2005

Computer vision-based monitoring of abrasive loading during wood machining

Bhavin S. Vora

Computer Vision-based Monitoring of Abrasive Loading during Wood Machining.

By

BHAVIN S VORA

A thesis submitted to the graduate faculty of
Rochester Institute of Technology in partial
fulfillment of the requirements for the degree of
Master of Science

Industrial and Systems Engineering
Rochester, NY
June 2005

APPROVED BY

A. L. Carrano

Dr. A L. Carrano
Industrial and Systems Engineering Dept.
Chair of Advisory Committee

Ferat Sahin

Dr. F. Sahin
Electrical Engineering Dept.

Thesis/Dissertation Author Permission Statement

Title of thesis or dissertation: COMPUTER VISION BASED MONITORING OF ABRASIVE LOADING DURING WOOD MACHINING

Name of author: BHAVIN VORA
Degree: MASTER OF SCIENCE
Program: INDUSTRIAL & SYSTEMS ENGINEERING
College: KATE GLEASON COLLEGE OF ENGINEERING

I understand that I must submit a print copy of my thesis or dissertation to the RIT Archives, per current RIT guidelines for the completion of my degree. I hereby grant to the Rochester Institute of Technology and its agents the non-exclusive license to archive and make accessible my thesis or dissertation in whole or in part in all forms of media in perpetuity. I retain all other ownership rights to the copyright of the thesis or dissertation. I also retain the right to use in future works (such as articles or books) all or part of this thesis or dissertation.

Print Reproduction Permission Granted:

I, BHAVIN VORA, hereby **grant permission** to the Rochester Institute Technology to reproduce my print thesis or dissertation in whole or in part. Any reproduction will not be for commercial use or profit.

Signature of Author: B. S. Vora Date: 6/8/2005

Print Reproduction Permission Denied:

I, ______________________, hereby **deny permission** to the RIT Library of the Rochester Institute of Technology to reproduce my print thesis or dissertation in whole or in part.

Signature of Author: ______________________ Date: __________

Inclusion in the RIT Digital Media Library Electronic Thesis & Dissertation (ETD) Archive

I, BHAVIN VORA, additionally grant to the Rochester Institute of Technology Digital Media Library (RIT DML) the non-exclusive license to archive and provide electronic access to my thesis or dissertation in whole or in part in all forms of media in perpetuity.

I understand that my work, in addition to its bibliographic record and abstract, will be available to the world-wide community of scholars and researchers through the RIT DML. I retain all other ownership rights to the copyright of the thesis or dissertation. I also retain the right to use in future works (such as articles or books) all or part of this thesis or dissertation. I am aware that the Rochester Institute of Technology does not require registration of copyright for ETDs.

I hereby certify that, if appropriate, I have obtained and attached written permission statements from the owners of each third party copyrighted matter to be included in my thesis or dissertation. I certify that the version I submitted is the same as that approved by my committee.

Signature of Author: B. S. Vora Date: 6/8/2005

Abstract

VORA, BHAVIN S.

Computer vision-based monitoring of abrasive loading during wood machining. (Under the direction of Dr. Andres L. Carrano)

Surface quality is an important characteristic commonly assessed in wooden products. Sanding relies on coated abrasives as tooling for both dimensioning and surface finishing but their performance is dependent on chip loading and grit wear. Traditionally, the useful life of abrasive belts in sanding operation has been manually assessed. This type of inspection is highly subjective and dependent upon individual expertise, consequently leading to under utilization or over utilization of the abrasive. This, in turn, affects the production costs and quality of the product. In this work, an intelligent classification method that determines the optimal replacement policy for a belt exposed to known manufacturing parameters is developed. Controlled experiments were conducted to develop abrasive belts of known exposure, followed with digital microscopy to capture images and process them with pattern recognition and classification algorithms. Grit size and machining time were the parameters of interest while response of the experiments included image information from the abrasive sheets after every experimental run. These images were used in training an artificial neural network that in turn, help in determining data to categorize the useful life of the abrasive. The results show a 95% success rate in accurately classifying abrasive images of similarly conditioned abrasives. Also, the results show that the classification of interpolated and extrapolated times of abrasive usage are classified with a 95% success rate. A classification of abrasive images is proposed to be used as one of the inputs to a decision system that would help in evaluating the life of the abrasive and replacement policies. Further research on the relationship between the different parameters affecting the useful life of the abrasive is proposed.

Personal Biography

Bhavin Vora was born on 18th April 1979 in Mumbai, India. He did his schooling at G. D. Somani Memorial School, Mumbai followed by pre-university at G. N. Khalsa College of Science, Mumbai. After schooling he joined K. J. Somaiya College of Engineering, part of University of Mumbai, for his Bachelor in Engineering for Production Engineering. He then moved to Rochester, NY, USA for pursuing his graduate studies in August 2001, with Industrial and Systems Engineering department at Rochester Institute of Technology. After completion of his Master's degree in Industrial and Systems Engineering, he plans to work with Fairchild Semiconductor Corp. in Mountain Top, PA, USA.

Acknowledgements

The author would like to express deepest gratitude to his advisor Dr. Andres Carrano for his continuous encouragement, support and invaluable guidance throughout the course of this research project. He would like to thank Dr. Ferat Sahin for his enthusiastic involvement and being on his committee. He would also like to thank Dr. James Taylor for his help and insight on the manufacturing aspect of the project.

This research was partially funded by the U.S. Department of Agriculture (USDA) grant number 99-03035 through a subcontract from the wood machining and tooling research program at North Carolina State University.

Thanks to Dr. Richard Lemaster, Mr. Daniel Saloni, WMTRP and NCSU for their support and help in experimentation for this research project.

Thanks to Mr. Amit Chaudhary, Mr. Siddharth Mestry and Mr. Amit Rege for a helping hand during the course of this project.

Finally, the author expresses thanks to his family members for the encouragement and support they have given him in all his ventures.

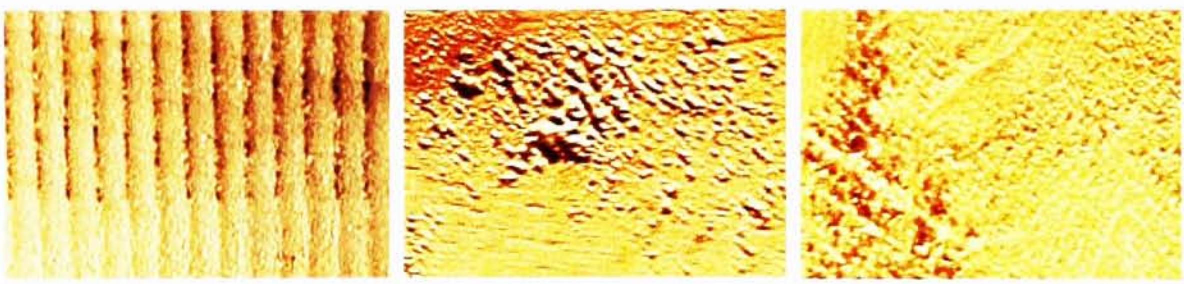
Table of Contents

LIST OF FIGURES

LIST OF TABLES

1. Introduction

Wood is a very important raw material for industry. There are approximately 5400 firms manufacturing wooden products for millions of homes and apartments across the United States thereby making wooden products manufacturing an important industry (Prak, and Myers, 1981). These firms extensively manufacture products like furniture, cabinets and wood for flooring. Wood as a raw material is acquired in the form of lumber or plywood from the forests specially harvested for this industry. The lumber is air or kiln dried and stored in lumber yards. The rough end cuts the lumber into strips or rectangles of rough sizes, length, width and thickness. These are then glued or cut to size. The cutting operations in the rough end stage are carried out using cutoff saw, facer, planer and ripsaws. These processes bring about rough surfaces and a part free of major defects. These rough cut parts are then cut to precise sizes using shapers, profilers, routers and other CNC machining equipment. Most of these processes use machines with knifes on revolving cutter heads that may produce a surface with various defects as shown in figure 1.1. These marks show up eminently under a polished surface. For wooden products to be used safely as decorative and utility products in homes it is of importance that these marks be removed.



(a) (b) (c)

Figure 1.1 (a) Surface waviness, (b) Torn grain and (c) Fuzzy grain
(Courtesy of wood machining and tooling research program at NCSU)

Sanding operations are almost universal practice for achieving final dimensioning and smoothening surfaces. The main function of sanding is to prepare the wood surface for finishing and to remove marks produced by other machining processes. Sanding is usually implemented for different applications and there are different kinds of sanding machines for

each application. There are many types of sanding machines ranging from the simple orbital hand sanders to the large electronically controlled multiple wide belt sanders. Figure 1.2 shows a wide belt sander.

Figure 1.2 Wide belt sander (Source: www.osha.gov)

Sanding operations are regarded to be one of the most expensive machining operations in the wood manufacturing sequence and involves use of coated abrasive belts, commonly known as sandpaper, as tooling. Abrasive belts are usually made of fine abrasive particles glued to the flexible baking paper or cloth using epoxy resin as shown in Figure 1.3.

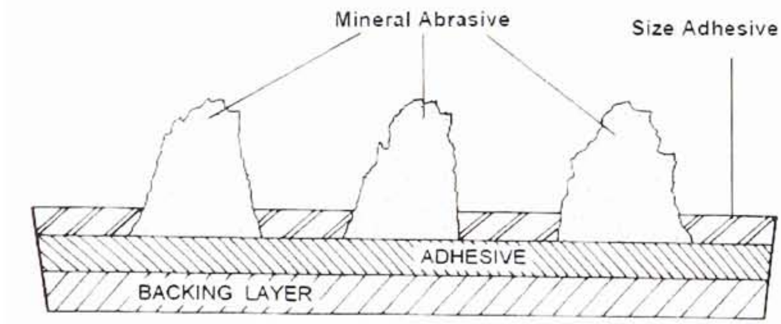


Figure 1.3 Schematic of an abrasive belt

The fine matrix consists of small, crushed, sharp particles of an abrasive material. The abrasive particles are strong, able to cut wood and withstand the pressure and load in the sanding operation. There are several different abrasive minerals which are used in making these coated abrasive belts, including garnet, aluminum oxide, alumina/zirconia and silicon

carbide. Abrasive grains are chosen based on the hardness required for the particular sanding operation. Aluminum oxide and silicon carbide are the most commonly used abrasive minerals, as they are harder and tougher than the rest. Also they are less prone to fracture as compared to the rest. Coarser grains are used for heavy material removal needed to remove the torn grains and knife marks whereas the smoother grit abrasives are used for cutting blanks to precise thickness. Abrasive belts of the same abrasive material are classified by the grit size of the abrasive particle. As many as twenty different grit sizes of the abrasive belts are available in the market and used in wood industries.

The abrasive particles or grains are sharp and thus act like cutting tools to remove material. In this material removal process, the grains undergo structural and physical changes. Due to high pressure and temperature in the cutting process the particles tend to undergo wear and fracture thereby developing uneven structures. This process is a self-sharpening process for the abrasive particles. Subsequently, due to this process, the particle size decreases causing the useful life of the abrasive to deteriorate over time.

Another factor causing useful life of abrasive to decrease is chip loading. During the sanding operation, wood chips tend to settle down between the abrasive particles flattening the sharp uneven particle of the abrasive belts. Figure 1.4 illustrates the loading of wooden chips between two or more abrasive particles. Because the overall tooling profile is lowered and the channels for chip removal blocked, the performance of the abrasive tooling decreases with this phenomenon. Consequently useful life is directly affected which in turn affects the material removal rate, quality of surface finish and rate of production.

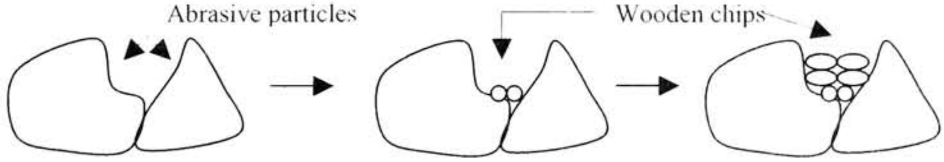


Figure 1.4 Abrasive loading

1.1 Statement of Problem

Common industry practice and experience have been used to estimate replacement of the abrasive belt under the circumstances stated above. The difficulty is in finding the optimum moment to replace the abrasive. In many cases, the inspection for such abrasive belts is being done manually.

Monitoring the abrasive belt and replacing it at an optimal period of time would generate better and cost effective surface finish. There are two possibilities that can occur depending upon the person monitoring the abrasive; first, the abrasive may be replaced before the total use of its useful life, in which case production costs increase due to under utilization of the expensive abrasive belts. Secondly, if the abrasive is replaced much after the expiration of its useful life then the surface quality and the material removal rates decline generating possible rework and rejection of material. This is currently assessed by individual experience in a manual method.

Manual inspection has its own problems in industry, and it is significantly time consuming as stated by Chen (1994). Monitoring the abrasive belt closely, inspecting it to high precision and taking decision about its useful life is necessary for determining when to change the abrasive belt. All this can be achieved using computer/machine vision, which is a technology being widely used in inspection and decision analysis fields of manufacturing. This technology allows for automated inspection and monitoring process thus reducing errors significantly.

In order to optimize utilization of abrasive tooling, thus producing quality products consistently, investigation of the parameters and conditions of abrasive tooling wear and loading as well as development of an effective assessment system in needed. The knowledge of the tooling status would save the wood manufacturing firms rework, rejection, lower production times, which in turn will help decrease the costs. Research on providing the instant and useful life remaining of the abrasive will help evading this inherent problem and help formulate optimal replacement policies. The scope of this thesis is to setup a computer vision system that will be equipped with custom developed image and data processing

algorithms and a database to give input data for the decision system. This research looks at reducing the time and error inspecting the abrasive belt.

2 Background

2.1 Sanding Process

Sanding is the process of employing coated abrasives to smooth surfaces by hand or machine methods (Hackett, 1998). The wood is smoothed by the sharp edges of the abrasive grains in the abrasive belt. Nearly every wooden product is sanded in the course of its manufacturing and is absolutely necessary to achieve a high grade finish. Sanding operations may be classified as (1) *white sanding*, which includes all the sanding operations that are performed on wood prior to application of a finish. Such work includes dimensioning (or abrasive planning), sanding for removal of mill marks, glue stains, minor machining defect among others. This process is commonly addressed as any other machining process in which material is removed at some rate; (2) *finish sanding*, which includes all those sanding operations that occur between applications of the various finish coats. This class of work is performed to smooth the surface and to prepare it so that the next finish coat will adhere. Since it is does not remove a significant amount of material, this polishing-like process is not considered among the machining processes. The term "abrasive machining" refers to the action of grit-like surfaces in removing fibers from a wood surface (Lemaster and Dornfeld, 1993). Machining of wood for the preparation of a surface produces chips or bundles of wood fibers as the by-product.

User's of coated abrasives desire a good surface (scratch pattern) on the work piece and fast removal rate with low power consumption, low wood temperatures at the abrasive-wood interface and long belt life.

Machines used for sanding operations are called *sanders* and there are many different types and sizes. A number of specialized sanding machines have been developed. They are becoming increasingly important in the mechanization of the wood process; in fact, it is sometimes found that the sanding process constitute a bottleneck among the machining processes. This is no surprise if considering that mechanized operations for production work are usually supplemented with hand and portable power sanding. Some common equipment

utilized for sanding is: belt sanders, disk sanders, drum sanders, stroke sanders, edge sanders and wide belt sanders. A detailed description of each of these sanders is found in Koch (1964).

2.2 Abrasives

A coated abrasive is a product that consists of a thin layer of abrasive grain attached to a substrate such as paper, cloth etc. coated abrasives come in a variety of forms such as sheets, discs, rolls, specialties, or belts. The coated abrasives usually consist of five different components: the abrasive mineral, the backing paper, the bonding agent, and the size and make coats. Figure 2.1 gives a representation of a typical coated abrasive composition.

