

Colour Sorting of Red Oak, Yellow Poplar and Maple Veneers using Self-Organizing Map: Comparisons between Different Camera Genres

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Research Article

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Posted Date: August 1st, 2022

DOI: <https://doi.org/10.21203/rs.3.rs-1892867/v1>

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Title

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Abstract

Colour sorting is a vital process in manufacturing of high-quality wood products, however hitherto a relatively manual process in majority of facilities in Malaysia. Automation is an ideal solution; however, costs are prohibitive for small-medium industries (SMI). Thus, this project aims to produce a flexible solution that can cater for different scales of manufacturers. Three cameras of different price ranges are used: i) Hikrobot® MV-CE200-10UC (Hikrobot), ii) Logitech® C920 (Logitech), and iii) Sony® RX0 II (Sony). Having set up a veneer imaging prototype, human sorted images of American red oak (*Quercus rubra*), yellow poplar (*Liriodendron tulipifera*), and maple (*Acer* spp.) are acquired. After performing image preparations and calibrations, 26 features are extracted from each image. The features are based on the average and standard deviation of the wood basal colour and wood grain colour. The salient features are obtained using the Sequential Forward Selection (SFS) method. The most salient features are then used to train a Self-Organizing Map (SOM), and the resulting maps are observed. From results, it is affirmed that the colour of the basal colour is highly correlated with human sorted colour groups. As expected, Hikrobot topped the charts being of industrial grade. It is interesting that Logitech exhibited comparable performance. Sony performed the worst due to software limitations. This proposed system can achieve accuracy of 89.0% for red oak, 94.3% for poplar and 96.4% for maple. This research will assist the SMI to develop an affordable vision system for colour sorting.

Keywords: colour sorting; natural veneers; red oak, yellow poplar, maple; sequential forward selection, linear discriminant analysis; self-organizing map

69 **1. Introduction**

70 Wood is a natural material that, thus manmade wood products inherit the vast natural variations
71 present in the timber they are made from. Colour sorting of wood is a labour-intensive operation in
72 most modern woodworking mills in Malaysia. Maintaining the consistency of the sorting output is also
73 challenging largely due to human factors such as the different judgements of colour similarities
74 between different workers, fatigue, and the ever-revolving labour workforce.

75 There is a recent shift towards using computerized vision system to replace manual colour sorting.
76 Existing industrial equipment in the marketplace are prohibitively expensive, therefore there is a need
77 for solutions that are more affordable especially for the small and medium woodworking industries
78 that may not be able to justify purchase of solutions from established players such as WoodEye
79 (Microtec Linköping, Sweden), Wood Inspector (Poland) and Weinig AG (Germany).

80 The two most critical elements in any vision system are the sensor hardware (camera system)
81 and the software. The camera system (sensor and lighting) determines the quality and consistency of
82 the image obtained, while the software does all the necessary image enhancement, feature extraction
83 and classification of the images.

84 In previous studies, area scan cameras are by far the most common in the realms of research
85 (Bianconi et al., 2013; Kurdthongmee, 2008; Nurthohari et al., 2019) as they are easier to setup.
86 However, obtaining evenly lit images requires the use of dome lights. Alternatively, the image had to
87 be cropped to where the light intensity is most even. Line scan setups (Wang et al., 2021; Zhuang et
88 al., 2021) are far superior in terms of obtaining even illumination, with the added advantage of being
89 able to acquire long lengths of timber in a single frame without needing the additional work of
90 stitching the images together. Line scan setups are also the most common setup in industrial
91 applications due to their higher speed capabilities.

The species in focus of past research correlates very closely to frequently used wood in woodworking mills. Images taken of wood in most scientific literature are typically that of solid timbers. In colour studies, oak (*Quercus* spp.) appeared to be the most popular specie, which correlates with its popularity as the most popular hardwood specie in the Western hemisphere, particularly Europe (Krackler et al., 2011) and the United States (Barbu & Tudor, 2021; Tan & Ng, 2019). Several others focus on high value species such as teak (*Tectona grandis*) and cherry (*Prunus* spp.), and European beech which is a popular specie in Western Europe (Krackler et al., 2011).

Earlier studies have used typical image processing and classification methods. In general, the features from the image can be separated into colour features and texture features. Among those different techniques using colour features are the use of raw colour histograms (Kurdthongmee, 2008), or computation of histograms such as soft colour descriptors, colour percentiles, marginal histograms and 3D colour histograms (Bianconi et al., 2013), and homogeneity, slope and entropy (Shivashankar & Madhuri, 2018). For those employing texture features, Histogram of Oriented Gradient (HOG) (Nurthohari et al., 2019) and colour moments (Wang et al., 2021) were used. In terms of classifiers, clustering methods such as K-Nearest Neighbour (kNN) (Bianconi et al., 2013; Shivashankar & Madhuri, 2018; Wang et al., 2021) and Self-Organizing Map (SOM) (Kurdthongmee, 2008) are popular. Other common classifiers such as Fuzzy Logic (J. Faria et al., 2008) and Support Vector Machine (SVM) (Nurthohari et al., 2019) had also been employed.

Also, from anecdotal exchanges of ideas with woodworking personnel, we strongly believe the basal wood colour plays a large role in the overall colour of the wood, while the grains (amount of it, and how dark it is) plays only a secondary role. Two pieces of wood with similar basal colour but different amounts of grain are deemed more similar than two pieces with similar grains but different basal colour.

Based on our review, no attempts had been done to compare the ability of different cameras in performing colour classification of wood, and none are performed on raw veneers. Studies on the

performance of cheaper camera alternatives may be useful in future development of more affordable solutions for small workshops. In this paper, we aim to compare the colour sorting performance between different camera genres, namely an industrial grade camera, a prosumer action camera, and a webcam. The performance of the camera will be tested by checking its ability to have its images classified correctly. Images of raw veneers from three species shall be used: i) American red oak (*Quercus rubra*), ii) yellow poplar (*Liriodendron tulipifera*), and iii) maple (*Acer* spp.). Features extracted are soft colour descriptors (mean and standard deviation) of the basal wood colour and grain colour. From these descriptors, salient features are found using the Sequential Forward Selection (SFS) method. Finally, the SOM classifier are used to gauge and compare the performance of the different cameras. Methods used in this paper shall also be instructive in testing other cameras such as handphone cameras, etc.

