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Timber 4.0

A Computer-Vision Approach for Visual Grading Low-Grade Plantation Hardwood

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Abstract: The objective of this study was to develop a proof-of-concept for using low-cost, off-the-shelf RGB-D computer vision techniques to assess grading and defect features in low-grade plantation hardwood. It is framed within a wider research project that proposes the integration this data within a Cyber-Physical System allowing real-time design and material feedback within a computational design and fabrication workflow.

Keywords: Computer vision; plantation timber; digital fabrication; computational design.

1. Introduction

The value-capture of low-grade plantation hardwood (LGH) is fundamental to the long-term viability of Australia's timber industry. The majority of plantation hardwood in Australia is managed for pulplog production (Downham and Gavran, 2017), which is maintained as un-thinned and unpruned, resulting in material unsuitable for traditional construction applications.The emergence of novel softwood-based engineered-timber solutions in Europe, such as cross-laminated-timber (CLT) and Glulam, has seen the implementation of smart manufacturing pipelines that demonstrate a paradigm shift away from timber as a simple material resource towards an increasingly digital-based ecology.

The introduction of computer vision (CV) enabled grading methodologies and cyber-physical smart-manufacturing pipelines provide opportunity to harness Australia's extensive reserves of LGH. Intermixed with bespoke computational design and robotic fabrication, the potential for new value-propositions and innovative construction systems in utilising LGH is even greater. The coupling of a low-cost CV system and fabrication process, integrated into a design methodology accommodates the utilisation of LGH at a bespoke, end-user level.

The scope of this paper describes a proof-of-concept, technical approach to RGB-D (red, green, blue and depth) CV in order to qualify benefits of automated assessment of timber boards versus current industry practice. Following, the paper discusses immediate and long-range research goals of CV techniques within a digital fabrication or cyber physical production pipeline.

2. Context: Australian Low-grade Hardwood

Australia's plantation timber reserves comprise of approximately 1,037,000 hectares of softwood and 928,000 hectares of hardwood forests. While softwood plantations are almost exclusively managed for sawlog grade timber, 82% of hardwood plantations are primarily managed for pulplog production (Downham and Gavran, 2017). Consequently, softwood plantations are directed towards profitable structural grade materials for the construction industries, while hardwood plantations are destined for low-value fibre industries such as chip, pulp and paper.

Sawlog grade plantations are managed and maintained to ensure straighter, larger trees that contain minimal defect features for a high-value market. Pulplog plantations however, are generally left to grow without regular maintenance, allowing the trees to grow irregularly, demonstrating a significantly higher defect feature rate. In a low-value fibre market the highly featured nature of LGH is of little importance. The demand for sawlog grade hardwood is still present and is met by either logging native forest reserves or, the increasingly common importation from overseas (Derikvand *et al,* 2017). Australia's hardwood plantation is primarily Tasmanian Blue Gum (*E. globulus*, 52.7%) and Shining Gum (*E. nitens,* 25.2%), both of which are unsuitable for high-value markets when managed as a pulplog resource.

This mismatch between demand and quality presents a significant opportunity to investigate alternate material and fabrication methodologies that lend themselves to value-adding to the LGH market.

3. Related Work

While the introduction of CV techniques in the timber industry is not new, there is little research into its application with LGH grading and processing. Due to the length of the timber production cycle (grow, harvest, sawmill, drying, grading) a variety of techniques can be applied at different stages of the production process. While this study focuses on timber assessment at the point of fabrication using low-cost methodologies, there is significate precedent concerning the use of low and high-end CV techniques in a variety of forestry and production industries.

3.1. Computer vision in forest management

Significant developments in LiDAR scanning (Light Detection and Ranging) has allowed forest management to be increasingly optimised. When coupled with GPS enabled airborne systems LIDAR has the capacity to scan entire stands of forest and measure the topography of land, distribution of plant canopies and likely vegetation structural characteristics (Lefsky *et al* 2002). When paired with traditional data such as species and age, predictions can be made about the maturity of the forest, potential yield and suitable strategies for further management and harvesting (Lima *et al*, 2003). While these conclusions can be made using traditional field work and analyses, there is significant cost savings in utilising a digital system (Means *et al* 2000).