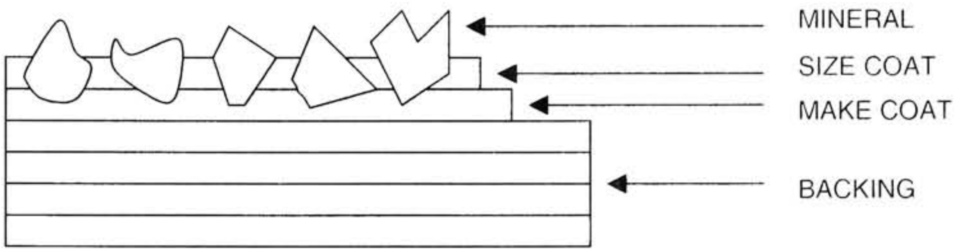


Figure 2.1 Components of coated abrasive

2.2.1 Abrasive Grain

Coated abrasives are manufactured using abrasive grains, the most common being aluminum oxide, zirconium, silicon carbide and garnet. The crude grains are crushed and separated into sizes called grit sizes, using calibrated screens. Below is a description of the five most common abrasive grains:

Flint: *(Quartz* S_iO_2*)* A grayish white to faint pink silicon dioxide quartz found in large natural deposits in many areas of North America. It is still found on common sheet sandpaper for manual sanding. Although flint breaks up into sharp fragments and is low in cost, it is not often used for industrial application because of its hardness and durability. It is available in grit meshes from 36 to 180.

Garnet: *(Almanite* $Al_2O_3FeO_3SiO_2$*)* Is a mixed orthosilicate of iron, aluminum, calcium and magnesium. It is red inn color. The northeastern part of the United States is one of the

important sources of these crystals. Garnet crystals, when crushed, provide light wedged-shaped grits that are harder and sharper than flint. They were found to be very inconsistent when compared to the synthetics and are primarily used in wood working as it dulls too quickly to be used in metal working. It is available in grit meshes 36 through 320.

Aluminum Oxide: *(Al_2O_3)* First created synthetically in 1900. It is a reddish brown smelted derivative of bauxite ore. This is heated in an electric furnace to approximately 3500°F, together with a small amount of coke and iron fillings, generates a product that contains as much as 50 percent aluminum oxide. Aluminum oxide particles are the toughest of the abrasives under discussion and are exceeded in sharpness and hardness only by silicon carbide. In combination with a resin bond, it is very resistant to breakdown, and is widely accepted for sanding applications requiring high pressures. Aluminum oxide is available in grit meshes 24 through 500.

Silicon Carbide: *(SiC)* Blue black in color, was first experimentally produced in the early 1890's by The Carborundum Company and is still frequently called carborundum. It is manufactured commercially by combining a mixture of sand (silicon dioxide), powdered coke (carbon), and a small quantity of sawdust and salt in an electric furnace at about 4000°F. The sawdust makes the mass porous and aids in the escape of carbon monoxide. The salt helps remove iron impurities by forming a volatile chloride. Although silicon carbide is the hardest and sharpest of the minerals used in the manufacture of coated abrasives, it is the most readily crumbled because of its brittleness. It is excellent for light sanding operations, such as removing raised fibers from previously sanded wood. It is also an efficient abrasive for sanding hardboard and particle board, which have resin binders. Silicon carbide is available in grit meshes 12 through 600.

Zirconium-based Grit: This is an alloy of aluminum oxide and zirconium oxide that became commercially available about 1972 under the trade names *Cubacut* (3M) and *Norzon* (Norton Company). *Cubacut* grit is brownish black, while *Norzon* grit is white or gray. The zirconium-based grit, i.e. aluminum zirconia, is used for heavy stock removal and high pressure grinding. It is suited for use on abrasive planners and is available in grit meshes 20 through 220.

2.2.2 Grain Size

Coarse paper has grains of large size while fine sand paper has grains of smaller size. The size of grains is carefully controlled to insure uniformity and standard identification numbers that permit the selection of the sandpaper best suited to the application. Some of them are shown in the following table.

Table 2.1 Typical grain sizes and their applications in furniture industry

Grade Number (CAMI)	Applications
20 – 24	Rough planning, removes up to 1/4" of stock
36 – 40	Finish planning, removes up to 1/16" of stock
60 – 80	Primary sanding, planning of wood edge banded panels
100 -120	Secondary sanding, veneer tape removal
120 – 220	Finish or polish sanding
360 – 500	Topcoat rubbing and polishing

The sizes of the particles used on coated abrasives are established by sifting the grit through screens of standard mesh. The fineness of the mess is part of the trade designation. The finest screen, constructed of silk threads, has 220 openings to the linear inch or 48,400 openings per square inch; grains finer than this are segregated by sedimentation or by air flotation. Grain sizes range from 12 (coarsest) to 600 (finest) in the CAMI grade system or from P-12 to P-2000 in the European grading system.

2.2.3 Backing Material

Backing is the foundation of the coated abrasives. Paper, cloth, vulcanized fiber, and combinations of the foregoing are frequently used as baking materials. Paper backing comes in a wide range of thickness or weights. The thicker papers are naturally stronger but less flexible and also more cost more per square foot. As paper backing is not strong or flexible enough, cloth backing is an alternative. In general, there are two types of cloth backing: "Jeans" and "Drills", where jeans are the lighter and more flexible and drills are the heavier and stronger of the two. Combination backing is laminated paper and cloth, and is very sturdy and shock resistant. The paper and cloth combination is, however being displaced by the increasingly popular vulcanized fiber.

Vulcanized fiber is made from cotton rag base paper treated with zinc chloride, which gelatinizes the cotton cellulose. Multiple sheets (5 to 7) of this treated stock are vulcanized and calendared to give the surface a smooth finish. Backing material largely determines the cost of coated abrasives. Cloth is more expensive than paper, and the weight of the paper determines the price paid for paper-backed belts.

2.2.4 Bonding Agent

Adhesives which bong grit to backing are applied in two layers: the *make coat* in which the grit is initially secured, and the *size coat* applied later, in combination as follows:

Table 2.2 Adhesives used in grit bonding

Make Coat	Size Coat
Hide glue	Hide glue
Hide glue	Urea resin
Urea resin	Urea resin
Hide glue	Phenolic resin
Phenolic resin	Phenolic resin

An all glue adhesive bond has the lowest cost and the lowest mineral-holding strength, in part because it softens with heat and high humidity. An all-resin bond has the highest cost and the greatest mineral-holding ability. Due to the relative freedom from tackiness of the resin bond, the tendency of the abrasive to fill or load is considerably reduced. Thermosetting and waterproof resin bonds have significantly broadened the efficient application so the coated abrasives. Resins and glues can be used with all types of backings. Sheet goods are generally made with the cheaper hide glue because they are used in operations producing little heat. High grade animal glue is one of the most frequently used. In wet sanding or where the heat is produced or where particles receive mechanical shock, resin adhesives give better service.

2.2.5 Coating

Coated abrasives are manufactured in a continuous multistage operation commencing with unreeling and imprinting the backing. Printed with product name, mineral and grade, the

continuous web receives a closely controlled "make coat" of adhesive and a carefully monitored and distributed coat of abrasive. Continuously dried in an oven, the strip then passes through a second machine that applies the "size" adhesive coat, and is finally dried in a second continuous oven. There are two different coatings available depending on the spacing between the abrasive grains bonded to the backing.

Closed Coat: It means the abrasive grains are adjacent to each other with no space between them. On closed coat adhesive strips, the abrasive particles completely cover the adhesive of the backing. The majority of applications will benefit from closed coat material because it allows for more material removal.

Open Coat: It means the grains are set apart from each other, achieving a surface coverage of about 60% or more. In situations where loading is likely, open coat will resist loading and clogging and extend the useful life of the abrasive.

2.3 Computer Vision

Vision to humans is natural and the processing capability of the human vision system is regarded as pristine, with its image processor and robustness in the sense that it rarely is incorrect. This is because the human vision system takes into consideration other signals as information, making replication of its function by any machine difficult. Computer vision is a technology that, with the help of algorithms provides useful information can be extracted from a single image or images using a special or general purpose computer. The information derived is used to compute different attributes of interest of the particular object in consideration. These attributes of interest would then help in devising conclusions for decision making pertaining to that object. Computer vision is most widely used for measurement of features and pattern classification based on the images. Typical industrial applications of computer vision include determination of part length, width or surface area from an image as well as part inspection. These numerical values are processed through a set of decision rules, which in turn help recognizing certain features in the image. These decision rules are also called pattern classification rules, which help in associating the work piece to a particular class based on the features.

2.3.1 Basic Computer Vision System

A computer vision system typically consists of a vision system connected to a computer. The vision system acquires the image of the work piece and converts the image into data that can be easily interpreted by the computer. This data received by the computer is then processed by image processing tools to suit the pattern characterizing algorithms to be used for the particular application. Figure 2.2 shows a classical computer vision system and its different subsystems. The vision system consists of a camera, lens, frame grabber and a data acquisition board (DAQ). The combination of a camera and lens helps acquiring the image of the work piece. The frame grabber helps convert the image into numerical data that can be easily interpreted by the computer. This data is input into the computer using a data acquisition board.

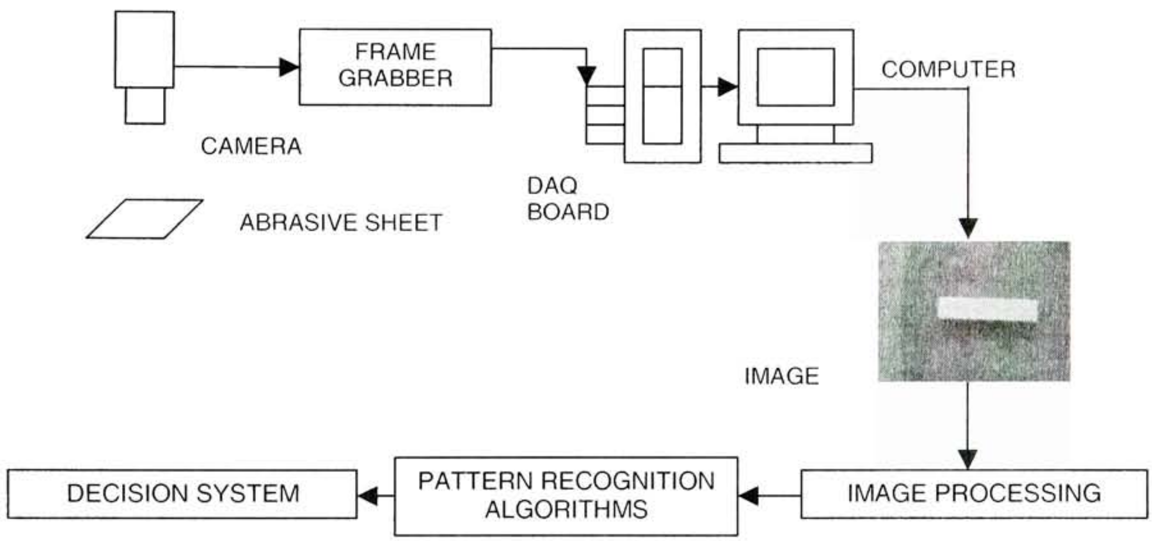


Figure 2.2 Basic computer vision system

Before the image can be processed through the pattern recognition algorithms it is run through image processing tools. Image processing tools are basically feature measurement tools. These tools differ upon the application of the system and on the features or data important for the pattern characterization. These tools also depend upon the kind of image, i.e. bitonal, gray scale, color images. On collection of features and data from the image; the data is processed through the pattern recognition algorithms, which then help the decision system in arriving at accurate decision making.

2.3.2 Requirements

For a computer vision system to work efficiently and give accurate results, it is imperative to have a good vision system that will seize images with the features pertaining to the application and good image and pattern characterization algorithms to interpret and analyze the input images. A few considerations before buying or building a computer vision system are listed below.

Work piece positioning: For quality images it is highly crucial to have a good fixture for the work piece to be positioned under the camera accurately or precisely depending upon the application.

Camera and Lens: This is the soul and brain of the system as without the image the system wouldn't be a vision system. It is decisive to analyze what kind of images are required and also determine the amount of magnification or resolution required from the vision system. This would determine the type of camera and the lens required for the vision system.

Frame grabber: This is the hardware that converts the images into numerical data that the computer understands and thus plays a very important role in the system. The quality of the data received by the computer depends on the frame grabber. Now-a-days cameras come with inbuilt frame grabber making this selection an easier process.

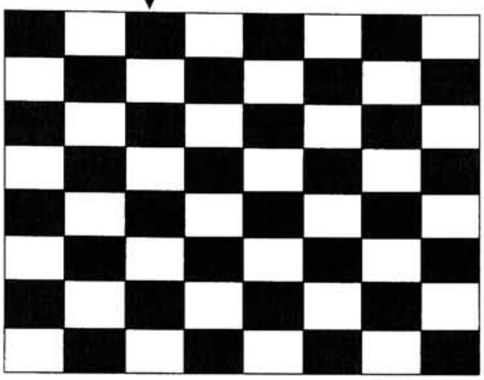
Data Acquisition Board (DAQ): The DAQ board is the medium between the vision system and computer that helps input the numerical data into the computer. It works like a translator for the computer. Interprets the numerical data and helps it convert the numerical data into an image for the viewer or user.

2.4 Digital Images

Rays of light reflect off objects in a scene; these reflections from each visible point in the scene, when collected on a single plane form an image. This image is a pictorial representation of that scene or object. Images are usually a continuous analogue function of some property in the visual scene. Continuous analogue signals from a camera cannot be interpreted by the computer. The frame grabber converts this analogue signal into a digital

image by quantization and sampling. The frame grabber converts the image into a matrix or a grid, as shown in Figure 2.3. This grid has numerous squares which individually known as pixels. Each pixel has a particular numerical value depending upon the type of image. Pixel is the smallest discreet accessible address in a digital image. Figure 2.3 show an image converted in a grid and the different pixels with a certain value.

GRAY SCALE IMAGE



DIGITAL IMAGE

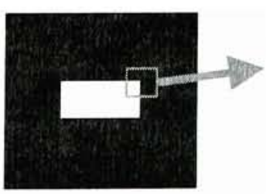
GRID OR MATRIX

PIXELS

0	255	0	255	0	255	0	255
255	0	255	0	255	0	255	0
0	255	0	255	0	255	0	255
255	0	255	0	255	0	255	0
0	255	0	255	0	255	0	255
255	0	255	0	255	0	255	0
0	255	0	255	0	255	0	255
255	0	255	0	255	0	255	0

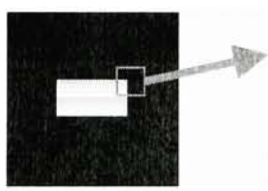
Figure 2.3 8 bit grayscale image and its pixel representation matrix

There are three kinds of digital images, namely bitonal images, gray scale images and color images. Bitonal and grayscale images are similar to each other in all respects except that the bitonal images have only two levels of brightness, i.e. 0 and 1 corresponding to black and white respectively; where as the grayscale images have 256 levels of brightness, i.e. 0 to 255 corresponding to black and white respectively. The Figure 2.4 shows a grayscale image and a bitonal image and their pixel matrix.



0	0	0	0
0	0	0	0
1	1	0	0
1	1	0	0

BITONAL IMAGE



0	0	0	0
0	0	0	0
154	154	0	0
164	164	0	0
174	174	0	0
184	184	0	0
194	194	0	0

GRAYSCALE IMAGE

Color images on the other hand are different as they have a third dimension which corresponds to the numerical information of colors. Like the bitonal and grayscale images color images have two dimensional matrix or grid that stores the information of each pixel in the image. Each pixel also carries color information. This color information is stored in the third dimension in the form of R-G-B values. R, G and B stand for red, green and blue respectively. RGB is typically used for defining colors displayed on screen, since those are the phosphor colors used in monitors. Color image is typically represented by a bit depth ranging from 8 to 24 or higher. With a 24-bit image, the bits are often divided into three groupings: 8 for red, 8 for green, and 8 for blue. Combinations of those bits are used to represent other colors. A 24-bit image offers 16.7 million (224) color values. Figure 2.5 shows a color image and shows the pixel representation.

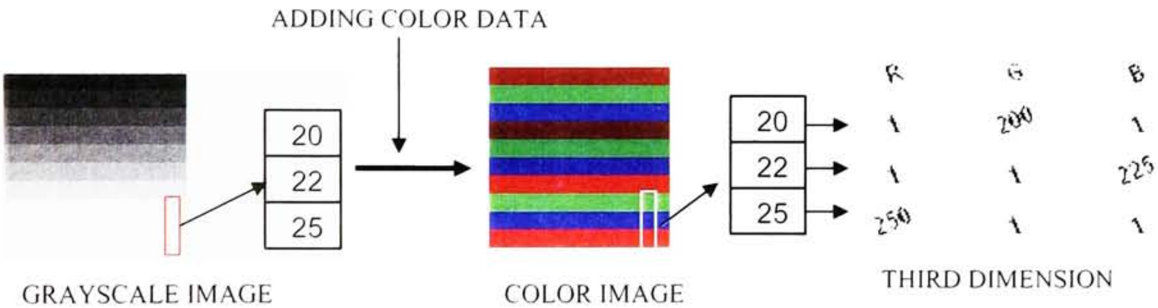


Figure 2.5 Color image with pixel representation

Figure 2.5 shows the difference between a color image and a grayscale image. Also the figure clarifies that each pixel has different combinations of RGB values to form the numerous variations in color.

