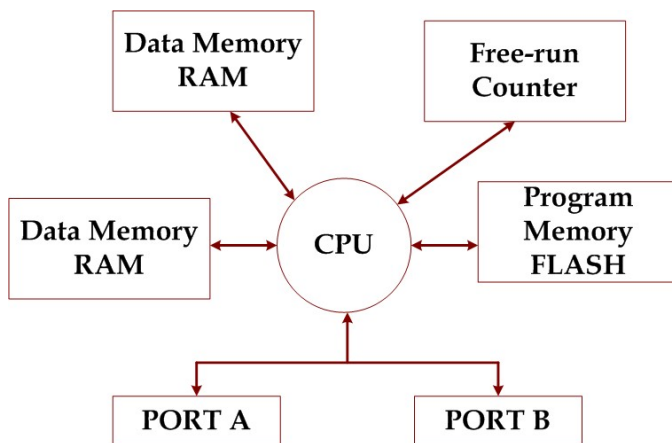


Fig. 9. PIC 16F84A Microcontroller outline

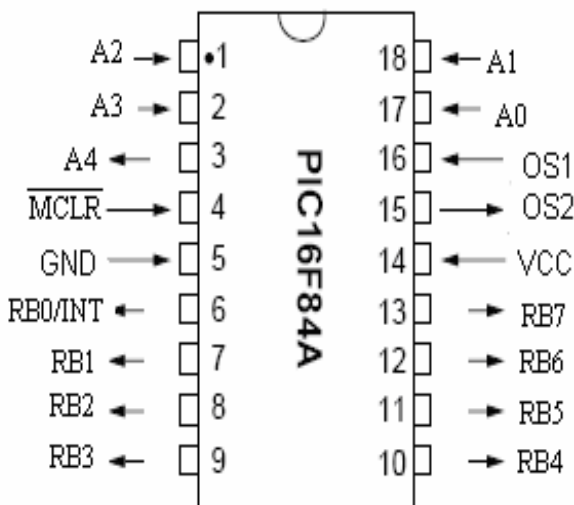


Fig. 10. PIC16F84A

PC parallel port and hence provides extra protection against potentially dangerous feedback voltages that may occur if the circuit fails. The diode connected across the power supply and the collector is used as a freewheeling diode and also to protect the transistor from the back EMF of the motor inductance. The motor used in this experiment is two STM 901 from Srijan Control Drives. The common of four parallel ports are connected with the power supply (VCC) of 5V and head of four parallel is connected to the respective of printer port pin no 2, 3, 4 & 5 and pin no 25 is connected with common point of ground of the circuits.

During normal operation, the output pattern from the PC drives the buffer, and corresponding transistors are switched on. This leads to the conduction of current through these coils of the stepper motor which are connected to the energized transistor. This makes the motor move one step forward. The next pulse will trigger a new combination of transistors, and hence a new set of coils, leading to the motor moving another step. The scheme of excitation that we have used here has already been shown above. In this construction, 50V- 470 μ F capacitor is used for filtering or discharging voltage while converting to pure DC from AC power supply. Regulator IC 7812 is used for voltage transferring down from 24V to 5V. Then a positive voltage (+ve) is supplied from the board to one of the motors (red) and the other wire point is used for grounding (maroon). LED is used for examining the proper voltage supply to the circuit. Capacitor is used for discharging so that no charge is hold. Regulator IC 7805 is used for transferring down voltage from 12V to 5V. Resistance of 330ohm, 10k ohm is used to guard the LED from impairment. For getting pure DC voltage from supplied AC voltage, diode IN 4007 is used. From this circuit, a positive voltage is supplied to the other motor of our experiment just like the other transformer board and the point is grounded.

4. Experimental results

The performance of the Textile Defect Detector is determined based on the cross validation method. The average result is provided in Fig. 12. Here, notice that the recognizer can