Brouwer (2013) argues that aerial LiDAR scanning remains at a high price point suitable for large forestry companies, and that the development lower-cost methodologies is required for smaller applications and scenarios. Brouwer's research suggests that RGB-D based scanning can provide low-fidelity data that can contribute to plantation forest assessment and management. Off-the-shelf RGB-D devices can be restricted by daylight sensitivity and scan range. However, Brouwer found daylight interference was minimal due to scanning being located on the darkened forest floor and that scan range was comparable to traditional methods of forest assessment. Although Brouwer's proof-of-concept investigates softwood plantations, there is significant cross-over to hardwood plantations.

3.2. Advanced imaging in sawlog processing

Internationally computer tomography (CT) scanning is employed within many sawmills to increase the yield of recoverable material from saw logs (Taylor *et al* 1984; Fredriksson, 2014). Complimentary research has been conducted that assesses CT imagery via artificial neural networks and machine learning techniques to increase the accuracy and reliability of feature detection within a sawlog (Nordmark, 2002). In simulations Rias *et al* (2017) found that an average 20% yield increase occurs when CT processes are utilised to optimise log rotation within a sawmill. These studies demonstrated that CT scanning is able to identify a number features (knots, internal checking, heartwood) that increase the yield from the sawlog.

The majority of research in sawlog scanning is situated within the softwood industry, which requires adaptation to a plantation hardwood supply chain as demand for the resource increases. Additionally, CT and x-ray scanning within a sawmill production line is a financially significant investment that, in the context of the Australian market, is unlikely to be utilised widely. This suggests a case for investigating novel digital processes that occur post-sawmill processing that integrate feature identification within a potentially lower grade sawn board. There is opportunity for CV to be employed at the point of design and/or fabrication, utilizing off-the-shelf scanning techniques that provides a methodology for an increase in low-value timber utilisation.

3.3. RGB-D scanning in alternate production environments

Within other production environments a number of research groups have utilised RGB-D scanning techniques in the context of both increasing yield and improving production line efficiency. It is common for proof-of-concept studies to utilise low cost off-the-shelf hardware solutions in order to capture data for assessment of product quality. Both Spoliansky *et al* (2016) and McPhee *et al* (2017) utilise Microsoft Kinect hardware as a means of collect real-time data within the livestock industry. These studies couple RGB-D scanning with digital image processing and machine learning to establish a method of assessing physiological characteristics food-based production animals. The introduction of RGB-D based CV in this scenario aims to increase the value, efficiency and yield of production process.

4. Method

4.1 Current hardwood grading practices

A significant challenge to the adoption of LGH for construction purposes is an efficient method for assessing each board's unique functional, structural and visual idiosyncrasies. Native forest hardwood is generally commoditised as manually graded, clear faced length as per AS2082-2007. This allows sawn boards to be visually graded against a series of features and categorised into 4 structural grades. If a board doesn't meet one of the criteria, it is downgraded accordingly (Standards Australia 2007). This process is usually undertaken manually within a sawmill and consequently, a large volume of material is dismissed, often due to a single defect, resulting in a significant material wastage and monetary loss.

Feature rich plantation hardwoods are unable to be visually graded for structural use. No equivalent to AS2082-2007 exists for LGH. As demand for hardwood products increases and supply from native forests is reduced and exhausted, new grading standards need to be developed that are able to assess plantation LGH. Additionally, the parallel development of novel construction systems based on the use of plantation LGH need to be commercialised (Derikvand *et al*, 2017). The understanding of LGH as part of an engineered system could accommodate out of grade material in a manner that maximises usage of finite resources and value adds to the lifecycle of traditional timber production methodologies.

4.2 Scope of prototype

The scope of the proof-of-concept was to establish a low-tech workflow that utilised RGB-D scanning to determine sawn board features (live and dead knots) in plantation *E. globulus* (Figure 9). Live and dead knots present significantly different structural capacities (Kretschmann and Hernandez, 2006) that impact the suitability of a material for a certain task. This suggests that when considered on a board-by-board basis, feature rich LGH has potential in construction, particularly within bespoke manufacturing and engineered system scenarios.

