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Investigation of a 'Field Factory' to Harvest and Grade Tree Stock in a Forestry Nursery

A thesis

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Abstract

Primary industries are facing an ever increasing labour problem. Major concerns with labour include lack of staff training, high costs, poor efficiency, non-optimal quality control and health and safety issues. While automation is commonplace in factory environments, such technologies have not yet migrated to an outdoor, agricultural environment. Forestry nurseries are no exception, where the most problematic and labour intensive task is lifting and grading tree stock.

Mechanical lifting of tree stock is already performed commercially; however, these machines are incapable of performing the additional steps required by this research, particularly root trimming, coupled with a machine vision system that can replicate the human decision making process for selecting 'good' and 'bad' tree stock. In particular, there are strict criteria for root structure which must be assessed. Currently, human graders are proving to be poor assessors of this, to such an extent that tree stock is graded up to three times before being shipped to the customer. Additionally, there is the need to remove expensive pack houses. This research investigates a *field factory* capable of processing forestry tree stock in the field, from lifting through to grading and boxing.

The machine vision component of the *field factory* was tested in controlled conditions, on a sample of 200 trees. There was good agreement between machine vision measurements and manually measured tree features. There is much ambiguity in the grading process, with three experts only reaching a consensus 75% of the time when grading a sample of trees. The machine vision grading system performed very well, showing less bias than human graders. The machine agreed with the specification 96% of the time, significantly higher than the experts' agreements of between 86 and 90%. While classification systems such as fuzzy logic and artificial neural networks seem to be a good match for this research, they did not outperform the 'crisp' grading system.

A *field factory* for harvesting and grading forestry tree stock proved to be feasible; however, further development, particularly on mechanical systems, is required to produce a machine reliable enough to be implemented commercially.

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Chapter 1

Introduction

1.1 Overview

Productivity in agriculture has improved greatly over the years. The most significant developments in agriculture occurred during the 20th century with the introduction of the tractor. Henry Ford & Son corporation started mass production of Fordson tractors in 1917, made possible by their assembly line techniques. A multitude of implements pulled and powered by tractors were developed to mechanise crop production in different steps from tillage to harvesting [1]. Productivity has been increased further by the blending of sensors with machinery in many agricultural operations.

Despite this progress, many 'in field' operations remain highly labour intensive, with labour contributing about 40 percent of operational cost in horticultural operations [2]. There is increasing research into taking automation into the field and applying it at the point of harvesting; however, there is not yet a commercial solution for most crops. The continuing reliance on seasonal labour for most 'in field' tasks has many associated issues and needs to be addressed. Issues with seasonal labour include:

- High costs.
- 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.

The introduction of automation and the assembly line in factories greatly reduced the reliance on manual labour, improved efficiency and revolutionised the manufacturing industry. Although automation requires more costly equipment and highly trained staff, this cost is generally offset or overcome by the fewer number of staff required [3]. Automation works well in a factory environment, for example automobile production, where the tasks required are repetitive, parts are in fixed locations, have known sizes, and the environment is controlled. It has taken some time for 'smart' machinery to transition from conventional factories into the agricultural environment due to the additional challenges associated with this type of environment, including:

- Difficulties handling organic produce where there is significant variation in size and shape of objects, and their location.
- Produce is delicate, highly sensitive to pressure and easily damaged.
- Dealing with an outdoor environment, for example, the weather, variable lighting conditions, dust and dirt.
- Required portability of equipment and distances over harsh terrain.

While post harvesting processing systems are relatively well developed for many fruits, little attention has been given to other industries such as forestry. Forestry nurseries rely heavily on manual labour for many tasks including taking and setting cuttings, and lifting and grading tree stock.

1.2 New Zealand Forestry Industry

Managed forestry plantations are relatively juvenile in New Zealand. Land in New Zealand was mostly covered with native forest when European settlement began in the mid nineteenth century; however, by 1913, rapid native deforestation was becoming unsustainable, threatening many native species with extinction. Since then, restrictions on harvesting native forests and the conservation effort has increased, prompting mass plantings of exotic species. In 2015, 99.7% of all lumber harvested was from plantation forests [4].

Forestry has grown to be a significant industry in New Zealand. It contributes approximately 1.6% of New Zealand's GDP and directly employs around 25,000 people. Wood products are New Zealand's third largest export earner and commercial forestry covers approximately 6.4% of New Zealand's land area. 45% of all lumber was exported in 2015 for a value of 4.8 billion NZD, the largest market being China, followed by Australia [4].

Radiata pine is by far the most widely grown species, constituting approximately 90% of New Zealand's plantation forests. The next most popular species is Douglas fir at around 6%. The remaining forest is planted with eucalypts, cypress and other exotic species. It is estimated that commercial New Zealand forestry nurseries sold over 52 million seedlings in 2016, which equates to around 48,000 planted hectares [5].

New forests are propagated from cuttings or seedlings grown in a nursery, collectively known as tree stock. Seedlings are grown from seeds sown directly into the nursery beds, while cuttings are propagated from cuttings taken from mother plants. Tree stock is raised in nurseries, usually for a year, to ensure healthy product and maximise survival potential when planted out in the forest. A small portion of tree stock is raised in containers in greenhouses, but the vast majority is bare root stock that is planted directly in flat prepared nursery beds, as pictured in Figure 1.1.

Beds are raised slightly and spaced to allow room for tractor wheels. When first formed they are approximately 150 mm high, but this varies over time due to compaction and erosion of soil. Tree stock is densely packed in both directions: trees are planted in eight rows at an inter-row spacing of 125 mm, and spaced at 70 - 120 mm along the length of the beds (intra-row spacing). Details of the layout of the nursery beds are pictured in Figure 1.2.

Figure 1.1: Typical beds at a forestry nursery in New Zealand

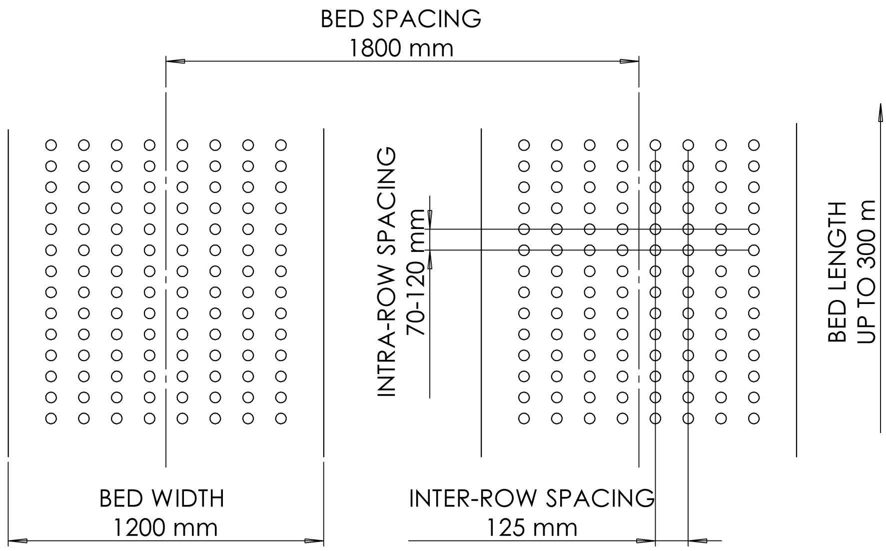


Figure 1.2: Layout of nursery beds

The process for raising both cuttings and seedlings starts differently, but once planted, subsequent processing is the same. Seedlings are sown directly into the nursery beds in spring [6] with a tractor-drawn drum seeder. Alternatively, cuttings approximately 100 mm in length are taken from mother plants in early to mid winter [6] and set into precise holes in the nursery beds formed with a dibbling machine. Dibbling methods will be elaborated on in Section 1.4.

Tree stock undergoes various operations during the year, including watering, undercutting, wrenching, fertilising, frost protection, and weeding. Undercutting and root wrenching can increase the hardiness of tree stock and improve survival potential. Undercutting is performed by passing a sharp blade underneath the nursery bed at a depth of approximately 100 mm. After undercutting, a blunt wedge shaped wrenching blade is passed under the bed to break off newly formed deeply penetrating roots and aerate the bed, typically 2-3 months before lifting [7]. This causes shoot growth to cease, while root growth continues, creating a compact mass of fibrous roots and a hard woody stem. Roots are also laterally pruned by passing coulters in between the rows [8]. If required, topping can be performed to control tree height in autumn before lifting [6].

Tree stock is lifted and graded in winter and on-sold to forestry companies. This happens to order, as bare-root tree stock can not survive for long out of the ground.

1.3 Lifting and Grading

In New Zealand, lifting and grading is performed by crews of seasonal workers with no mechanised assistance. There are several steps to the lifting and grading process:

1. A tractor-drawn lateral root pruner and undercutter are passed under the beds to loosen soil and separate roots, reducing effort required to lift tree stock.

2. Trees are lifted from the nursery beds by hand, one at a time.

3. Workers remove excess soil by striking the roots against their legs.

4. Trees are graded by visual inspection to the customer's specification, relying on worker training. A significant portion of trees are rejected and heaped into piles at the edge of nursery beds.

5. Workers bundle 'good' trees together and trim the roots to the correct length with hand shears, using their hand as a gauge. Saleable trees are boxed by the hundred.

6. Boxes of accepted trees are quality checked by a supervisor in the field.
7. Boxes are transported to the nursery cool store where they are often quality checked again before being shipped to the customer.

