Chapter 1. Introduction

1.1 Motivation

Color has been a great help in identifying objects for many years. The process of color classification involves extraction of useful information concerning the spectral properties of object surfaces and comparing that information with a set of known objects to find the best match. The primary objective for some computer vision systems is to automatically analyze multispectral images of object surfaces. Upon identification of the object, it is then necessary to discover the best match from a set of known descriptions or class models to implement the recognition task. However, color classification is not an easy problem for many types of objects. For example, natural materials such as wood show random textures which make identifying different types of wood by color a difficult process [1].

This thesis starts from a foundation based on the work done by Zhao [1]. In his thesis, he initially used the *minimum distance classifier* as a classification method. The minimum distance classifier method basically finds centers of classes and measures distances between these centers and the test image's center. In this method, the test image belongs to the class whose center is closest distance to the test image's center. Zhao implemented the classification with uniform color quantization and with nonuniform color quantization [1]. He used minimum distance classifiers using *Euclidean distance* and *city-block metric distance* measures as well as the others. His results show a classification success rate of from 67.0% to 96.7% with a variety of methods. Because some of the results show room for improvement, the goal of this thesis is to investigate the use of alternate methods, such as *radial basis function networks* (RBFNs). In the literature, RBFNs were successfully applied to several pattern recognition problems [2], [3], [4]. Radial Basis Functions (RBFs) are nonlinear functions. Therefore, RBFNs solve nonlinear classification problems successfully.

1.2 Background

Automatic vision-based classification systems have been developed at Virginia Tech to classify finished wooden components. These components are kitchen cabinets and vanities manufactured by the American Woodmark Corporation (AWC) [42]. AWC needs to classify finished wooden cabinets because during production the same wood type can be stained with different colors. These components move on the conveyor without pre-classification of the wood. Therefore, all different colors and species of wood can be together on the conveyor. Since there is a great number of component types, and many of them are very similar in appearance, it is tedious, labor-intensive, and error-prone work to classify these components manually [1]. The finished components are made of several species of wood and are painted or stained in a number of colors. There is sometimes only a slight difference between the colors. The variation in the texture and the grain of the wood create slight, yet noticeable differences between the species of wood. As a result of these problems, it is sometimes difficult even for human eyes to accurately identify and categorize the finished product. For these reasons, it is desirable to develop a machine-vision system to improve the inspection process, creating a simple, accurate, and cost-effective classification system.

1.3 Hardware Review

The experimental system for identifying the color and species of the test images is shown in Figure 1.1. The red-green-blue (RGB) images of the samples, taken from components moving on a conveyor, are created by a JVC TK-1070U color camera. A frame grabber, located in a 486-based PC, takes these images. After the image is captured, the program that performs RBFN simulation finds which colors and species the image sample belongs to.

1.4 Objective and Contributions

The goal of this research is to develop a new approach to classify the species and color of painted or stained wooden components in a real time industrial setting. In [1], the minimum distance classifier is employed to classify the finished wooden components. Our objective is that since RBFNs can perform nonlinear classification, they can give a higher rate of correct classification than that of minimum distance classifier. The minimum distance classifier does not perform a nonlinear classification. An XOR problem is introduced in Chapter 3 as an example of nonlinear classification using RBFNs. Another reason for using RBFNs is that they are proficient in defining class regions because Gaussian-like functions are employed. Detailed information is given in Chapter 3.

Sample images of the finished wooden components can be seen in Figure 1.2. As can be seen, some images look almost the same. The database of 480 images, grabbed by an automatic machine-vision system, is available from the Spatial Data Laboratory at Virginia Tech. These images are stored in *raw* format. The files in *raw* format do not have header information or the size of the image. They have only color information of each pixel. Since the *raw* formatted files have no header and size information, it is very easy to use these files in a C++ or a Matlab program. The image structure can be seen in Figure 1.3. Every image has 16,384 (64x256) pixels. Every pixel has red, green, and blue components. Every color is represented by eight bits. Therefore, every pixel is represented by 24 bits (3 bytes), and the total image size is 49,512 bytes (16,384x3).

