Machine vision system grading of pine tree seedlings

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Abstract

A PC-based machine vision system for grading pine tree seedlings has been tested at a forestry nursery. The machine has been designed to be implemented in the field at the point of harvesting, removing the need for extra handling steps. The machine measures the height, RCD and root quadrants and makes a decision whether to reject or accept the tree.

The grading specification for pine tree cuttings and seedlings appears to be black and white, with clear rules defining whether a tree is acceptable or not; however, the organic nature of the product introduces ambiguity into the decision. Three experts were gathered and asked to independently grade a raw lift of 200 trees with no knowledge of the other experts' decisions. A consensus was not reached on one in every four trees. The same set of trees was graded by placing them in the machine one by one. The machine achieved 97% agreement with the group of experts, ignoring the decisions on trees where they did not all agree.

The machine has been proven to be capable of making decisions on pine seedling quality comparable to that of an expert. It performed well in a shed under controlled conditions; however, the effect of an outdoor environment has yet to be determined.

Background

Robotics and smart automation is commonplace in controlled factory environments; however, in outdoor agricultural environments many processes still remain highly labour intensive. This is due to additional challenges associated with introducing automation into this type of environment, including:

Difficulties handling organic materials where there is much variation between objects, and their placement

- Dealing with the elements, lighting conditions etc.
- Required portability of equipment

Forestry is a significant industry in New Zealand; it contributes approximately 3 % of New Zealand's GDP, earns five billion dollars of gross profit annually, and directly employs around 20,000 people (Ministry for Primary Industries, 2017a). It is estimated that commercial New Zealand forestry nurseries sold over 52 million seedlings in 2016 (Ministry for Primary Industries, 2017b). Trees must be extracted from the ground, soil removed, roots trimmed, graded and sorted. The nursery this study is based on employs a crew of between 30 and 40 people to lift and grade approximately six million trees annually, making it the most labour intensive and expensive operation in the nursery. There is a need to automate the process due to the many problems with seasonal labour, including:

Health and safety issues.

- Undertrained workers as a result of high staff turnover.
- Poor staff reliability.
- Difficulty securing required staff numbers.
- Poor efficiency and accuracy of quality control.
- High costs.

Mechanisation of lifting is standard in large markets such as the US; however, these machines are not suited to NZ's requirements as they are not capable of additional processing such as root trimming and grading. There has been work by other researchers into automatically grading seedlings, but nothing has been found which has been implemented commercially, and nothing performed in the field. Early studies used potentiometers and optical sensors for measuring tree features with success (Buckley, Reid, & Armson, 1978), (Ardalan & Hassan, 1981), (Grift & Oberti, 2006); however, such systems lack flexibility. As such, the majority of work since the late 1980s has been based on computer vision systems integrated into pack houses. These still require manual labour to load seedlings onto the conveyor with the orientation loosely constrained. Area scan cameras have been investigated by several researchers with similar results, typically using RCD, shoot height and root volume as the grading criteria (M. P. Rigney & Kranzler, 1988), (Suh & Miles, 1988) (Wilhoit, Kutz, & Vandiver, 1995). Rigney & Kranzler (1988) claimed a possible grading speed of over three seedlings per second; however tests were only performed at approximately half this speed to facilitate manual placement of seedlings onto the conveyor. A grading classification error rate of 5.7 % was achieved in a sample of 100 loblolly pine when compared to manual measurements. An additional 2.3% weren't able to be graded due to needles extending down past the root collar or roots bent upward past the root collar. Rigney and Kranzler (1989) upgraded their equipment and installed the system at a grading facility. The grading algorithm took approximately half a second to complete, half of which was to identify the root collar location.

There was a shift in later work to line scan cameras, due to grading being performed on conveyors. A line-scan concept was proposed (M.P. Rigney & Kranzler, 1990), and later implemented (M. Rigney & Kranzler, 1997). Processing time was around 0.25 s for a 500 mm tall tree. Poon (1996) also developed a prototype machine vision system based on the conveyor and line-scan concept. Unlike Rigney and Kranzler's device, Poon's was able to scan up to 14 seedlings at the same time using only one camera. A row of 14 seedlings was scanned in 8 seconds, equivalent to a rate of 1.75 seedlings per second, with an average classification error of 9 %. This method suffered from the same limitations as work done by Rigney & Kranzler in that it could not grade trees with roots or needles protruding into the root collar zone.

