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AUTOMATED VISION INSPECTION OF TIMBER SURFACE DEFECT: A REVIEW

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Abstract

Automated inspection has proven to be of great importance in increasing the quality of timber products, optimising raw material resources, increasing productivity as well as reducing error related to human labour. This paper reviews automated inspection of timber surface defects with a special focus on vision inspection. Previous works on sensors utilised are presented and can be used as a reference for future researchers. General approaches to solving the problem of wood surface defect detection can be categorised into segmentation and non-segmenting approaches. The weaknesses and strengths of each approach are discussed along with feature extraction techniques and classifiers implemented in timber surface defect detection. Furthermore, insights into the practicality of implementing automated vision inspection of timber defects were also discussed. This paper shall benefit researchers and practitioners in understanding different approaches, sensors, feature extraction techniques as well as classifiers that have been implemented in automated inspection of timber surface defects, thus providing some direction for future research.

Keywords: Automated vision inspection, defect detection, wood inspection, timber defect detection, non-destructive testing

1.0 BACKGROUND

Automated inspection of wood defects has proven to be of great importance in the wood industry. Due to decreasing forest resources and the increasing cost of wood, the application of automated inspection is seen as a solution to optimise resources and save production costs while maintaining a reliable quality of product output. In secondary wood industries such as furniture manufacturing, the cost of timber accounts for about 30% to 70% of the total production cost, depending on the type of products manufactured. Thus, it is essential for such a production line to improve their timber processing from the earliest stage of rough milling in order to increase timber yield.

A study has shown that human error in timber inspection resulted in 22% rejected timber which reduced the overall yield from 63.5% to 47.4% [1]. Similarly, Huber [2] claimed that the performance of human operators in locating and identifying surface defects is only about 68%. They highlighted that by applying automated inspection processes, an improved yield could be obtained because machines are not affected by human weaknesses such as tiredness, boredom and other inconsistencies [2]. Buehlmann [1] suggested that automated vision inspection may be able to solve this kind of error if the detection ability is 50% better than the human detection ability observed in his study. He also pointed out that the payback for such investment could take at least one year. Buehlmann and Thomas [3] further concluded that a 25% improvement in detection accuracy could increase yield by 5.3%, which could in turn contribute to significant cost savings for an average sized rough mill. Kim and Koivo [4] also agreed that automated inspection could overcome the problem of suboptimal performance and inconsistencies of human operator judgement due to the variability of defect characteristics themselves. Furthermore, according to Kline, Surak and Araman [5], automated timber grading was found to be more accurate and consistent than human graders. They further concluded that conventional inspection processes are not efficient enough in optimising timber resources, thus, the secondary wood industries must innovate to survive in the current competitive market [5].

Meanwhile, substantial research effort has been spent to automate the inspection process in wood industries ranging from research on detection of defects, defect characterisation, identification of defects, wood grading, and cutting optimisation to hardware related development such as applying sensor fusion. Various wood products have been tested including wood veneer/plywood [6–16], logs [17–31], bamboo strips[32], parquet [33–36], particle boards [37–39], wood chips [40], wooden poles [41, 42], slabs [43–46] and pallets [47]. Compared to other wood products, research on timber was seen to be quite extensive and ongoing until recent years. Table 1 lists related works on the inspection of timber.

Table 1 Related works on automated inspection of timber

Years	References	Sensor
Prior to the year 2000	[48],[49],[50],[51],[52],[53],[4],[54],[55]	Vision sensor
After the year 2000	[56],[57],[58],[59],[60],[61],[5],[62],[18],[63],[64],[65],[66],[67]	Vision sensor
	[68]	Ultrasound
	[69]	Vibration sensor
	[70],[71]	Infrared thermography

Timber is one of the major raw materials used by secondary wood product industries producing wood products such as furniture, doors, decorative items, construction structures, components and stationery. In relation to inspection of timber boards, a review on past literature indicated that surface defects are commonly researched with the application of vision sensors, which shows the relevancy and worthiness of further research. All the listed references in Table 1 utilised various types of vision sensors except for the last four references. While L. Wang *et al*. [68] used an ultrasound sensor, Ni Song *et al*. [69] implemented modal analysis (vibration test), and Pervan *et al*. [70] and Lopez *et al*. [71] utilised infrared thermography sensors in their studies. The following discussion will work towards a review of automated inspection of timber boards focusing on vision sensors and how these sensors are being used to detect and identify timber surface defects.