Our system has a *training* step. The classes, species, and colors are taught to the system in the training step. This teaching process is called training in a classification system. Some of the 480 images are used for training the system. Since the training samples have to represent the classes optimally, the same training samples as in [1] are used. Additionally, this provides an accurate comparison between our method and the methods in [1]. Ninety-five of the images are used as training samples while the remaining 385 images are used to test the system.

Another objective of this study is to investigate an effective training method. *Inductive learning* is implemented in [1] to train the system. Training happens in two different places in the RBFNs. A radial basis function network is a neural network approached by viewing the design as a curve fitting problem in a high dimensional space. RBFNs are feed-forward neural networks.

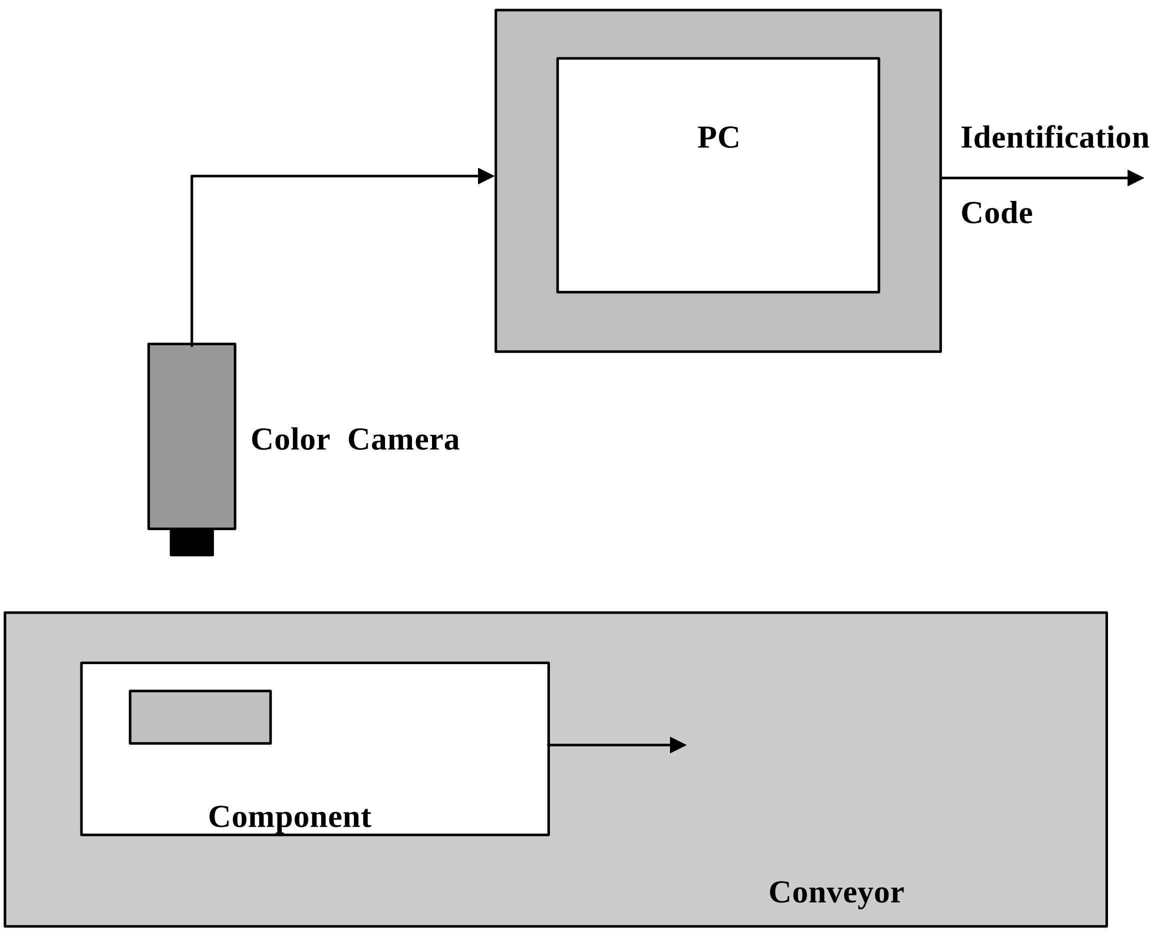


Figure 1.1. The layout of the color and species classification system.