2. Materials and Methods

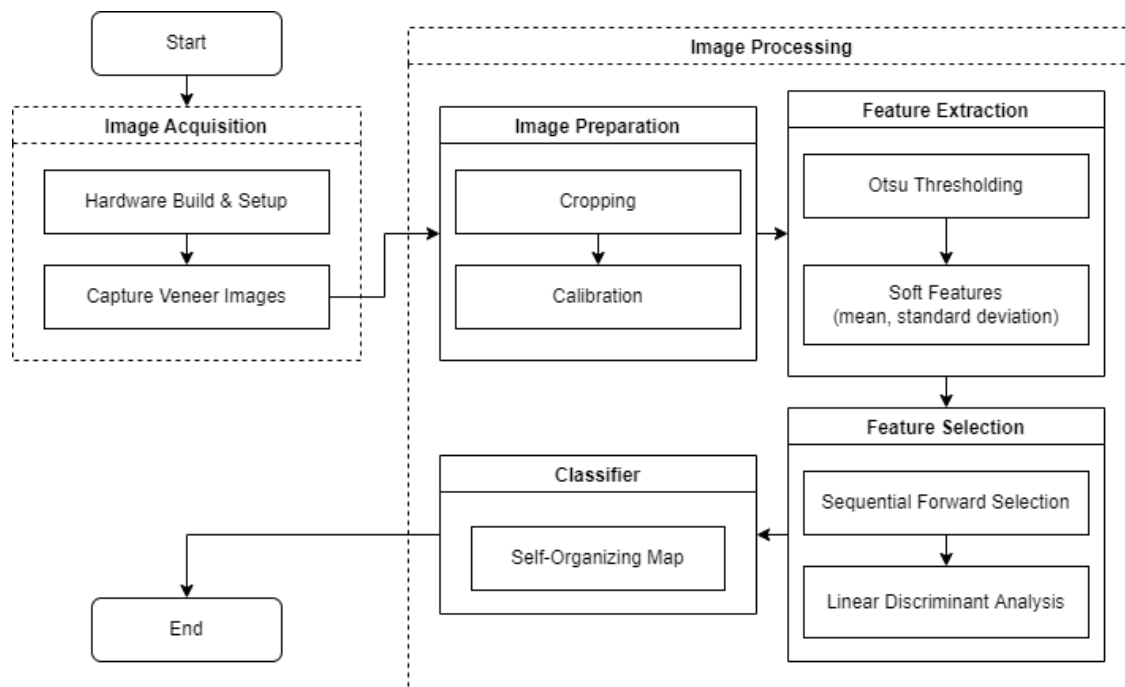


Figure 1 Flowchart of methodology for wood colour sorting system.

In this section, the overview of this research's methodologies is presented here, summarized in Figure 1. There are two major components in this study, namely: i) image acquisition (the hardware), and ii) image processing (the software).

2.1. Image Acquisition

2.1.1. Hardware Build and Setup

An image acquisition rig is constructed as per Figure 2. Since veneers are rarely flat, a flat dome light is used (CCS LFXV-300SW) with a 300 x 300 mm aperture placed 28 mm to the veneer surface to avoid any shadows that may arise due to undulations on the veneer surface.

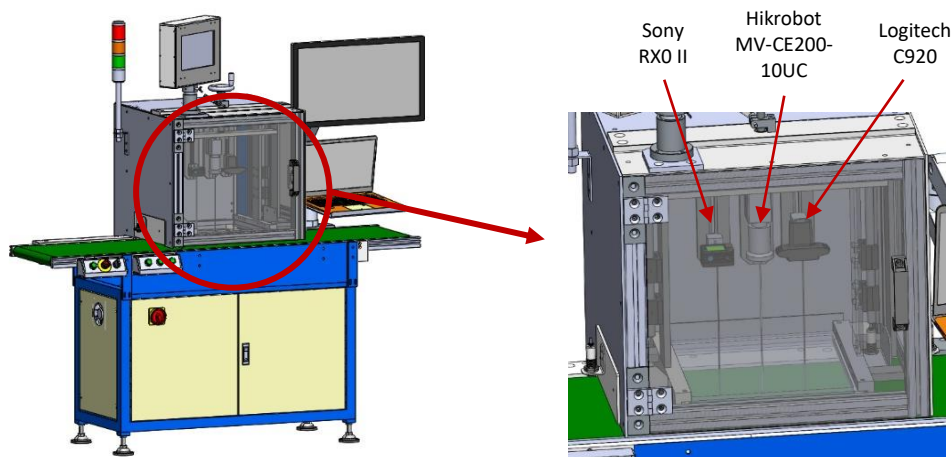


Figure 2 Test rig used to acquire images

Three cameras selected for this study, each selected to represent the three common genres of cameras, namely the Logitech C920 (Logitech), Sony RX0 II (Sony), and Hikrobot MV-CE200-10UC (Hikrobot). For expedience, the three cameras are set up inline along the axis of the conveyor. The industrial camera is positioned in the middle, while the other two, having wider fields of view, are located on either side of the industrial camera.

2.1.2. Capture Veneer Images

Red oak, yellow poplar, and maple veneer samples were obtained, generously provided by Weng Meng Industries Sdn Bhd. Images were taken over six different dates to capture images from different batches of incoming veneers as shown in Table 1. The veneers had been pre-sorted by human workers (factory staff), and the colour groups of each image taken is noted. A total of 1,289 distinct images of veneers had been obtained for each camera (totalling 3,867 imaged for three cameras).

Prior to each image acquisition session, images of X-rite Colorchecker Passport Photo 2 (Colorchecker) colour reference target are taken by each camera for purposes of calibrating the session's images. Use of a colour reference for calibration is vital in colour research using cameras (Bianconi et al., 2013) as different cameras and lighting produces different image response curves.