2.0 SENSOR

Research on inspection of internal timber defects in secondary wood industries is uncommon due to the fact that most internal defects are eliminated through earlier processing of logs in the primary wood industry. Timbers sent to the rough mills of secondary wood industries are usually checked for surface defects prior to cutting the timber to the desired size. Table 2 presents related studies on sensors used for inspection of external timber defects. It is apparent that optical cameras are commonly used in the research into inspection of timber surface defects.

Laser based sensors are applied mostly in conjunction with other sensors to characterise geometry related defects on timber boards. Previous studies have also demonstrated the application of laser based sensors for log surface scanning in detecting loose bark from logs [20, 72, 73] . On the other hand, optical distance sensors work by measuring the distance between the sensor and timber samples and use the information to reconstruct the timber profile [57]. The commonly used optical camera, scanner and video camera provide the output of black and white or colour imaging resulting in the ability to comprehensively characterise and analyse surface defects.

Table 2 Related studies on vision sensors for inspection of external timber defect

Vision Sensors	References
Laser scanner	[58]
Optical scanner	[48], [49], [4], [54]
Optical camera	[74], [51], [55], [75], [61], [62], [65], [66], [76], [77]
Video camera	[60], [63], [64]
Optical distance sensor	[57]

As shown in Table 3, a considerable number of studies have been conducted using a multi-sensor approach to timber defect detection. Due to the ability of this approach to detect both internal and external defects, the outcomes of defect detection seem to be more promising than those that use single sensor applications. Despite better defect detection performance through a multi-sensor approach, the high cost incurred in implementing such sensors has hindered the practical use of it in industrial environments.

Table 3 Related studies on multi sensor approach to timber defect detection

Sensor Fusion	Reference
Colour line scan camera Laser based camera X-ray scanner	[52]
Optical camera Line laser	[53]
Laser scanner Video Camera	[59]
Laser profile detector Colour camera X-ray scanner	[5]

Sensor Fusion	Reference
Colour line-scan camera IVP CMOS camera Infrared laser	[18]
Video camera Laser scanner	[67]

Among the various sensors widely used to detect timber defects, the optical sensor has proven to be a promising sensor in automated vision inspection (AVI) of timber surfaces due to its practicality, fast implementation and fast inspection capabilities. Moreover, it may help to introduce low-cost inspection setups with reliable computational capability either in the research lab or in industry. Estevez *et al*. [60] agreed that visual inspection can be made possible at a lower cost with the fast technological advancement in computer and optical sensors, despite the better performance offered by inspection via multiple sensors.

Most wood industries are small or medium sized and therefore often do not have sufficient funds to invest in expensive multi-sensor equipment. Since optical sensors are relatively inexpensive, the development of timber defect inspection processes based on surface images is worth further investigation. Although it cannot completely detect internal defects, having such a system in place would at least help to increase productivity in the inspection process. Hopefully, other internal sensors such as X-ray scanners will also become increasingly common in the future with the advent of cheaper sensor technology.

There are many types of sensors that can be applied to wood inspection problems depending on the specific requirement. However, most of these sensors remain experimental [60]. Although some of the sensors have demonstrated good performance in lab studies, it seems difficult to achieve improved cost efficiency if introduced to small industries [78]. Despite recent developments in multi-sensor approaches, optical sensors seem to be the most favourable especially in detection of wood surface defects [35]. Optical sensors are seen to be sufficient to assist in the inspection task on wood surfaces similar to visual inspection by humans [79]. Moreover, the output image from optical sensors contains a large amount of information which may contribute to the characterisation of surface defects. The following discussion will further analyse studies related to the application of optical sensors as a single sensor or as part of sensor fusion, for the inspection of timber surface defects.

3.0 GENERAL DEFECT DETECTION APPROACH

The approach taken by previous researchers on wood defect detection can be divided into two categories: a segmentation approach and a non-segmenting approach. In a segmentation approach (also known as a global approach), segmentation is done using various combinations of image processing techniques to identify regions containing timber defect objects, for example, thresholding, connected component labelling and region merging. Previous researchers have demonstrated the implementation of this approach to detect timber surface defects [4, 5, 18, 51, 58, 62, 63, 74, 80]. Once the objects have been segmented, features are extracted from the objects to construct feature vectors. The features are then trained with chosen algorithm and tested to classify them into defect classes.

