칼라 컴퓨터시각을 利用한 闊葉樹 部材의 色에 의한 選別+

Color Grading of Hardwood Dimension Parts with Color Computer Vision

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摘 要

본 연구는 칼라 컴퓨터시각을 이용하여 가구에 이용되고 있는 활엽수 부재의 색에 의한 선별법을 제시하고자 수행되었다. 붉은 오우크 가구 부재를 대상으로 칼라 컴퓨터시각 시스템을 이용 화상을 얻은후 R,G,B 농도값을 근거로 나무결, 나무결함, 3가지의 색깔 즉 핑크색, 흰색, 갈색의 나무부분, 이밖에 배경에 대한 지식 베이스화를 행하여 각 부재에 대하여 이들의 비율을 quadratic Bayes classifier를 이용 구하였으며, 이 중 나무결, 나무결함, 배경을 제외한 3 가지 색상에 대하여 부재가 갖는 상대적인 비율을 근거로 qadratic Bayes classifier와 neural network를 각각 이용하여 핑크색, 흰색, 갈색의 3가지 부재로 구분하였다. 선별의 정확도는 기존의 육안에 의한 선별을 기준으로 비교하였는데 qadratic Bayes classifier에 의한 선별이 91.7%, neural network을 이용한 선별이 96.7%의 높은 정확도를 보였다. 따라서 가구의 품질향상을 위한 색에 의한 부재 선별에 칼라 컴퓨터시각이 유용하게 이용될 수 있을 것으로 판단되었다.

I. Introduction

In order to improve productivity, competitiveness and quality of wood products manufacture, automation of labor intensive processes is needed.

In recent years, computer vision usage by wood product industries has undergone rapid growth. In manufactuing of furniture, wood dimension parts before assembly often exhibit various surface characteristics : color, roughness, defects, grain patterns and so on. Variability can lower the quality of the wood dimension parts and thus the uniformity and value of the furniture. Sorting parts by color is usually performed by human inspection. It is often difficult for the inspector to grade consistently because of the variability of the wood dimension parts(Huber et al. 1985). Therefore, It is desirable to use a computer vision system to sort the parts.

Many researchers have applied computer vision to wood manufacturing and have studied surface defects detection systems and a variety

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of image processing techniques for identifying, classifying and locating various defects in lumber(Butler et al. 1989 ; Cho et al. 1990 ; Conners et al. 1983,1985,1991 ; Forrer et al. 1989a, 1989b ; McMillin et al. 1984 ; Szymani et al. 1981). Surface roughness measurement for maintaining the quality of wood products has also been studied(Faust 1987 ; Precetti et al. 1992 ; Gibson et al. 1992).

In order to ensure the uniformity of wood dimension parts for improving the quality of furniture, not only defects and roughness but also color is an important feature of the surfaces. The wood surface is very complicated due to the anatomical differences within species and samples. The various wood colors, grain patterns, mineral stain, material and machinery defects must be considered. Therefore, evaluating the color of the wood surface in comparison with standard color is very difficult. Since sorting of wood dimension parts which are perceived as being of similar color classes by human vision needs to be maintained to assure uniformity of furniture and therefore, establishing a method for the automatic sorting is of great importance. Several people have researched color characteristics of wood and proposed color models for extracting useful color information (Brauner et al. 1968 ; Conners et al. 1985 ; Ito et al. 1976 ; Sullivan et al. 1967a, 1967b ; Webb et al 1964). However, a workable approach on sorting wood by color for automated wood processing using computer vision has not yet been made.

A color computer vision approach for color sorting of a wood dimension part was established in order to improve the quality of furniture and results are presented.

II. Materials and Method

Computer vision system

The computer vision system used for image acquisition and processing is shown in Figure 1. A Data Cube Max Vision AT－1 image processing system was used as an image processor and hosted by an IBM－AT compatible Fivestar 286 personal computer. The Max Vision AT－1 image processor can process 512 * 512 pixels 8 bit images in the red, green, and blue spectral bands which make up an RGB color space. A Sony M－852 CCD color camera was used as a vision sensor which has red, green, blue, and composite analog signal outputs. Images were displayed on a 19″ Sony Trinitron model PVM－1910 color video monitor and image data were stored in a hard disk of the host computer and transferred to a SUN SPARC workstation for evaluating the color class of a wood dimension part.

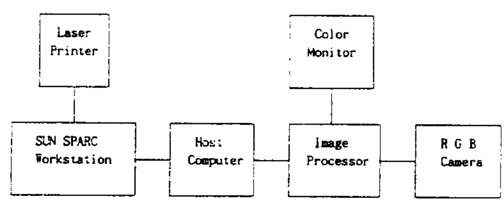

Fig. 1. The computer vision system used for image acquisition and processing.