Soil removal is necessary to reduce weight and volume, and facilitate the trimming of roots, but care must be taken as it results in some loss of roots and mycorrhizae, which adversely affects tree stock quality [10]. A mycorrhiza is a symbiotic relationship between a fungus and roots which assists in absorption of minerals and water from the soil.

Typical grading criteria for a tree includes:

- The root collar diameter (RCD) must meet a minimum value. This is measured as the diameter of the stem 5 mm above the soil line for seedlings and 10 mm above the uppermost root development for cuttings.
- Sweep, a measure of stem straightness, must not exceed 30 mm. This is measured by placing the tree on its side on a flat surface and measuring the gap formed between the surface and the most raised part of the stem.
- Roots must be spread relatively evenly around the base of the stem. Tree stock is inspected from underneath and will typically be rejected if there is a region greater than 180 degrees with no roots present.
- Tree height must be within a certain range, typically 300-400 mm.

An example of an acceptable cutting is pictured in Figure 1.3. The left image shows a side profile of the tree, and the right shows the root structure of the same tree when viewed from underneath. Note that the needles have been removed from the right image for clarity. The tree is straight, of acceptable height and thickness, and the roots are growing evenly around the base of the stem. Root structure is an important feature for determining quality, as above-ground morphology is not always an accurate predictor of performance after outplanting [11].

The number of quadrants where there are roots present is used as a measure of root quality by nursery management and their customers. Seasonal workers

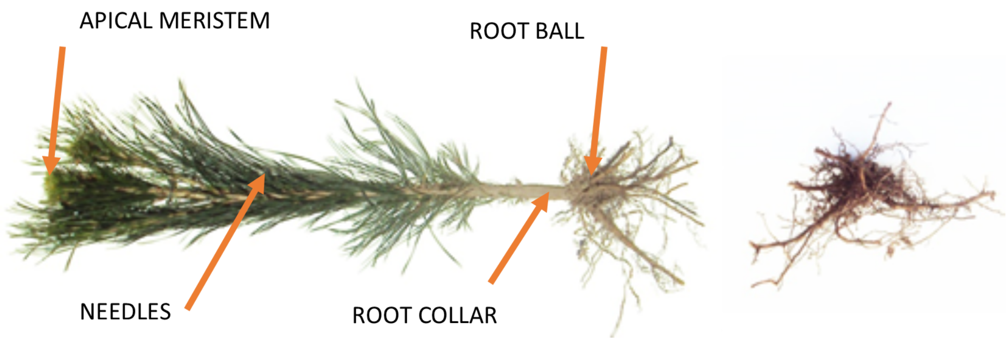


Figure 1.3: Example of an acceptable cutting

are typically given instructions like "the root structure is acceptable if there are roots from 12 o'clock to 6 o'clock". Figure 1.4 shows a diagram of how root quadrants are classified. Typically, tree stock with two opposite, three, or four quadrants will be accepted. Survival rate may not affected by the number of quadrants, but height and diameter growth can be significantly better for cuttings with four quadrants [6].

Cuttings are predominantly rejected due to inadequate root structure. Figure 1.5 (left) gives an example of root structure for a rejected cutting. The roots all project from one side of the stem, covering an angle shown by the red arc of only around 90 degrees, or only protruding into one quadrant. Figure 1.5 (right) shows the root structure of a typical seedling, which is superior to that of cuttings. Seedlings are generally rejected due to being too short or having a stem which is too thin.

Some nurseries lift manually and then grade tree stock back at a pack house. At this point they must be singulated before they can be graded. Singulation is time consuming as trees are very difficult to separate once bulked together. Some research into mechanising the singulation of tree stock contained in a hopper has been conducted, but with limited success [12]. Grading tree stock in pack houses is not common as it is significantly more expensive due to the multiple handling steps required. For example, at one nursery in New Zealand tree stock is lifted by hand, loaded onto a trailer and transported to a pack

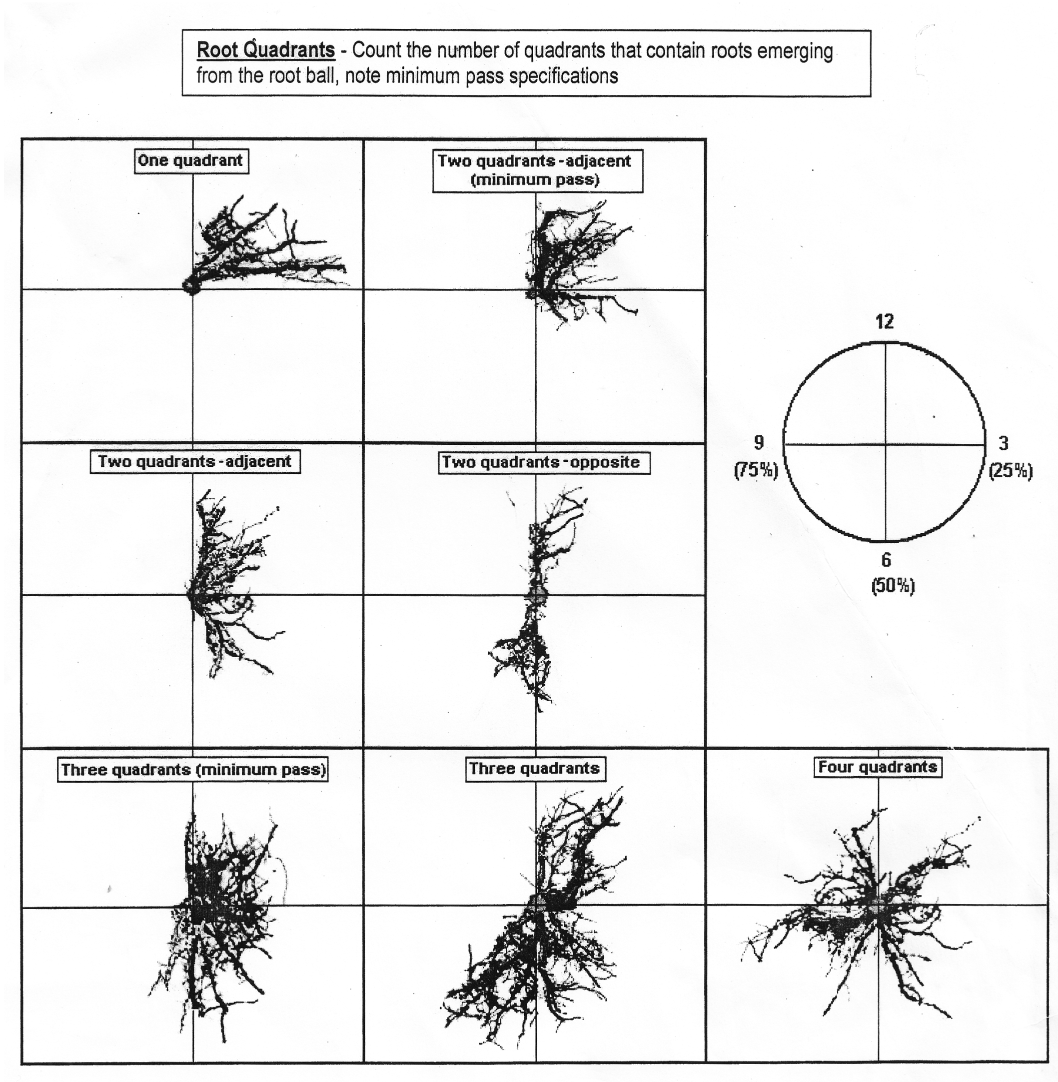


Figure 1.4: Classification of root quadrants

house. Bags of tree stock are carried to workstations where they are graded by eye, and roots are trimmed using a guillotine, as pictured in Figure 1.6. Tree stock then travels down a conveyor and is boxed by another worker.

A streamlined system is needed to handle tree stock from lifting to planting site [13], which could be achieved by automation. An integrated solution results in fewer handling steps which has further benefits:

- Reduced labour costs.
- Health and safety benefits by removing workers from repetitive and dangerous tasks.
- Reduced risk of physical damage to seedlings from rough handling.

Figure 1.5: Example of a cutting rejected due to root structure (left), and strong root structure typical of a seedling (right)

Figure 1.6: Manual trimming and grading in a pack house

- Reduced risk of desiccation as trees have a shorter exposure time to the elements. Root exposure reduces both survival and growth of bare-root stock [10].

One of the largest driving forces for automation of the lifting and grading processes in forestry nurseries are health and safety concerns. Nursery workers are historically prone to injury, with one early study claiming up to 31% injury rate in British Columbia nurseries [14]. Workers are at risk of cutting themselves when they are trimming the roots to the correct length: they grasp the tree roots and use their hand as a gauge, bringing the shears very close to their hand. Additionally, repetitive movements can cause occupational overuse syndrome (OOS), particularly in wrists and hands. Back sprains are frequent as workers must bend over to lift the short tree stock. Recent introduction of the Health and Safety at Work Act 2015 in New Zealand puts personal liability onto people of significant influence in the company or business, such as directors, chief executive officers (CEOs) and partners. The most serious breach of the act could bring a penalty of up to 5 years imprisonment, up to a $600,000 fine, or both.