In a non-segmenting approach (also known as a local approach), the original image is divided into non-overlapping rectangular regions regardless of the contents of the image. Features from the local regions or sub-images are extracted, trained and tested to classify the local regions into defect types. This approach has been implemented by many researchers in wood surface defect inspection ranging from timber to wood panel, logs and wood chips [31, 32, 40, 48, 49, 56, 61, 65, 81, 82]. Contrary to the segmentation approach where an object will be segmented exactly to its shape, for a non-segmenting approach, each defect will be bounded by a rectangular shape boundary. Some previous studies use a hierarchical or multilevel approach where a combination of segmentation and a non-segmenting approach is applied [4, 18, 34, 47, 83].

For certain applications that require only rough segmentation, for example, timber cutting, bounded rectangles covering the defect area as in the non-segmenting approach are considered sufficient to guide the cutting process which is done vertically. It was proven that rough segmentation was found to be fast enough in providing accurate cutting boundaries since it does not need detailed segmentation [84]. On the other hand, with the segmentation approach, the segmented object will be useful for grading purposes because some grading rules require information on shape, size and quantity of defects present, thus, would require the object to be segmented exactly to its size and shape. Normally, a grading application is needed more in primary wood industries where logs are being cut to timber boards and graded before being sent to secondary wood industries according to the grades required by the customers. Whereas for secondary wood industries, defect inspection is required at the rough mill before the timber is cut to the required size for producing components. Therefore, it can be concluded that, the choice of defect detection approach is highly dependent on the type of application and the manufacturing stage targeted.

In terms of processing the images, the segmentation approach requires that the whole sample be digitised before allowing the segmentation process to continue. For a timber inspection process in a rough mill, board lengths range from 2 to 5 feet for short lengths and 6 to 20 feet for long lengths. Therefore, a sufficient amount of storage is needed to store the image data for the samples currently being inspected. In contrast, for the non-segmenting approach, the image is divided into sub images and can be processed in sections locally as the timber is being scanned continuously. Although the computational load to calculate the features for each local region seems high, this approach has the advantage of allowing an implementation of parallel processing. Foundational to this is the basic goal of any image analysis problem which is to not just design an approach to achieve accurate classification but also to ensure that the process is computationally efficient with regards to processing time [48]. Kauppinen [81] concluded that the segmentation approach may fail to detect defects with similar colours as the clear wood and having unclear boundaries, thus, making the non-segmenting approach more suitable for defect detection. However, the non-segmenting approach is not suitable for applications requiring measurement of defect size [85]. Pham and Alcock [86] were also concerned that small defects may not be characterised well in a large region. Therefore, one must also be careful to choose the right region size as smaller regions mean higher computation requirements and larger regions could lead to reduced detection accuracy [56, 61]. Patricio and Maravall [47] further agreed that selection of local region size is important to guarantee that enough information is captured in that local region to enable accurate classification.

4.0 FEATURE EXTRACTION FOR DEFECT CHARACTERISATION

Feature extraction is a process to characterise the samples being studied and the results are used as an input into the classification process. Features used by previous researchers in the automated inspection of wood can be categorised according to the detection approach; features of the local region in the non-segmenting approach and features of the object segmented in the segmentation approach.

For the non-segmenting approach, tonal and textural features were commonly used. Conners *et al*. [48] used mean variance, skewness and kurtosis as tonal measures and a gray level co-occurrence matrix (GLCM) for textural features. The statistical features from the GLCM used are inertia, cluster shade, cluster prominence, homogeneity, energy and entropy. Similarly, Niskanen *et al*. [56] and Silven *et al*. [61] employed tonal measures using RGB histogram centiles, while for textural features, local binary pattern (LBP) and GLCM were used. Another related study utilising GLCM used mean, variance, contrast, cluster shade, cluster prominence, local homogeneity, angular second moment, entropy and correlation to sort wooden tile accordingly to its quality class [34]. However, the GLCM parameters such as equal probability quantisation (EPQ), displacement and orientation that had been used were not clarified in all the above studies. A recent study by Athilakshmi [87] implemented simple descriptive features such as mean, median, mode, min, max, variance, covariance and standard features, combined with common GLCM features which are energy, entropy, homogeneity, inverse different moment and angular second moment. Each GLCM feature was calculated using four different orientations (0^0, 90^0, 45^0 and 135^0), though displacement and the EPQ parameter were not stated. Rinnhofer *et al*. [18] also implemented tonal and textural features, but did not mention the details of the features.