Figure 9: Live (above) and dead (below) knots in dressed timber boards.

4.3. Timber samples

Dressed 140x35mm *E. globulus* boards were selected for the experiment (Figure 10). The samples originated from a 16-year-old Tasmanian plantation that had been managed for pulplog. They demonstrated a typical range of features including clear wood, gum vein, live and dead knots, at a low-to-medium frequency as would be expected from a pulp-managed forest. 20 samples were used, ranging in length from 450mm to 2100mm.

Figure 10: A sample of *E. Globulus* boards used for testing

4.4. Prototype

4.4.1. Setup: Hardware

A Microsoft Kinect was selected as the CV hardware for the prototype, providing an adaptable off-the-shelf solution. The Kinect development framework provides access to low-level data streams from the depth sensor (512x424 infrared active, 0.5-4.5m range) and the HD camera sensor (1920x1080, 30 fps) which are utilised within the prototype. The RGB sensor offers 2,073,600 pixels of data at a field of view of 84.1x53.8 degrees. The infrared sensor provides 217,088 depth voxels at a field of view of 70.6x60 degrees (Diaz *et al*, 2015; Lachat *et al*, 2015). The Kinect offers relatively high sensor quality considering is purchase price.

The Kinect's sensors allow an easy transition from proof-of-concept to commercialisation as they are easily substituted for high quality, specialised components suitable for a production environment. Additionally, open software platform support (SimpleOpenNI and libfreenect2) allows the Kinect, or substituted hardware, to be adapted to a wide variety of scenarios

4.4.2 Setup: Software

The Kinect provides support for a number of software platforms including python, C/C++, Matlab and visual basic. However, as the proof-of-concept sits as a part of a wider project, an architectural CAD package was chosen as the development platform. This choice is critical to the development as it provides a fluid environment in which CV data can be directly integrated and visualised with a design and fabrication software workflow. McNeel's Rhinoceros 3D 5.0 (Rhino) was selected as a platform, in addition to the Grasshopper visual scripting plugin.

This combination provides a graphical environment to develop within, allowing the datasets to be contained within the same geometry based platform as the wider project (adaptive design and robotic fabrication). A significant difficulty of using a CAD package for live RGB-D is the inability to handle large datasets. The Tarsier plugin (Newnham, 2016) provides Grasshopper with near real-time access to the Kinect data stream by treating the RGB-D voxel data stream as a single point cloud. Tarsier additionally includes a number of parsing tools to filter the stream for environmental interference and data that is out of the prescribed scan range.

4.4.3 Setup: environment

Two scenarios were established to test the Kinects RGB-D scanning fidelity over short-range (600mm) and long-range (3000mm), as shown in Figure 11. The long-range tests were scanned horizontally, while the short-range test was scanned vertically. In both cases, the boards were scanned in a single pass, and the sample and Kinect were aligned to ensure minimal perspective distortion. In a production environment, the short-range scanning arrangement is more suitable due to the increased resolution and lends itself to development as a lineal scanning process (broom-stick) to accommodate longer timber lengths common in production-line manufacturing.

The hardware/software interface was controlled in two stages within Grasshopper, as shown in Figure 12 . The first stage controlled the RGB-D scanning and identifies knot locations and type. Additional parsing filters eliminate unnecessary scan data, control the size threshold of a knot (clusters of similar colours or depths), and compares RGB and depth streams to establish which features are live or dead knots within the board.

The second stage combines the board data (size and features) to a unique ID and exports the information into a text based data format. The information contained relates to the resulting usable length/s of the board in its entirety; usable lengths after dead knots are removed; and usable lengths with all knots removed. The CSV text format allows this information to be either stored in a database for future use or integrated immediately in a production workflow.