Table 1 Sample images taken per camera, broken down by human-classified colour groups*, for red oak, yellow poplar, and maple

Date	Red Oak				Yellow Poplar			Maple		
	D	O	W	Y	D	W	Y	R	W	Y
10/3/2022		14		43	11	39	22			
21/3/2022					27	26	20			
31/3/2022	64	42	37	37	37	62	46	67	60	
20/4/2022	50	59	50	76				63	47	47
28/4/2022	46									51
12/5/2022					40		46			63
Subtotal	160	115	87	153	115	127	134	130	107	161
Total		515				376			398	

* D = Dark, O = Orange, R = Red, Y = Yellow, W = White

2.2. Image Processing

All analyses are performed using MATLAB ver 9.12 (R2022a) on two PCs with the following specifications: i) Intel® Core™ i7-9700 CPU with 16GB RAM, and ii) Intel® Core™ i7-11700 CPU with 16GB RAM.

2.2.1. Image Preparation

The preparation step is a vital one that prepares all the images so that features can be better extracted. Image preparation involves two steps: i) extraction of wood image (remove the background), and ii) colour calibration using the Colorchecker.

For extraction, the image is first standardized by locating the common boundaries in images of the same wood taken by the three cameras where they overlap. This is done by taking photos of the same measuring tape and using these images to determine the image's relative position to each other. Boundaries are also adjusted to exclude any visible 'feathering effect' caused by the edges of the dome light. Images are then crop to those boundaries.

To remove unwanted backgrounds from narrow veneers (where conveyor is still visible in the frame), the image is analysed slice by slice and analysis of moving average's gradient of the red channel is used to determine where the edges of the veneers are, as summarized in Figure 3.

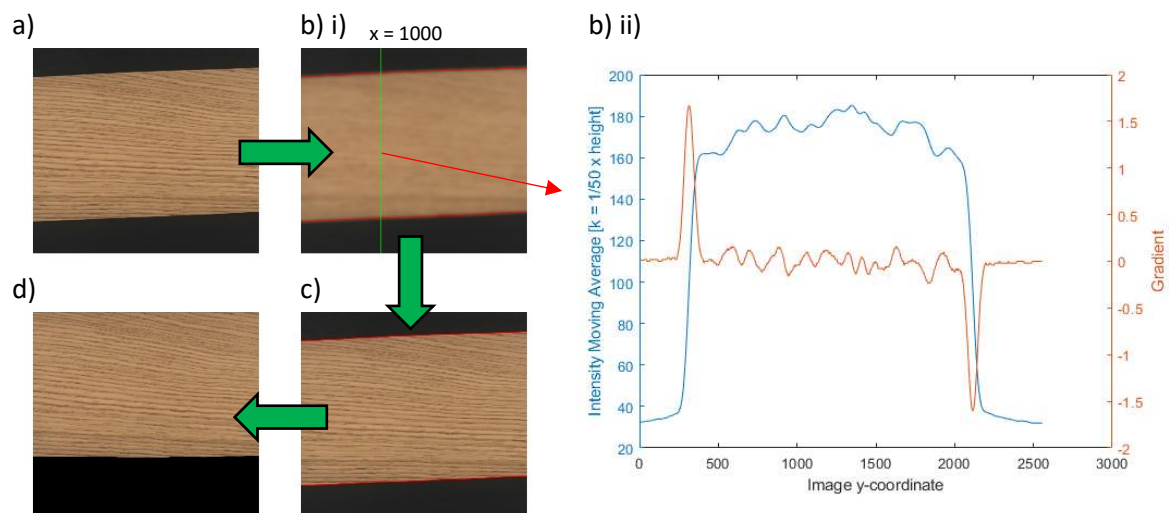


Figure 3 The moving average gradient analysis process, where the a) original image is b) Gaussian blurred, and each x-coordinate slice's moving average red channel intensity gradient (shown here b) ii) is for plot $x = 1,000$) is analysed, and the minimum and maximum of the gradient plot is deemed where the c) transition from conveyor to wood is, and the image is then d) top justified with the remaining regions under the wood set to $[R, G, B] = [0, 0, 0]$

Using images taken of the Colorchecker, all images taken during each day session are colour calibrated to the chart from the first day as reference. The colour values of each reference point on the Colorchecker on each day are correlated with the values of the reference image and the graph is

observed for any deviations from parity. These deviation values are then used to perform correction on all images taken on that particular day.

Images acquired from the Hikrobot camera underwent an additional gamma correction process ($\gamma = 1 / 2.2$) to convert all acquired images from their linear encoded gamma to gamma encoded images to better emulate human visual response curve to light intensities. Both Sony and Logitech cameras, as with most consumer camera products, produce JPEG files, which by convention are already gamma encoded images. Next, using Hikrobot calibration image as reference, all images taken from Logitech and Sony are then adjusted to best fit the reference Hikrobot plot with the assumption that the plots are linear.

