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Image Collection for Non-Segmenting Approach of Timber Surface Defect Detection

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Abstract

This paper describes data collection procedure for non-segmenting approach in solving automated timber surface defect detection problem. An overview of Malaysian wood species and the characteristics of the species under study are presented. Description on common defect types is also provided. This paper further explained the details of timber samples being considered, image acquisition setup as well as the steps involved in processing the captured images in preparing the samples for quantitative evaluation. This study shall benefit other researchers by providing useful reference and example on preparation of samples for non-segmenting approach.

Keywords: *Automated vision inspection, Defect image collection, Non-segmenting approach, Optical sensor, Timber defect.*

1 Introduction

1.1 Problem background

Malaysian wood industry has shown significance contribution to Malaysian export market, with a total of 20 billion export value in 2011 [1]. In reaching the target of 53 billion annual export earnings by 2020 as envisage in the National Timber Industry Policy (NATIP) launched in 2009, one of the strategy is to encourage and support the industry in the area of innovation and technology [2]. Manufacturing process has to be made efficient, hence, requires a reliable quality control procedure to support the increasing rate of production. There has been growing interest in the research of automated visual inspection in wood based industry. Automation of the quality control process has been viewed as an option to facilitate human worker in ensuring efficient production and quality output.

Previously, a substantial research effort has been done in the automation of timber defect detection due to the weakness of human labour in delivering accurate inspection, inconsistency and human inability to work on repetitive task over a long period. Past studies have proven that human grader’s accuracy was about 60% with a lot of error made on defect inspection, thus contribute to reduction in the overall timber yield [3–5]. Visual inspection in a manufacturing environment is the most difficult and time consuming process, therefore needing computer assistance. Thus, an automated visual inspection (AVI) is favoured than human grader for the reason of being faster, consistent and able to work in a longer period.

Motivated by the above, we extend the work on automated inspection of timber boards to Malaysian timber species with the hope that the outcome will be beneficial to the local wood product industries. To the best of the author’s knowledge, none of previous work on timber defect detection has utilized Malaysian timber in their studies. Additionally, all timber species considered in past studies are from hardwood category with oak and pine being frequent. Hashim, Hashim and Muda[6] provides a review on automated vision inspection (AVI) of timber, discussing problem related to timber inspection as well various approaches from previous studies working on timber defect detection.

Our work shall focus on the non-segmenting approach to defect detection, where image of timber board will be divided to local non-overlapping regions and classified to either clear area or defect area. Non-segmenting approach (also known as local approach) works by dividing original image into non-overlapping rectangular regions regardless of the contents of the image. Features for the sub-images will be extracted, and classified to respected classes. Although the computational load of calculating the features for each local region seems high, this approach has the advantage of allowing the implementation of parallel processing. This approach has been implemented by many researchers in wood surface defect inspection ranging from timber to wood panel, logs and wood chips [4, 7–15]. Contrary to the segmenting approach where objects will be segmented exactly to its shape, for non-segmenting approach, defects will be bounded with rectangular shape boundary and deemed to be suitable for application that requires fast segmentation without detail segment boundary. This approach is applicable to timber cutting in rough mill of secondary wood product industry where bounded rectangle covering defect area is considered sufficient to guide the cutting process which is done vertically. Conversely, the segmenting approach is much favoured on application that requires detail object segmentation such as timber grading. In short, the choice of defect detection approach is highly dependent on the type of application and the manufacturing stage targeted. In our work, we focused on developing automated defect detection prior cutting in rough mill, hence applying non-segmenting approach.

Next section will present some overview of Malaysian timber species with focus on the characteristics of the timber species considered in our study. It will also provide a description of defect types commonly found on timber.

1.2 Overview of Malaysian Timber Species

Malaysian timbers are classified into four categories; heavy hardwood, medium hardwood, light hardwood and softwood. Distinction between hardwood and softwood is based on normal botanical convention. Hardwoods are classified based on wood density at 15% moisture content, with the exception that heavy hardwood place durability measure higher priority than density. Some species which have average medium density are placed in heavy hardwood category, instead of medium category due to having higher durability. Additionally, distinction between medium and light category are based solely on average density. The classification system is summarized in Table 1 as below:

Table 1: List of Malaysian Timber Classification Based on Density [16]

Classification	**Density Range (15% moisture content)**
Heavy hardwood	800-1120 kg/m^3
Medium hardwood	720-880 kg/m^3
Light hardwood	400-720 kg/m^3
Softwood	Botanical distinction

Durability refers to natural durability of the heartwood of the timber. Classification is based on its performance in graveyard testing where a 50x50x600mm test sticks are buried in test ground [16]. The basis of measurement is depending on the number of years that the stick last in test ground. Durability can be classified into four groups as shown in Table 2.