Kim and Koivo [4, 49] derived textural features from the parameters of the Causal Auto Regressive Model (CAR) and concluded that by combining with another feature which is the mean of the grey level, the classification performance was better than using texture alone. Weidenhiller and Denzler [31] tried colour co-occurrence matrices by calculating 22 textural features from the matrices of six channel combinations of the RGB colour space. Weidenhiller and Denzler [31] reported that the features from colour co-occurrence matrices yield promising results in the problem of bark detection on logs compared to using tonal features alone. It was further suggested that if texture features were to be used alone, a potential improvement might be based on grey level co-occurrence matrices to optimally utilise texture information [31]. Cavalin *et al*. [88] demonstrated that features from a grey level co-occurrence matrix achieved similar performance when compared with colour tonal features. It was further concluded that choosing grayscale over colour features would reduce overall cost of implementation without having to compromise on the inspection accuracy [88].

It was also noted that for most studies which attempted to classify many types of defect, both tonal and textural measures were applied. On the other hand, for simpler problems which involved one type of defect as in Ziadi *et al*. [65], tonal measures were found to be sufficient to contribute to good detection performance [88].

For the segmentation approach, features were extracted from the segmented object to be classified into different types of defect. Previous studies have shown that common features used for the segmented object are tonal, textural and geometrical features. Earlier studies on classification of defects on timber boards utilised area, average gray level, centre of mass, minimum bounded rectangle, elongatedness, perimeter, compactness and a flag indicating whether the object is touching the boundary of the board [51, 74]. Later, Estevez and Fernandez [55] implemented 24 geometrical features with 48 tonal measures from four colour channels. Estevez [60] furthered their work by using 182 features comprising of geometrical and tonal features from the segmented objects as well as from the 64 by 64 pixel windows geometrically centred in the object. Kline *et al*. [5] similarly applied tonal and geometrical features to the segmented defect object including intensity, height, width, perimeter, area, edge, centre of mass, compactness and elongatedness, measured from six channels of x-ray, laser and colour images. Further work classifying splits and holes only utilised four geometrical features: width, length, compactness and roundness [58]. Research by Hu *et al*. [62] found that tonal and geometrical features were useful in identifying sound knots and dead knots. In recent studies for classifying four types of wood knot, pseudo colour features were used, where each pseudo colour is the average normalised pseudo colour on the interior, exterior and boundary area of the segmented knot [89]. Using a similar feature approach to the similar knot identification problem, Zhang [90] selected four colour features of the red channel from the interior, exterior and boundary areas of knots segmented, together with the knot size for the classification of four types of knots: sound, dead, rotten and pin knot. Using textural features alone in some applications was proven to produce good accuracy as well. Wooten *et al*. [40] tried textural features such as intensity variance, intensity mean square error (MSE), angular variance, angular MSE and variation of intensity gradient to classify bark from wood chips, demonstrating more than 90% accuracy.