This numerical information from digital images can be analyzed using algorithms or image analysis tools to gather feature measurement data, which can be used as inputs to pattern recognition algorithms.

2.5 Artificial Neural Networks (ANN)

Artificial neural network is a system loosely based on the human brain network and has a strong similarity with it. It is an attempt to simulate with the help of specialized hardware and sophisticated software, the multiple layers of simple processing elements known as neurons.

Artificial neural network is a system loosely based on the human brain network and has a strong similarity with it. It is an attempt to simulate with the help of specialized hardware and sophisticated software, the multiple layers of simple processing elements known as neurons. Each neuron is connected to its certain neighbors with certain coefficients of connectivity that represents the strength of these connections, more commonly known as weights. Learning is accomplished by adjusting these weights to help the overall network to output suitable results.

2.5.1 Neuron

The basic unit of neural network, as explained above, a neuron simulates the four basic functions of the human brain neuron. A neuron receives a number of inputs from its neighbors; each of these inputs has a particular weight, as shown in figure 2.6. Each input is multiplied by its particular connection weight. The summation of these products is fed into a transfer function to generate an output. This output is then released to other neurons. This scenario is shown in figure 2.6.

Although almost all artificial neural networks are built from this basic building block there are a few variations that can be implemented to achieve the goal of the system. Construction of the ANN is usually a trial and error that evolves into a satisfactory design. According to L. Fausett (1994), designing of neural networks is complex and is also a major concern for system developers due to the various decisions to be made.

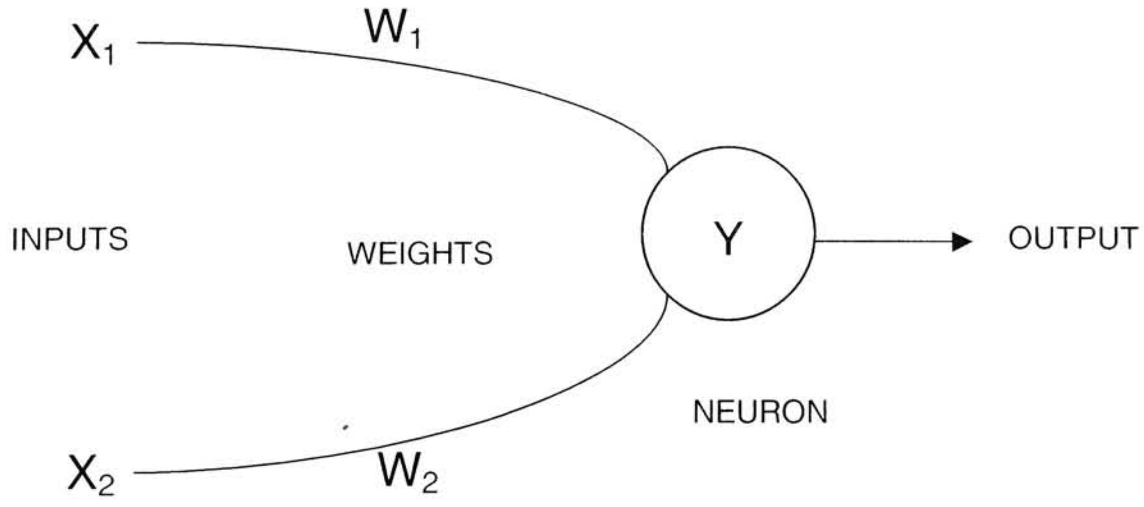


Figure 2.6 Single neuron

$I = \Sigma X_i W_i$; Summation

$Y = \mathbf{f}(I)$; Transfer function

Designing of a neural network consists of:

- Deciding the number of layers or the number of hidden layers
- Arranging neurons in various layers.
- Deciding the type of connections between neurons
- Deciding the starting weights of each connection
- Determining the learning technique for adjusting weights using a training data set.

2.5.2 A Network

An ANN inherently has three kinds of layers, namely input layer, output layer and the hidden layer. Each ANN consists of multiple neurons or nodes as shown in Figure 2.7.

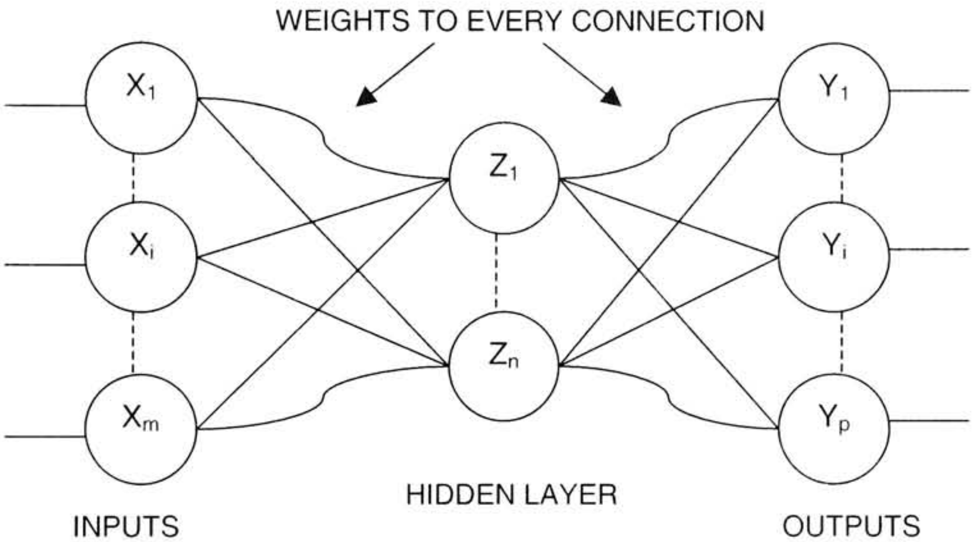


Figure 2.7 -Multi-layer ANN network.

Input layer is a layer with all the inputs to the network. Hidden layer is the layer with neurons that do not give outputs but do affect the output; they are not present in every ANN but are necessary for non-linear problems. Usually a network does not need more than a single hidden layer as shown in the Figure 2.7, but ANN's can have numerous hidden layers. Output layer consists of neurons that give the output of the network. All neurons are

connected to each neuron in the subsequent layer with a unique weight. The neurons in the hidden and output layer are decision-making points in the network. These neurons work on the principle of a water tank for decision-making. When all the inputs add up to a threshold value set for the neuron, it fires to give an output as 1; at other times it gives 0.

This threshold is set to a default value of 0.5, for example the formulae for the output of neuron Z_i would be as shown below.

$$Zi = 1 \quad \text{if } \theta = \sum_1^m Xj.Wij \geq 0.5 \ldots\ldots (2.1)$$

$$Zi = 0 \quad \text{if } \theta = \sum_1^m Xj.Wij < 0.5 \ldots\ldots (2.2)$$

θ = threshold,

X = neurons of the subsequent layer,

W = Weight between the two neurons

i = number of the neuron under consideration

j = number of neuron of subsequent layer (j = 1 to m)

2.5.3 Learning Methods

The human brain identifies and learns from experience. Similarly neural networks also learn from experience. The neural networks are also called as machine learning algorithms as they learn from training data. Training data sets is a set of inputs and output targets. The training data gives the network the inputs and the corresponding outputs, which help to adjust the weights in order to give correct out puts. The learning ability of the network is determined by its architecture and by the algorithmic method chosen. There are three training methods that can be applied to networks, as explained below.

Unsupervised learning: This type of training states that the neurons in the network would only have the inputs as training data. The neurons would have to organize themselves and outputs for test samples would be given on similarities.

Reinforcement learning: This training method gives the network inputs and outputs as training data and the network reshuffles the weights to get the outputs correct for the training

data. This is also called supervised training as the training set depicts a teacher and the network as the student.

Both unsupervised and reinforcement learning methods are slow and inefficient as they rely on a random shuffling of the weights to find the correct connection weights.

Back propagation: This training method is similar to the reinforcement training method with the exception that in this training the errors are sent back to the neurons and are used for adjusting the connection weights between the layers. This improves the performance and has been found to be highly successful with multilayered neural nets. It is a form of supervised learning method.

2.5.4 Learning Laws

Training of the neural net is as dependant on the learning laws used as it is on the learning method used. Learning laws are mathematical algorithms used to update the connection weights. Most of the laws are upgrades or variations of the best known and oldest learning law, Hebb's Rule.

Hebb's Rule: Introduced by Donald Hebb in 1949, depends on the basic principle: "If a neuron receives an input from another neuron and if both are highly active (mathematically have the same sign), the weight between the neurons should be strengthened."[1]

Hopfield Law: This law is similar to the Hebb rule with the exception that it specifies the magnitude of strengthening or weakening. This learning rule introduced the fundamentals of learning rates and learning constants.

Delta Rule: This rule continuously modifies the weights of the input connections to reduce the difference or delta between the output required and the actual output. The rule changes the weights so as to reduce the mean squared error of the network. This learning rule is highly successful with back propagation learning method.

Kohonen's Learning Law: This learning rule was developed by Teuvo Kohonen and states that the neurons should compete for the opportunity to learn. The neuron with the largest

[1]Donald Hebb (1994), "The Organization of Behavior".

output is declared as the winner and can update weights not only of itself but also its neighbors. This rule is most successful with unsupervised learning method.

2.5.5 Applications

Neural networks are performing successfully where other methods do not, recognizing and matching complicated, vague, or incomplete patterns. ANN's have been used in solving variety of problems. There are five main categories of application of artificial neural networks. These are listed below with a simple example:

Prediction: This kind of a network would use its inputs to predict some output. e.g. predicting stock information.

Classification: This kind of a network uses input values to determine the classification. e.g. classification of input into alphabets.

Data Association: This is like classification but it also determines classes of inputs with errors. e.g. identifying alphabets with missing inputs.

Data Conceptualization: Inputs are analyzed for grouping relationships. e.g. forming clusters in a database of most similar products.

Data Filtering: Smooth an input signal. e.g. removal of noise from an input signal.

Although one may apply neural network systems for interpretation, prediction, diagnosis, planning, monitoring, debugging, repair, instruction, and control, the most successful applications of neural networks are pattern classification and recognition. Such a system classifies the object under consideration as one of the numerous possible categories that, in return, may trigger the recommendation of an action.

2.6 Image Classification

Image classification and recognition are the most popularly used information extraction techniques in computer vision as stated by Brown (1987). Image classification is a process of assigning the image to information classes. Information classes are the categories of interest

to the users of the data that emerges from the images. In image space 'i', a classification unit is defined as the image segment on which a classification decision is based. A classification unit could be a pixel, a group of neighboring pixels or the whole image, states Sonka et al. (1998).

There are three popular methods of image classification

1. Supervised
2. Unsupervised
3. Hybrid

2.6.1 Supervised Classification

Information classes for supervised classification method are identified before hand by the user. Depending on the classes and the difference between them a database of various images of all classes is created. Foody (2004), states in his article that this database is required to extensive in the order to map any and all possibilities that can occur for that particular information class. The success of a classification system based on supervised classification method is solely based on the extent of variability that the database can withstand as far as the image or dataset is concerned, states Foody (2004). The image processing software or program is then used to develop a statistical characterization of the information classes or the difference between the information classes. This stage may involve developing a characterization as simple as the mean or the range of the each class, or as complex as a detailed analyses of the mean, variance and covariance over all the axes of the image data.

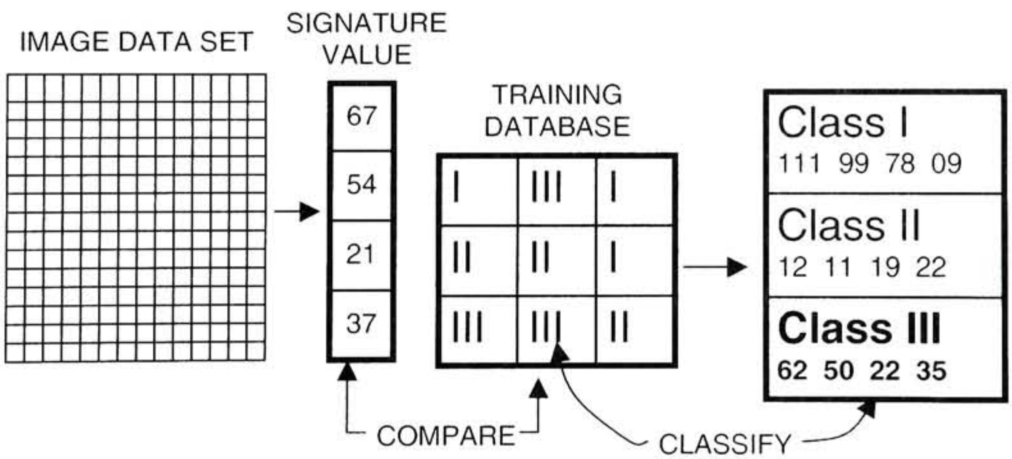


Figure 2.8 Steps in supervised classification

Once a statistical characterization has been achieved for each information class, the image is then classified by examining this characterization, which is also called as signature analysis in remote sensing image analysis; and making a decision about which of the classes it resembles the most, states Eastman (1997).

2.6.2 Unsupervised Classification

In unsupervised classification method a large number of unknown images are divided into a number of classes based on groupings of textures, features, and color or image data values. This method does not require analyst or user specified training data. In other words there is no need to create a training database. Eastman (1997) states that the basic premise is that the values in a given group or class should be closely resembling each other in the measurement space i.e. have similar gray levels or RGB values; whereas images in different classes should be comparatively well separated.

The classes or groups that result from unsupervised classification method are based on the natural groupings of the image values, the identity of these groupings will not be initially known, must compare the classified images to some of the reference images to determine the identity and the informational values of the natural groups. Unsupervised classification is becoming increasingly popular in applications land cover mapping and remote sensing states Foody (2004).

2.6.3 Hybrid Classification

A hybrid classification method combines the advantages of the conventional supervised and unsupervised methods to produce image classification that is better than if just a single method was used. One hybrid approach is to use the supervised classification methods to do an initial classification and then use unsupervised classification to refine the classification and correct the obvious errors. With this approach it is possible to get a reasonably good classification quickly states Behnke (2003).

Supervised classification method has an upper hand on unsupervised classification due to one of the major factors of control, which is to group images by the users' information and data requirements rather than allow the computer to form groups based on a characterization that needs to be evaluated after the groups or classes are formed. The flip side of the scenario is that supervised classification requires a lot of images or data for training. It is very cumbersome, costly and requires heavy data storage and access capability to get all varieties of images to form a complete database for training, which are usually not available, states Eastman (1997). Hybrid is a good option to cover for the pros and cons of both these methods but requires complex computations for transferring data from one method to another and to check for any errors caused due to the system.

3. Literature Review

Research in the field of abrasives, and factors affecting its utilization and optimization is limited. A classical paper by Franz and Hinken (1954) stated the effect of standard factors like pressure, load, belt speed, contact area and moisture content, on material removal rate, power consumption and belt life. Ferrari and Stancanelli (1998) analyzed that reducing the cost of sanding will reduce the cost of wood manufacturing and to do so it is essential to control the factors governing the quality of output of the sanding operation, such as abrasive belt life. Abrasives are used to provide surface finish to wood, and this finish is directly proportional to the quality of the abrasive. Wettschurack, et al. (1999) presented that quality of the abrasive vastly depends on factors like temperature, operating conditions, depth of cut and forces applicable under working conditions. Prasad, et al. (1998), also proved abrasive wear to depend on other factors like abrasive particle size, applied load, fracture toughness and loading of the abrasive, which in turn directly affects the quality of surface finish. Zhou, et al. (1997) has shown that normal and compressive stresses cause the abrasive particles to fracture and wear out, which causes variation in the finishing of the wooden surfaces. It has been analyzed by Faust (1987) that variation in surface finish caused the production costs to reach new peaks, as a direct result of reworking causing higher production times. The wooden chips formed in the surface finishing operation tend to accumulate between the abrasive particles and flatten the crests and troughs of the abrasive belt causing the material removal rate to decrease with respect to time.