Rising labour costs are also driving the need for automation. The recent coalition deal by the New Zealand government aims to increase minimum wage by 27% to $20 per hour by 2021. This will have a significant impact on the economics of the industry, and will push already slim profit margins. Lifting and grading is the most expensive operation in a forestry nursery, representing between 30% and 50% of a nursery's total production costs [9]. A break down of associated costs per 1000 saleable trees is presented in Table 1.1. A typical NZ nursery selling four million trees per annum would incur an expense of around $233k annually for lifting labour alone, which is by far the largest expense.

There are many additional issues associated with the reliance on seasonal labour. The high staff turnover causes many problems, including:

- Lack of productivity: The cost of wages can be more than the sale price of tree stock, particularly when workers are new to the job.
- Wasted product: A large number of 'good' trees end up being rejected.
- Long training periods: Training is required every season and it takes significant time to get workers up to a competent level.
- Inefficiencies: Trees are checked multiple times as the graders' decisions cannot be fully relied upon.

Table 1.1: Cost of lifting and grading (NZD per 1000 trees)

Labour	
Lifters	58.30
Supervisor	1.88
Tractor driver	1.88
Quality control	6.20
Equipment	4.75
Drug Testing	0.66
Tractor Expenses	6.25
Total	79.92

- Difficulties obtaining staff: Staff numbers required for lifting and grading can not be fully sourced locally, resulting in a reliance on imported labour.

These issues present a strong case for automating the lifting and grading process, which would avoid all of the problems associated with seasonal labour. The need for mechanised lifting [9] and machine vision grading [15] [16] in forestry nurseries has already been identified, attributed mainly to the rising labour cost. Manual labour has long been known as an inefficient method for grading in forestry nurseries due to human error and machine vision could be a better option [17]; however, currently there is no commercially viable alternative. Additional benefits could be realised with machine vision, including [15] [16]:

- Analysing data obtained for every tree lifted to influence where each seedling was planted when on-sold. For example, trees with heavier root systems could be transplanted to harsher sites.
- Increased yields by sorting and marketing alternate grades.
- Higher number of saleable trees.

- Improved nursery practices by correlating morphology statistics with factors such as seed source and weather.
- Flexibility to easily adapt grading criteria to customers requirements.
- Accurate tree counts and statistics can be recorded as data is available from every tree.

1.4 Nursery Automation

This work is part of an ongoing research relationship with ArborGen Australasia, a wholly owned subsidiary of ArborGen Inc. ArborGen is New Zealand's largest producer of forestry tree stock producing around 25 million trees per annum. They have several nurseries throughout New Zealand, located in Tokoroa, Kaikohe, Nelson, Whakatane, Puha, and Edendale. This research is based at the Tokoroa nursery which produces around 4 million saleable bare root trees annually. Radiata pine and Douglas fir are planted in similar proportions to the national average, at a ratio of roughly 1:1 seedlings to cuttings.

There are many inefficiencies in the nursery, with a strong reliance on manual labour, and most equipment remains relatively unchanged since the 1970s. The nursery suffers from all of the issues listed in the previous section. They identified the need to embrace automation to improve productivity in order to remain profitable. The first inefficiency addressed was the process of forming holes in nursery beds for planting cuttings and containerised seedlings, known as dibbling. The majority of holes were dibbled with a tractor drawn implement as pictured in Figure 1.7 (left). This operates relatively quickly, but produces poor quality holes. The trajectory of the pins forms a groove rather than a hole, as pictured in Figure 1.7 (right). Poor quality holes increase the chance of cuttings being set on an angle, which causes sweep in tree stock and results in rejected product.

The other dibbling method relied on boards with an array of pins, which were pressed into nursery beds using the weight of two operators, as shown in

Figure 1.7: Traditional tractor-drawn dibbler

Figure 1.8. The boards are highly labour intensive, time consuming, and they compact and crack the soil.

Figure 1.8: Manual dibbling boards

The author was given the task of producing a piece of 'smart' machinery to perform the dibbling. A robotic dibbler was produced based on pneumatics, which was configurable to varying depths, spacing and diameters for different tree types [18]. The machine was commissioned in 2013, and has been used successfully for five seasons, dibbling approximately 10 million holes during this time. An image of the dibbler during testing is shown in Figure 1.9. A video of the dibbler can be viewed at https://youtu.be/7RdTun1eAt4. The robotic dibbler has benefited the nursery in three main ways:

1. Reduced labour cost.

2. Estimated increase in productivity while setting trees of 30%.

3. Improved yields due to lower rejection rate.

Figure 1.9: Robotic dibbler during testing

The robotic dibbler highlighted the potential for increased productivity by introducing more advanced equipment in the nursery. As identified, the single greatest benefit in a forestry nursery would be from automating the lifting and grading processes. The nursery employs around 30-40 seasonal workers to perform this task during June to September. Labour units could be reduced dramatically by producing a machine capable of lifting and grading forestry tree stock in the field. Such a machine would require a shift of 'smart' technology from the factory to field environment, and remove the need for costly pack houses. As such, it has been dubbed a 'field factory' by the author.

To be commercially viable, the *field factory* would be required to harvest at the same rate as the manual team, which on average is 120,000 saleable trees per day. Typically, approximately 65% of cuttings and 95% of seedlings are accepted. As the nursery is planted half with cuttings and half with seedlings, the overall acceptance rate can be averaged at 80%. This means approximately 150,000 trees are required to be lifted to provide 120,000 saleable trees per day. Assuming an actual lifting time of 8 hours per day, this equates to 5.2 trees per second. If necessary, this could be reduced by extending lifting hours and working 6 days a week instead of 5. A 6 day working week would reduce the required rate to 4.3 trees per second.

A list of key criteria for the *field factory* is given below. The complete list can be found in Appendix A.

1. Lift approximately 5 trees per second.
2. Perform all handling steps from lifting through to sorting, i.e. lifting, soil removal, root trimming, grading and sorting.
3. Operate in harsh conditions typical of winter in Tokoroa.
4. Cheaper than manual labour.
5. At a minimum measure root quadrants, height and RCD.
6. Simple interface which can be operated by nursery staff.

Chapter 2

Critical Review

This chapter reviews mechanisation and robotics in crop harvesting, specifically research applied to lifting and grading forestry tree stock. An overview of machine vision systems is given, with commonly employed techniques and algorithms. Two popular classification systems, fuzzy logic and artificial neural networks (ANNs) are also reviewed. Finally, the research objective and methodology of this thesis is presented.

2.1 Sources

The sources used in this review include predominantly journal and conference papers, as well as text and reference books, and internet sources. Direct communication with ArborGen managers was a major source of information in this research.

Google Scholar and Engineering Village, and relevant engineering journals were mostly used. Key phrases included things such as 'robotic harvesting' and a combination of 'machine vision' and 'agriculture', 'grading', 'forestry', 'cuttings', 'seedlings' and 'pine'.

There are thousands of papers in the area of robotic harvesting and machine vision for grading in agriculture. This text examines papers that were important or of relevance to this thesis, particularly those concerned with forestry tree stock and grading of horticultural produce.

Rigney and Kranzler have published the most literature in terms of automated grading of forestry tree stock. They have investigated machine vision grading in a pack house environment on a conveyor, using both area and line scan cameras.

2.2 Harvesting Machinery and Robots

Efficiencies can be realised in bulk harvesting operations where 'smarts' are not required, i.e. operations where a decision does not need to be made such as grading and sorting, and where the entire crop needs to be harvested. Such processing is typically applied to crops which can tolerate rough handling or some damage. Combine harvesters are probably the most significant example of bulk harvesting machinery which has increased productivity and reduced labour needs in the agricultural sector.

Digging machinery exists for harvesting a variety of underground crops, commonly applied to potatoes but adapted for other crops including peanuts [19], cocoyam [20], carrots [21], garlic, sweet potato and onions. A blade is passed underground which lifts the crop with the soil onto a digger chain. Soil is separated from the crop as it is conveyed upwards and shaken, causing it to fall through the chain. More controlled harvesting can be achieved with top lifters, also typically applied to underground crops such as carrots, parsnips and sugar beet. These machines pass an implement under the crop to loosen the soil and lift the crop from the ground using a pair of counter-rotating rubber belts. This type of machinery requires crops to be planted in a relatively straight line so that the belts can come in contact with the foliage of the plant. While these two methods are typically applied to root crops, they have been applied to forestry tree stock, which will be described in Section 2.3.

Tree shaking and catch machines have been applied to crops such as oranges [22], grapes [23], walnuts, pecans, pistachio nuts [24], limes [25], cherries [26], coffee beans [27], and apples; however, these can only be used on protected crops (e.g. nuts), or those that can tolerate rough handling or some damage. Oranges and apples harvested this way are typically only suitable for juicing.

Many crops require selective operations such as grading and sorting, which standard machinery is not capable of performing. Sorting is sometimes performed in the field, using manual labour and a trailing conveyor; however, grading and sorting is usually conducted in pack houses. This requires double handling of produce, increasing potential for damage, and requires significant infrastructure. It is increasingly common to have automated pack houses, often applied to round fruits which can be handled relatively easily, do not dessicate quickly and are quite firm. Systems have been implemented commercially for grading fruits, for example, BBC Technologies produces machinery for small round fruits such as blueberries, cherries and cherry tomatoes [28] and Compac processes fruits including apples, citrus, avocados and kiwifruit [29]. A citrus packhouse implemented by Compac is pictured in Figure 2.1. Automated grading systems typically use machine vision for inspection. Grading criteria can include colour, size, shape, weight, surface defects and internal qualities such as brix (sugar content) and firmness.