In previous studies a variety of features have been tested for defect characterisation. In conclusion, there is no one solution to uniquely represent defect features because choice of features is obviously dependent on the problem itself. However, it is worth to note that textural features are regularly applied, with co-occurrence matrix being a common approach due to its good performance in discriminating textures. Conners *et al*. [48] stated that co-occurrence matrix has been proven to show a good performance on a variety of texture related problems due to its capability in matching human perceptual performance. It is agreed by Weidenhiller and Denzler [31] that features based on co-occurrence matrix could help to improve the optimal utilisation of textural information. de Andrade and Gonzaga [76] strongly suggested that textural measures are useful in analysing the variability of wood defect patterns and they employed co-occurrence matrix in their study. The capability of co-occurrence matrix was further proven with classification accuracy showing substantial improvement when co-occurrence features were added to supplement tonal and geometrical features [84]. Likewise, Kauppinen [85] clearly stated that the limitation of tonal measures in wood defect detection should be supplemented by textural features and again pointed out that utilising texture to recognise wood defect properties is natural to human perception. Kyllonen and Pietikainen [33] further agreed that the challenging classification of wood surfaces due to the variability in wood appearance could be improved by combining colour and textural information. Additionally, hardwood properties were found to be best represented by textural features [18]. This is proven by the ability of textural features, specifically from grey level co-occurrence matrix to achieve high accuracy in solving the wood texture recognition problem [91]. There are many variations to the implementation of co-occurrence matrix on the choice of grey level over colour as well as varying parameters of EPQ, displacement and orientation. This all leads the authors to believe that co-occurrence matrix is a prospective solution to most kinds of wood defect detection problems provided that proper parameter analysis is done to ensure appropriate choice of parameters that match the problem being addressed.

5.0 CLASSIFICATION OF DEFECTS

There are two general approaches in timber surface defect detection, which are the segmentation method and the non-segmenting method. For the segmentation method, features extracted from the object segmented will be fed to a classifier for training purposes and to generate a classifier model to be used in testing stage. Earlier studies on timber surface defect detection using the segmentation approach mostly applied either fuzzy logic, several variations of artificial neural networks, and rule-based classifiers to the segmented object. Cho *et al*. [74] applied fuzzy logic to the segmented defect object and discovered that small knots and large knots containing checks (cracks or flaws in timber) were correctly identified on a sample of oak board, while wane and holes were identified correctly on a sample of cherry board. Cho and Conners [51] further compared an artificial neural network (ANN) and a k-nearest neighbour (KNN) classifier and concluded that in differentiating between clear wood and defects, the performance of ANN and KNN were comparable, which was around 80% accuracy but ANN seemed to work better in classifying different types of defect classes with an accuracy of 75% compared to 72% for KNN. In this study, defects considered were splits/checks, holes, wane and knots [51]. Similarly, Estevez *et al*. [60] implemented an ANN classifier and achieved up to 80% classification accuracy in classifying 10 types of defect with the feature vector reduced by a genetic algorithm (GA).

Another study showed that a timber grading system applying fuzzy logic was 31% more accurate than a human grader. Hu *et al*. [58] used eight recognition rules to identify splits and holes and achieved 94.5% accuracy. In another work to distinguish between sound knots and dead knots, the classification accuracy also exceeded 90% [62]. Pham *et al*. and Ruz *et al*. [63, 64] tried a unique approach in solving the defect segmentation problem by using a Fuzzy Min-Max neural network (FMMIS), constructing a hyper box enclosing the defect by using an initial seed as input into the network. The seeds were selected by applying an adaptive thresholding method. Another recent work by Lee and Araman [67] employed several variations of an ANN modularly to identify several types of defect. In their study, a multi-layer perceptron (MLP) was used to identify clear wood, a radial basis function network (RBFN) was used to identify knots and decay and a final competitive network further made final classification on a pixel-by-pixel basis. The combination of these networks was reported to achieve 96.7% classification accuracy.

For the non-segmenting approach, local regions divided from the original image were classified directly into defect types. In earlier studies, many classification solutions have been suggested such as distance based on chi-square classifier, pairwise classification, decision tree and Bayesian classifier, among others. Conners *et al*. [48] managed to achieve 88.3% correct classification of 10 types of defect using two sequential classifiers: distance based on chi-square to separate defect and clear wood, as well as pairwise classification for identifying other types of defect. Koivo and Kim [49] implemented a decision tree to classify eight types of defect and obtained 96.6% classification accuracy. However, the sub-images used for training and testing were limited to only 20 samples per class. Kim and Koivo [4] furthered their work by applying hierarchical recognition combining thresholding, freeman chain code for identifying shape and a Bayesian classifier for classifying texture features. They created three sets of data to simulate samples in a dusty environment. As a result, a cleaned surface achieved 92.2% correct classification, while the classification result decreased on dusty surface to 81.2%. However, on a dusty fan-cleaned surface, the classification accuracy was up to 89.6% [4].