Research is still being pursued to investigate how the defects of wear and loading can be extricated or even lower their effects so that the production costs can be kept to a minimal. One of the ongoing researches by Trezona, et al. (1999) deals in experimentation on composite matrix abrasive materials and trying different backing paper and adhesives for the abrasive belts. Since abrasives are expensive and cannot be wasted by under utilization, it is imperative that factors affecting its life are looked into and a relationship be found. Mondal, et al. (1998) carried out a study on the combined effect of load and size of abrasive particle and concluded that the effect of load on wear rate of the abrasive was found to be

comparatively higher than that on the work piece. Thus it is necessary to find relationship between the main factors affecting the abrasive life and the requirements of surface finish. On controlling these factors optimization of abrasive life, manufacturing high quality surface and decrease in production times can be expected. Constant inspection and monitoring of the abrasive in working conditions can help analyze this relationship.

Industry knowledge and expertise has commonly been used to estimate replacement policies of abrasive belts used in sanding. The difficulty lies in finding the optimum replacement time. If the abrasive is permanently replaced before reaching the end of its useful life then production costs increase due to under utilization of expensive tooling. On the other hand, if the abrasive is replaced after the end of its useful life, then the surface quality and material removal rates decline generating possible rework and rejects. In most industrial settings, the inspection of abrasive belts as well as replacement decisions are taken manually or by monitoring time usage without considering varying process and product conditions. Chen (1994) concluded that manual inspection presents systematic problems such as large error percentages and efficiency causing bottlenecks and consuming significant time. Also, in case of abrasive it is very easy for a human to make an error in judgment and thus this type of inspection is taken out of contest.

Previous work in the field of abrasive wood machining (Carrano, et al. 2002 and 2004; Taylor, et al. 1999; and Stewart, 1976 and 1978) have investigated the effect of process parameters on surface quality and material removal rates, but have not determined the impact on abrasive life. Also, literature on abrasive belt monitoring (Lemaster, 1992 and 1993) has mostly been limited to acoustic emission and vibration analysis methods. Lemaster (1992), states that acoustic emission method was successful to an extent, in monitoring the abrasive machining process.

However, Braggins (2000) and Chen (1994) state in their articles that computer vision systems are widely used for industrial application for both inspection and monitoring and also proven to be a cost justified technique. Groover et al. (1986), mentions in his book that machine vision involves sensing of visual data, its interpretation and analysis by the

computer, thus reducing the chance of errors to nil. Wang and Asundi (2000) have analyzed that computer vision based inspection systems are not only useful for monitoring and quality control but are also useful in lowering costs of raw materials, reducing scrap and speeding up the process of inspection. Braggins (2000) warranted computer vision as a cost justified technique by saying that the application of this technology will decrease if not eliminate most problems, like under supplying, over supplying, tolerances, rejections and other measurements of importance, for companies' profits. Wang and Asundi (2000), in their article, say that by using this technology, segmenting the images to specific features depending on the object of interest and enhancing these features to get a better analytical conclusion is made easier.

Likeminded Phan et al. (1998), and Kulkarni et al. (2001), state that computer vision is being used in wood and furniture industry for inspection of wood surface for finish defects, ridges, and other such defect detection processes; it is also being used in veneer grading, edge detection and pattern recognition. But has not yet, been used effectively in the field of abrasives and optimum utilization of abrasive life. This technology has advanced significantly in the last decade; it is been termed as a powerful and affordable inspection process by Braggins (2000) and Chen (1994). All this makes it the best candidate for this research project. Howlett and Jain (2001), state in their book that radial basis function is a technique that uses neural networks to classify images precisely, thus this can be used as an important algorithm development technique for image classification and data analysis. This technique of image classification has been successfully implemented, by Sahin and Bay (2000), for classification of wood types.

For this research project it was determined that supervised classification method would be suited due to the fact that user defined classes were more important and viable than a computer defined classification. Classes or groups needed to be generated, depending on the useful life of the abrasive, even before making the system and hence supervised classification method was identified.

4. Methodology

4.1 Overview

Laser technology, acoustic and vibrations monitoring are some of the techniques that have been researched to be used to acquire useful life status of an abrasive. Computer vision and image analysis algorithms have been proven to be useful tools in the inspection and monitoring fields and are being employed in the industry for varied automated inspection process. This research project uses computer vision and image analysis to determine the useful life of abrasives.

4.1.1 Procedure

By classifying an abrasive image into a known category of abrasive images, which were used to train the ANN, it would be possible to determine parameters that would be inputs to a decision system for replacement policy of abrasive sheets. This study developed the procedure shown in the schematic in Figure 4.1 and Figure 4.2. The RGB camera acquires the image of an abrasive that has been exposed to machining conditions for a known amount of time, which is transformed into digitalized data for the computer. The ANN system needs its inputs to be in a format it was designed to handle. This data is run through image processing algorithms, shown in Appendix A, to make the data compatible for the ANN system. In the case of this study the ANN inputs need to be as a vector of RGB values, its variances, covariance's and the grit size of the abrasive. This processed data is stored as a vector.

In this work the first experiment was run in order to create a training database which consisted of training vectors and initial validation vectors. The ANN requires training in order to accurately perform characterization of the images, thus the training vectors from the training database were used for training the ANN. The initial validation vectors from the training database were used to test the ANN on vectors similar to the training vectors to observe and document the ANN performance and cross validate the training. These vectors

out in order to select machining time for the first experiment. Section 4.2 explains the different categories and their selection basis. Each category has a specific set of parameter set to it, which helps in defining and characterizing the abrasive image in question.

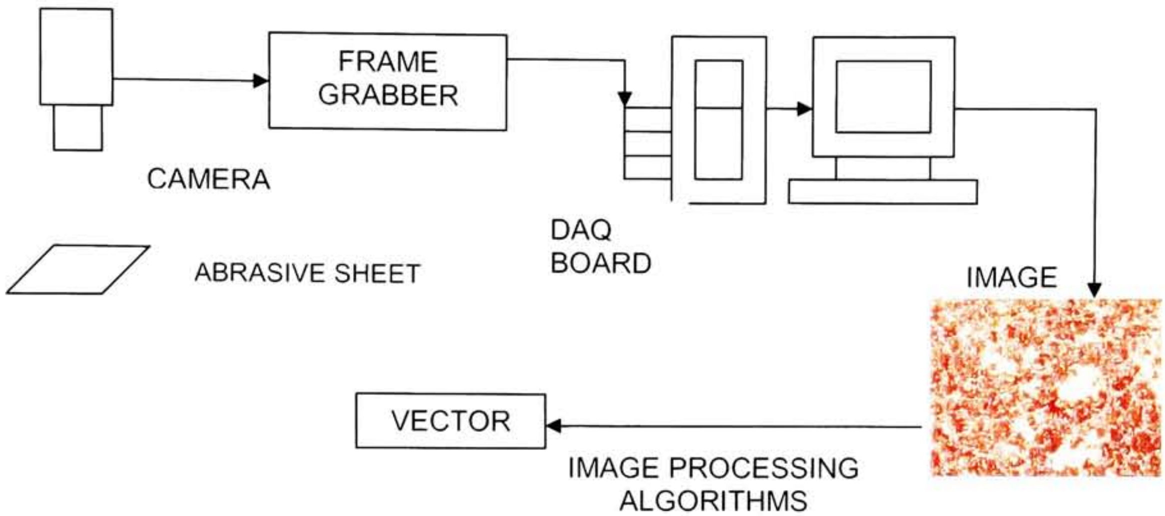


Figure 4.1 Schematic of the vision system

This parameter set available as the output of the computer vision system is then to be used as an input to the decision system to make decisions on the replacement policy and useful life of the abrasive sheet. The categories in this work are defined based on the grit size and the machining time. This parameter set for each of the category would define the abrasives' machining or useful life remaining thus assisting in replacement decision.

The development of the computer vision system for this research study was conducted in four stages. These stages are discussed in detail below.

Stage I: Preliminary experiment

Stage II: Creation of initial database (training set and initial validation set)

Stage III: Development and training of ANN algorithm

Stage IV: Creation of 'Final test' image database

Stage V: Testing

Stage V: Testing

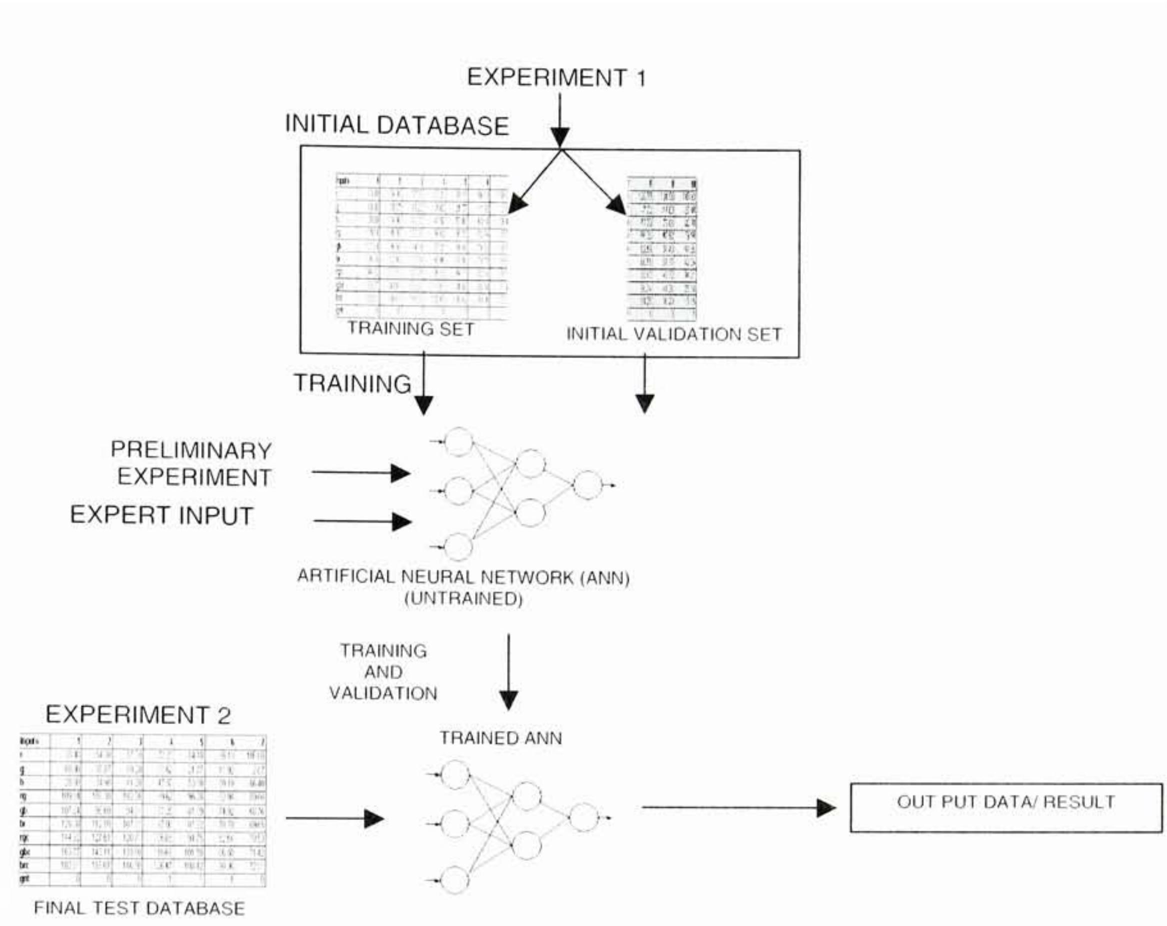


Figure 4.2 Schematic of the methodology

4.2 Stage I: Preliminary experiment

It is necessary to define the categories or classes for the abrasive images, and in order to do this the grit size of the abrasive to be chosen for this work needed to be determined. Abrasives are commercially available in grit sizes from 60 to 280. To observe the changes in the abrasive usage extreme grit sizes were selected based on their utility in the manufacturing environment, i.e. 80 and 220. A preliminary test was run to plot the material removal rate (MRR) vs. time to determine the abrasive life curve using an 80 grit size abrasive.

A bench belt sander, hard maple (*Acer saccharum* Marsh) conditioned at EMC 6% and 6"X48" P220 aluminum oxide abrasive belt were used to run this test. The MRR curve is

a uniform quality of product. This MRR curve in Figure 4.3 also helped in developing the four categories for each kind of abrasive grit size selected. The criterion for selecting the categories was to cover all the different performance areas on the MRR curve.

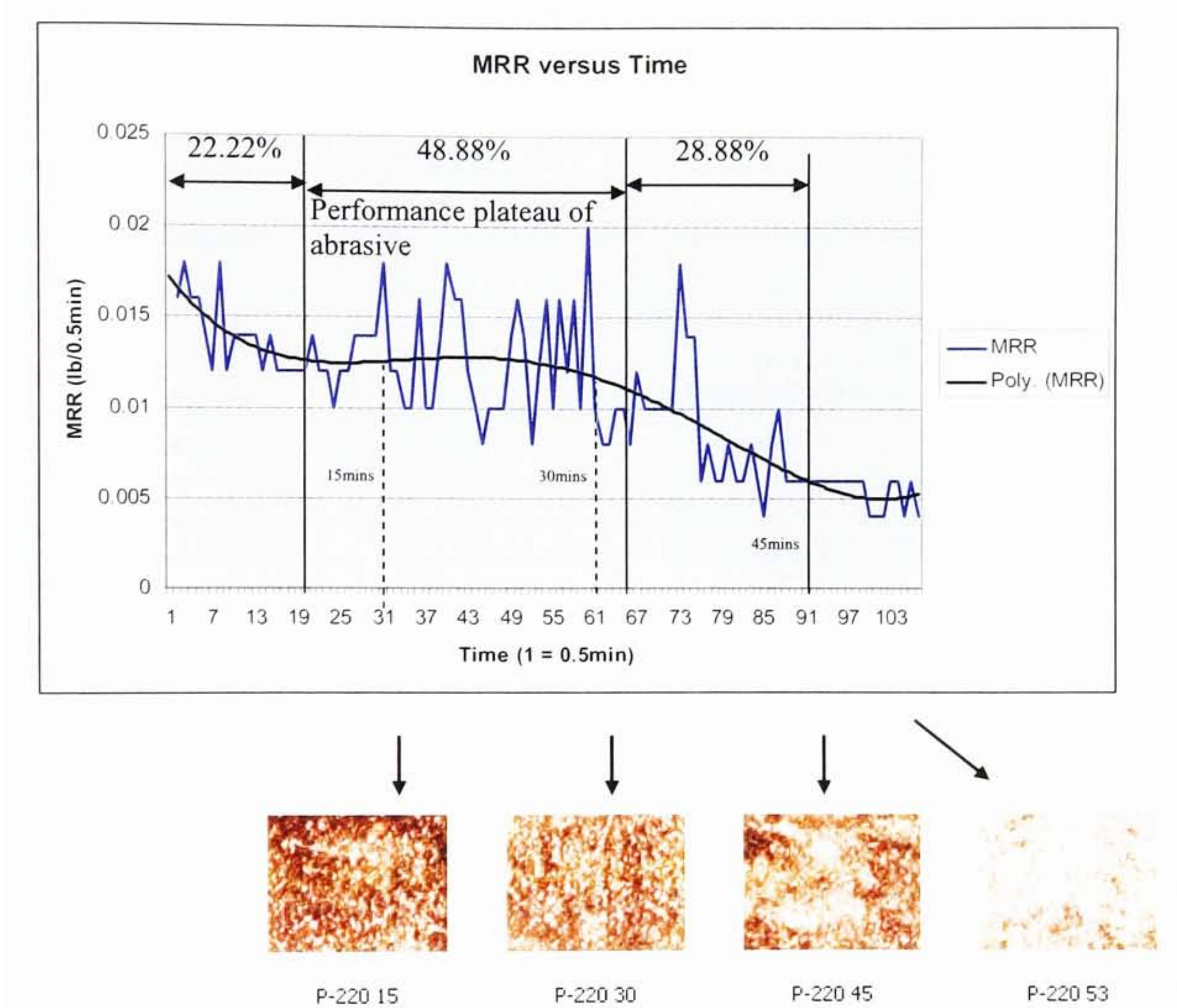


Figure 4.3 MRR vs. time (Preliminary experiment P-220)

The four categories selected (0, 15, 30 and 45 minutes) for each abrasive grit size, was based on the fact that 0-15 minutes was considered as the conditioning time for the abrasive, 15-30 minutes was considered the performance plateau for the abrasive and beyond 30 minutes was considered as end of life for the abrasive as shown in Figure 4.3. Thus 0 minutes was considered a category for conditioning period of the abrasive life, 15 and 30 minutes was considered as the performance plateau of the abrasive life and 45 minutes was regarded as

considered a category for conditioning period of the abrasive life, 15 and 30 minutes was considered as the performance plateau of the abrasive life and 45 minutes was regarded as the end of abrasive life and the categories were determined. The determined categories are shown in Table 4.1. The ANN classifies the image into one of these categories; the output of ANN is in values -1 or 1. It gives a zero or a negative to all the categories that do not match, but gives a positive or one to the category that matches with the input image.