Image acquisition

Sixty red oak dimension samples were obtained randomly from an Indiana wood manufacturing company and classified by human inspection into three different color classes : white (14), pink(33) and brown(13) color class, respectively. Images of samples were acquired by the computer vision system in the range of red

(R), green(G) and blue(B) spectral bands under normal room lighting conditions using fluorescent lamps and black paper as background.

Image analysis-multi-stage classifier

In order to investigate the color characteristics of wood, mean gray valus, standard deviation of gray values and gray level histograms in R, G and B spectral bands were obtained.
The surface of wood has various color, grain patterns, mineral stain, material and machinery defects and their colors are different from each other. Through consideration of color variability of each part, color evaluation of the wood dimension part should be made. In this paper, two-stage classifications were carried out to evaluate the color class of wood dimension parts. Figure 2 shows the overall image analysis procedure for separating the parts by the color described in this study.

For the first stage classification, a three-dimensional knowledge base, a quadratic Bayes classifier was built and images of wood dimension parts were classified into six classes : background, defects, grain patterns, white, pink and brown color wood parts. The number of pixels and percentage in each class in an image were obtained and the relative percentage values among white, pink and brown color wood parts, except background, defects and grain, were calculated for the second-stage classification.

In order to eliminate the complexity of classification, the relative pecentage values of white, pink and brown color wood parts were used for the second-stage classification. Classifications for evaluating color class of the wood dimension parts were performed with the quadratic Bayes classifier and a neural network. Neural network simulation software used in this research was Nets(Baffes, 1989). The neural network was configured as a three layered back-propagation network including input, hidden and output layers. The input layer was composed of a 1 x 7 array of binary coded units. Input codes were made based on a comparision among the relative percentage values of white, pink and brown color wood parts and their ranges as shown in Table 1. The hidden layer had 14 nodes and the output layer had 2 nodes. Table 2 shows the output layer codes based on the color classes of wood dimension parts.

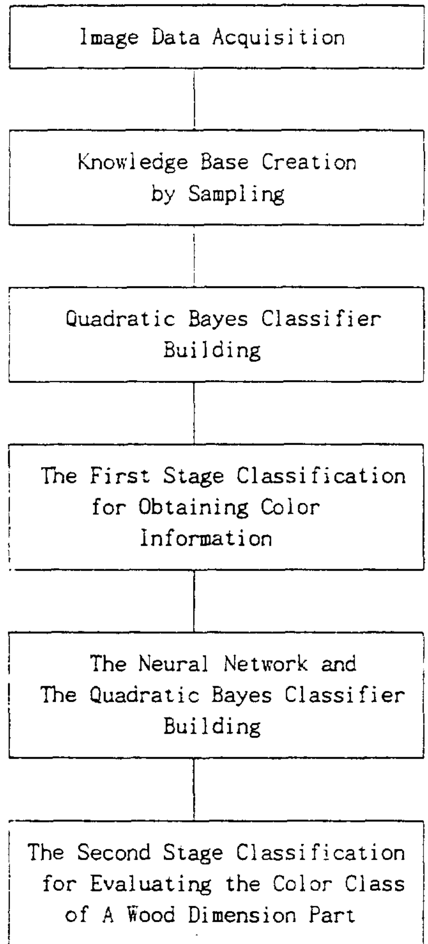

Fig. 2. The overall image analysis proceduce for wood dimension parts grading by color.

Table 1. Input layer codes of the neural network.

Comparison of percentages	Code	Range of Percentages	Code
W≥B>P or W>B=P	000	L≥70% and M≤30%	0000
W≥P>B	001	70%>L≥60% and 40%≥M≥30%	0001
P≥B>W	010	70%>L≥60% and 30%>M>15%	0010
P>W>B	011	60%>L≥55% and 45%≥M≥35%	0011
B>W≥P	100	60%>L≥55% and 35%M≥25%	0100
B>P>W	101	60%)L≥55% and 25%>M>20%	0101
W=P=B	110	55%>L≥50% and 50%≥M≥40%	0110
		55%>L≥50% and 40%>M≥30%	0111
		55%>L≥50% and 30%>M>22.5%	1000
		50%>L≥45% and 50%>M≥40%	1001
		50%>L≥45% and 40%>M≥30%	1010
		50%>L≥45% and 30%>M>25%	1011
		45%>L≥40% and 45%>M≥40%	1100
		45%>L≥40% and 40%>M>27.5%	1101
		40%>L≥33.3% and 40%>M≥35%	1110
		40%>L≥33.3% and 35%>M>30%	1111

* W,P,and B letters indicate the relative percentage values of white, pink, and brown colored wood dimension parts, respectively.

** L and M letters indicate the largest and second largest percentage values, respectively.

Table 2. Output layer codes of the neural network.

Class	Code
White	00
Pink	01
Brown	10

The neural network was trained until it derived an error less than 10%.