Niskanen [56], Niskanen *et al*. [61], Silven *et al*. [75] tried a different approach using non-supervised clustering based on a self-organising map (SOM) for wood defect detection. It was reported to perform well with approximately 31% false alarms, 5% error escape and 72% defect detection accuracy. Although it was claimed that human involvement in training is minimal in unsupervised clustering, selecting appropriate features for classification is still practically supervised [56]. In a recent study, Rinnhofer *et al*. [18] employed a maximum likelihood classifier for classification of 12 defect classes based on textural features and claimed to have classification accuracy greater than 97%. Another recent study reported over 73% detection accuracy using an ANN to classify between sapwood and heartwood [65].

Unfortunately, it is very difficult to compare classification performance results between these studies because each study has employed different image acquisition settings, timber species, types of defect, and even if a similar set of features was used, the extraction parameters were dissimilar in different studies. However, it is worth noting that most classifiers used were supervised classifiers and only a few were using an unsupervised method. This is due to the limitations of unsupervised methods in identifying defect type despite having good detection performance.

Although supervised classifiers were commonly used, in reality, samples of various defects are not easy to collect. Different timber species have different types of common defects. While some defects are common and more prominent in one species, they might be rare in others. That is why, as seen in most previous studies, the samples are limited to one type of timber species only. However there are some studies that have reported using multiple species [50, 51, 67].

6.0 DISCUSSION

In this paper, we have reviewed past works on automated inspection of timber surface defects. Many types of sensor have been used to automate the inspection of timber, targeting the detection of internal and external defects. While some of the sensors demonstrated good performance, most of them remain experimental. Difficulty in industrial implementation especially within small and medium sized industries is mostly related to the large investment cost involved. For easier implementation and lower costs, optical sensors seem to be the most favoured. Although their capability is limited to inspection of surface defects, they would at least contribute to productivity improvement in the inspection process.

There are two main approaches to the timber surface defect detection problem: the segmentation approach and the non-segmenting approach. The choice of approach depends on the targeted application. The segmentation approach may be suitable for applications that require detailed information on the defect detected such as timber grading. The non-segmenting approach, however, provides less detail but faster detection and sufficient defect boundary identification for applications such as timber cutting. For the non-segmenting approach, choosing the appropriate local region size depends on the structure of the texture. In that case, we recommend that a feature analysis be done before the classification stage. This is to ensure that the choice of local region size is sufficient to capture enough textural information in order to discriminate between types of defect.

Common features extracted from the segmented defect object using the segmentation approach were tonal, textural and geometrical features. On the other hand, tonal and textural features were frequently applied in the non-segmenting approach. Textural features were seen to be promising as it was claimed that they best represent hardwood properties. Features from a co-occurrence matrix were seen to be prevalent in most studies as co-occurrence matrices have proven to demonstrate good performance in a wide array of studies. Nonetheless, the key aspect of ensuring well characterised timber defect textural properties is through a proper parameter analysis of the co-occurrence matrix. Appropriate choice of co-occurrence matrix parameters will support the development of reliable features thus contributing to good classification performance.

It is worth noting that in some studies, a combination of classifiers were implemented with terms such as sequential, hierarchical, multi-level and multi-layer classification being used interchangeably. Despite good detection and classification performance shown in previous studies on timber surface defect detection, it does not seem fair to compare between them as each of the studies applied different types of sensors, used different timber species and covered different types of defect. Additionally, most of the studies were seen to limit their samples to only one type of timber species. Therefore, it will be difficult to bring the outcome of any of these particular studies to the industry if the model trained is tuned to fit to only one type of species when, as we know, wood industries are processing multiple species at a time. However, the outcomes of previous studies are important to help us understand what are the things that are workable especially in defect detection, thus avoiding unnecessary efforts which are unrealistic.

Although certain defects are more prominent in one timber species than another, there seems to be more similarity than dissimilarity in the defects presented across different species. That assumption enables us to draw a certain research direction towards characterisation of timber defects using common features. However, finding the appropriate common features to represent many types of defect across multiple timber species remains a challenging problem in automated inspection of timber defects. To conclude, the computational methods for analysing the images of timber surfaces for reliable and real time defect detection, and exploiting the output of surface defect detection to determine optimal timber cutting and grading strategies remain an open research topic.

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