Figure 2.1: Citrus packhouse implemented by Compac

Research has been conducted into automated harvesting of crops in greenhouses including strawberries [30], tomatoes [31], cucumbers [32] and eggplants [33]. There are fewer challenges automating in a controlled environment when compared to outdoors.

An example of a greenhouse robot is a cucumber picking machine, as pictured in Figure 2.2 [32]. The machine used heating pipes mounted on the ground as rails for guidance and support when moving along aisles. It contained a 7 degree of freedom (DOF) manipulator for positioning the end-effector during harvesting. The end-effector consisted of a gripper and suction cup to grasp the fruit and a thermal cutter to detach the fruit from the plant. A dual camera system was used: one camera detected fruit and determined ripeness, the other was used for stereo imaging during the final approach to cucumber. During image processing the fruit was separated from leaves by applying different wavelength filters to the two cameras. Leaves have approximately the same reflectance at each wavelength but the reflectance of cucumber varies significantly. The ripeness of the fruit was assessed by estimating the weight of the fruit based on a geometric model. The computer vision system was able to successfully identify 95% of cucumbers in the greenhouse and could pick 80% without human interference. Unfortunately, 45s was needed to pick one cucumber which is far too long to be commercially feasible.

It is more difficult to perform such tasks in uncontrolled and unstructured outdoor environments. Researchers have attempted to mechanise and automate harvesting crops in the field, such as apples [34] [35], asparagus [36], oranges [37] [38] [39] [40], peppers [41], radicchio [42], kiwifruit [43] and melons [44] [38], but all are much slower than a single human. Many research projects concerned with robotic harvesting have not made implementation stage, due to excessive cost of the system, inability to execute the task, low durability of the system, and inability to adapt to slight changes in context [3]. The pick and place nature of the harvesting of many crops results in low picking efficiency and throughput [45]. For example, a prototype orange picking robot

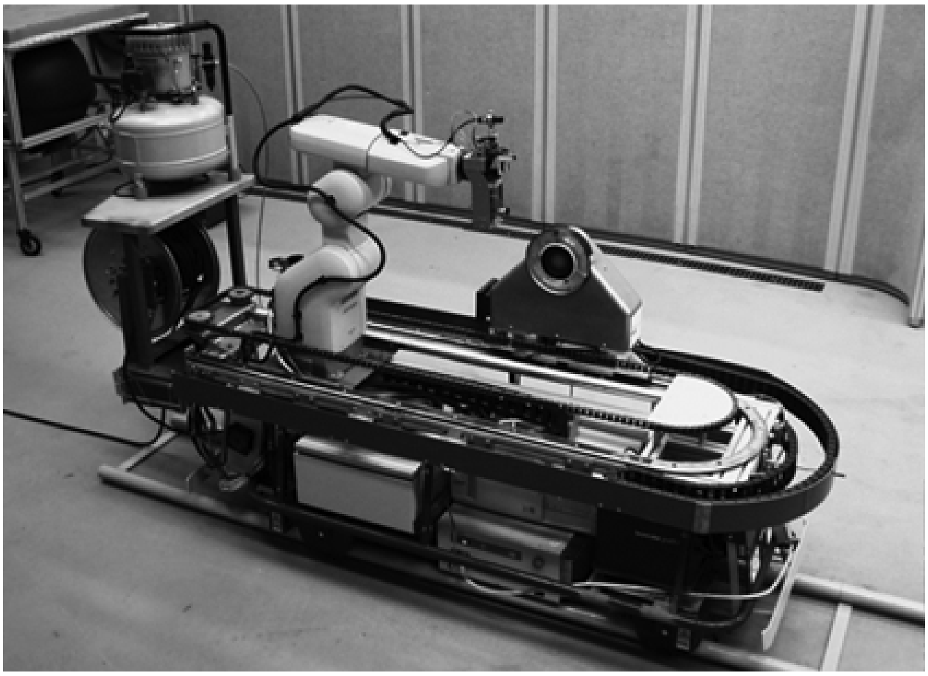


Figure 2.2: Prototype greenhouse cucumber harvester

required 7 s to pick a single fruit [38]. Even when selective harvesting is not required, i.e. every fruit is to be picked, such machines perform poorly and are far from being an economic alternative to manual labour. Although such technologies are not commercially viable yet, they do show potential.

An example of an autonomous field robot is pictured in Figure 2.3, which has been developed to harvest kiwifruit [43] [46]. The vehicle is approximately 2.3 x 2.0 m and weighs 1.5 tonnes. The machine autonomously navigates using vision systems when under kiwifruit canopies; GPS and a compass are used when not under a canopy. Fruit is identified by eight cameras and harvested by four robotics arms. Bins are filled and automatically returned the end of the row. It was claimed that the robot performs better than other contenders in many areas including navigation, handling of fruit and speed. 83.6% of the crop was able to be identified using machine vision, and an average picking speed of 1.4 s per fruit, per arm, was achieved, outperforming other fruit picking robots. Development has continued to date, but is yet to be implemented commercially.

Figure 2.3: Prototype kiwifruit harvesting platform [46]

It is difficult to automate the harvesting of fruit crops due to the three dimensional nature of trees, which means end effectors need to move into the tree and navigate around branches in order to reach fruit. There is increasing development and redesigning of orchards and farms for automation. For example, tomatoes have been grown in a greenhouse in an inverted (hanging) orientation, in order to promote spatial separation of tomatoes to aid harvesting [31]. New orchard architectures are being investigated, such as very narrow 2 dimensional canopies for apples where the majority of fruit is visible and accessible to machines [47]. Unlike fruit, forestry tree stock has the advantage of being planted in relatively regular straight lines which is conducive to automation. Mechanisation of seeding and dibbling operations [18] ensures this.

2.3 Mechanisation of Lifting Tree Stock

There has been success mechanising the harvesting of forestry tree stock in foreign markets such as the United States. These markets have different requirements for lifting: typically trees are not graded at all, but sometimes diseased or small trees are discarded in pack houses. Trees are bulk lifted at a rate of about a million trees per day at a single nursery. Mechanization of lifting forestry tree stock began with the development of rigid wrenching-type under cutting blades [48]. This consists of passing a sharp, thick, inclined blade at a depth of 4-7 inches underneath the soil surface [49]. This system disturbs the soil and reduces the effort required during manual lifting. Agitating under cutters have also been developed to loosen soil and improve root separation, as pictured in Figure 2.4. These systems slightly ease the labour demand, however, labour requirements are still very high [48].

Figure 2.4: Agitating undercutting to aid manual lifting

In 1956, work began developing the first mechanical forestry tree stock harvester [50], to try and further ease the labour requirement. Three concepts were proposed: two based on a modified potato digger, and one based on rubber belts for lifting and mechanical agitators for removal of soil from the roots. Interest in mechanised lifting increased during the late 1960s and various machines were produced, lifting from 1 up to 8 rows simultaneously [51]. Commercial lifters use both the potato digger concept (e.g. Grayco and Fobro) and the belt lifter concept (e.g. J. E. Love and Whitfield) [52].

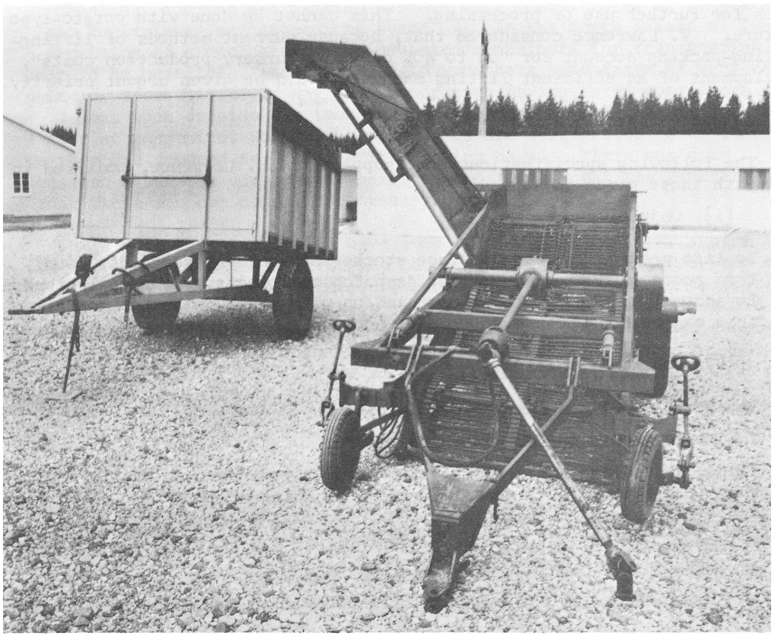


Figure 2.5: Potato harvester adapted for lifting forestry tree stock [9]

The potato digger lifter has an under cutting blade, backed up by a series of digger chains or tines, which mostly lift the tree out of the ground and remove soil by shaking [53]. Figure 2.5 shows an image of the potato digger concept applied to harvesting forestry tree stock. These lift an entire bed at a time, generally do not damage roots, and no specially trained operators are required [54]. The position of the lifter on the bed and depth of the blade are controlled by hydraulic controls in the cab. There are considerably less people involved with lifter-shakers when compared to manual labour, and the workers are not on the ground [55]; however, a number of problems have been reported with these types of lifters [50] [53] [54]:

- Seedlings come off the shaker chains in disarray and require sorting.
- Long lateral roots become entangled and damaged.
- Trees are transported slowly, which may result in desiccation.
- High noise levels.
- Excessive wear to mechanical parts, including sprockets and chains.