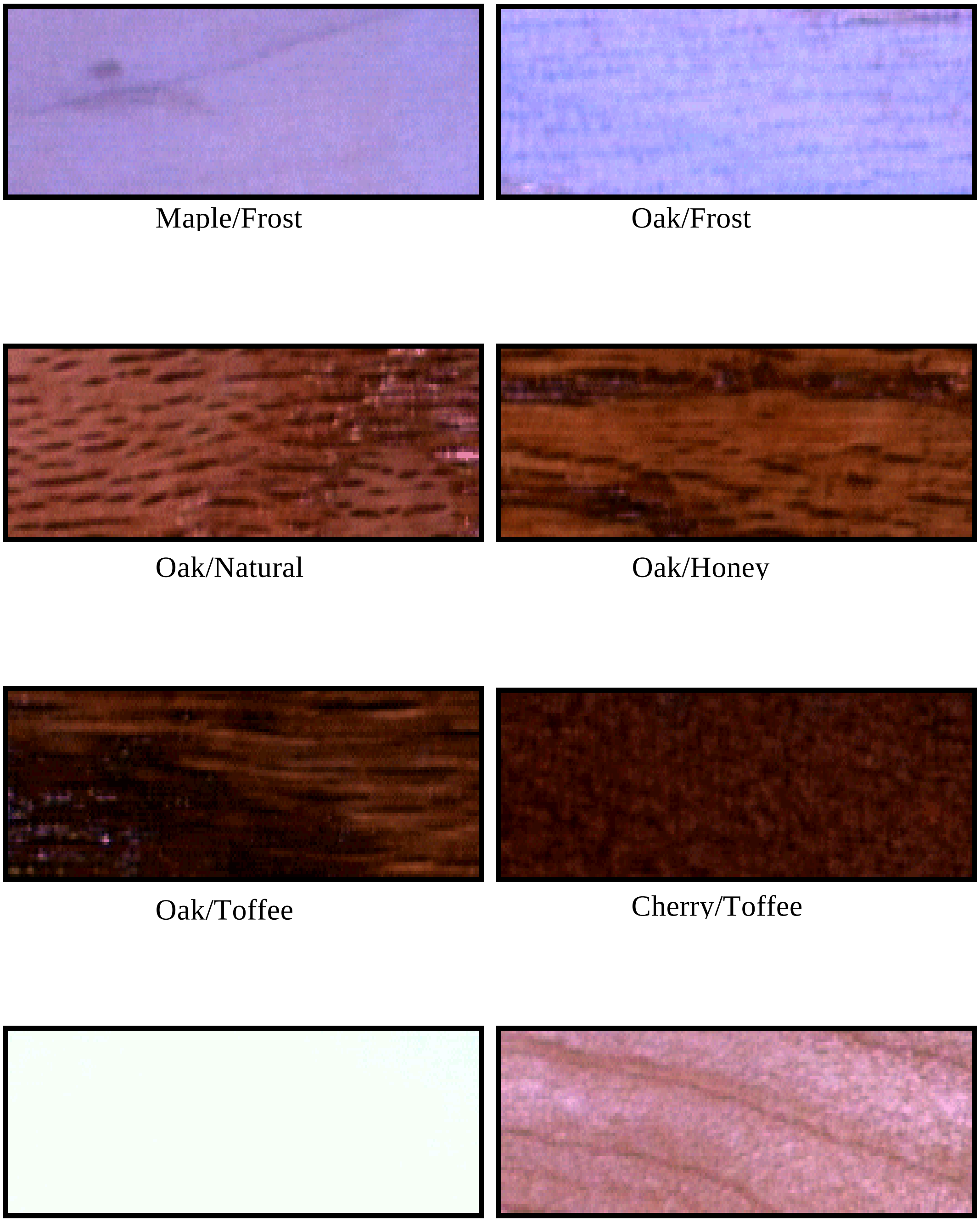
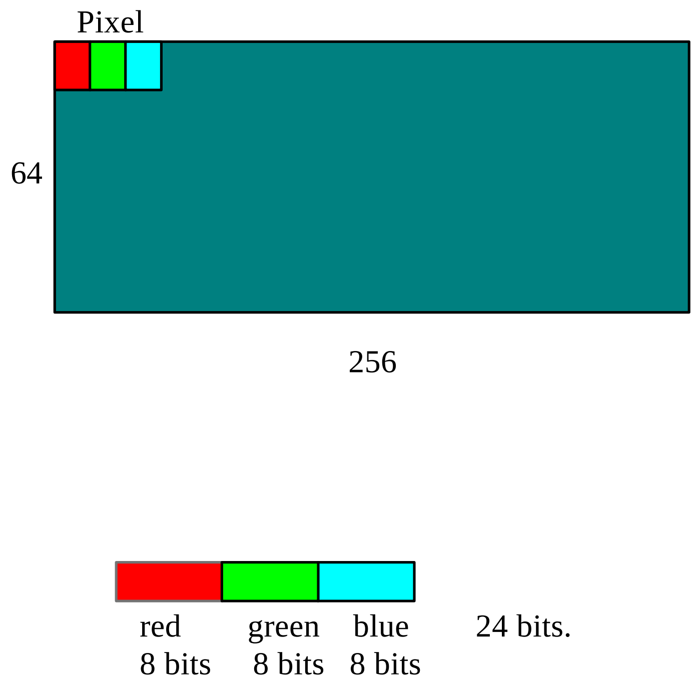