Methods

An infield lifter-grader was designed to meet the requirements of the forestry nursery. After mechanical processing, the tree is transitioned into a grading unit, as pictured in the schematic in Figure 1. The grading process is as follows:

1. Tree triggers an optical proximity sensor, and rests horizontally in the grading unit.
2. Images are acquired from 3 monochrome area scan GigE cameras, each capturing a defining feature of the tree – roots, RCD and height.
3. Images are processed and tree features are measured.
4. A decision on the quality of the tree is made, and sorted into 'good' and 'bad'.

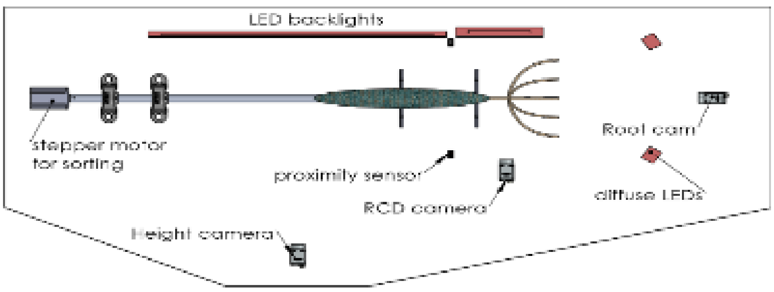

Figure 22. Top view of the grading unit

The framework and interface for a machine vision system has been developed using C# and the .NET framework. EmguCV has been used to wrap the C++ OpenCV libraries to C#. Figure 23 shows an example of the raw image captured by the camera (left), and a processed binary image with unnecessary detail removed. The machine vision system measured the RCD using the steps below.

1. Image is converted to black and white using a thresholding operation.
2. Unnecessary detail such as needles and roots are removed from the image by iterating through rows and columns and removing thin lines from the image.
3. The RCD is measured in pixels at each column in the image.
4. The smallest value for the RCD is selected and converted to millimetres.
5. The centre of the stem is traced to the root ball so that a vertical offset can be applied when processing the roots image.

Figure 23. Raw RCD image (left) and processed image with detail removed

Height was measured using the following algorithm:

1. An upper limit is set at the first column and a lower limit at the last column of the image.
2. The column corresponding to an average tree height is inspected first. If this column contains at least 10 consecutive black pixels, jump halfway towards the upper limit, else jump halfway towards the lower limit.
3. If jumping towards the upper limit, set lower limit to the last column inspected. Else set the upper limit to the last column inspected.
4. Repeat until upper and lower limits are within 10 pixels.
5. Convert height of tree in pixels to mm.

Figure 24 shows an example of a raw image of the roots (left) and a processed image on the right. Roots were analyzed as follows:

1. Image is converted to binary using an appropriate threshold to remove background detail.
2. The offset calculated when measuring the RCD is applied to locate the centre of the stem.
3. Starting at a radial offset from the centre of the stem, the stem is rotated around and roots are identified where there are a certain amount of pixels in the radial and tangential directions.
4. The largest angle between roots is calculated in degrees.

Three experts were gathered and asked to independently grade a raw lift of 200 trees, with no knowledge of the other experts' decisions. The trees were also measured manually – the RCD and height were measured as per the information provided by the nursery. The root angle was measured by printing the images acquired by the machine vision system and measuring the largest region void of roots with a protractor to the nearest 5 degrees. The same features were then measured automatically using the equipment described above. Equation 1 was used as the grading criteria.

Equation 1 - Grading criteria

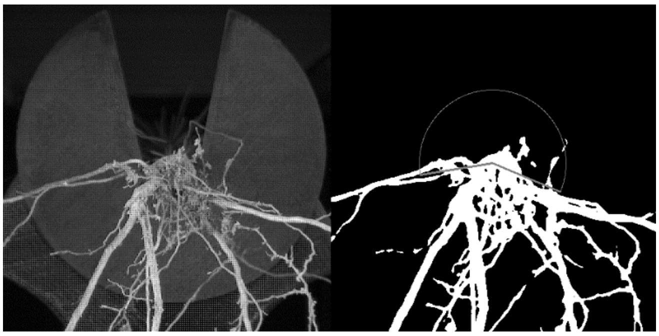

Figure 24. Raw roots image (left) and processed image showing measurement (right)

Results

Figure 25 shows the count of the difference between the measurements taken manually and by using machine vision. 84.0% of RCD measurements were within half a millimeter. 96% of height measurements were within 10 mm. Note that the minimum height measureable by the machine was 240 mm – trees shorter than this have been excluded from this calculation. There was higher variation with analyzing roots, with 56% of measurements within 20 degrees.