Table 2: Natural Durability Classification based on Years [16]

Group	**Number of years**
Very durable	Exceeding 10 years
Durable	5-10 years
Moderately durable	2-5 years
Non-durable	0-2 years

Table 3 presents the characteristics of hardwood timber species considered in our study. Appearance of timber can be described with information on colour difference between heartwood and sapwood, nature of grain as well as texture.

Table 3: Characteristics of Four Types of Timber Species [16]

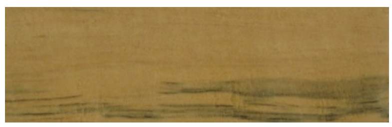
Species / Characteristics	**Merbau**	**Rubberwood**	**Kembang Semangkok (KSK)**	**Meranti**
Botanical name	Intsia palembanica, I.bijuga	Hevea brasiliensis	Scaphium spp.	Shorea spp.
Family	Leguminosae	Euphorbiaceae	Sterculiaceae	Dipterocarpaceae
Sapwood	Pale yellow	Sapwood almost similar with heartwood, pale cream in color often with a pink tinge	Lighter in shade	Sapwood is well defined from heartwood, which is light pink to light red or light brown
Heartwood	Yellowish to orange-brown when fresh; weathering to brown or dark red-brown	N/a	Yellow-brown, light buff, light brown	N/a
Grain	Interlocked	Straight to shallowly interlocked	Straight or shallowly interlocked	Interlocked
Texture	Coarse but even	Moderately coarse but even	Slightly coarse and uneven	Coarse and even
Growth ring	Distinct		Distinct	
Density	515-1040 kg/m3	560-640 kg/m3	515-755 kg/m3	385-755 kg/m3
Durability	Durable	Non-durable	Moderately durable	Non-durable
Uses	Growth ring figure and deep color makes it an attractive wood for decorative work including flooring, furniture, veneer, door/window frame, etc	Popular for manufacturing of furniture, suitable for paneling, flooring, etc.	Decorative plywood, interior finishing, suitable for furniture, paneling, partition	Wide variety of uses including decorative work, furniture, paneling, partitioning, flooring, ceiling, shelving, show cases, counter tops, fancy boxes, veneer and plywood

1.3 Overview of Timber Defect

Visual surface inspection on timber is done to seek for anomaly based on texture, colour or shape. This anomaly is called wood defect. Wood defect can be defined as flaw or deficiency found in wood and it can also be visible on wood surface. Wood defect can be classified as mechanical defect and natural defect. Mechanical defects are defects caused during the processing or manufacturing of timber such as during drying process, sawing process and moulding process. Examples of mechanical defect are fuzzy grain and roller mark. On the other hand, natural defects are biological defect caused during the growth of tree where the timber originates e.g. knots and bark pocket. Depending on grading rules, defect can also be categorized as permissible (minor defects allowed on timber) and non-permissible (major defects not allowed on timber).

No timber is entirely free from defects. The same wood defects, mechanical and natural, are likely to occur in all species. Moreover, certain defects may be common to certain wood species than on others. However, regardless of wood species, the characteristics of defects are mostly similar. Wood defect affect the appearance, aesthetic value and strength of the wood. The effect of certain defect on the quality and strength of the timber is similar regardless of wood species. Therefore, wood defect detection and identification on timber surface seems essential on various stages of timber processing including grading, optimization of cutting and sorting to maintain the quality of final product. Further works in this study will focus on defect which can be visually inspected on timber surface. Table 4 shows some common defect types with its description and images.