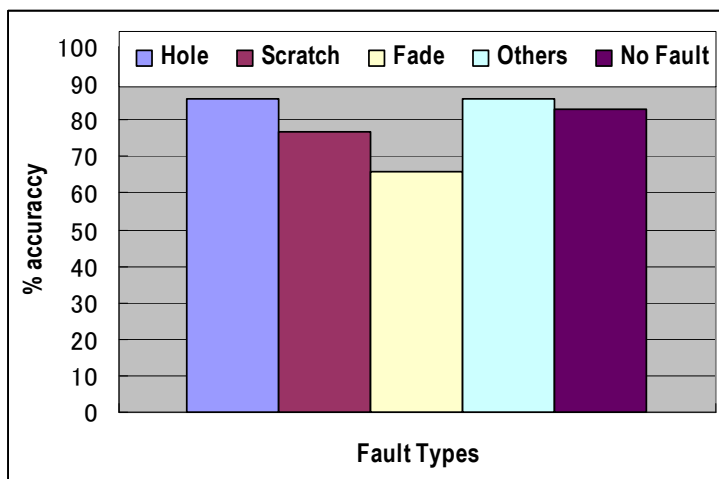


Fig. 12. The bar chart for the performance accuracy of the system

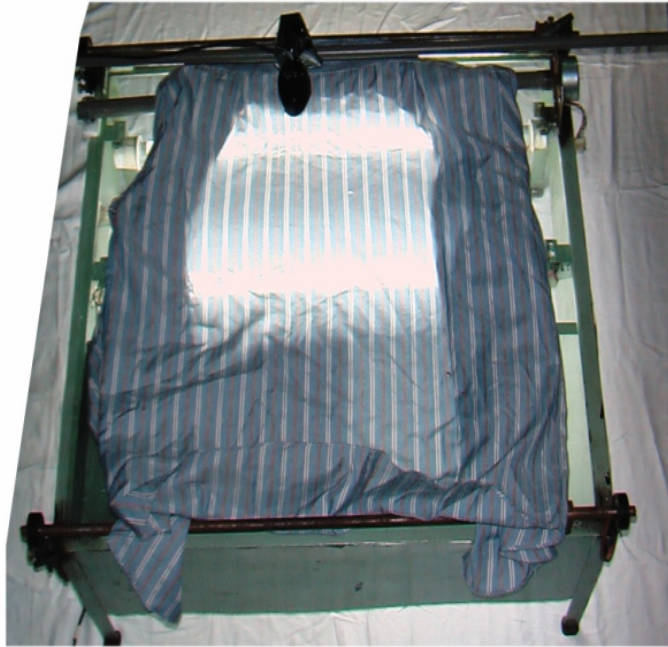


Fig. 13. The real test-bed implementation

successfully identifying Hole type faults with 86% accuracy, 77% of Scratch type faults, 86% of the Other type faults and 83% No faults. Later, the neural network is updated to detect the fade type faults also and the accuracy is 66%. Thus, the average performance of the system determining the defects in textile industry is 74.33% and the overall all performance of the system is 76.5%.

5. Conclusion

In most of the textile garment factories of LDC(s) the defects of the fabrics are detected manually. 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 automatic visual inspection protects both: the man and the quality. Here, it has been demonstrated that Textile Defect Detector System is capable of detecting fabrics' defects with more accurately and efficiency. In the research arena, the proposed system tried to use the local threshold technique without the decision tree process. Since, our recognizer deals with different types of faults and fabrics, therefore the recognition system cannot access a general approach for local thresholding technique.

The image processing system works very well except the quality of the web camera. Because of which sometimes the perfect fabric is also found as faulty part. However, this problem is easily defeatable by using a good quality camera. Additionally, the proposed research

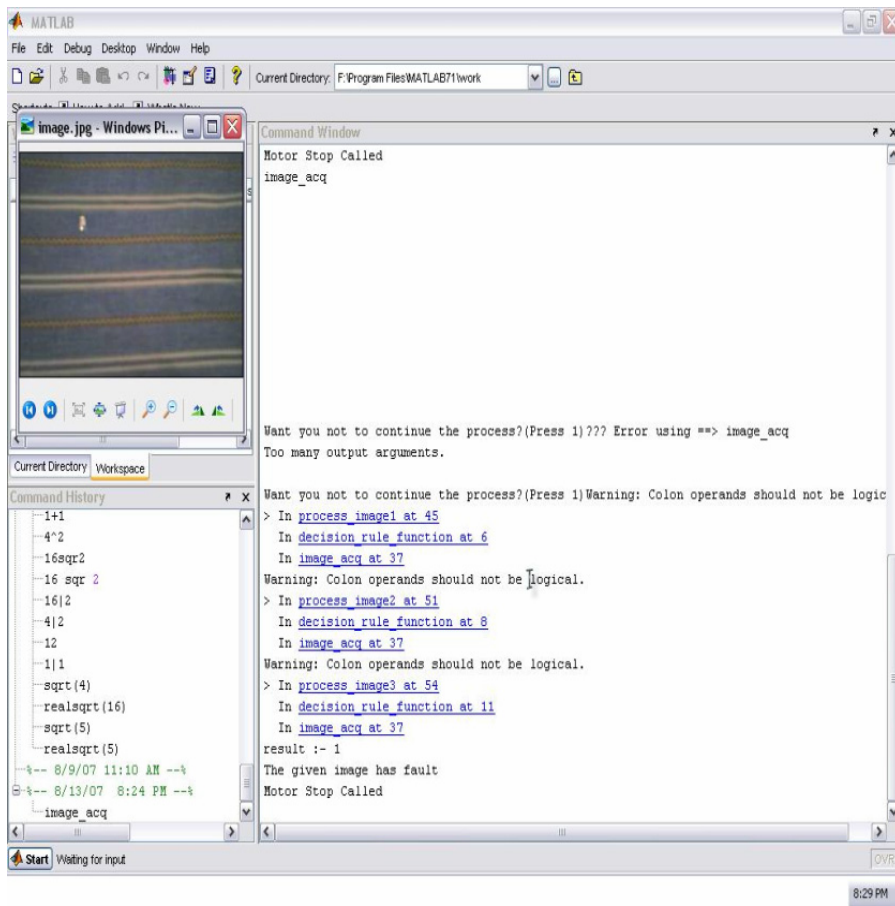


Fig. 14. The MATLAB software interface

observes that there are a large percentage of misclassifications using Widrow-Hoff learning algorithm and Resilient back propagation training algorithm to recognize the defects or non-defects of fabrics for the variations of area of faulty portion, number of objects and sharp factor. As a result, a variation of performance is noticed, in identifying other faults than hole and scratch faults. The Textile Defect Detector can detect few amounts of multi-colored defect fabrics. There have many types of defects, which are not within the scope of the above recognition system. Thus, the system performs quite well except some of false negative classification problems, where it fails to classify the good fabric as good and marks it as faulty fabric; the future versions of the system will try to notice this problem more precisely.

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