2.2.2. Feature Extraction

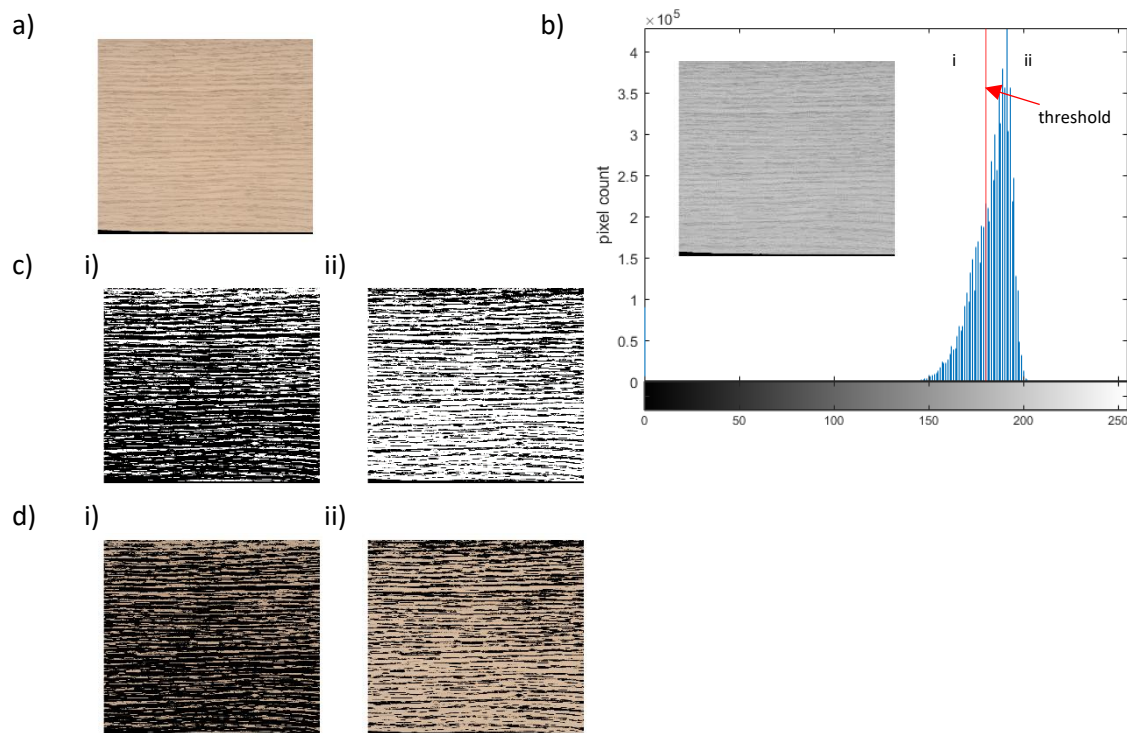


Figure 4 OSCD starts with a single Otsu thresholding of the same a) original image and b) grayscale histogram, where each bifurcated halves i) (lower colour stratum) and ii) (upper colour stratum) is converted into bit masks c), which are then used to d) extract the colour layers from the original colour image

The technique we are employing for feature extraction is what we term as Otsu Soft Colour Descriptors (OSCD). Figure 4 shows the steps for this method. The raw image (Figure 6a) is converted into grayscale. Then images' grayscale cumulative histograms are split into two intensity strata using Otsu thresholding as shown in Figure 4 b). We assume (based on our assertion that there are two colour groups in the image: 'basal' and 'grain') that the overall histogram consists of two overlapping normal distributions – one that of the basal wood colour (higher intensity), and one that of the grains or any darker streaks on the wood (lower intensity). Depending on specie, the basal colour largely overwhelms the grains, and their mean intensities may be close together, but the bimodality of the plot is assumed to be present. Since Otsu searches for thresholds that bisects the histogram where the interclass variance is the largest, the threshold that it returns should be indicative of where the basal wood intensity and the wood grains bifurcate. It must be emphasized that we are not strictly looking for the bottom of the valley of two peaks, but to determine the separation of basal wood from its grains from a combined distribution of intensities from two unequal normal plots.

Table 2 Indices of the 26 features extracted from each image and their description

Description	*[R, G, B] descriptor	Feature index number	
		Full resolution	Half resolution
Otsu threshold		1	2
Lower colour stratum	$[\mu_R, \mu_G, \mu_B]$	[3, 4, 5]	[9, 10, 11]
	$[\sigma_R, \sigma_G, \sigma_B]$	[15, 16, 17]	[21, 22, 23]
Upper colour stratum	$[\mu_R, \mu_G, \mu_B]$	[6, 5, 8]	[12, 13, 14]
	$[\sigma_R, \sigma_G, \sigma_B]$	[18, 19, 20]	[24, 25, 26]

* μ = mean, σ = standard deviation

Based on the separation threshold as shown in Figure 4 b) found using the Otsu method, the wood pixels can be classified as lower colour stratum, Figure 4 c) i), and upper colour stratum, Figure 4 c) ii). Their corresponding pixels in the original image are then extracted into lower and upper strata as can be seen in Figure 4 d). Based on Figure 4 d), the colour histograms for R, G and B are extracted, and their respective means and standard deviations are calculated and used as features. The images

are then halved in resolution, and their Otsu thresholds and soft colour descriptors are obtained. Indices of each feature are indicated in Table 2.

2.2.3. Feature selection

Reducing the number of features can facilitate data understanding and reduce the computational load (thus, processing time) for practical applications. Furthermore, it may improve performance due to the well-known ‘curse of dimensionality’ and the requirements of requiring a larger training set. The Sequential Forward Selection (SFS) method is well known to be an exemplary method for feature selection. Since the SFS is a wrapper method of selecting feature, a classifier must be implemented together. The Linear Discriminant Analysis (LDA) classifier is a simple classifier that gives acceptable performance in most cases. Since the SFS approach will first find the single feature that gives the best performance. The winning feature will then be paired with another feature to find the best combination of a pair of features. This process will be repeated until the stopping criterion is met. The stopping criterion can be N number of features or reaching a certain accuracy or if there are no more improvement in the accuracy even if more features are added. For this study, the first ten combination of features are found.

In this study, the five-fold cross validation approached is used to find the winning features. The data set is first split into five approximately equal sizes. Four of the sets are used for training the LDA while the remaining set is used for testing to gauge the performance of different feature combinations. This is repeated four times so that all the sets are used as testing sets at least once. The final performance is the average performance of all the five testing sets.

2.2.4. Classifier

Self-Organizing Map (SOM) is a very popular unsupervised classifier first described in the 1980s (Kohonen, 1982). It is an artificial neural network that can be used to reduce the dimensionality of a huge dataset into an easily visualizable two-dimensional map. It works by first looking for the closest

node to the training dataset, and then updating weights of that node and its surrounding nodes (called neighbourhood) to approach that dataset at a certain training rate. This is iterated across the entire dataset, and then reiterated multiple times with a decaying neighbourhood size and training rate. This is sometimes termed as competitive learning, as nodes that have more training datasets associated with it or within its neighbourhood will form clusters. Hence, similar datasets nodes tend to cluster together, while different ones will cluster further away, forming chasms in between these clusters.