Table 4: List of Common Timber Defects

No	Defect	Description	Image
1	Knot	A knot is a part of branch which has become embedded in the wood by the natural growth of the tree. It is usually round or oval in shape. Unsound knot is softer than the surrounding wood, contains decay, hole or checked across its face	
2	Blue Stain	Stain is a discolouration or variation from the natural colour of the wood, generally caused by sap-stain fungi.	
3	Brown Stain	Stain is a discolouration or variation from the natural colour of the wood, generally occur during drying	

4	Surface check	Breaks in the wood normally occurring across the annual growth rings; as a result from strains developing during seasoning	
5	Split	Breaks of the wood through the piece due to tearing apart of the wood cells	
6	Bark pocket	Patches of bark, partly or all enclosed within the wood. Sometimes resin or gum may be present in the bark pocket	
7	Borer holes	Holes in timber caused by boring insects	
8	Wane	Wane is the lack of wood on any face of a piece of timber, normally caused by a portion of the original rounded surface of a log remaining on the piece.	
9	Rot	Decomposition of wood material or decay caused by bacteria and fungi	

2 Data Collection Method

2.1 Timber Samples Collection

Experimentation of any algorithm proposed for automated wood inspection is best applied with material used in industrial setting [17]. Therefore, for this study, real samples are collected from the industries. Our study is focusing on detection process targeted for rough milling task in secondary wood industry. Hence, the timber samples were obtained from rough mill section of several secondary wood product factories located in Bukit Rambai Industrial Area, Melaka, Malaysia. Bukit Rambai Industrial Area is one of the primary area in Peninsular Malaysia with high concentration of secondary wood industries.

Availability of timber species are very much influenced by the types of end products being manufactured by the factories during samples collection. Some products may require heavy, medium or light hardwood depending on the required quality. For that reason, samples are limited to three species of Malaysian light hardwood which are Rubberwood, Kembang Semangkok and Meranti, as well as one species of heavy hardwood which is Merbau. Additionally, sawn timbers considered are ungraded, dressed, dried and free of dirt for use in rough milling. Timber samples collected were of 45 to 70 mm in widths, 100 to 150 mm in length, and 18 to 22 mm in thickness. Although sawn timbers at rough milling area are ranged from 6 feet length and above, shorter samples are used in this study as the images are processed for research purpose.

2.2 Image Acquisition Setup

Various sensors has been used for inspection of external wood defect in past studies, for example, optical camera, optical scanner, laser based sensor and video camera. Among them, optical camera has proved to be a promising sensor to be used on inspection of external wood defect due to its practicality, fast inspection capabilities and for being inexpensive. Additionally, optical camera is economically feasible for a setup targeted either in a research lab or in the industry. This is further supported by fast technological advancement in computer and vision sensors in introducing a low-cost vision inspection. According to Conners et. al.[7], optical imaging device is most suitable for applications which require detection of surface defect such as in furniture making industries, where appearance plays an important role. Although it cannot completely detect internal defect, having such system would at least help to increase some productivity in the inspection process.

Several studies have employed low cost automated vision inspection (AVI) in their research setting. Estevez, Perez, & Goles[18] captured the surface image of timber samples that of shorter length than the actual used in rough mill area using colour video camera with an image capture board and a microcomputer. In another work, it was suggested that initial research should employ standard imaging hardware to minimize hardware cost [17]. Thus, in their work, a standard RS-170 solid-state camera with colour filters allowing images of 8 inches by 8 inches square areas was considered [17]. Other studies employing optical sensor are listed in Table 5.

Table 5: Previous Studies Employing Optical Sensor in Wood Surface Inspection

Sensor	**Wood Product**	**Reference**
Optical scanner	Wood panel	Chen, Wang, Xie, & Wang [19]
Optical scanner	Timber boards	R. W. Conners et al. [7]
Optical scanner	Timber boards	Koivo & Kim [8]
Optical scanner	Timber boards	Kim & Koivo [20]
Optical scanner	Timber boards	Hagman [21]
Optical camera	Bamboo strips	X. Wang et al.[11]
Optical camera	Log surface	Weidenhiller & Denzler [15]
Optical camera	Timber boards	T.-H. Cho, Conners, & Araman [22]
Optical camera	Timber boards	T. Cho & Conners [23]

Optical camera	Timber boards	P. Estevez & Fernandez [24]
Optical camera	Timber boards	Niskanen [25]
Optical camera	Timber boards	Silven et al. [4]
Optical camera	Timber boards	Chuanshuang S Hu, Tanaka, & Ohtani [26]
Optical camera	Timber boards	Ziadi et al. [9]
Optical camera	Timber boards	Kurdthongmee [27]
Optical camera	Timber boards (pencil production)	de Andrade & Gonzaga [28]
Optical camera	Timber boards (pencil production)	Rodrigues & Roda [29]
Optical camera	Cork stopper	Chang & Han [30]
Optical camera	Varnished surface	Ana, Angel, Le, & Mar [31]
Video camera	Wood chips	Wooten et al. [14]
Video camera	Timber boards	P. A. Estevez et al. [18]
Video camera	Timber boards	D. Pham, Eldukhri, Soroka, Ruza’b, & Estéveza [32]
Video camera	Timber boards	Ruz, Estevez, & Perez [33]
Video camera	Wooden pallets	Patricio & Maravall [34]