Figure 11: Long-range (left) and short-range (right) experiment setups

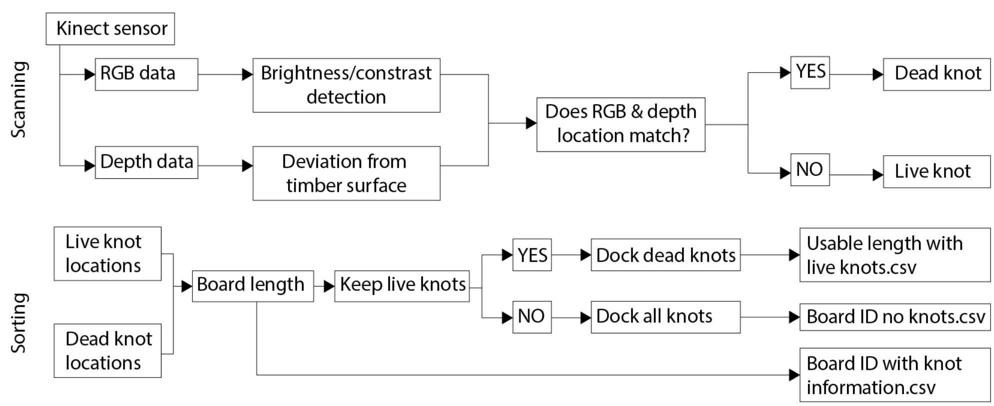

Figure 12: Knot identification and board sorting workflows

The parsed and clipped raw data form the Kinect is shown in Figure 13. The prototype allows for the fine adjustment of the scan feed including depth range, scan density, smoothing and frequency. Live knots are detected in relation to the depth of the scan, compared against the thickness of the board. A depth threshold was set at 5mm, with any voxels having a greater depth greater identified as potential dead knots and clustered together.

The processing of the detected dead knot cluster is shown in Figure 14. If a cluster of points has size larger than the specified diameter it is isolated. The minimum usable length of timber was specified as

500mm and considered against the knot location and the overall length of the board. Figure 14 shows the usable board indicated in green, with the un-marked section too short for use.

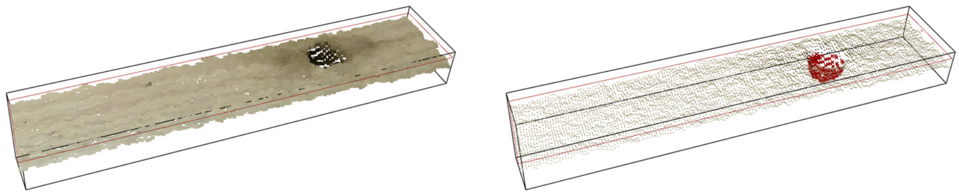

Figure 13: Raw data displayed as coloured voxels (left) and with dead knot detection (right),

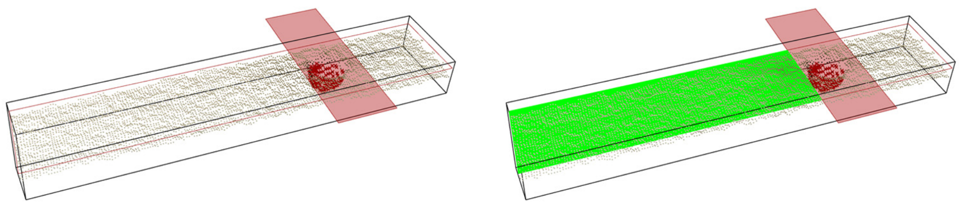

Figure 14: Dead knot isolation (left) and usable length output in green (right)

4.5 Results

Figure 15 illustrates typical results obtained from the long-range scans. After RGB and depth comparisons the red zones indicate dead knot locations and the blue zones are linked to live knots. The green areas identify useable lengths within the board after knots are removed, while the uncoloured area are lengths are shorter than the specified minimum-length.

Figure 15: Live scan and knot identification

The long range tests demonstrated a high level of success in identifying knot defects via RGB scanning techniques. However, the depth scanning technique offered less successful results at this range in determining dead knots. The most probable reason for this is related to the lower density of scan points detected over larger distances, making smaller features harder to detect. The short-range tests were able to detect much smaller defects in the timber samples and demonstrated a higher level of correlation between RGB and depth data in the determination of live and dead knots. The output of scan results to raw data (Table 3) groups the information according to the sample identification. Although the experiment was conducted in a workshop environment, environmental interference resulting from sunlight was evident. Again, this is a larger issue in the long-range scans.