There are several ways to determine where each group is in the training set. One is by taking these training datasets and have them manually labelled (for instance, its wood colour group) and fed into the trained map grouped by the labels (the same colour group). Where majority of these similarly labelled training datasets appear in the map shall be where the clusters are most closely associated with that particular label.

To test an unknown sample, its weights just need to be compared with each node's weights. The closest node, also known as Best Matching Unit (BMU) is where the sample reside, and if the map had already been labelled, the sample belongs to that labelled group. Therefore, SOM is computationally very light and fast (complexity $O(1)$), suitable for deployments where speed is necessary.

In this study, salient features derived from SFS shall be used in training the SOM, and that shall be compared with the performance of full feature dataset. Performance is measured by observing map of each human categorized colour group plots and perform a count on misclassifications. A naïve winner-takes-all approach is employed – the colour group with the most members in the node shall occupy that node (node shall be classified as that colour), and any other colour group members with lesser numbers falling in that node shall be counted as misclassifications. The conformance rates (which is the complement of misclassification rates) are observed, and this shall be repeated for different numbers of SOM epochs.

3. Results and Discussion

3.1. Calibration

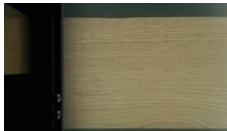
Table 3 shows the calibration parameters to correct for the drift that was found on each of the equipment's colour channels. Logitech performed reasonably well, within 1% of the reference values respectively. After adjustments, Logitech showed very close conformance to Hikrobot's reference points.

Table 3 Colorchecker calibration points' correlation plot percentage drift

Date	Hikrobot			Logitech			Sony		
	R	G	B	R	G	B	R	G	B
10/3/2022*	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
21/3/2022	82.1	99.5	83.7	99.7	99.7	100.0	99.9	100.0	100.0
31/3/2022	99.9	99.5	98.4	99.5	99.6	99.8	98.0	98.0	97.8
20/4/2022	99.5	98.7	97.6	100.0	100.0	100.0	99.2	99.2	99.3
28/4/2022	98.6	98.0	96.6	100.0	100.0	100.0	94.4	94.3	94.0
12/5/2022	97.6	97.9	96.9	100.0	100.0	100.0	97.2	97.3	97.2

* calibration reference target

Table 4 Sample oak veneer images undergoing the image preparation processes

Step	Hikrobot	Logitech	Sony
Original			
Cropped			
Wood Extraction			
Colour Calibrated			

However, Sony's plot was very scattered, and there are signs that the image may have been overexposed. Because the parts of the field of view of the camera include dark areas in the rig, this is evident that some form of high dynamic range, exposure compensation or white balancing is being performed on the image. Therefore, adjustment parameters derived from the reference image worked poorly with the actual wood image for Sony, while Hikrobot and Logitech worked extremely well and looked very similar to each other, as can be seen in Table 4.

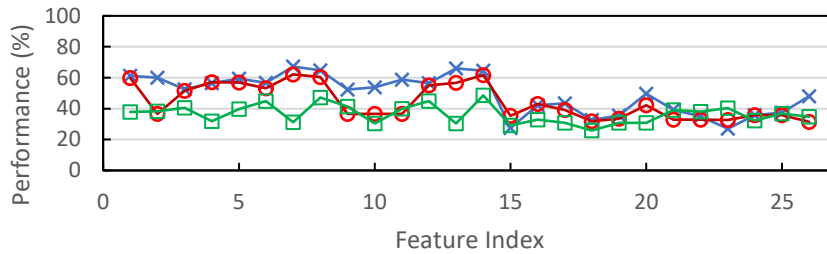
There appeared to be slight drifts in calibration images for all the cameras on different days of image acquisition. This could be because the use of a laptop and a PC on different occasions (both Hikrobot and Logitech are powered via USB). Within the same day, minimal drift is observed. Also, quite surprisingly, Logitech offered the highest consistency in terms of colour stability. This also means the drift is unlikely to be due to the lighting which would affect all three cameras similarly. Hikrobot experienced an inexplicable large dip on the second day of data collection, which highlights the need for some form of calibration to be performed prior to each run, even when using an industrial grade camera.

3.2. Feature Selection

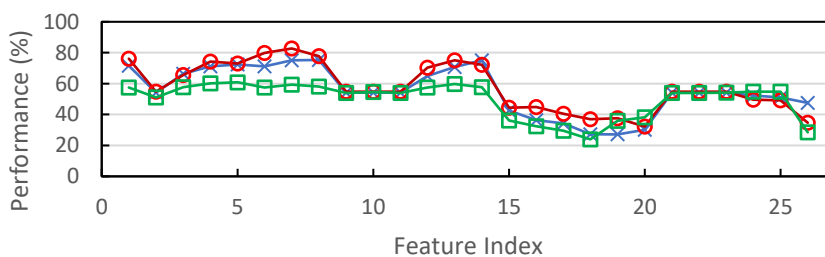
Figure 5 shows the performance of the 26 individual features for the different cameras and species. Performances of Logitech and Hikrobot are similar while Sony exhibited the worst results of the three cameras with belligerent performance – reasons for this shall be discussed. Among the features particularly for Logitech and Hikrobot, we see dips in performance in features 9 to 11 – this corresponds to the lower strata [R, G, B] values, which is in strong agreement with our assessment that grain colour is poorly correlated with human perceived colour similarity. Also, elevated performance is noted around features 3 to 8 (full resolution [R, G, B] values, both stratum), and features 12 to 14 (half resolution [R, G, B] for upper strata), with most plots scoring peaks at feature 7 for Hikrobot and Logitech. This shows that differences in feature 7, which is green intensity value of the upper strata (basal colour at full resolution, is what humans distinguish best between the different

colour groups. This is consistent with the fact that in human psychophysiology, our eyes are most sensitive to green light (Dowling, 1987).

a)



b)



c)