Motivated by the above, we decided to employ optical sensor in our study. Two types of optical imaging device can be used for this purpose; line scan cameras or area scan cameras. While line scan camera is more practical in industrial setting, however, in research setting, a low cost setup using area scan camera is ample to provide sample of images for algorithm testing.

The imaging setup for our study comprised of a charged-coupled device (CCD) digital camera with controlled illumination inspired by previous studies using similar type of digital camera [26, 35–37]. The camera is mounted on a fixed tripod and positioned to face the top of inspection table as shown in fig. 1. A fixed distance between samples and camera is maintained throughout the acquisition process. Compact fluorescent lighting with diffuser is used and located at both side of the inspection area with an angle of approximately 45 degrees, adjusted to obtain uniform illumination over the samples. The camera is configured for a 17cm view, which is enough to cover most samples’ width, with a resolution of 1024 by 768 pixels (300dpi). Previous studies as in Table 6 provide some indication that this resolution is sufficient for most application of timber defect detection. The images captured were of 24 bit depth, containing 256 intensity levels for each colour channel (red, green and blue). These basic channel is considered sufficient as it was reported that transforming RGB to other colour spaces for wood images yield no significant advantage [38]. H. Kauppinen & Silven[39] further agreed that classification accuracy of knot detection from timber surface is not affected by the various illumination variations under RGB colour space, showing the robustness of RGB space to changes in illumination.

Fig. 1: Image Acquisition Setup

Table 6: Data Collection Setting of Past Studies on Timber Defect Detection

	Reference	**Samples**
1	R.W. Conners et al.[7]	Image size :512x512 Black and White 256 gray level Quantity : 500 boards Each board contain one or more defects
2	Koivo & Kim[8]	Image size: 512x512 Black and White 256 gray level Quantity: 120 boards Sub image size: 8x8 (20 samples/class)
3	T.-H. Cho, Conners, Araman, et al.[40]	Image size: 480x512 Color 256 level/channel Quantity: 30 boards
4	T. Cho & Conners [23]	Image size: 480x512 Color 256 level/channel Quantity: 20-40 boards/species 20 samples/class Testing : Leave-one-out
5	Kim & Koivo[20]	Image size:512x512 Black and White 256 gray level Quantity: 30 samples Set 1: Cleaned surface Set 2: Surface with thin layer of dust Set 3: Dusty fan-cleaned surface
6	P. Estevez & Fernandez [24]	Image size: 320x240 Color 256 level/ channel Quantity : 900 images (100 samples/defect)

		Training set: 540 Validation set: 180 Test set: 180
7	Niskanen et al.[12]	Sub image size: 40x40
8	C S Hu, Tanaka, & Ohtani [41]	Image size: 340 x 360 Training: 280 samples Testing: 1 sample containing 5 defect regions
9	S.-M. M. Lee, Abbott, & Schmoldt [42]	Image size: 256 x 256
10	P. A. Estevez et al.[18]	Image size: 640x480 Reduced to 320x240 Color RGB Training set : 1000/defect Validation set: 200/defect Testing set: 200/defect
11	Silven et al.[4]	Quantity: 42 board images with 1000 labeled defects
12	Kline, Surak, & Araman [43]	Color 256 level/channel Training set: 300 (40 examples/defect) Testing set: 89
13	Chuanshuang S Hu et al.[26]	Color image Training set: 142 sound knot, 80 dead knot Testing set: 54 sound knots, 35 dead knots
14	Rinnhofer et al.[44]	Color image Quantity: 23000 sub images
15	D. Pham et al.[32]	Image size: 320x240 Color Quantity : 900 images (90 samples/class) Training set: 600 Testing set: 300
16	Ruz et al.[33]	Image size: 320x240 Color Quantity : 900 images (90 samples/class) Training set: 600 Testing set: 300
17	Ziadi et al.[9]	Image size: 1024 X 775 RGB Colour 256 level/channel Training set: 70%

		Testing set: 30%
18	S. Lee & Araman [45]	86 yellow poplar 90 red oak boards

2.3 Image Labeling and Processing

Fig. 2 illustrates the overall process of data collection for our study. Timber surface images were captured using the low-cost acquisition setup described in section 2.2. The timber samples were marked with sequential numbering for reference. Subsequently, the image files related to the surface of the timbers were named using similar numbering. The images were then labelled and sorted according to wood species and defects present, supervised by industry experts.