Figure 1.2. Representative images of eight different wooden cabinets.



The Number of Total Pixel : 64x256 = 16384

Each pixel has 24 bits (3 bytes)

Total image is 16382x3 = 49152 bytes.

Figure 1.3. Structure of the images.

RBFNs have three layers : input layer, hidden layer, and output layer. In the hidden layer of the network, radial basis functions are employed. Each RBF is defined with a dilation and a mean since they perform Gaussian type of transfer function. In the system training, first *means* and *dilations* of the RBFs are calculated by statistical methods, as explained in detail in Chapter 3. Second, the weights of the RBFN are calculated using the means and dilations of the RBFs. The RBFN obtains the weights using a method which is equivalent to the least-mean-square (LMS) algorithm. That is, the training of the weights is performed in a LMS sense. The details of this calculation are discussed in Chapter 3.

The major contributions of this research include the following:

a) An improved color and species classification method has been developed using RBFNs. Statistics, including histogram, are used as pattern recognition cues.

b) A new kind of radial basis function network is developed for the classification problem of species and colors of the finished wooden components. Every color has its own RBFN in the proposed structure. The proposed structure is discussed in Chapter 3.

c) Several input features such as the color histogram, average values, mean values, and standard deviations of the three colors are employed and tested.

e) The proposed method is less complex than the methods in [1] because RBFNs do not require a great deal of calculation.

1.5 Outline of The Thesis

The following chapters describe the problem and the classification methods that have been implemented by RBFNs. Chapter 2 contains a broad literature review about color spaces, color representations, and classification algorithms. Chapter 3 gives a review of radial basis function networks and their applications. The overview of the experimental system in the Spatial Data Analysis Laboratory at Virginia Tech is presented in Chapter 4. Chapter 5 contains the results of all methods using RBFNs. These methods differ from each other in either the type of input feature used or in the RBFN structure used. Chapter 6 has a conclusion and a comparison between this research's results and the results in [1].