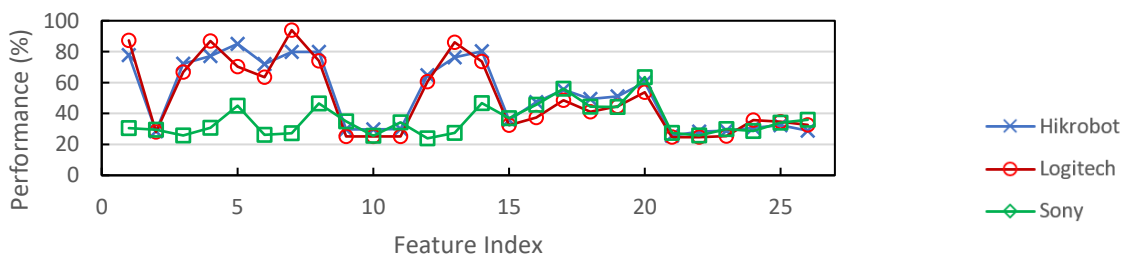


Figure 5 Individual feature's performance plot of different cameras for a) red oak, b) yellow poplar, and c) maple; indices are as described in Table 2

Individual features are not necessarily ideal features to use in isolation, and combinations of features may produce better results. Figure 6 shows the best performance values of the different numbers of combination of features selected from SFS when applied using the five-fold cross validation of the different cameras on the different type of wood. It is evident that Hikrobot performed the best for red oak and maple, while Logitech performed the best for yellow poplar. Only four features were required to reach the optimal performance for Hikrobot and Logitech. Sony on the other hand required up to eight features to reach its optimal performance. It is interesting to note that, with

close agreement to conventional wisdom, smaller subsets of SFS selected features performed better compared to using all features.

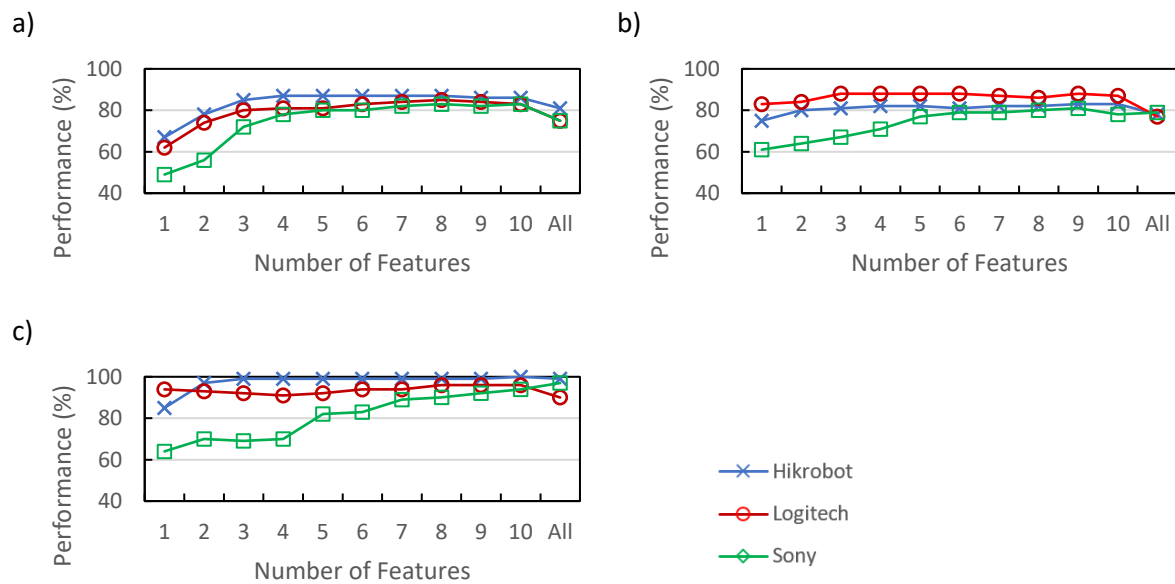


Figure 6 SFS performance of the different cameras for a) red oak, b) yellow poplar, and c) maple, for one to ten selected features scoring the highest, as well as results if all features were used in the selection

Based on ranked features (Table 5), similar to observations of individual feature performance results in Figure 5, feature 7 is the dominant feature to use, followed by feature 6 (which is red intensity of the upper strata at full resolution). Red is the most common colour component in brown (pure brown defined as $[R, G, B] = [128, 64, 0]$), which is the dominant colour in wood.

Table 5 Top five (5) ranked features for each specie for each equipment*

Rank	Feature Index								
	Red Oak			Yellow Poplar			Maple		
	H	L	S	H	L	S	H	L	S
#1	7	7	14	8	7	5	5	7	20
#2	6	6	13	7	14	9	4	15	17
#3	5	25	6	5	13	10	2	4	16
#4	4	3	5	20	26	11	3	20	11
#5	1	21	1	17	5	3	1	6	10

* H = Hikrobot, L = Logitech, S = Sony

It is evident from results in **Error! Not a valid bookmark self-reference.** that for Hikrobot, red oak's yellow and white categories are easily confused with each other, as do the dark and orange categories. For yellow poplar, likewise, white and yellow veneers are easily confused, but there's also some overlap in categorization between yellow and dark. This is a perfect illustration of the problems associated in trying to segregate an entire spectrum of wood colour available in nature into extremely limited bins where specimens with boundary characteristics present a wide band of ambiguity.

Table 6 Confusion matrix for the different species for Hikrobot where the columns are for human categorized groups, and rows are categorized by SFS

Specie	Colour Group* Confusion Matrix (count)				
Red Oak		D	O	W	Y
	D	154	27	0	0
	O	6	88	0	1
	W	0	0	83	15
	Y	0	0	4	137
Yellow Poplar		D	W	Y	
	D	91	0	12	
	W	2	118	8	
	Y	22	9	114	
Maple		R	W	Y	
	R	130	4	0	
	W	0	103	0	
	Y	0	0	161	

* D = dark, O = orange, R = red, W = white, Y = yellow

Additionally, we can see that white and dark groups are almost always mutually exclusive (no confusion) except for two outlier cases with yellow poplar, which lends us confidence on the viability of the features used in this study. The two outliers could be mis-categorization on the part of human assessors.