Table 4.1 Categories with their replacement decision

Category	Grit Size	Machining Time (Min)	Replacement Decision
I	80	0	Useful Life 30-45 minutes
II	80	15	Useful Life 20-30 minutes
III	80	30	Useful Life 5-15 minutes
IV	80	45	Replace the abrasive sheet
V	220	0	Useful Life 30-45 minutes
VI	220	15	Useful Life 20-30 minutes
VII	220	30	Useful Life 5-15 minutes
VIII	220	45	Replace the abrasive sheet

4.3 Stage II: Creation of Initial Database (training set and initial validation set)

Once the machining times for the experiment were selected based on the MRR curve, a first designed experiment was run to collect images and create a database of the training samples and initial validation samples. The designed experiment is shown in Table 4.2; one replication per treatment level was run. Two different grit sizes of abrasive belts were used for this experiment as stated before 80 and 220. The experiment was run with a constant pressure of 0.75 psi at room temperature. The pressure and temperature were kept constant in order to avoid any skewing of data due to these factors, which may affect the useful life of an abrasive. The experiment apparatus was kept the same as the one used in the preliminary test. This experiment was conducted at Wood Machining & Tooling Research Program (WMTRP) laboratory in North Carolina State University, Raleigh, NC. After the experiment was completed, 400 images (240x320 pixels, 50 images from each treatment level random spots on the abrasive were selected) were acquired using the vision system assembled in the Brinkman Manufacturing Laboratory at Rochester Institute of Technology.

The size of the training database depends on the number of inputs and connections in the ANN. In order to increase the number training samples each image (240x320 pixels) was split into four images (160x160 pixels) as shown in Figure 4.4; making 200 images from each treatment level and a total of 1600 images in the database.

Table 4.2 Experimental design

Treatment Level Combination	Grit Size	Time (minutes)
1	80	0
2	80	15
3	80	30
4	80	45
5	220	0
6	220	15
7	220	30
8	220	45

Also this helped in implementing the split sample validation. One from the four split for each 320 X 240 pixel image was randomly used for validation. While splitting the images, it was necessary to make sure that none of the data was lost and so the split images were required to be 160 x 160 pixels which would actually overlap and thus ensure no loss of data. The overlap ensures and prevents white spot errors. White spot errors are when a part of the image of the abrasive has loading and part does not. Splitting such an image would not hold its characteristics after splitting. Thus while taking images it was ensured that such an image is not captured and overlap while splitting is a preventive measure for white spot error.

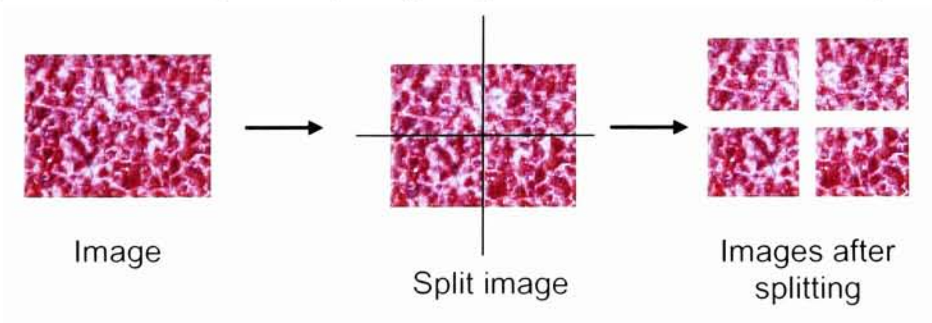


Figure 4.4 Split sample validation

ANN requires its inputs to be in the form of a vector. Therefore these images are converted in to a vector using image analysis tools. Each image has corresponding vector for the ANN input. These vectors are stored in the database. This database is called the 'Initial database'. The initial database was divided into two sets of images. Using split sample validation procedure 400 images were chosen as test images for initial validation of the system. This set of images is called the *'Initial validation set'*. The rest (1200 images) are stored as the *'Training set'*. This training set was used to train the ANN. Once the images were processed and based on the information that could be extracted, it was important to decide the inputs to the ANN and design an ANN that would classify the abrasive images successfully. The next stage describes the development of the ANN and its training.

4.4 Stage III: Development and training of the ANN

An ANN based image classification tool was developed in this research as a part of the image analysis procedures required in computer vision system. ANN is widely applied for matching and recognizing complicated, noise induced or incomplete patterns (Fausett, 1994). ANN is an imitation of the network of neurons in the human brain.

4.4.1 Designing the ANN

The most important parameter to determine, before designing a feedforward ANN, is the number of inputs to the ANN and the number of categories or classes for output. The categories for output were determined to be eight, as displayed in Table 4.3. This decision was based on the designed experiment carried out for developing the 'Training' database and because they map into categories with well determined replacement decisions. On the other hand it was necessary to make sure that the ANN was designed so that the number of training samples present in the 'Training' database was enough to train the ANN successfully.

The number of inputs, outputs and connection neurons of the ANN help in calculating the number of weights in the ANN which in turn helps in calculating the training samples required to train the ANN successfully as shown in Equation 4.1 (Fausset 1994).

$$W = P \times e \qquad \text{(Eq. 4.1)}$$

Where W = Number of weights

P = Number of training sets

e = Allowable error

Since the number of outputs was already decided; keeping the number of inputs low was the only way to insure the database would be enough to train the ANN successfully. Thus, for deciding the number of inputs to the ANN various techniques were used to concise the image data into a vector that would capture the features and texture of the abrasive images, and still meet the requirements of a low number of inputs.

Table 4.3 Output categories of the ANN

OUTPUTS	DESCRIPTION
P80-0	Unused P80 abrasive
P80-15	P80 abrasive used for 15 minutes
P80-30	P80 abrasive used for 30 minutes
P80-45	P80 abrasive used for 45 minutes
P220-0	Unused P220 abrasive
P220-15	P220 abrasive used for 15 minutes
P220-30	P220 abrasive used for 30 minutes
P220-45	P220 abrasive used for 45 minutes

The following techniques were explored to define the inputs to be used for the ANN

1. Image pixel intensity histogram
2. Fast Fourier Transform (FFT)
3. Discrete Cosine transform (DCT)
4. R-G-B values

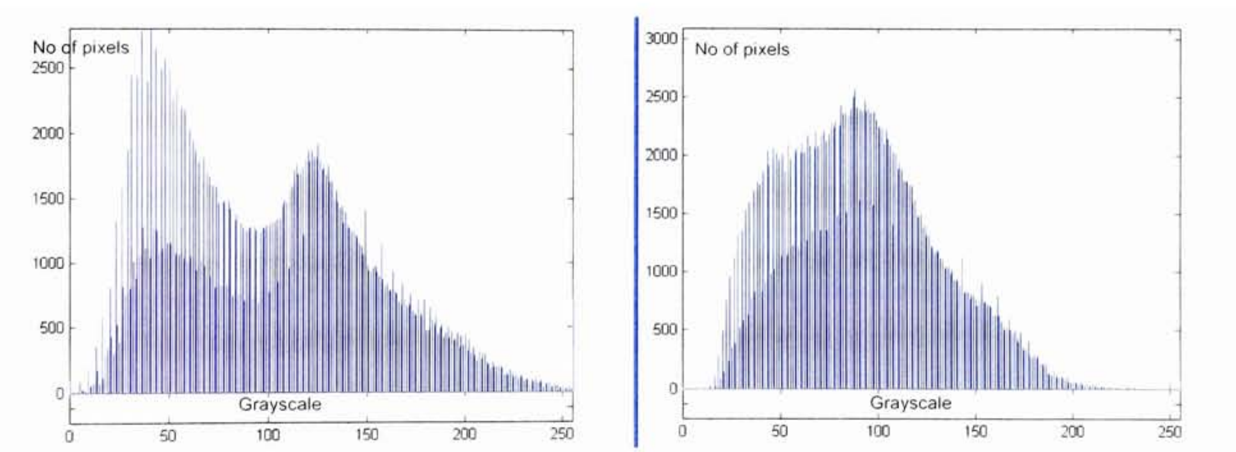
1. Image Pixel Intensity Histogram:

Every digital image is divided into small squares called pixels. Each pixel contains a value depending upon the image type. For a general 8 bit image this value ranges from 0-to-255. These are known as the image pixel values. A single image in this project had 160 x 160 pixels. A histogram of these pixel values is able to capture the texture information from the image. Thus pixel intensity histogram was explored for inputs to the ANN. However on

implementing this in a preliminary test, it was determined that the ANN with this input had two major drawbacks for this application.

Firstly, due to the 255 inputs from the pixel intensity histogram the ANN would require a very extensive training database for successful training. This meant that the number of weights for the ANN were high and thus to maintain a particular allowable error would require an intensive training set. Using the Equation 4.1, it was determined that approximately 347,160 training sets were required in order to train an ANN at a 5% allowable error and a single hidden layer.

Secondly, it was found during the preliminary test that the ANN with inputs as the histogram was successful only if the image was similar to that of the standard, i.e. training sample; making the ANN sensitive to change in image quality and intensity.



Training p80 30min Grayscale histogram   Validation p80 30min Grayscale histogram

Figure 4.5 Histogram comparison

Shown above in Figure 4.5 is the comparison of two histograms of images taken from the same abrasive belt (P80 grit size machining time 30 minutes). The figure clearly shows a shift in the histogram from 0.2 in the validation image and 0.3 in the training image. Also the peaks for the histograms are at different spots with different number of pixels.

Thus due the two reasons stated above this approach was considered unsuitable for this work.

2. Fast Fourier Transform (FFT):

The FFT converts the image from the spatial domain to a frequency domain. By doing so it captures the image's features and textures in a small amount of pixels. Thus it is possible to reconstruct a considerably similar image to that of the original image by using some of the FFT coefficients. Due to this quality of the FFT, it was explored as a technique to develop inputs for the ANN. It was ascertained that by using a few FFT coefficients the feature information of the image could be retained and thus classification could be achieved.

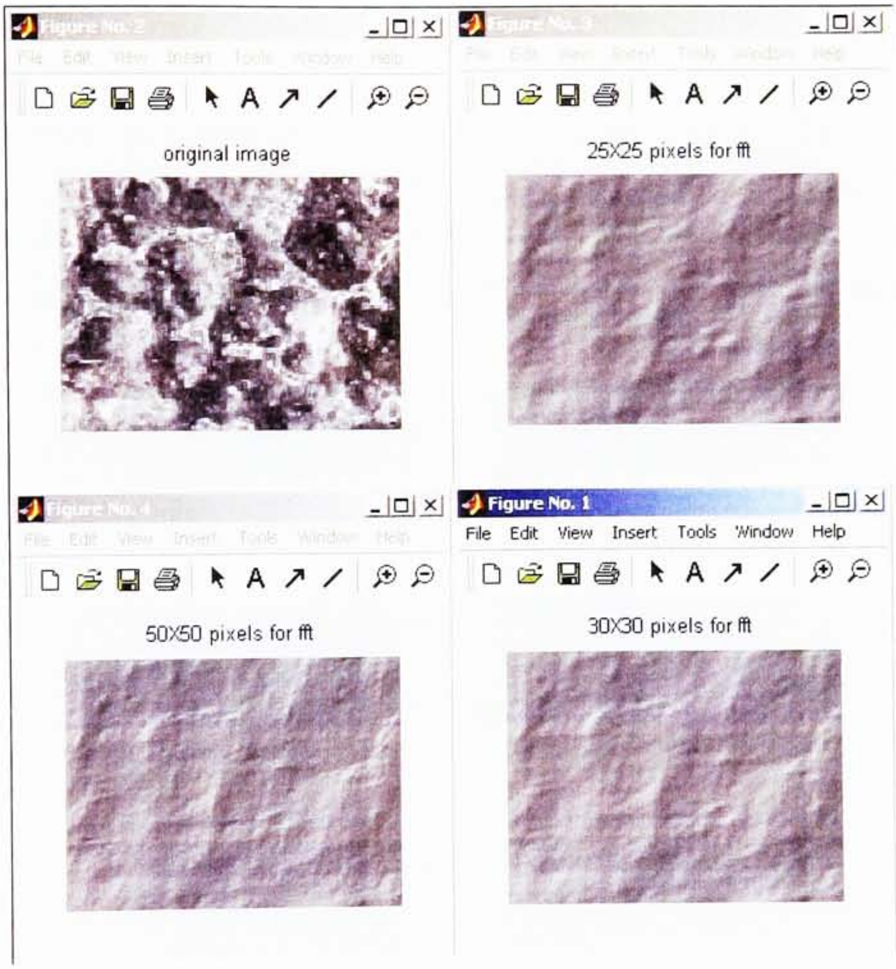


Figure 4.6 Reconstructed images from FFT coefficients

On carrying out the preliminary test of building an ANN using the FFT coefficients as inputs, it was ascertained that a 160 x 160 resolution image needed more FFT coefficients to get a considerable amount of information from the image as an input to the ANN than 25 x 25. A

few FFT coefficients only capture the low frequency texture information of the image and the high frequency information is lost. Due to the nature of the abrasive particle being small and clustered together causing it to be high frequency information, it is important for accurate classification to have this information. In order to capture the high frequency texture information more FFT coefficients needed to be captured. Thus, requiring increased size of inputs. This number of inputs would require an extensive training set that was not available in this research. Also, it was observed that reconstruction of the image using FFT coefficients was not as expected as shown in Figure 4.6. Thus, this tool was also considered unsuitable for this research.

3. Discrete Cosine Transform (DCT):

The DCT works in a similar fashion as the FFT. It converts the image into frequency domain. Even though the similarity, the DCT is less effective than the FFT due to it using only the cosine element of each transform. The FFT uses both the sin and the cosine elements while calculating the coefficients.

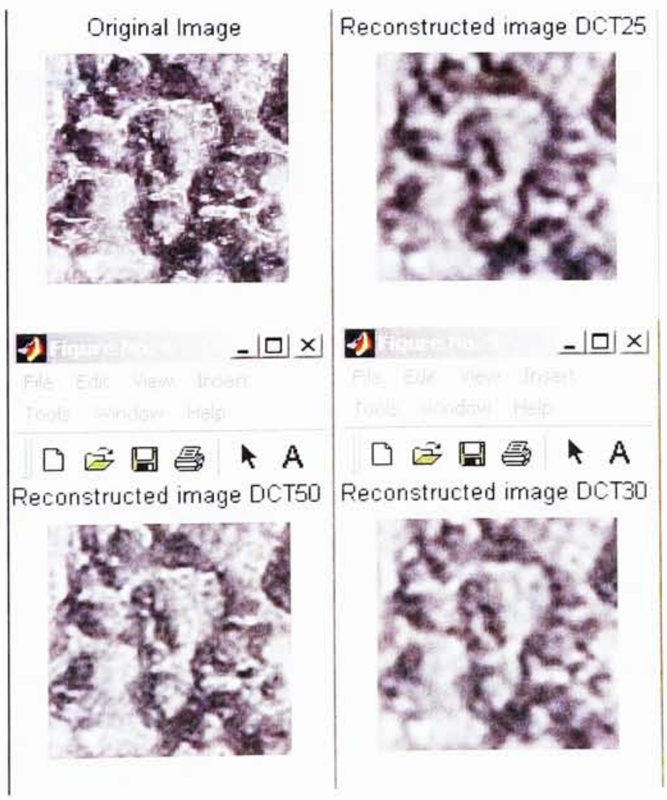


Figure 4.7 Reconstructed images using DCT coefficients

When the preliminary test was conducted using DCT, the initial results were found to be much better than that of the FFT as the reconstructed image was as expected and it stored most feature and texture information of the image in fewer coefficients. Though the DCT coefficients had better results than FFT in both areas tested, viz. reconstruction of the image and fewer (50 X 50) inputs to the ANN as shown in Figure 4.7; its number of inputs was still high to get a successful training using the training database developed in this research work. Thus it was decided to explore other techniques and tools for inputs to the ANN.