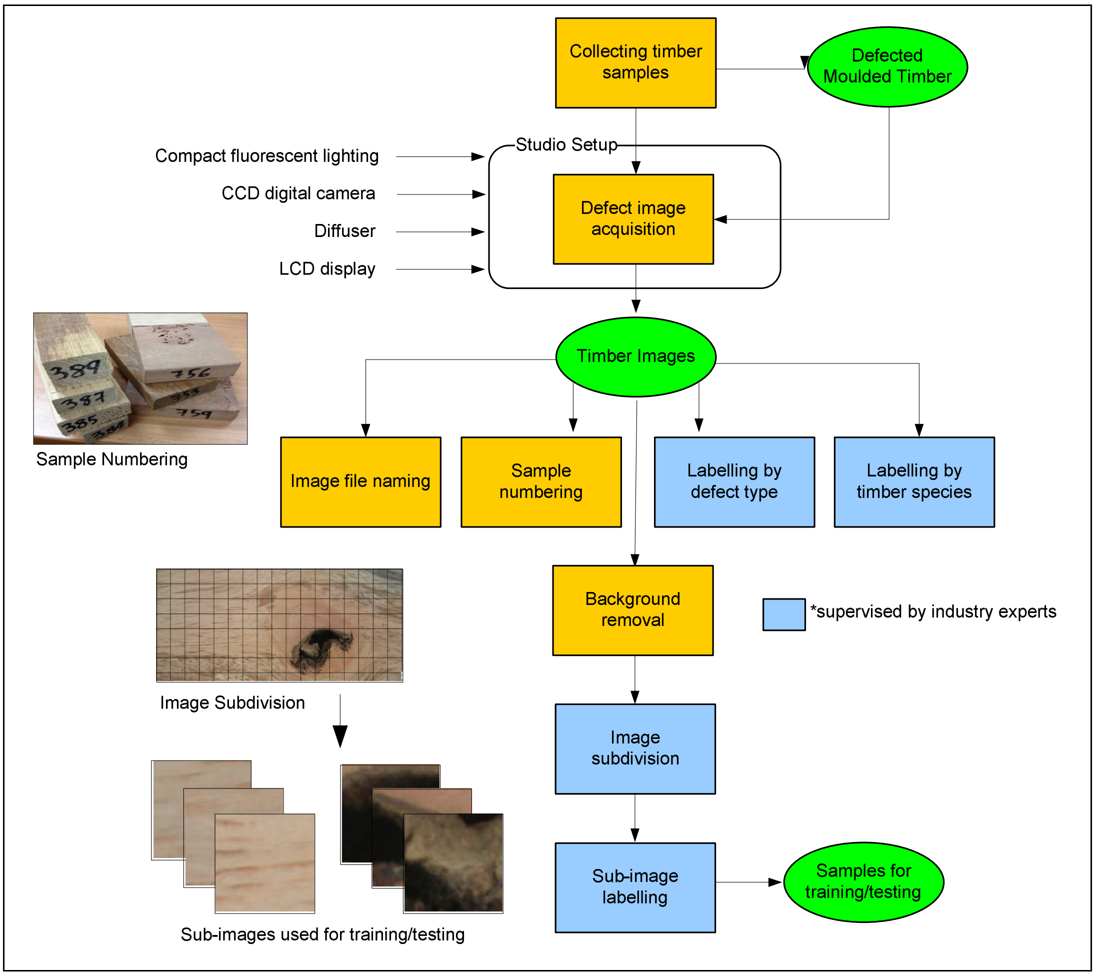


Fig. 2: Data Collection Process

Fig. 3 shows some examples of image acquired. Each sample will contain at least a defect. Image of the timber is acquired twice per timber samples, on both top and bottom surfaces.