The performance garnered from using this technique of feature selection shows that the features used can reproduce very closely the colour segregation of veneers done by humans. This also shows that Otsu thresholding can reliably split the wood histogram into two colour groups that represent the basal wood colour and the grain colour. It must be acknowledged that there are many thresholding techniques available in the image processing toolkit, and there is scope for future studies to test these

different variations. Also, this technique has only been tested on red oak, yellow poplar, and maple, and may not be a universal feature of all species of timber. Having said that, most timber species have similar characteristics, so this may well work in a large majority of situations.

3.3. Self-Organizing Map

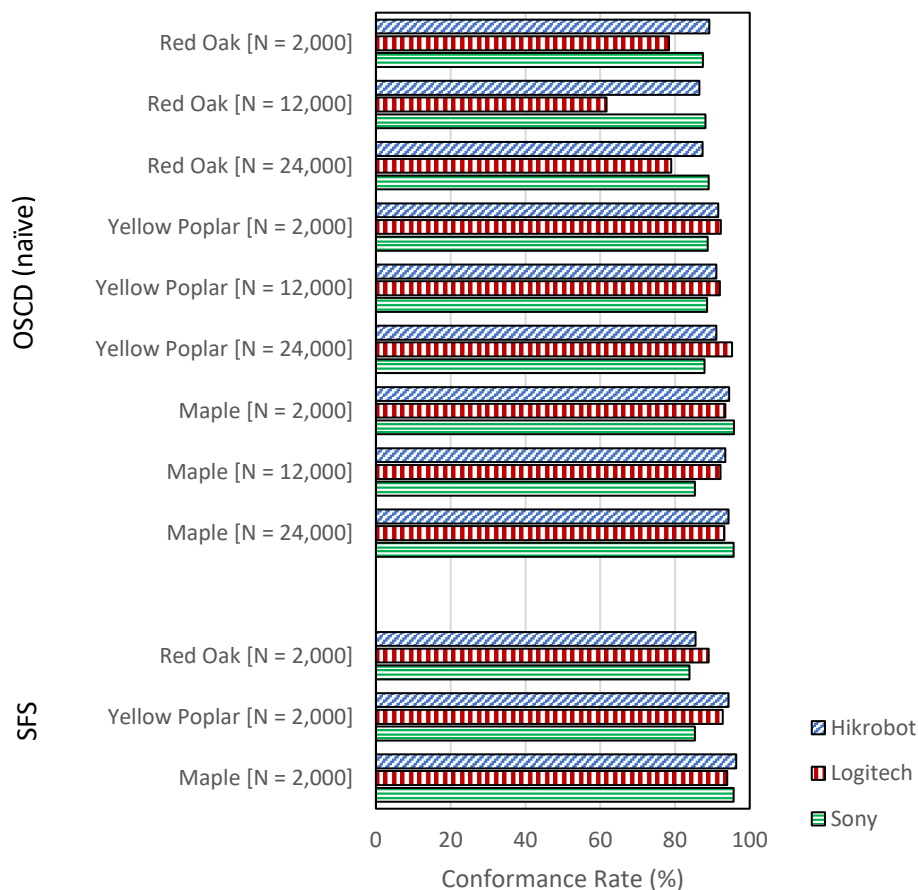


Figure 7 Performance comparison based on human-SOM classification rate of conformance

Figure 7 exhibits the performances measured by conformance rate of various SOM epoch numbers, as well as naïve feature set versus SFS selected feature set. Increasing the number of training epochs does not improve overall performance, in fact to its detriment in most cases. Also, SFS feature set clearly trumps that of naïve feature set, which goes to show targeted set of features outperforms a full dataset (as suggested by LDA results). Overall, our suggested setup can achieve 89.0% for red oak (Logitech), 94.5% for yellow poplar (Hikrobot) and 96.4% for maple (Hikrobot).

The map for the highest scoring configuration, which is maple using SFS feature set on the Hikrobot camera, is shown in Figure 8. It can be seen in the map that the colour groups are very clearly demarcated (using the winner-takes-all model of selecting the node's colour group association), with very few outliers. There is a curious schism in the middle of the map which warrants further discussion.