4. RGB values:

It was observed that the abrasive sheet tends to change the color patterns from its original to white, especially when using the abrasive and wood species in this work, due to loading when exposed to machining conditions. The longer the exposure more the loading causing white patches. These white patches range from randomly spaced loaded areas to the whole surface of the abrasive depending upon the usage as illustrated in Figure 4.8. This change in color was used in this research as a major factor in classification of abrasive images.

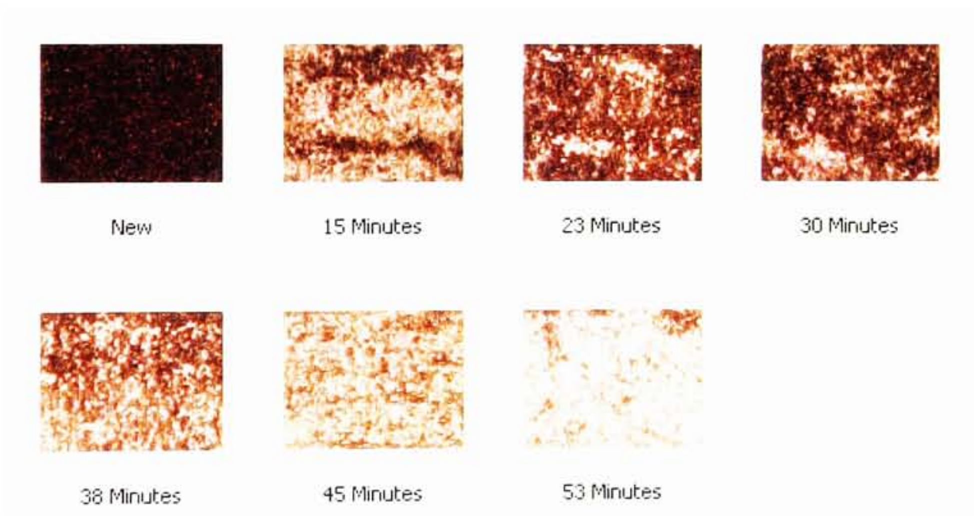


Figure 4.8 P-220 abrasive loading progression over time

Color images are represented by a three dimensional matrix. Two dimensions represent the gray scale features and intensity where as the third dimension consists of red- green-blue (RGB) values for every pixel in the image. A preliminary examination of the RGB values was carried out which helped in understanding that the arithmetic average of the RGB values

would need support from the variances and the covariance between the RGB values as inputs to the ANN.

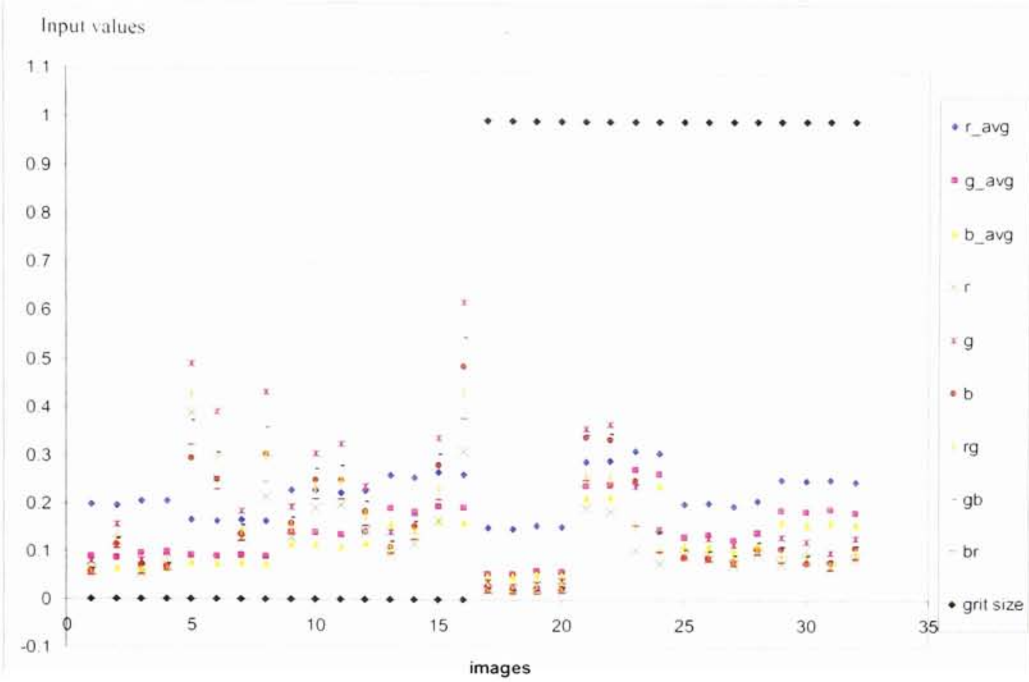


Figure 4.9 Inputs to the ANN

The average RGB values by themselves were found to have no significance in classifying the abrasive images. The Figure 4.9 shows the RGB values for 32 different images (16 image of P-80 abrasive and 16 of P-220 abrasive), which makes it clear as the RGB values for all the images range from 0 to 0.2. The grit size input for P-80 is '0' and for P-220 is '1'. Four images from each category were picked for this chart, i.e. P-80 0 minutes, P-80 15 minutes etc. Thus they do not have significant difference by themselves. But Figure 4.9 shows that RGB values with RGB variances and covariance show a significant difference which has materialized as a classification basis for this research. Figure 4.9 shows the different inputs, considered in using this technique, to the ANN used in this research. The values of the inputs as shown in figure 4.9 are normalized to a 0-1 scale. Thus there are 10 inputs to the ANN which are described in Table 4.4. The values for these inputs as shown in Table 4.4 were averaged for the entire image, i.e. 10 X 160 pixels; in case of the variance and covariance every pixel was considered to give a value for input.

Table 4.4 Inputs to the ANN

INPUTS	DESCRIPTION
R_{avg}	Arithmetic average of R values for that image
G_{avg}	Arithmetic average of G values for that image
B_{avg}	Arithmetic average of B values for that image
R_{var}	Variance between R values
G_{var}	Variance between G values
B_{var}	Variance between B values
RG_{covar}	Covariance between R and G values
GB_{covar}	Covariance between G and B values
BR_{covar}	Covariance between B and R values
Grit	Grit Size of the abrasive (0:P80; 1:P220)

Various networks with different combinations of hidden layers and the number of hidden layer neurons were trained to design an ANN with minimal error percentage. This error is the percentage of the images that the ANN could not comprehend or learn. This percentage meant that those kinds of images would not be accurately classified by the ANN. Leading to inaccuracy or faulty classifications. Thus it was very important to get the right number of neurons and hidden layers in the ANN.

The minimum number of neurons in the hidden layer for a particular ANN is obtained by Equation 4.2 (Fausset, 1994)

.

$$n_H = 0.25[(n_I + n_O) \times N_H] \qquad \textbf{(Eq. 4.2)}$$

Where n_H = Number of neurons in hidden layer

n_I = Number of inputs (10 in this case)

n_O = Number of outputs (8 in this case)

N_H = Number of hidden layers (2 in this case)

This equation is used to approximately start a trial and error process for creating an ANN structure that will give the optimum result. Optimum result in measured as the error percentage, which is the amount of training samples that could not be resolved by the ANN

structure. Thus various ANN structures need to be developed and run in order to achieve the optimum structure for a particular objective.

The hidden layer is generally used when ANN is applied for non linear modeling problems. Image classification in this research is not accounted as a linear model due to external factors affecting the abrasive sheet and sanding process. The ANN described above is shown in Figure 4.10 and is a feedforward three layer neural network using back propagation algorithm as the training principle.

Different structures of ANN, like 10-10-8, 10-8-8, 10-12-8, 10-5-5-8, 10-7-7-8 and 10-8-8-8 were trained to see the error percentage and to observe and select the best ANN design to accomplish the objectives. Finally, a 10-7-7-8 ANN was selected as its error percentage was observed to be 5.14 as shown in Table 4.5. A 10-7-7-8 network means it has 10 input neurons, 8 output neurons (8 categories in this case) and two hidden layers with 7 neurons each.

Table 4.5 Different structures of ANN and their error percentages

ANNs				Error % after training
Input Layer	Hidden Layer1	Hidden Layer2	Output Layer	
10	10	0	8	37.60
10	8	0	8	41.12
10	12	0	8	39.40
10	5	5	8	17.68
10	7	7	8	5.14
10	8	8	8	5.63

The ANN was developed in MathWorks MATLAB version 6.0.0.88 software using the neural network toolbox version 4.0 and the image processing toolbox version 2.2.2. The ANN was designed with randomly generated weights ranging between -0.5 to 0.5 for each connection between the neurons. These randomly generated weights were kept common for all the different ANN's designed and stated in Table 4.4.

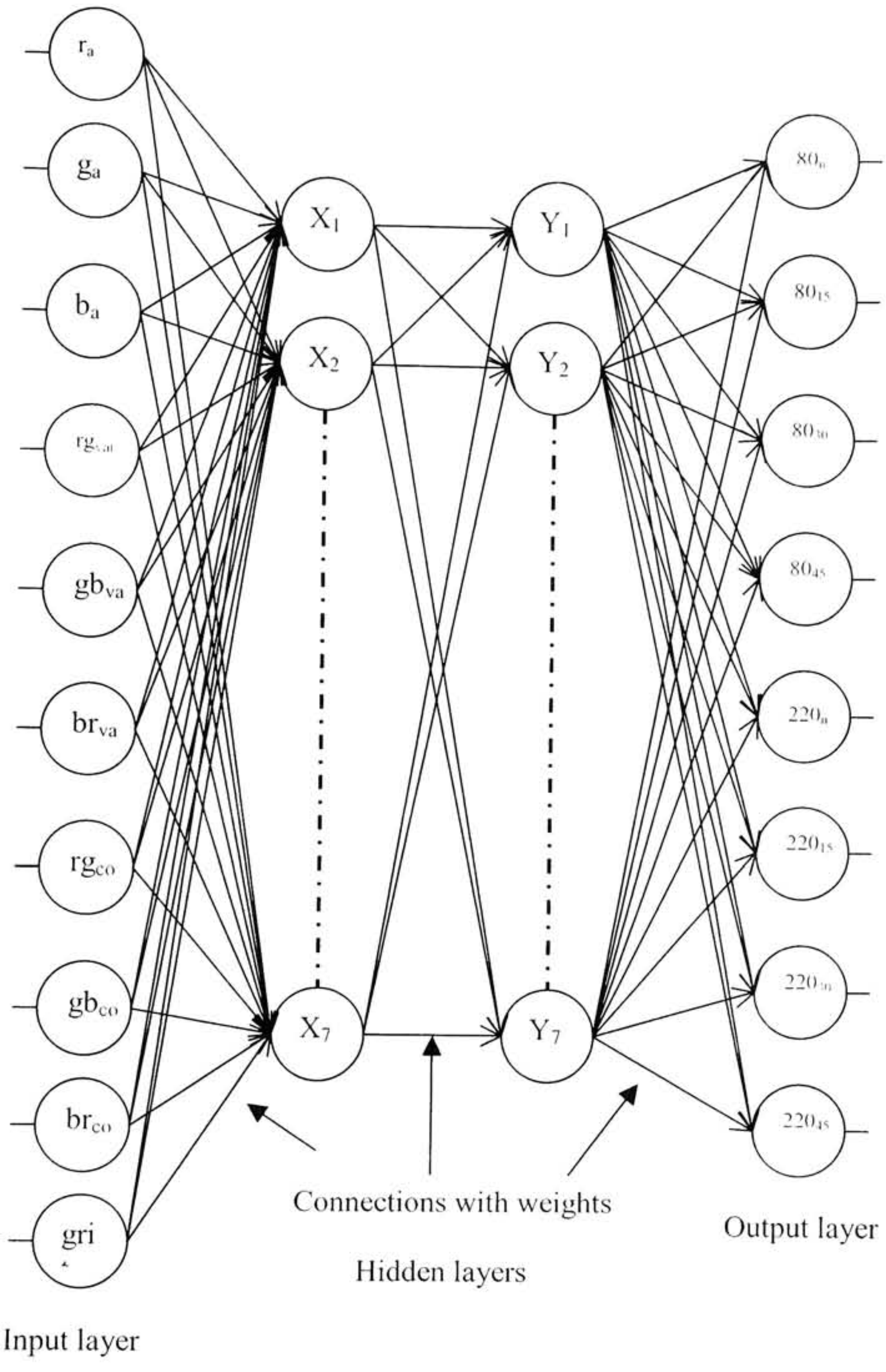


Figure 4.10 Final ANN configuration (Feed forward back-propagation network)

4.4.2 Training the ANN

Once the ANN was designed the database of images needed to be converted to match the design format of the ANN in MATLAB software. The images were converted in vector form with 10 inputs from each image. The training database also had the corresponding output values for each input vector. Before starting the training procedure for the ANN it was necessary to determine the learning rate of the ANN. This is a factor that is put into the training program code that determines the step size of the learning to reach the goal, i.e. speed vs. accuracy factor. It was observed in all the preliminary tests done in this research that by varying the learning rate the goal was achieved rapidly without surpassing the optimum training, i.e. over train or under train the ANN. While in training, Matlab produces an error percentage graph. This graph helps in monitoring for optimum training. Thus, the training of the ANN was carried out in steps of decreasing learning rate varying from 2.00 to 0.15 as shown in Table 4.5.

Table 4.6 Learning rate/Step size

Learning Rate (Step Size)	Error%
2.00	70
1.50	50
1.00	35
0.50	25
0.25	15
0.15	5
0.05	0

The training set (1200 images) from the training database was used to train the ANN with its input and expected output vectors. The lowest percentage of error for the training acquired was 5.14%, and this was considered to be the completion of the training for the ANN.

As stated before in this chapter, 400 images were randomly stored as 'Initial Validation Set'. These images were converted into vectors for inputs to the ANN. These vectors were set into the ANN and their outputs from the ANN were analyzed. The objective of the 'Initial Validation Set' was to determine that the ANN is able to recognize the set of images which

are similar to those images that it was trained with, (i.e. produced under identical conditions) but at the same time the ANN has never seen these images. Thus helping in achieving the validation for proving that the ANN was trained and did classify images similar to the ones it was trained on.

4.5 Stage IV: Creation of 'Final Test' image database

Once the training and the initial validation of the ANN was completed, the next step was to develop a new database of images that can be tested on the ANN system. A second experiment was carried out to collect images for the 'Final test' database. The objectives of this experiment were to collect images to test the ANN for the times it was trained for, i.e. 15 minutes, 30 minutes and 45 minutes; and to gather images to test the ANN for extrapolation and interpolation and analyze the outputs obtained as shown in Table 4.6. The reasoning behind the extrapolation and interpolation testing was to see if the ANN would be able to give an output close to some category than the others or not converge on any category per se and give multiple categories hinting it does not know the category and thus could not classify the image..

Table 4.7 'Final Test' image database experiment

Treatment Level Combination	Grit Size	Time (minutes)
1	80	15.0
2	80	22.5
3	80	30.0
4	80	37.5
5	80	45.0
6	80	52.5
7	220	15.0
8	220	22.5
9	220	30.0
10	220	37.5
11	220	45.0
12	220	52.5

On the other hand it was determined to test the ANN with images captured from abrasives exposed to different process conditions other than those used for training. This experiment

was run using similar apparatus as the experiment run for the training database. A Grizzly bench sander, aluminum oxide 6" X 48" (P80 and P220) abrasive sheets and hard maple (*Acer saccharum* March) conditioned at EMC 6%. This experiment was run to gather image information on each level to test the ANN, making this collection of images the 'Final Test' database. This second experiment was run in the Brinkman Manufacturing Laboratory at Rochester Institute of Technology. The images were acquired using the same vision system, and using the parameters of illumination and magnification specified earlier in this chapter.

4.6 Stage V: Testing

The ANN needed to be validated to observe the pattern of outputs it gave for different abrasive images. It also needed to be tested for accuracy and robustness. These objectives were achieved by using the two sets of images collected as stated in stage I and III described earlier in this chapter. The ANN was initially validated using the 'Initially Validation Set' to observer whether it could classify a set of images, which belonged to the same group of images it was trained with.

The ANN needed to be tested for robustness, in other words interpolation and extrapolation. Images of abrasives from the test experiment shown in Table 4.6 were collected as explained in stage III. This database of images was separated into two sets to test for two different objectives. It was ascertained that approximately 150 images would be enough to test the system and thus a total of 144 images were collected from all the treatment combinations in this experiment. The first set was of 72 images from P80 and P220 aluminum oxide abrasive for 15 minutes, 30 minutes and 45 minutes. This set was used to test the robustness of the ANN.