Fig. 3: Sample of images acquired

The images as shown in fig. 3 contain some background which is not part of the timber. This background was cropped manually to remove background area. Weidenhiller & Denzler[15] similarly marked the background manually in his work, claiming that for later application, additional processing may separate the samples from its background.

After background removal, the images were subdivided into 60 x 60 non-overlapping sub-images as shown in fig. 4. According to Kyllonen[46], training samples should be selected with special care to achieve good performance. Thus, in our study, samples of defect and clear wood sub-images were selected carefully from the original image under industrial expert supervision. The selected sub-images provide ground truth information that will serve as a basis for accuracy assessment.

Previous studies [4], [26], [47] have used various sub-images sizes in their studies, for example, 8 x 8, 32 x 32 , 64 x 64 and 64 x 48. The choice of sub-images size depends on whether it could capture enough feature information for class distinction. Therefore, from previous studies, it was often chosen heuristically. D. T. Pham & Alcock [48] concerned that small defect could not be characterized well in a large region. It was further suggested that the right region size should be cautiously chosen as smaller regions mean higher computation and larger region could lead to less detection accuracy [4, 12, 34]. In our study, features extracted from the sub-image will be analysed in later work to determine the appropriateness of the chosen sub-image size in providing adequate feature information to differentiate between classes.

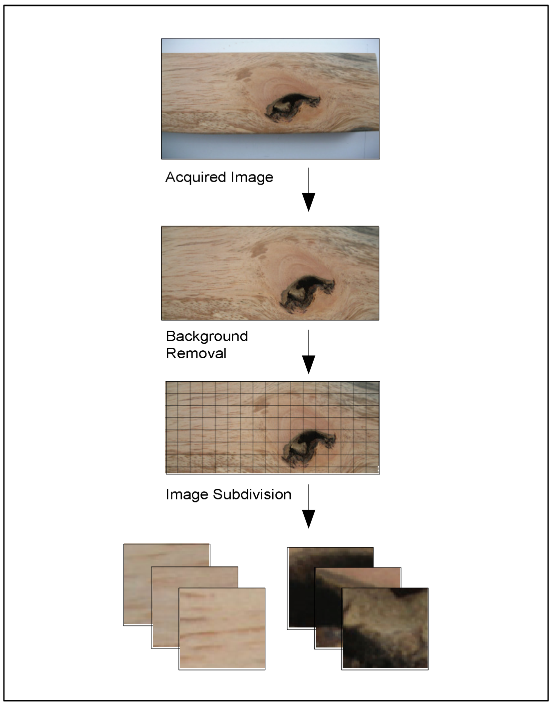
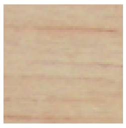
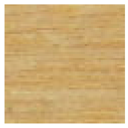
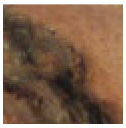
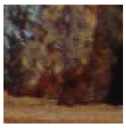
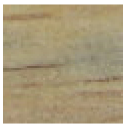


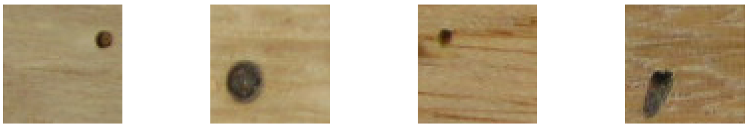
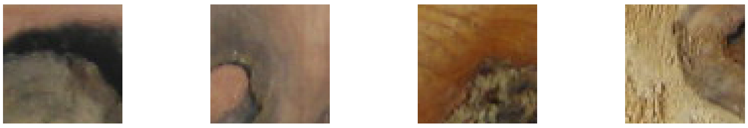
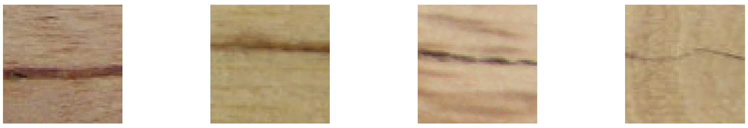
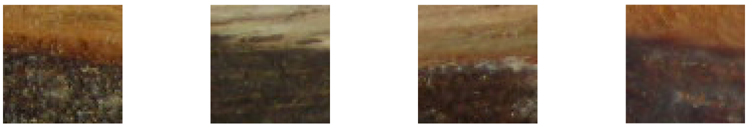
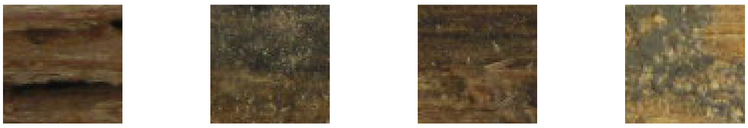
Fig. 4: Subdivision of original image into sub-images

3 Findings

The basic requirement for achieving reliable performance for the proposed approach is availability of enough image samples. The more samples that are available, the better estimates of the performance can be made [49]. Table 7 lists example of sub-image collected for each class. It is obvious that the appearance of defects is almost similar regardless of wood species.