Belt type lifters use rubber belts to lift the trees out of the ground, and usually incorporate beaters or agitators to remove excess soil, as shown in Figure

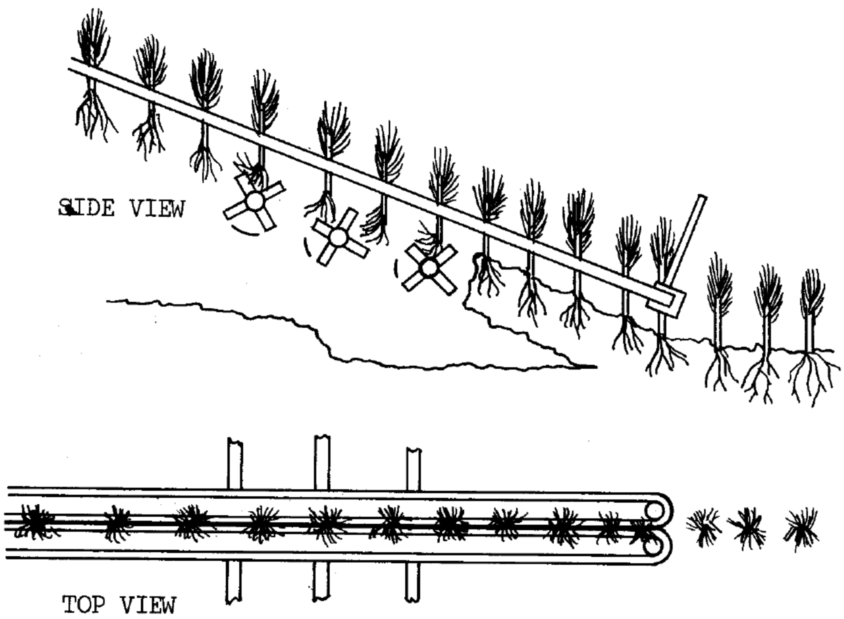


Figure 2.6: Schematic of belt lifting and soil removal principle [50]

2.6. The first working belt lifter was deemed superior over the potato digger type, being "95 percent effective in harvesting slash and loblolly seedlings" [50]. Once lifted, trees were tipped by an adjustable bar onto a cross conveyor, and transported into a container. A crew of six was required, including the tractor driver. A significant increase in productivity was realised with this machine: traditionally 200 man hours were needed to lift one million seedlings, while the machine achieved the same using only 48 man hours.

Commercial belt lifting machines remove soil using both oscillating bars and rollers systems, and one particular machine is capable of automatically bundling seedlings [52]. An example of a commercial harvester is pictured in Figure 2.7. This harvester operates at rates of 100,000 to 150,000 seedlings per hour, and requires between 2 and 6 people to operate [56].

Machines to lift forestry tree stock have been considered in New Zealand since the early 1970s [9], at which time concepts based on the potato digger and belt lifter were demonstrated. More interest was shown in the belt type lifters as they could maintain trees in order and pack as required, meaning packing sheds could potentially be eliminated. In 1974, a single row belt lifter was produced in New Zealand, of which four were eventually made [57]. One

Figure 2.7: Commercial belt type lifter by JE Love Co

person was required to drive the tractor, one to steer the boom to ensure tree stock was lifted, and two additional operators on the back. Figure 2.8 shows the machine in operation. These lifters did not remove soil or trim roots. The machine straddled the adjacent bed and used a spear tip shaped implement to break up the soil under the bed, similar to a wrenching operation.

Figure 2.8: Single row lifter in use in New Zealand during the 1970s

Unfortunately, these machines were decommissioned due to a number of issues. They were not very effective in wet conditions, at which time the manual crew needed to be called in. The poor effectiveness of the lifters was worsened by the high clay soil type at the nursery. Problems encountered were stripped trees, mud build up on belts, and slipping in beds due to high traffic from multiple passes [58].

2.4 Automated Grading of Tree Stock

There has been interest in automatically measuring tree stock features since the late 1960s, however, nothing has been found that has been implemented commercially. A number of devices have been investigated which required careful manual manipulation of the tree in order to measure various features [59][61][60][62]. These were based on photoelectric and potentiometer technologies for measuring RCD, potentiometers for height, and root area using line scanners and photocells. These devices were not very productive and not suited for commercial implementation, as manual labour could outperform the machines, and they were typically only used for training new graders. Systems based on machine vision intended to be integrated into pack houses have also been investigated. Tree features measured included RCD, height and shoot and root area, and factors derived from these such as shoot-root and sturdiness ratios. No researcher has analysed root quadrants as required by this study.

Potentiometer systems physically contact the tree, displacing a potentiometer, outputting a voltage proportional to the desired measurement, i.e. stem or height. Photo-interrupter based technologies rely on the object (tree stem) blocking one or more receivers, and timing how long the receiver is blocked for. The optical method has many advantages over the potentiometer including no contact with the seedling, no moving parts, and good high speed performance [64]. The time the receiver is obstructed for is directly proportional to the seedling diameter for a single receiver system [64]. This requires a constant known velocity of the tree past the receiver so time can be correlated to diameter. Dual receivers can be used to determine to calculate the speed of the tree, and measure the diameter. While this does not require the speed to be known, it does require the speed to be constant [60]. Devices which do not control the speed of the seedling can be inaccurate. For example, relying on an operator passing the tree past a pair of receivers by hand produced a maximum systematic error of 9.5% (left image in Figure 2.9). The error was reduced to 1% by modifying the device to move the remove operator error. The sensor was moved relative to the tree at a constant acceleration using a counter balanced device, as pictured in Figure 2.9 (right) [60].

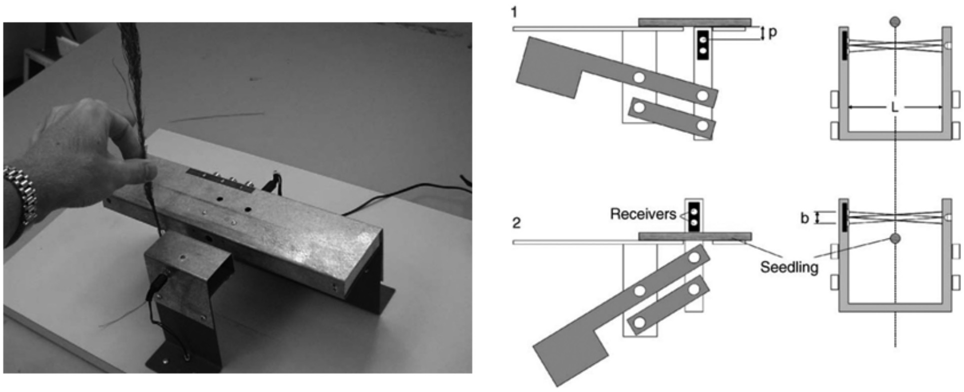


Figure 2.9: Sliding edge concept (left) and counterbalance concept (right) [60]

Root surface areas of tree seedlings have been estimated by flattening roots into a single plane, and using backlighting to produce a silhouette of the roots. Root area can be calculated by quantifying the dark area in the image. This has been achieved using a simple photocell and galvanometer [62], and also by more sophisticated methods using electronics to determine whether individual pixels are black or not [59].

An early device for measuring RCD, shoot height and root area is pictured in Figure 2.10 [59]. The device was based on both potentiometer and line-scanning techniques. Careful manual manipulation of the tree into the device was required: the roots were placed onto the area covered by the line scanner (G); the stem was pressed into the diameter transducer caliper (E); the height caliper (F) was manually set by the operator; and a clear press plate (D) was lowered onto the test sample to ensure the roots were pressed into a thin plane. A caliper was displaced by the stem which adjusted a potentiometer to measure the stem thickness. The voltage was read by a digital volt meter calibrated to output 1 V for every millimetre using a voltage divider, i.e. the voltage output (V) was equivalent to the physical diameter of the stem (mm). A similar principle was used for measuring height. An accuracy of 0.5% was achieved for the diameter, and 0.3% for the height. The root area scanner used back lighting and a line scanner to determine root area.