The second set of 72 images was from P80 and P220 aluminum oxide abrasive for 22.5 minute, 37.5 minutes and 52.5 minutes. This set was used for testing the capability of classification for interpolation and extrapolation of abrasive usage times by the ANN. This set of images were run through the same image processing algorithms as the initial validation set to form a matrix of inputs for testing. The inputs were feed column by column (vector by vector). The outputs were collected for analysis.

As discussed in this chapter, the ANN was created and was trained using the training set from the training image database. An 'Initial Validation Set' was developed to validate the ANN and observe the outputs after training. A 'Final Test' image database consisting of two sets of images was developed to test the ANN for robustness, extrapolation and interpolation. These tests were run as part of 'Stage IV' of the 4-stage procedure defined in methodology.

5. Results and Discussion

As discussed in the previous chapter, there were two different tests carried out on the ANN after it was trained. The first test was carried out using the initial validation set from the training database. This test was to cross validate the ANN on images similar to its training set and ensure the error percentage observed during training. The second test used the final test database to verify the robustness and capability of the ANN. The final test database had images from a second experiment and thus the images were different from the training database. The results to these tests were analyzed and are summarized in Table 5.1.

Table 5.1 Summary of results

Tests	Sub-Tests	Total No. of Images	Images Classified	Images not classified	Error %
Initial Validation		400	377	23	5.75
Final Test	Robustness	72	56	16	22.22
	Interpolation/Extrapolation	72	68	4	5.56
	TOTAL	144	124	20	13.88

Training of the ANN, using the images from the training set in the training database, predicted 5.14% error. This error percentage is approximately a percentage of the number images that the ANN could not train on. Thus images similar to the 5% that could not be trained would be classified incorrectly. It is necessary to check if similar images could be classified by the ANN.

In the summary of the results shown in Table 5.1, it states that the 'Initial Validation' test revealed that 5.75% of the images from the 400 total images could not be classified by the ANN. This successfully helps in concluding that the ANN was trained to classify images at the expected or allowed error. This result helps in understanding that the ANN was capable to classify the images in to the correct categories with a success rate of 94%. These images in the initial validation set were images taken via the first experiment, which was also used to create the training set for the ANN.

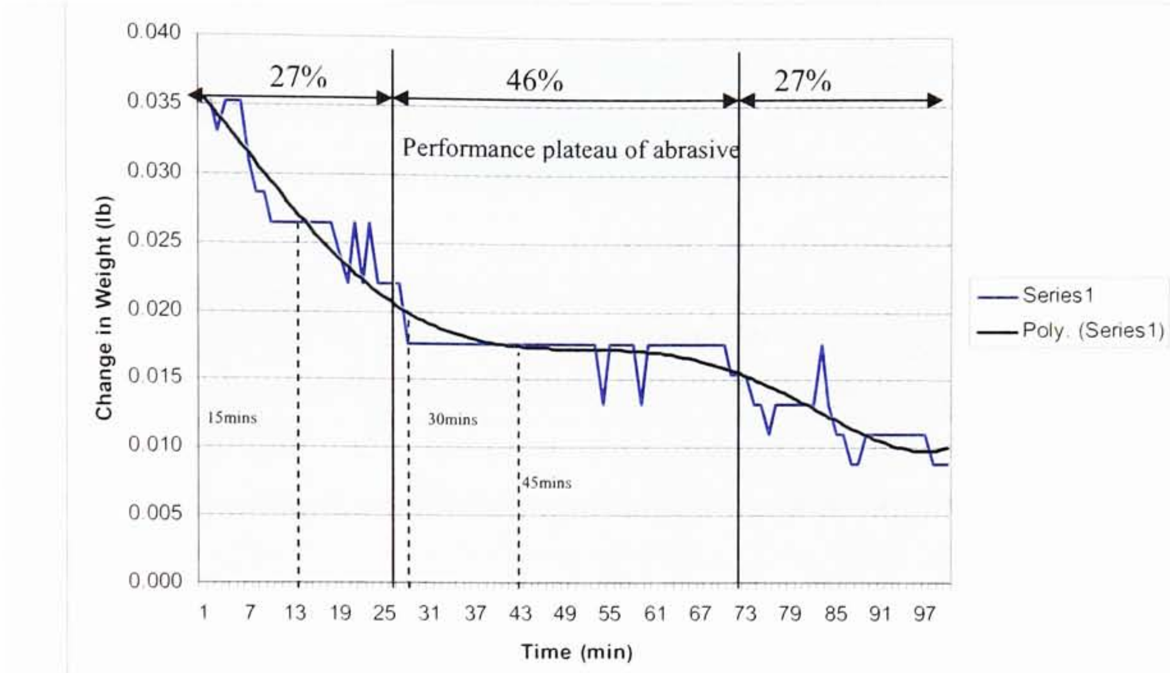
The final test database consisted of a total of 144 images. The second experiment carried out in the Brinkman Manufacturing Laboratory at Rochester Institute of Technology helped in capturing these images. 72 images from the database were images from similar grit size and similar machining times. This was required to prove the robustness of the ANN as these images were from a second experiment and thus had different conditions. The other 72 images were from machining times that were interpolated and extrapolated. This was done in order to test the ANN on its capability of interpolation and extrapolation. The second experiment was a short experiment and thus only a total of 144 images were captured. This number was ascertained to be enough to test the ANN for the objectives mentioned above.

The result summary shown in Table 5.1 identifies the sub-tests, i.e. Robustness and Interpolation/Extrapolation. Result Table 5.1 shows that the test for robustness of the ANN in classifying images from a different experiment was poor due to the 22% error. It indicates that 16 images out of the 72 total could not be classified. On analyzing the data from the output of ANN for the robustness test indicated that 12 out of the 16 images that were classified incorrectly belonged to grit size P80 with a machining time of 30 minutes. The percentage of successful classification on the removal of the P80 grit size was 89%, viz. an error of 11%. Thus the robustness test for the abrasive grit size P220 showed successful classification. On removal of grit size P80 machining time 30 minutes from the results it showed the accurate classification by 93%. These percentages showed that there was something incorrect with the images of the grit size P80 with machining time 30 minutes.

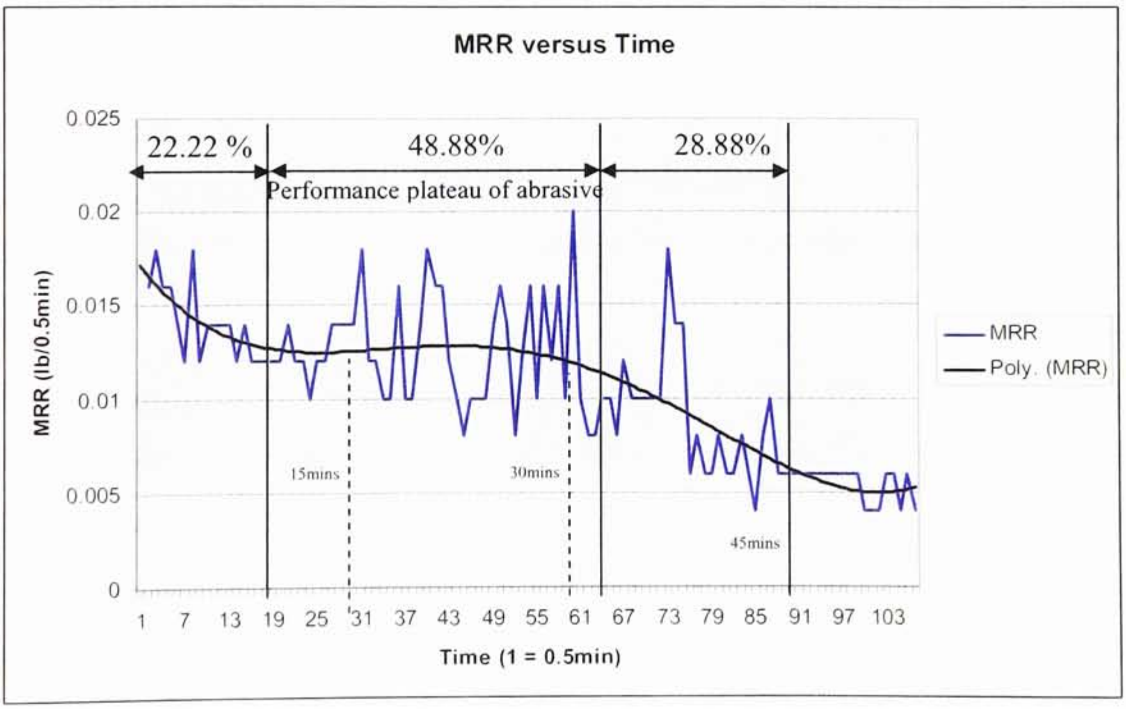
To decipher the failure of robustness test for P80 a few tests were run on the images of the abrasives. The first test was to compare the histograms of the images obtained from the test database and the training database. This test did not give enough information to reason the failure.

Thus another experiment was run where a P80 abrasive was utilized to develop the MRR curve. The MRR curve showed that for a P80 abrasive with a machining time of 45 minutes was not the end of its useful life. The MRR curve for P80 shown in Figure 5.1 distinctly shows that for a P80 abrasive with machining time 30 minutes and 45 minutes have

approximately the same MRR, which leads to a conclusion that the loading and wear should be of similar pattern in both cases making the classification difficult.



P80 MRR Curve



P220 MRR curve

Figure 5.1 P80 and P220 MRR curves

The MRR curves in Figure 5.1 also shows that the performance plateau, which is the region of optimum performance for the particular abrasive, is for about 50% of the life of the abrasive. The ideal selection for classification categories for an abrasive with grit size P80 should have been 0 minutes, 30 minutes, 60 minutes and 90 minutes. In case of this research these categories were 0 minutes, 15 minutes, 30 minutes and 45 minutes. All the machining times used in this research for P80 belong to the performance plateau causing the ANN to misclassify the P80 images.

The ANN was trained with images of P80 and then tested with the initial validation set; this test was successful even though the P80 categories seem to be close to each other and tend to over lap on the MRR curve. The initial validation set is a set of images from the same experiment that was used in creating the training sets. The 400 images were randomly picked from the training database and held for testing. Thus they are similar to the training images. Also these images were split images from a 320 X 240 pixel image, which explains the similarity and thus successful classification due to ANN training. The final test database consisted of images from a second experiment and thus the images of P80 abrasive may have had more variation than expected even tough all the parameters mentioned in the previous chapter, like pressure, temperature, EMC of the wood, were kept constant.

To determine the similarity between the images of abrasive grit size P80 with machining times 30 and 45 minutes, a progression of loading and wear on P80 was developed and is shown in Figure 5.2.

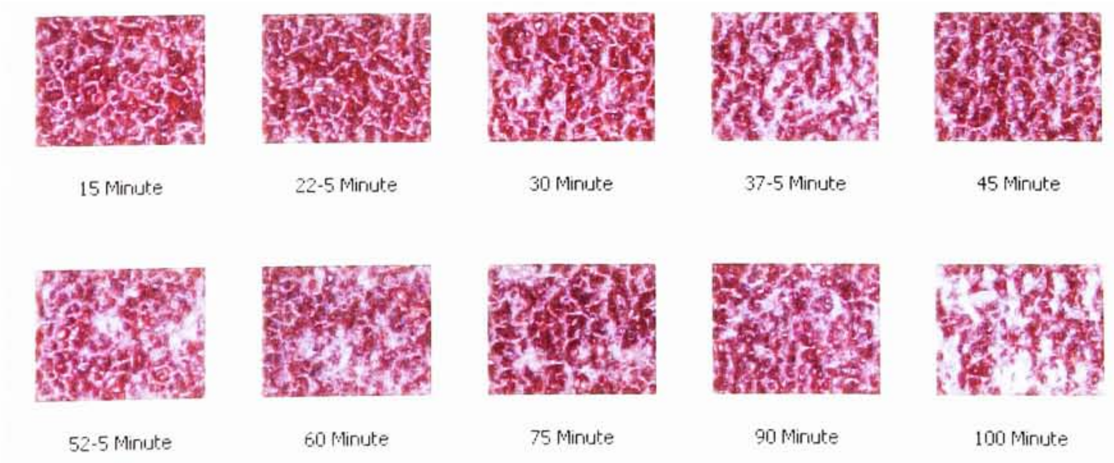


Figure 5.2 P-80 abrasive loading and wear progression.

The images in Figure 5.2 supports the MRR curve by showing that the loading and wear for the P80 grit size abrasive with machining times 22.5, 30, 37.5 and 45 minutes are similar. Suggesting, the MRR to be relatively equal. Since the images of these machining times are close, i.e. no significant difference in texture, the ANN has a hard time classifying one from the other, causing the error percentage to increase.

The data collected during this confirmation test was used to develop the input chart as shown in Figure 5.3. It shows that by selecting the correct categories the inputs show a distinct variation where as the earlier graph shown in Figure 4.9 shows that the inputs for P-80 abrasive were close and did not have a distinct separable features causing incorrect classification.

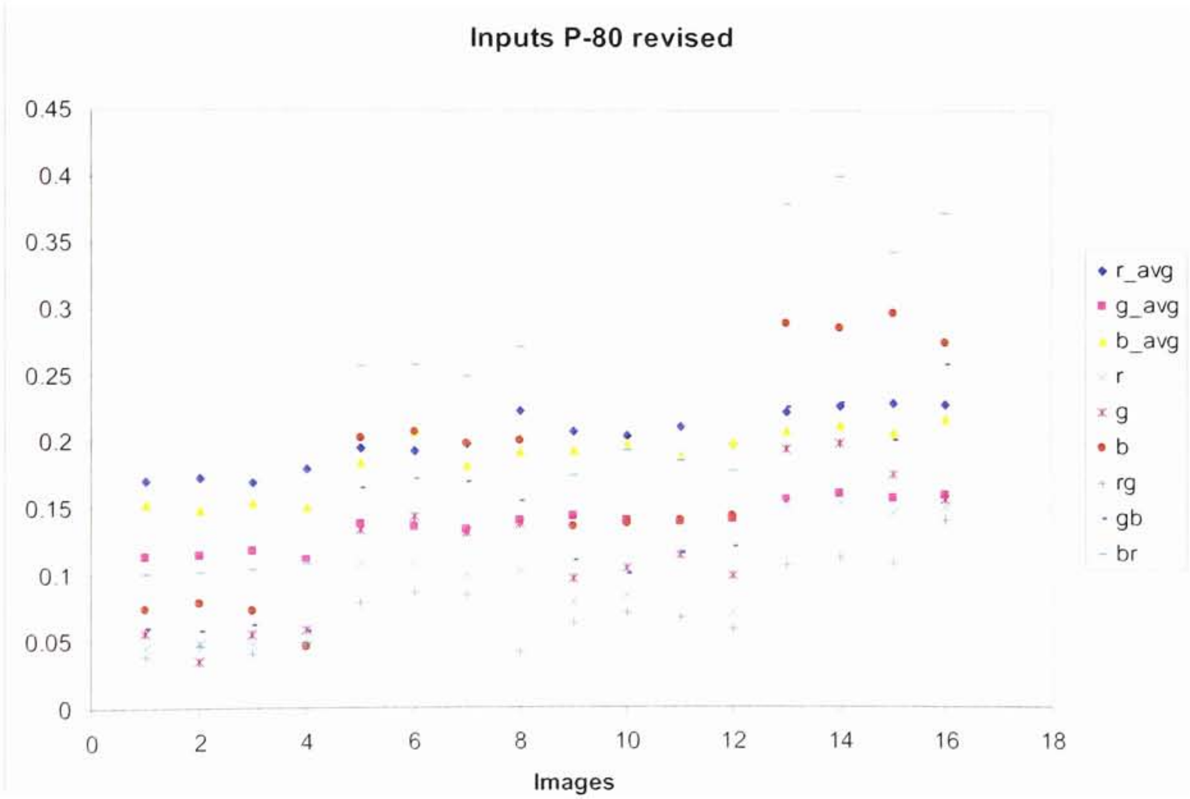


Figure 5.3 Revised P-80 inputs

The last test carried out as shown in Table 5.1 was for testing the capability of the ANN to interpolate and extrapolate. The images from this test set were expected to be classified by

the ANN into the subsequent category. This is because the machining times for these images were chosen to fall between the categories defined. The ANN does not have categories for these images and thus classification into the subsequent categories. The abrasive grit size, machining time and their respective categories are shown in Table 5.2.