Table 3: Sample of knot location output

Sample ID	Length (mm)	Live Knot Location	Dead Knot Location	Usable Lengths (mm)
N001	465	159, 316	62	-
N002	614	249, 401	560	594
N003	1072	227, 602	-	1072
N004	820	260	-	820
N005	796	745	187	776
N006	1241	842	-	842
N007	1229	405	82	1209
N008	1065	651, 835	350	1045
N009	824	534	-	534
N010	824	564	564	804
N011	1021	-	-	1021
N012	1186	887	-	1186
N013	498	438	249	-
N014	783	667	-	783
N015	812	724	-	812
N016	812	-	-	812
N017	1113	525, 917	-	1113
N018	1250	-	1227	1200
N019	2100	714	1997	1980
N020	2100	-	601	1450, 580

A combined 21.6 lm of samples were scanned with 18.0 lm determined as usable. This represents an 87.5% recovery return in system that has a 500mm minimum usable requirement. For comparison, a 54.7% recovery rate was apparent when the minimum length was specified as 900mm.

5. Discussion

5.1 Industry 4.0: Cyber-physical manufacturing processes

The fourth industrial turn, often referred to as Industry 4.0, posits a shift in manufacturing from the automation of generic, dangerous and repeated tasks towards the establishment of reciprocal interactions between physical processes and increasingly aware and intelligent computational decision-making strategies. Sedlar *et al* (2016) states that:

> "Based on the merging of digital computation resources with physical objects, a Cyber-Physical System (CPS) represents a novel paradigm that aims not merely to be able to gather information about the state of the physical world but also to influence it based on the gathered data."

As such, CPS provides the conceptual and technological framework upon which a smarter, open-ended and resource efficient manufacturing sector can be established. CPS accommodates an unprecedented opportunity to value-add to the existing supply chain of Australian hardwood. Information containing origin, management type, growth rate, feature distribution and density can be integrated, allowing designers and fabricators access to material information previously unviable. Capacity to specify intrinsic visual and performance based characteristics of LGH allows designers and fabricators to match design and supply within a digital manufacturing process to ensure that the highest vale and material return is achieved. Additionally, forestry management and harvesting strategies could be enhanced allowing for more productive and valuable methodologies to be established.

5.2. Digital supply & manufacturing

Bespoke modes of production are especially relevant to stick-based timber construction systems that could comprise elements of differing performance (functional grading) and dimensional properties (length, width and depth). The potential of this approach is demonstrated by the recently completed *Sequential Roof* project at ETHZ, that utilises short length graded timber elements in conjunction with an automated robotic fabrication system (Apolinarska *et al*, 2016). While this project doesn't utilise an adaptive CV/fabrication process, it establishes precedent for architectural scale systems consisting of thousands of unique timber parts.

In the context of this research, the proposed RGB-D scanning prototype accommodates the utilisation of LGH within a bespoke deign/fabrication process. The prototype essentially creates a database of usable timber that can be integrated into a computational design process – the performance based design solution is adaptable to the material that is immediately available. When coupled with digital manufacturing, complex arrangements of material can be managed with specificity.

6. Future Work and Conclusion

This research provides a proof-of-concept data generation solution for two integrated CPS design-to-production pipelines; intelligence at the point of work (fabrication) and; intelligence in regard to the sourcing of timber from a big-data archive. There is much work to be undertaken in order for it to be utilised within a larger cyber-physical design/fabrication system however.

Empirical testing and comparison of RGB-D results and traditional visual and mechanical grading requires further investigation to allow accurate integration machine learning based predictive assessment of LGH at the point of fabrication. Further work is necessary to determine the type of solutions that are viable with this type of dataset, particularly focused on how it would integrate with performative design workflows that are linked to direct fabrication capabilities.

The proof-of-concept outlined in this paper provides a starting point for the LGH timber industry to reassess its strategies around production and delivery attempting to increase the value of an otherwise overlooked and under-valued resource.

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