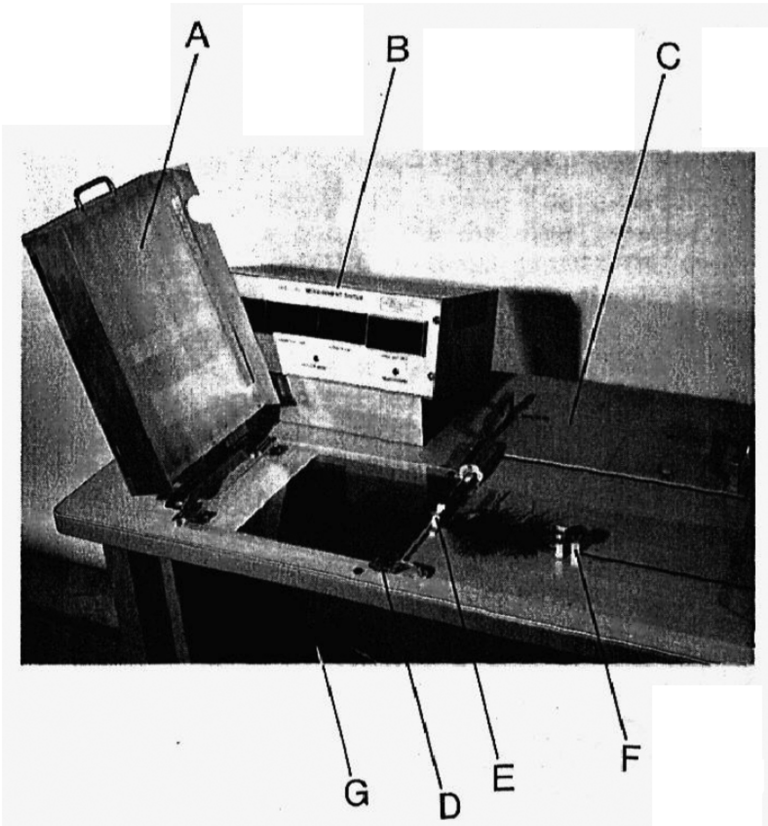


Figure 2.10: Device for measuring tree stock characteristics. (A) light source in raised position; (B) display and control unit; (C) digital data coupler; (D) press plate; (E) diameter caliper; (F) height caliper; (G) root area scanner [59]

The potentiometer and photoelectric concepts have also been applied to an automated tree planting machine, which intended to automate the feeding of tree stock [64]. It relied on the assumption that taped seedlings were attainable, spaced at random intervals between 25 and 200 mm. Seedlings were fed at a rate of over 2 seedlings per second. Two methods were used to measure the stem thickness of seedlings: one based on a single optical transmitter and receiver, and the other on a linear displacement potentiometer suited for continuous inspection as pictured in Figure 2.11. Both methods were deemed suitable for future implementation with minor modifications. Superior measurements were claimed with the potentiometer system, but this could likely be solved by controlling the seedling speed more accurately.

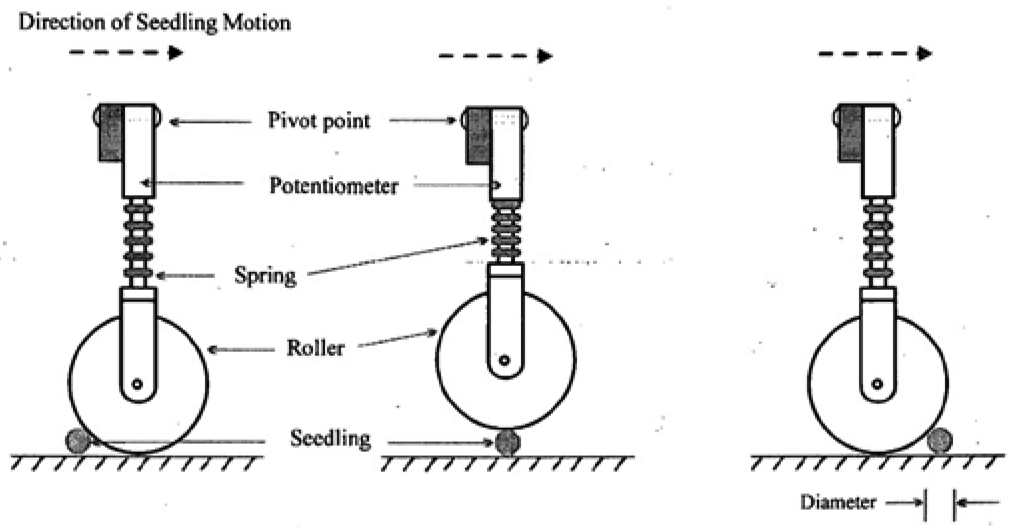


Figure 2.11: Linear potentiometer device for measuring RCD of tree stock [64]

The optical and potentiometer type systems lack flexibility and are only capable of measuring one characteristic of tree stock. The majority of work since the late 1980s focused on computer vision systems which are capable of measuring various attributes without additional equipment and sensors. These systems have been designed to be integrated into conveyors and used in a pack house. They require manual loading of seedlings onto the conveyor, keeping tree stock singulated and loosely constrained.

Both area scan cameras [65][68][67][66], and line-scan cameras [70][69] have been used. The line-scan concept can increase resolutions up to 0.05 mm and grading rates as high as 15 seedlings per second have been claimed [16]. Accurate knowledge of the speed of tree stock is required as images are constructed line by line. Additionally, errors in imaging can occur if the subject is to move during image acquisition. A schematic of the line-scan principle is shown in Figure 2.12.

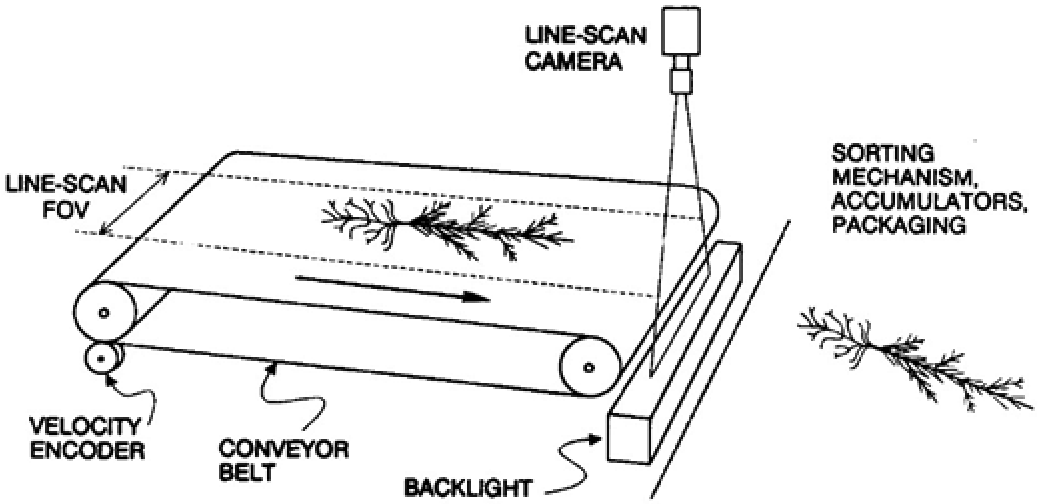
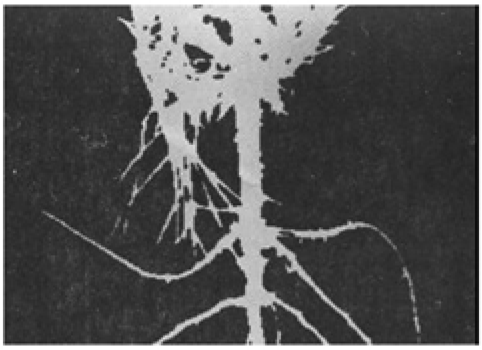


Figure 2.12: Line-scan seedling grader concept [16]

Machine vision systems typically use RCD, shoot height and root volume as the grading criteria. Black and white cameras are used, often using one to capture a close up image of the stem to provide the resolution required for RCD measurement, and the other to capture the entire seedling. Silhouettes of trees are captured using backlighting to create a high contrast between the tree and the background, and make image segmentation easy. Images were converted to binary using a threshold operation.

An example of the processing steps to measure tree features is presented below [65]. The first step is to identify whether or not a tree is in the frame. Successive images are captured and if the number of black pixels exceeds a certain threshold, a tree is assumed to be present in the frame and subsequent processing begins. The RCD has been located by counting the transitions from black-to-white and white-to-black in each row of the image. If on at least 6 adjacent lines there were two transitions and the thickness fell between a certain range, then it became an RCD candidate. If this test failed, the program tried again, this time searching lines with less than or equal to 6 transitions. Different threshold values were be used to improve location of the root collar. A low threshold limits the number of root collar candidate lines (left image in Figure 2.13), while a high threshold can eliminate needles, branches and roots located in the root collar zone (right image in Figure 2.13).



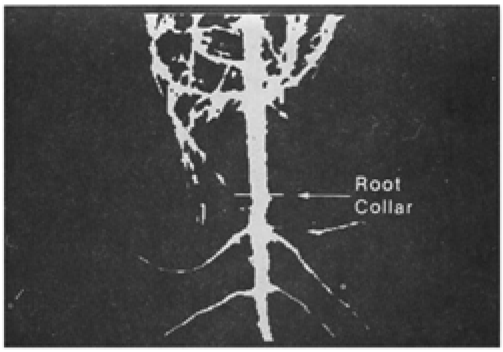


Figure 2.13: Effect of a low threshold (left) and high threshold (right) on the detection of the root collar

Height has been measured by checking from the top of the image for paired transitions which exceed five pixels, over at least four lines. To calculate the root area index, the number of black pixels below the RCD were counted. Similarly, shoot area is simply a summation of pixels above the RCD region. More complex methods have been investigated for analysing root lengths and diameter, but this method was time consuming taking between 20 and 42 s [63] and therefore not suited to continuous inspection.

Processing time of various rigs was around 2 - 4 trees per second [69][68][70]. This rate would be difficult to increase as these devices required trees to be manually loaded onto the conveyor, loosely constrained. The most difficult task faced by researchers was locating the RCD region, which was the most time consuming process, typically taking around half the processing time to locate [68]. The RCD location could often not be located due to needles extending down past the root collar or roots bent upward past the root collar.

Most of these devices inspected a single tree at a time, however a prototype machine based on the line-scan concept was used to grade containerised tree stock [70], capable of scanning multiple seedlings at the same time. Only one camera was needed as a fibre optic ribbon was used to map each tree to a different line of an area scan camera. It scanned an entire row of 14 seedlings in 8 seconds and measured height, RCD and plug integrity. This is equivalent to a rate of 1.75 seedlings per second. On a small sample of both seedlings and plugs, it was unable to classify the tree in 14% of cases. The principle is pictured in Figure 2.14.