III. Results and Disscussion

Images of the wood dimension parts in R, G and B spectral bands consist of small pixels with different gray values from 0 to 255. The gray values in each R, G and B channel reflect the color of a wood dimension part. As a base for comparison of the color of a wood dimension part, the averages of mean gray values of three different wood colors are shown in Table 3. The wood dimension parts were classified with the quadratic Bayes classifier to white, pink and brown color classes based on the mean gray values in R, G and B spectral bands. Classification results are shown in Table 4. The overall classification accuracy was 81.67% and most misclassifications occurred between pink and brown. Therefore, if a wood dimension part had no defects and uniform grain, it could be possible to separate the wood dimension parts into different color classes based on mean gray values. However, wood dimension parts usually include various grain patterns and defects. Mean gray values of the images are affected by these grain patterns and defects.

Table 3. Mean of average gray values of white, pink, and brown color wood dimension parts.

Wood Dimension Part	Spectral band		
	R	G	B
White	166	136	91
Pink	160	125	81
Brown	156	122	78

Table 4. The classification results with the quadratic Bayes classifier based on mean gray values of the images in R, G, and B spectral bands.

Wood Dimension Part	Color Class		
	White	Pink	Brown
White	12	2	0
Pink	0	29	4
Brown	1	4	8

Because a wood dimension part has various colors of grain patterns, defects and wood parts and their colors are slightly different even within a single wood dimension part, it was very difficult to find threshold values for image classification and to extract color information from the histograms in R, G and B bands.

To extract the color informations from a wood dimension part, The first stage classification was performed by classifying the images of a part with the quadratic Bayes ciassifier using the knowledge base. A knowledge base for building the quadratic Bayes classifier was established first by sampling images of wood dimension parts. Table 5 shows the mean gray values of the knowledge base from six classes : background, defects, grain, white, pink and brown color wood parts. Gray levels were different from each other in R, G and B spectral bands. Using this knowledge base, the quadratic Bayes classifier was built. Resubstitution and "leave one out" errors of the classifer were 3.47% and 3.50%, respectively.

Table 5. Mean gray values of the knowledge base.

Class	Spectral Band		
	R	G	B
Background	46	40	39
Defects	111	76	46
Grain Patterns	142	104	62
White Wood	170	146	105
Pink Wood	171	134	89
Brown Wood	157	126	82

The images of wood dimension parts were classified with the quadratic Bayes ciassifier into six classes and their class ratio percentages were calculated. The average relative percentages of white, pink and brown color wood parts except background, defects and grain patterns in white pink and brown wood dimension parts are shown in Table 6. In the white color wood dimension parts, it appeared that they included a lot of pink and brown color. However, in pink and brown color wood dimension parts, pink and brown colors are the largest percentages, respectively. And though defects and grains percentages were not used for sorting parts in study, it was considered that these percentages can be used for determining defects or a more precise classification of parts.

Using the relative percentages of white, pink and brown color wood parts, the second-stage classification was performed with the quadratic Bayes classifier and the neural network. Table 7 shows the classification result with the quadratic Bayes classifier. Five parts were misclassified and the overall classification accuracy was 91.7%. One white, two pink and two brown

Table 6. Average relative percentages of white, pink, and brown color wood parts in white, pink, and brown color wood dimension parts.

unit : %

Wood Dimension Part	Wood Part		
	White	Pink	Brown
White	32	39	29
Pink	5	59	36
Brown	2	25	73

wood dimension parts were misclassified compare with a human classification.

Table 7. The classification results with the quadratic Bayes classifier.

Wood Dimension Part	Color Class		
	White	Pink	Brown
White	13	0	1
Pink	0	31	2
Brown	0	2	11

Classification results by the neural network are shown in Table 8. Two pink wood dimension parts were misclassified by the neural network and overall correct classification percentages was 96.7%. The classification accuracy was slightly better than that of the quadratic Bayes classifier.

Table 8. The classification results with the neural network.

Wood Dimension Part	Color Class		
	White	Pink	Brown
White	14	0	0
Pink	0	31	2
Brown	0	0	13

One of misclassified pink dimension parts showed low gray values in R, G and B spectral bands due to its rough surface. So, it is considered that the roughness of a wood surface affects the results of classification and maintaining uniform surface roughness is important for color sorting of wood dimension parts by computer vision.

Most of the misclassification of wood dimension parts were between the brown and dark pink ones due to little difference in R, G and B gray values. Therefore, a change of the lighting condition or use of a color camera with filter is recommended for more exact color sorting.

Ⅳ. Conclusion

In order to improve the quality of furniture, maintaining the uniformity of wood dimension parts before assembly is important. In this paper, a color competer vision approach for sorting wood dimension parts by color was attempted. Images of red oak wood dimension parts were classified with the quadratic Bayes classifier and the neural network into 3 different color classes : white, pink and brown. Their classification accuracies were evaluated. It was shown that color computer vision can be used in sorting wood dimension parts by color thus improving the quality of furniture.

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