Figure 25– Count of difference between machine vision and manually measured features. RCD (top left), height (top right) and root angle (bottom).

The acceptance rate varied significantly between experts, ranging from 62.0 to 79.5 %. When compared individually to each other, the experts agreed on average 83% of the time, and a consensus between all three was reached 75% of the time. They agreed with the manual measurements on average 87% of the time, in contrast to the machine vision system which achieved a 97 % agreement rate. The machine vision system agreed on average 87% of the time with individual experts. The machine passed 2% of the trees which the experts all failed (potential rejects which would be included in the box), and failed 1% of trees which the experts all passed (potentially good trees which would be rejected). Ignoring the decisions on trees where the experts did not reach a consensus, the machine achieved an agreement rate of 97% with the experts.

Discussion

The grading specification for pine tree cuttings and seedlings appears to be black and white, with clear rules defining whether a tree is acceptable or not; however, the organic and variable nature of the product introduces ambiguity into the decision. It has been shown that grading of pine tree seedlings is a subjective task, even when grading to a strict criteria, with three experts only reaching a consensus 75% of the time. Trees which are clearly either in or out of spec will be agreed upon, however a proportion of trees lie close to the rejection criteria and could potentially be either accepted or rejected. The decisions differ mainly due to differing opinions on the quality of the roots, rather than height or RCD. In addition to disagreement between different graders, it is reasonable to assume that the same grader will make slightly different decisions when presented with the same set of trees more than once; however, this was not investigated in this study.

The machine vision system performed well and could be considered another expert, agreeing with the experts to a similar precision as they agreed among themselves; however, the machine vision system is far more consistent and agrees with the manual measurements to a higher degree than the experts did. On inspection of the six trees which the machine vision system disagreed with the experts on, it is clear the reason for disagreement was due to either sweep or roots, rather than height or RCD.

Due to the organic nature of the seedlings, it is not possible to get exact measurements. For example, the stem is non-cylindrical – the RCD on smaller trees can vary up to a millimeter when measured in different orientations, while larger trees can vary as much as 3 mm. There was significant variability in measurement of the root angle, however this did not appear to have an impact on the accuracy of grading. Accounting for sweep in the stem could improve accuracy of the machine vision grading, but previous work mechanizing the dibbling process has reduced the amount of sweeps to a negligible level. Sweep could be accounted for by utilizing the vertical offset of the stem from the RCD image as a strong indicator of a tree with sweep in it.

Control over handling from point of lifting means the tree can be presented to the grader with orientation well defined, eliminating the need for intermediate labour intensive handling steps, and simplifying image processing algorithms. Rigney and Kransler (1989) specified that half of the image processing time was locating the RCD region. This is not necessary in this case as the tree position well defined, meaning resources are not wasted scanning the entire tree for the RCD. This work did not suffer from the same limitations in measuring the RCD as other researchers, as it removed roots and needles protruding into the RCD region before making measurements.

Although grading is intended to be performed in the field, this was conducted in a controlled environment in a shed, and trees were manually dropped into the grading unit. The effect of outdoor conditions, such as soil and vibration is yet to be determined

Conclusion

1. The machine vision system is able to make decisions on the quality of pine tree cuttings comparable to the accuracy to the human experts.
2. There is much ambiguity in the decision making process – a consensus was only reached by the experts on 3 in 4 trees. Grading is not exact.
3. Machine vision grading could be made more sophisticated but there would be little benefit.
4. Grading is achievable in a controlled environment; however, in a field exposed to elements, vibration, soil, etc, there will likely be issues to overcome which can only be addressed as they arise.
5. Machine vision grading provides more consistent results that grading by humans

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