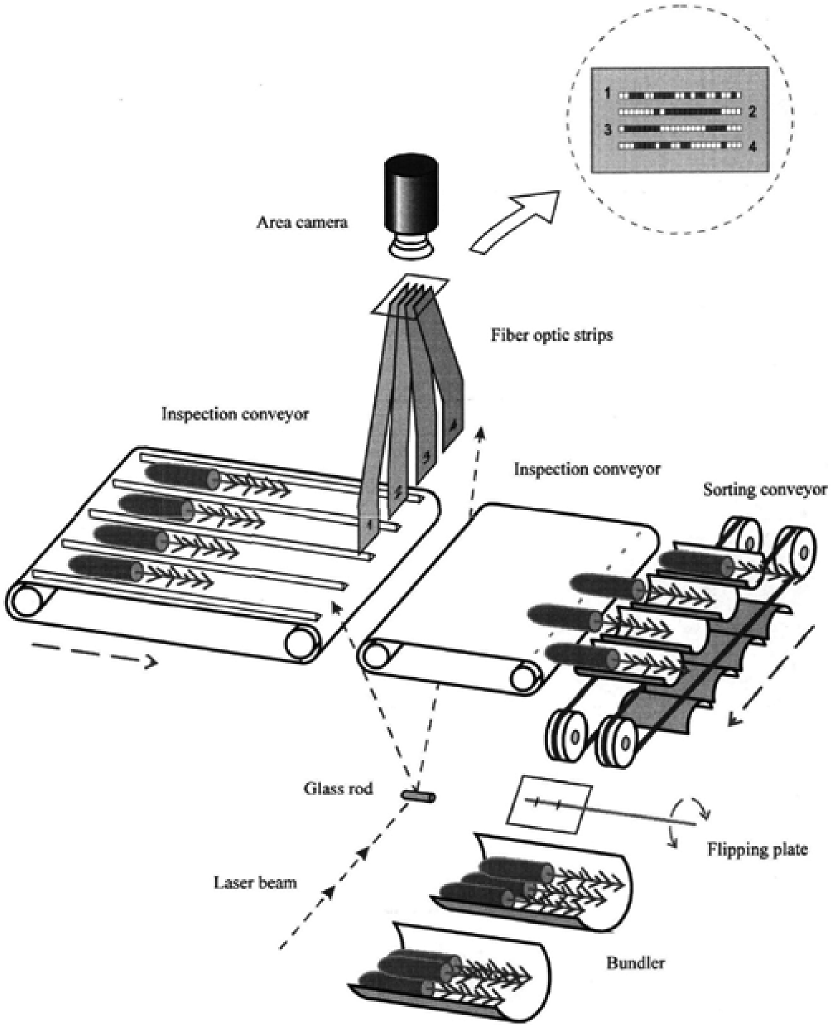


Figure 2.14: Line scan grading of multiple seedlings

It is difficult to determine a benchmark when comparing the accuracy of these systems, however, a classification error rate of 5.7% has been claimed in a sample of 100 loblolly pine [65]. Machine vision measurement is potentially more precise when compared to manual measurements: RCD was found to be over four times more precise, while height and root mass length were of similar precision [69].

Due to difficulties locating the RCD, neural networks have been investigated to classify lines of an image into four classes: stem, foliage, roots and root collar [71] . They claimed 'good' performance; however, the RCD location was predicted to be on the stem segment only 87% of the time. The inputs to the network were the number of line segments, sum of line segment length, distance between start of first line and end of last line, and 'filtered area', described as "this feature attempts to recognize a single run on each line which could be the seedling stem near the root collar". Two to five hidden nodes were used. A second neural network took the outputs from 15 lines from the first neural network to determine whether the centre line was the root collar, or not.

The automated classification of seedlings by computer vision is feasible; however, the grading rate efficiency still requires improvement. The problem is how to construct a precise, efficient system to satisfy production, which is an important task for future research [72] .

2.5 Machine Vision Systems

Machine vision is commonplace in factories for quality control and inspection of parts where placement and dimensions of parts are generally very well defined. Machine vision systems are far more objective, faster and less prone to error than human inspection. The advent of computing and increasing processing power has seen high growth in research into machine vision grading in agriculture. However, it is still not yet common in the field as there are difficulties associated with automating in outdoors environments, such as effects of lighting, variability of product, dirt and climate. Despite these issues, machine vision has been used in agriculture for a variety of applications: weeding [73][74]; row guidance [74][75][76][77]; evaluating quality of apples [78][79], eggs [80], seedlings [81], cuttings [82], potatoes [83], raisins [84], soy beans [85], lentils [86], asparagus [87], and mangoes [88]; recognition of oranges [89], tomatoes [90] and apples [91]; location of stems in pepper plants [92]; root growth rate in seedlings [93]; and crop yield when harvesting citrus [94].

Machine vision systems consist of, at a minimum, a lighting source, camera, software and outputs. In addition to monochrome and colour cameras, there are many other techniques commonly used. Multispectral and hyperspectral imaging are techniques where images are acquired at a number of wavelength bands. Multispectral images are acquired at a small number of wide bands, typically 3 to 10, while hyperspectral uses hundreds or thousands of narrow bands. This type of imaging has been used to discriminate weeds from crops [95] [96] and for disease detection in plants [97]. X-ray and magnetic resonant imaging (MRI) has been investigated for quality inspection of internal properties of fruit [98] [99] and onions [100]. However, these have had little application in the agricultural sector due to high cost and low speed. Other sensing technologies have been used for crops which provide depth information, such as laser scanners and time of flight (TOF) cameras. TOF has been used to calculate the position of asparagus [36], to build 3D models of dormant apple trees [101], and to detect fruit in trees [102].

2.5.1 Lighting

Machine vision can utilise different frequencies of light, depending on the application, including ultraviolet (200-400 nm), visible spectrum (400-700 nm) and near infrared (700-2500 nm). Information received from objects in invisible light regions can be useful for determining a number of things including maturity, disease, ripeness, plant variety, defects and composition [103].

Near infrared has been used, for example, to measure sugar content and acidity in citrus fruit in the field [104] and to identify areas of 'tight' or delaminated skin in dates [105].

Some compounds emit fluorescence in the visible colour region when illuminated with UV light. This has been investigated for defect detection on apples [106], and freeze damage in oranges [107].

Illumination is the major factor determining contrast. High contrast between the subject and background makes it easier to separate the two during processing. The main problem faced by machine vision systems is incorrectly selected light sources [108]. The highest contrast is achieved using back lighting, as such this should be used when possible [109]. However, this is only appropriate where a silhouette or outline of the object is required, as any additional detail is lost. For example, when inspecting bulk wheat samples for the presence of insects the best quality image was achieved using backlight illumination [110]. Physical design must actually allow the placement of a backlight. The most common uses for backlighting are detecting presence or absence of holes and gaps, part placement or orientation, and measuring objects [111].

Diffuse lighting provides multidirectional light and is most commonly used on shiny specular samples. Directional lighting typically comes from a point source and can generate contrast and enhance topographical detail [111].

One of the major issues with machine vision in the field is the effect of variable lighting on image processing. This is particularly an issue when operating outdoors under ambient conditions. Some approaches to dealing with ambient lighting are high power strobing with short duration pulses, physical enclosures, and pass filters which allow the light source through but block broad spectrum ambient light [111] [108].

2.5.2 Lens

The lens, coupled with the camera, determine magnification, working distance, resolution and depth of field, and introduces distortion [108].

When working with space constraints, a wide angle lens with a large field of view may be required, but this will increase distortion. Figure 2.15 shows a simplified schematic of lens geometry. The focal length of the lens determines the field of view. The dimensions of the subject plane can be calculated by Equations 2.1 and 2.2, where f is the focal length, d is the distance from the lens to the subject, a and b are the width and height of the sensor respectively, and x and y are the width and height of the image.

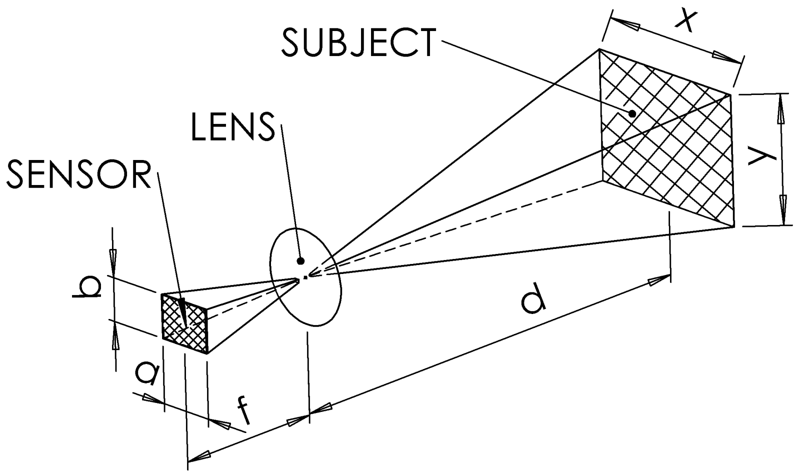


Figure 2.15: Basic camera geometry

$$x = \frac{da}{f} \tag{2.1}$$

$$y = \frac{db}{f} \tag{2.2}$$

2.5.3 Camera

There are two common types of sensor chip technologies in cameras: charge coupled device (CCD) and complementary metal-oxide-semiconductor (CMOS). The sensor consists of an array of sensing elements, gathering photons in each element. When an element receives a photon of light, a free electron is produced from the atom's valence band. This free electron is attracted to a positively charged 'gate' and held in place, accumulating a charge. The charge is converted into a voltage by electronics in the camera [108]. In a CCD camera, the charge is carried across the chip and read at one corner of the array. In a CMOS device, there are several transistors at each pixel which amplify the charge onto a common output line. CCD is the more mature technology, and typically provides lower noise and higher sensitivity, while CMOS is newer and faster growing, with higher speed and lower cost.