Table 7: List of Classes With Example of Sub-image Collected

Class	Defect	Rubberwood	KSK	Meranti	Merbau
1	Clear wood				
2	Pocket				
3	Blue Stain				

4	Brown Stain	
5	Hole	
6	Knots	
7	Split	
8	Wane	
9	Rot	

Meanwhile, distribution of defect samples collected is presented in fig. 5. From the fig., it is apparent that Merbau timber seems to contain fewer defects compared to other species. From the feedback by the factories involved, it was made clear that the Merbau timber purchased were of high quality grade meant for manufacturing outdoor furniture. Therefore, for this kind of grade, defects affecting timber structural properties were uncommon. However, it can be seen that brown stain occurs more frequently on Merbau timber than others. These are common stains found on Merbau timber which only affect the appearance of the timber. Brown stain is only a concern to end product which requires clear finishing. For other timber species, occurrences of defects on samples collected were almost similar since they are categorized under the same category which is light hardwood. Moreover, the uneven distribution of defects over samples collected was evident due to the fact that some defects are common to certain species while being occasional to others.

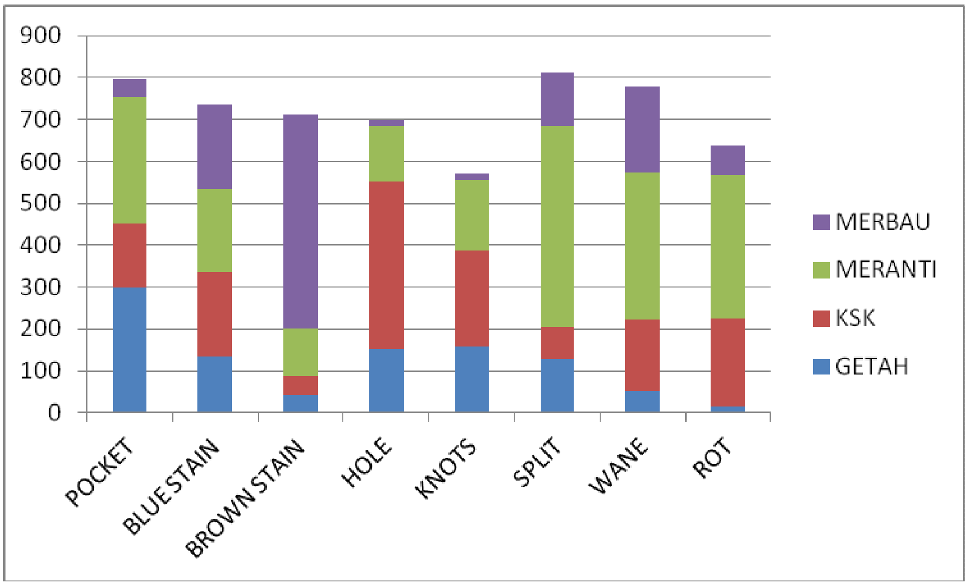


Fig. 5: Distribution of Defect Samples across Species

4 Conclusion

In this paper, data collection procedure for non-segmenting approach in solving timber surface defect detection problem is discussed. Optical sensor is used in image acquisition motivated by the idea of introducing a practical low cost vision inspection. Merbau, KSK, Meranti and Rubberwood timber species are considered due to its availability during sample collection and the characteristics of the species are also being defined. The paper further elaborated the steps taken to process the images as well as preparation of training samples which were supervised by industry experts. From the images collected, it's obvious that there seems to be more similarity than dissimilarity in the defects appearance across timber species. Furthermore, it was pointed out that the distribution of defect samples is apparently unbalanced between timber species and defect types. It can be concluded that certain defects are more prominent in a timber species than the other. The assumption of defects similarity across species and unbalanced distribution enable us to draw a certain research insight and direction towards finding appropriate common features to represent defect types as well as appropriate classification method to handle unbalanced data.

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