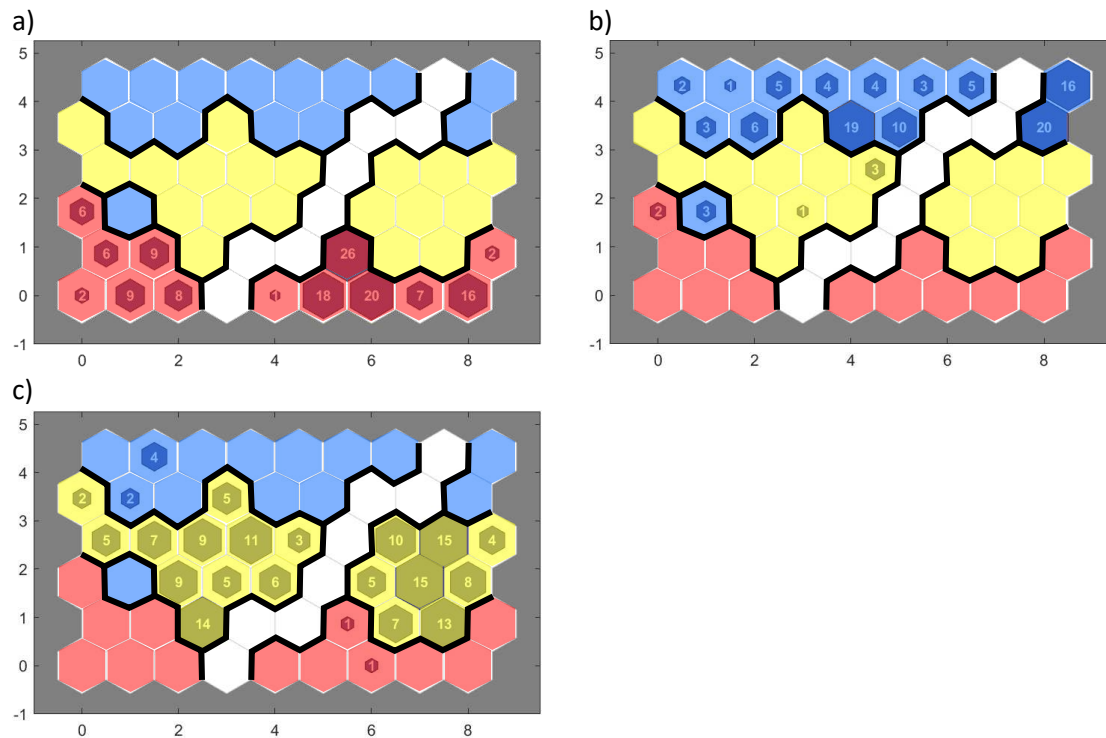


Figure 8 Map for maple using Hikrobot camera with SFS selected features showing colour group locales for human categorized a) red, b) white, and d) yellow veneers, and their approximate boundaries in red and green lines

SFS is seen to improve some of the results of the SOM, with the additional bonus of requiring less features to train and test in the neural network. This technique can be used in high-speed applications to boost decision making speeds.

There appears to be some outlier clusters in the resulting SOM maps. This may be due to a few factors, one being misclassification by the human worker. The samples were taken from different days, and classification of the veneers' colours were done by different workers – therein lies the difficulty in standardizing colour sorting among humans. A follow-up study utilizing images of these outlier veneers to determine which colour category they belong to is being planned.

Since SOM performs clustering without prior knowledge of the colour groups, the appearance of schisms within the colour clusters on the map does indicate there may be different ways the colour of the veneers can be sorted using the feature set used. This shall be the scope of future studies.

3.4. Sony RX0 II Performance Deficit

It is discovered that using the Sony Imaging Remote software, the auto-white balancing feature of the Sony RX0 II cannot be turned off, hence poor results in this study. Also, there may be some additional internal processing that is being done to the captured image – something that is very common with modern consumer cameras that attempt to automatically beautify the scenery. It may be necessary to utilize the Sony Camera Remote SDK to enable finer manipulation of the sensor's parameters. Despite calibration using the standard calibration chart, each resulting image appeared to have different colour profiles than the calibration image.

It is vital that camera settings such as aperture and shutter time are regulated and standardized, and any post-capture processing such as auto-white balance features and any other additional post-capture processing of consumer cameras be turned off to ensure standardized image capture. Alternatively, a standard colour chart should be present within the frame at every image capture so that the resulting captured image can be calibrated to a standard reference.

Therefore, the standard Sony Imaging Remote software may not be suitable for research use. It is therefore suggested that future studies utilizing this equipment use custom made connectors to the camera via the Camera Remote SDK to garner greater control of the camera settings. This goes for any other camera that will be used for any colour related study. Naturally, industrial cameras offer the highest degree of control over the settings, and fortunately, webcam's Windows driver, too, allow auto white balance to be turned off and do not have any fancy processing done on the resulting image. Also, results from the Sony camera in this study shall be given lower prominence.

3.5. Comparisons with Previous Research

The performance of our algorithm for the three different types of wood ranged from 89% (red oak) to 96% (Maple). This is comparable to other studies, such as rubberwood (95%) (Kurdthongmee, 2008), oak (95%) (Bianconi et al., 2013; B. M. Faria et al., 2015; Shivashankar & Madhuri, 2018), teak (90%) (Bianconi et al., 2013), and cedar (90%) (Nurthohari et al., 2019). It should be noted that most of the dataset of these studies are small, ranging from just one sample (J. Faria et al., 2008) to 30 samples per colour (Kurdthongmee, 2008). Some researchers generated more datasets by extracting overlapping segments from original images. In this research, we used over 80 distinct images per colour group per specie. Having more images acquired on different days create larger sample variability, creating more complexity in classification. The results from our study shall be more robust in actual industrial applications.

Also, soft colour descriptors (López et al., 2005) are used as features for the SOM, particularly the mean and standard deviations as they performed well in RGB colour space (Bianconi et al., 2013). Our technique differs from that of Bianconi; while he took average and standard deviation of the entire image, we split the image into two intensity levels and took the means and standard deviations of each stratum. This enables us to characterize the chromatic distribution of basal wood colours and grain colours into separate features for more robust sorting results.

4. Conclusion

This research confirms the viability of using SOM for colour sorting of red oak, yellow poplar, and maple veneers, especially using features that selected using the SFS method. Thresholding using Otsu appears to be provide reasonable results, which affirms our initial belief that wood colour may be split into two strata, with the upper stratum (wood basal colour) weighing heavily in colour sorting applications.

Also, Hikrobot performed the best among the three cameras, with Logitech ringing in at a close second. Sony performed the worst due to software limitations. Therefore, it is reasonable to use a high-quality webcam for colour sorting in place of an industrial camera in situations where budget is of concern, particularly if calibration is done correctly. However other considerations such as durability of the equipment had not been tested.

Acknowledgements

We extend our sincerest thanks Mr. George Yap (Managing Director of Weng Meng Industries Sdn. Bhd., WM, and Chairman of Malaysian Wood Moulding and Joinery Council, MWMJC), Mr. Jerry Maja (Operations Manager WM) and all the good folks at WM. for their unwavering cooperation in this research, the provision of veneer samples, and unfettered access to their facility. We would also like to acknowledge the huge support and encouragement given to us by Dr. Zamri Amin (Director of Industrial Development, Malaysian Timber Industries Board, MTIB) and Mr. Abdul Rafa (Senior Deputy Director of Industrial Development, MTIB).

This research is funded by SIRIM Machinery Technology Centre from industrial research fund named 'Automated Visual Inspection System for Inspection of Wood Colour, Size and Defect' (AVI Project 2021) provided by Malaysian Timber Industries Board (MTIB) in collaboration with MWMJC.

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