Table 5.2 Interpolation/Extrapolation categories

Grit Size	Machining Time (Min)	Classification category expected	Category Definition	Replacement Decision
P80	22.5	III	P80 30 minutes	Useful Life 5-15 minutes
P80	37.5	IV	P80 45 minutes	Replace the abrasive sheet
P80	52.5	IV	P80 45 minutes	Replace the abrasive sheet
P220	22.5	VII	P220 30 minutes	Useful Life 5-15 minutes
P220	37.5	VIII	P220 45 minutes	Replace the abrasive sheet
P220	52.5	VIII	P220 45 minutes	Replace the abrasive sheet

So if an image of P80 grit size with machining time 37.5 minutes was classified by the ANN as a P80 grit size abrasive with 45 minutes of machining time; it was regarded as a successful classification. The Table 5.1 shows that the ANN was capable in making the correct classifications for interpolated and extrapolated images with a success rate of 95%. The 4 images that were incorrectly classified by the ANN belonged to grit size P80 with machining time 22.5 minutes. These images were classified as category II, which is grit size P80 with machining time 15 minutes. After observing the MRR curve for P80 in Figure 5.1 and the progressive loading and wear images from Figure 5.2, it is clear that grit size P80 with machining time 15 minutes and 22.5 minutes are similar as compared to 30 minutes machining time which caused for the failure in classification. Overall the ANN was capable to make interpolated and extrapolated classifications.

The results and the discussion of the experiments conducted to support the results show that the ANN is capable of successfully classifying the abrasive images into the categories defined. At the same time the ANN has the capability to interpolate and extrapolate with a degree of robustness. However the ANN's performance is directly dependant upon the type of images input and the training it got. The categories in developing such an ANN should be accurate in order for the ANN to perform successfully.

6. Conclusions

This work focused on the monitoring and inspection of the abrasive to judge and make a decision on its useful life or replacement policy. Feasibility and capability of computer vision systems in this application was demonstrated in the previous chapters. The results showed that the computer vision system developed in the research was capable to successfully classify the abrasives and give a replacement decision based on the parameters preset as part of the categories. The system was however found to be sensitive to the quality of the image and its similarity with the training database. Grit size P-220 abrasive images were classified accurately with precision, but the P-80 abrasive images encountered some problem during classification. As discussed in the results and discussion section the ANN categories were on a preliminary test and expert input for P-220, which behaves differently than P-80 and thus the incorrect classification.

During the analysis of the confirmation test for results it was found that P-80 abrasive had a longer life span than the P-220 and this is due to P-80 being a coarser grain, which can withstand pressure and temperature to a better extent thus less fracture. This caused all the defined categories for P-80 abrasive to fall in its performance plateau region. The end of life for P-80 abrasive was analyzed to be around 90-100 minutes, which was not captured in the categories for this research causing ANN to classify P-80 images incorrectly.

On the other hand, P-220 abrasive images for all categories showed accurate classification. This was due to the fact that the preliminary run was based for P-200 abrasive and the category selection was based off P-220 MRR curve, which lead to couple of conclusions. Firstly, the ANN output categories need to be defined for each grit size specifically for correct classification as they behave differently. Secondly, it was concluded that by making a separate ANN for different abrasive types could solve the problem of different classes as well make the process more efficient as the number of outputs would decrease.

One of the decisions made while pursuing this research was to use color images instead of gray scale images. This was made due to the fact that different combinations of wood types

and abrasive types would not give an accurate input with grayscale as its analysis depends primarily on the change of intensity of black and white. Also it was observed that it was too sensitive to light intensity, which could potentially cause categorization issues. Thus R-G-B averages, variances and covariance were used. This was a novel approach for developing a classification algorithm and has been used by Sahin and Bay (2000) for wood image classification using radial basis functions, but has not been used for abrasive image classification or for determining useful life of abrasives.

The important aspect of the results that needs to be mentioned is that the system accurately classified images for interpolation and extrapolation opening a door for fewer categories, lesser outputs and better training for the ANN. In addition this accurate classification helps conclude that the ANN if trained efficiently is able to output replacement decisions for images with similar parameters and features.

Overall computer vision system is a feasible solution for replacement decisions on abrasive belts. Although a lot more research and data analysis is required to actually implement it in the manufacturing world.

7. Future research

Various variables affect the efficiency and useful life of the sanding abrasives. Temperature, working environment, humidity, temperature at operation, EMC of the wood, type of wood, type of abrasive mineral, pressure, grit size, backing material and depth of cut are some of the major factors that play a significant role in loading and wear of the tool, in this case abrasive sheet, which in turn affects the material removal rate. This research has dealt mainly with the abrasive grit size and the time of usage of the abrasive. The other factors mention above are as important as the ones considered in this research but for the sake of this research were either kept constant or assumed to be constant since the experiments were run in a controlled environment. These factors need to be explored and a similar solution to monitor changes in useful life of the abrasive needs to be developed. A computer vision system which would account for all these factors mentioned above would help in implementing this on a shop floor or a furniture industry.

While developing the ANN, this research was restricted due to the availability of the training samples. In the future research to make the ANN better and more reliable and accurate by creating an extensive database would be expected. Also the inputs to the ANN should be analyzed and a better fit with a narrow range of speculation for the ANN should be able to make the computer vision system more powerful.

Also a decision system based on the outputs of this computer vision system needs to be developed to optimize replacement of abrasive belts. Being able to monitor and detect the optimum replacement policy for the abrasive belts would allow in taking measures to limit or nullify loss of product value occurred.

Cost justification and economic gain from using an automated computer vision system for monitoring and inspection to make a decision on replacement of an abrasive is a major area that needs to be looked into. Computer vision would decrease the extent of early/late replacement of abrasives. Early replacement causes higher cost of abrasives due to inefficient utilization of tooling material. Where as late replacement causes heavy rework in process

causing higher cost of production. Also implementation cost a computer vision system needs to be evaluated in order to make a judgment on the economic gain.

References

[1] Behnke, S. (2003). "Hierarchical Neural Networks for Image Interpretation," Springer, pp 15-147.

[2] Braggins, D. (2000). "Cost justifying vision: the great benefits are often hidden." Advanced Imaging Journal v15, n9, pp 40-42.

[3] Brown, C. (1987). "Advances in Computer Vision," Lawrence Erlbaum Associates, pp 115-165.

[4] Chen, Y. H. (1994). "Computer vision for industrial inspection through linguistic fuzzy variable inputs," 20th International Conference on Industrial Electronics, Control, and Instrumentation, Bologna, Italy, pp 1349-1353.

[5] Clark, E. L., Ekwall, J. A., Culbreth, C. T., and Willard, R. (1987). "Furniture Manufacturing Equipment," North Carolina State University.

[6] Fausett, L. (1994). "Fundamentals of neural Networks," Prentice Hall, pp460.

[7] Faust, T. D. (1987). "Real time measurement of veneer surface roughness by image analysis," Forest Product Journal, v37, n6, pp34-40.

[8] Ferrari, R., and Stancanelli, R. (1998). "Control of abrasive belt: key point of the IMEAS sanding technology," 32nd International Composite Materials Symposium proceedings, Washington, USA. Mar 31st – Apr 2nd, pp174-175.

[9] Franz, N. C., and Hinken, E. W. (1954). "Machining wood with coated abrasives," Project no. 2082. University of Michigan, Ann Arbor, MI.

[10] Groover, M. P., Weiss, M., Nagel, R. N., and Odrey, N. G. (1986). "Industrial Robotics," pp480.

[11] Howlett, R. J., and Jain, L. C. (2001). "Radial Basis Function Networks 2," Physcia-Verlag, pp360.

[12] Kato, K. and Lemaster, R. L. (1992). "Generation of acoustic emission during chip formation," Proceedings of the 10th International Wood Machining Seminar, Oct 21-23, 1991, University of California Forest Products Laboratory, Richmond CA. pp146-158.

[13] Kulkarni, P. S., Cormier, D. R., Lee, Y. S., and Healy, C. G. (2001). "CAD based computer vision for pose determination of wooden parts," Thesis submitted to graduate faculty at North Carolina State University, Raleigh, NC, USA.

[14] Lecerf, A., Ouellet, D., and Arias-Estrada, M. (2000). "Computer vision camera with embedded FPGA processing," Proceedings of SPIE, v3966, pp299-308.

[15] Lemaster, R. L. (1992). "Monitoring abrasive machining process in wood with acoustic emission," Proceedings, Forth International Symposium on Acoustic Emission from Composite Materials. ASNT, Seattle, WA. Pp377-386.

[16] Lemaster, R. L. and Dornfeld, D. A. (1993). "The use of acoustic emission to monitor an abrasive machining process," Proceedings of the 11th International Wood Machining Seminar, May 25-27, 1993, The Norwegian Institute of Wood Technology.

[17] Lemaster, R. L., Lu, L., and Jackson, S. (2000). "The use of process monitoring techniques on CNC wood routers," Forest products journal, Vol 50(9), pp 59-64.

[18] Lepisto, L., Kunttu, I., Autio, J., and Visa, A. (2003). "Rock image classification using non-homogenous textures and spectral imaging," WSCG Short Papers Proceedings, Feb 3-7, 2003, Plzen, Czech republic. pp24-29.

[19] Mondal, D. P., Das, S., Jha, A. K., and Yegneswaran, A. K. (1998). " Abrasive wear of Al alloy $-Al_2O_3$ particle composite: a study on the combined effect of load and size of abrasive," Wear journal, v223, pp131-138.

[20] Paulus, D., Zobel, M., and Denzler, L. (2000). "Active computer vision," Proceedings of the 5th IEEE International Workshop on Computer Architectures for Machine Perception, Padova, Italy, pp18-27.

[21] Campisi, P. (20002), "A Multiresolution approach for tecture synthesis using the circular harmonic function," IEEE transactions on Image Processing, v11, n1, pp37-51.

[22] Phan, D. T., and Alcock, r. J. (1998). "Automated grading and defect detection," Forest Product Journal, v48, n4, pp34-42.

[23] Prak, A. L, and Myers, T. W.(1981). "Furniture Manufacturing Process," North Carolina State University, pp228.

[24] Prasad, B. K., Das, S., Jha, A. K., Modi, O. P., Dasgupta, R., and Yegneswaran, A. H. (1997). "Factors controlling the abrasive wear response of a zinc based alloy SiC particle composite," Elsevier Science Ltd., v28, n4, pp301-308.

[25] Russ, J. C. (1995) "Thresholding images," Journal of Computer-Assisted Microscopy, v7, n3, pp141-164.

[26] Sahin, F., and bay, J. S. (2000). "A comparison of classification methods to solve a real time color image classification problem," 4th International Conference of Imaging Science and Scanning of Wood, Virginia, USA, pp187-200.

[27] Singh, M., Modi, O. P., Dasgupta, R., and Jha, A. K. (1999). "High stress abrasive wear behavior of Al alloy- granite particle composite," Wear Journal, v233-235, p455-461.

[28] Sonka, M., Boyle, R., and Hlavac, V. (1998). "Image Processing: Analysis and machine Vision," PWS.

[29] Trezona, R. I., Allsopp, D. N., and Hutchings, I. M. (1999). "Transitions between two body and three body abrasive wear: influence of test conditions in the micro scale abrasive wear test," Wear journal, v255, pp205-214.

[30] Wang, J., and Asudani, A. K. (2000). "A computer vision system for wineglass defect inspection via gabor filter based texture features," Elsevier Information Sciences, v127, n3, pp157-171.

[31] Webb, J. A. (1994). "High performance computing in image processing and computer vision," 12th International Conference of Pattern Recognition, Los Alamtois, USA, pp218-222.

[32] Weissberg, R., and Buker, S. (1990). "Writing Up research," Englewood Cliffs, NJ, Prentice Hall.

[33] Wettschurack, K. P., Gibson, H. G., Cassens, D. C., and Krutz, G. W. (1999). "Factors causing ridge formation during wide belt sanding and corrective actions," Forest Products Journal, v49, pp82-88.

[34] Zhou, Y., Funkenbusch, P. D., and Quensel, D. J. (1997). "Stress distributions at the abrasive matrix interface during tool wear in bound abrasive grinding – a finite element analysis," Wear Journal, v209, pp247-254.

APPENDICES

Appendix A

1. Image Analysis Algorithms (Matlab code)

1.1 Image Splitting

```
function [a,b,c,d] = split(i)

for x = 1:160 for y = 1:160
      for z = 1:3
         a(x,y,z) = i(x,y,z);
         b(x,y,z) = i(x+80,y,z);
         c(x,y,z) = i(x,y+160,z);
         d(x,y,z) = i(x+80,y+160,z);

   end end end
```

1.2 RGB Arithmetic Average

```
function a = rgbavg(i)

r_avg = mean(mean(i(:,:,1))); g_avg = mean(mean(i(:,:,2))); b_avg =
mean(mean(i(:,:,3)));

a(1,1) = r_avg; a(2,1) = g_avg; a(3,1) = b_avg;
```

1.3 Covariance Matrix

```
function a = covac(i)

avr = mean (i(:,:,1)); avg = mean (i(:,:,2)); avb = mean (i(:,:,3));
av(3,160) = 0; av(1,:) = avr; av(2,:) = avg; av(3,:) = avb; av =
av'; a = cov(av);
```

1.4 Vector Formation

```
function a = covector (b,c)
```

```
a= b;
a(4,1) = c(1,1);
a(5,1) = c(2,2);
a(6,1) = c(3,3);
a(7,1) = c(1,2);
a(8,1) = c(2,3);
a(9,1) = c(1,3);
```

1.5 Square Root of Covariance Matrix Values

```
for i = 4:9 for j = 1:1200 tr(i,j) = sqrt(tr(i,j)); end end

for i = 4:9 for j = 1:400 t(i,j) = sqrt(t(i,j)); end end
```

Appendix B

2. Reading Images

```
A = imread('p22045001.tif');
[a,b,c,d] = input1(A);
tr(:,1051) = a;
tr(:,1052) = c;
tr(:,1053) = d;
t(:,351)= b;
```

```
/* tr is the training database, t is the initial validation set */
```

Appendix C

3. Back Propagation Network

```
Vorg = [rand(10,7) -0.5];


Vorg = Vorg';
V = Vorg;
Worg = [rand(7,7) -0.5];
Xorg = [rand(8,7) -0.5];
x1 = [-0.2533

   0.1266
   0.1926
   0.2474

  -0.1931
  -0.256
  0.1983];

b1 = x1;

x3 = [0.1440 0.1491 0.2922
  -0.4109
  -0.4953

   0.2299
  -0.3277
  -0.0327];


b3 = x3;


p = tr;
a = [-1,-1,1,-1,-1,-1,-1,-1; -1,1,-1,-1,-1,-1,-1,-1; 1,-1,-1,-1,-1,-1,-1,-1; -1,-1,-1,1,-1,-1,-1,-
1; -1,-1,-1,-1,1,-1,-1,-1; -1,-1,-1,-1,-1,1,-1,-1; -1,-1,-1,-1,-1,-1,1,-1; -1,-1,-1,-1,-1,-1,-1,1];
ta = trainopt(a);
S = 10;

X = ones(1,10);
Y = zeros(1,10);
/* Defining the network */
BPnet = network (10,3,[1;1;1],[X;Y;Y],[0,0,0;1,0,0;0,1,0],[0,0,1],[0,0,1]);
```

```
% Functions
BPnet.adaptFcn= 'trains';
BPnet.initFcn= 'initlay';
BPnet.performFcn= 'mse';
BPnet.trainFcn= 'traingd';


% Constant Parameters
BPnet.adaptParam.passes = 1;
BPnet.trainParam.goal= .05;
BPnet.trainParam.show =50;
BPnet.trainParam.time = Inf;


% Variable Parameters
BPnet.trainParam.epochs = 1000;
BPnet.trainParam.lr = 0.5;


for i = 1:10 BPnet.inputs{i}.range = [0 1]; end

BPnet.layers{1}.size = 7;
BPnet.layers{1}.transferFcn = 'tansig';

BPnet.layers{2}.size = 7;
BPnet.layers{2}.transferFcn = 'tansig';

BPnet.layers{3}.size = 8;
BPnet.layers{3}.transferFcn = 'tansig';

    for i = 1:10 for j= 1:5
       W(j,1) = Vorg(j,i);
       /* Defining
       Weights */

  end
  BPnet.iw{1,i} = W; end BPnet.LW{2,1}= Worg; BPnet.LW{3,2}=Xorg;
BPnet.b{1,1} = x1; BPnet.b{2,1} = x1; BPnet.b{3,1} = x3;
                      BPnet = train(BPnet,p,ta); /* Initiates training */
```