Cameras can be monochrome or colour. Colour cameras are usually just a monochrome sensor with a red, green and blue (RGB) filter overlayed. Each sensing element provides a value for red, green or blue, at that location, depending on what filter is overlayed over the element. Interpolation based on neighbouring pixels is necessary to combine these values into an RGB 3 colour using a demosaicing algorithm. Alternatively, more complicated three-chip systems are available where a prism assembly splits incoming light into RGB channels. This allows the true R, G and B value to be collected for each pixel, increasing resolution and reducing noise.

Resolution can vary significantly from 640 x 480 pixels, up to 4608 x 3288 pixels. High image resolution is not always better as increasing the number of pixels for the same sized sensor results in a smaller element size, which reduces sensitivity and increases noise. Alternatively, increasing sensor size adds cost to the sensor and associated lenses [108]. Also, transmitting and processing far more pixels significantly decreases performance.

Line scan cameras image a single line of pixels and build a 2D image line by line. Exposure time is very short, therefore, an intense light source is required. However, the area required to be illuminated is very small. Line scan cameras are often used on conveyor lines where there objects are moving at a uniform speed. Very precise knowledge of the speed of the product is required, so that an accurate 2D image can be constructed from individual lines.

Area scan cameras consist of a 2D array of pixels, so an entire image can be captured at once. The entire sensor can be exposed at once using a global shutter, or rapidly line by line using a rolling shutter. As rolling shutters do not expose the entire scene at the same time, distortion can potentially be introduced into the image, particularly in fast moving objects.

GigE, CameraLink and USB 3.0 are the most commonly available interfaces for machine vision. A frame grabber is a special interface card which is required for some interfaces. Of these three, CameraLink is the only one which requires a frame grabber. Table 2.1 provides a comparison of the most commonly used

Table 2.1: Comparison of camera interfaces [112]

	FireWire	GigE	USB 3.0	Camera Link
Bandwidth (MB/s)	80	125	400	680
Cable length (m)	4.5	100	3	10
CPU Usage	Low	Medium	Low	Medium
Consumer Acceptance	Declining	Excellent	Excellent	None
Difficulty of System Integration	Medium	Low	Low	High
Power Delivery (W)	45	15.4	4.5	None
Multiple cameras	Excellent	Good	Excellent	Fair
System cost (single camera)	Medium	Medium	Low	High

machine vision camera interfaces [112]. The use of FireWire is declining, and CameraLink is expensive. GigE and USB 3.0 are the most popular, and USB 3.0 has a performance advantage. The main advantage of GigE is the low cost cabling and long runs which are achievable; USB 3.0 has a maximum recommended cable length of only 3 m.

2.5.4 Image Processing

The most popular operating system for machine vision is Windows, however, use of Linux is increasing. Windows has a graphical user interface (GUI), and most users are familiar with it due to its popularity. There are many more software options available with Windows when compared to Linux due to its large user-base. However, it is not free and open source like Linux, which is built around the Linux kernel. Linux is also widely used, having a greater adoption with the technically minded such as server administrators and programmers. A GUI is available, but users commonly use the command line to perform tasks.

Commercial software packages are available for image processing which are typically targeted at Windows, for example Roborealm. Alternatively, open source packages are available such as OpenCV, which is available for a variety of system architectures.

There are typically four steps to image processing: preprocessing, segmentation, feature extraction and interpretation [108]. Preprocessing prepares the image for subsequent processing, for example, removing noise or correcting poor contrast. Segmentation separates an image into multiple segments so areas of interest can be isolated. A common method to achieve this is thresholding. Feature extraction applies algorithms to obtain information about the image, for example, the location or size of an object. Interpretation is the process of using information extracted from the image to produce an output, for example classification of fruit into different grades. There are a number of classification systems available, such as fuzzy inference and artificial neural networks (ANNs). These two systems will be described in Section 2.6.

2.5.5 A Machine Vision Fruit Grading System

There are many examples of machine vision systems used in agriculture. One application found in the literature was grading of oranges, apples and peaches [113]. It comprised of a three CCD camera, frame grabber and PC. Diffuse lighting was provided by a ring shaped fluorescent tube, semi-spherical enclosure painted white, and a reflector between the tube and the scene. A vacuum cup gripped the apple and was capable of rotating it into different orientations so multiple views could be captured by the camera. A custom application was developed in C, running under DOS. Offline training was performed first, using an expert to classify different regions into various classes: background, primary colour, secondary colour, general damage type 1, general damage type 2, specific feature, stem and calyx. The raw image (Figure 2.16a) was segmented into the above categories based on the RGB values for each pixel (Figure 2.16b). Unfortunately, this system needed to be retrained for every session due to the variability in colour between fruit. 8 connected pixels were considered as an independent region. A mode filter was applied to smooth the boundary between regions and remove isolated pixels. This was based on RGB rather than other colour spaces simply to reduce processing required as raw images were captured in RGB. A binary image of the apple was analysed, ignoring the stem and calyx regions (Figure 2.16c). The boundary of the fruit was extracted using a chain-code-based algorithm. Area and size was measured as the length of the principal axis of inertia (Figure 2.16d). The size and length of the blemishes were calculated in a similar way.

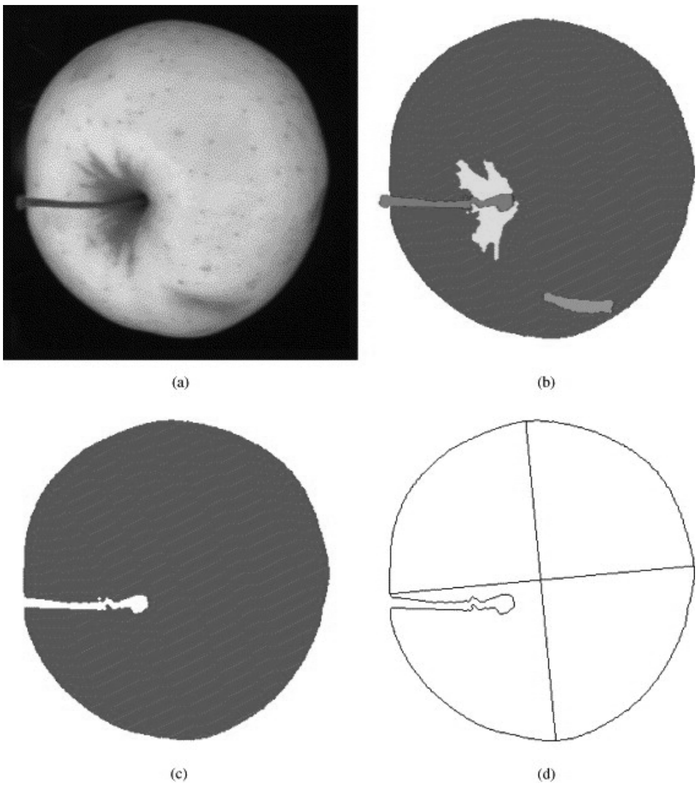


Figure 2.16: Processing of the fruit: (a) original image; (b) image segmented into different regions; (c) all regions except stem; (d) size estimation [113]

The background was correctly classified 100% of the time, therefore good results can be expected when estimating the size of the fruit. The repeatability of the expert was determined to be 94% when classifying fruit by size, and around 88% when estimating degree of skin damage. Since this was trained by experts, the maximum expected repeatability of the system is limited by the repeatability of the experts. The repeatability of the machine vision system came very close to this, 93% and 86%. 300 ms was required for analysis of a fruit.

2.6 Classification Systems

Knowledge-based systems are computer programs that solve complex problems within some defined domain. They differ from conventional computer programs because they solve problems by mimicking human reasoning processes, relying on logic, belief, rules of thumb, opinion and experience. Humans are well equipped to resolve complex problems when faced with uncertainty. Researchers have attempted to replicate this ability on computer based systems. By far the most commonly known type of knowledge-based system is the rule-based expert system, in which the experience and knowledge of a human expert is captured in the form of IF-THEN rules [114].

2.6.1 Fuzzy Systems

Fuzzy sets were first proposed in 1965 [115] to address ambiguity which is inherently present when dealing with certain sets of data. This can be especially relevant and necessary when translating human language into well defined sets. Applications of fuzzy systems include control of appliances, simulating the decision making process of a human, and object classification and identification. Fuzzy logic has been applied in agriculture to grade produce, and to distinguish between morphological features, for example, identification of plant features such as main stem, petiole, and leaf blade [116].

A fuzzy logic system consists of rules, fuzzifier, inference engine, and defuzzifier. Rules may be provided by experts and are expressed as a collection of if-then statements. The fuzzifier maps 'crisp' numbers into fuzzy sets. The inference engine handles how rules are combined and maps fuzzy sets into fuzzy sets. The defuzzifier maps fuzzy sets back into crisp numbers [117].

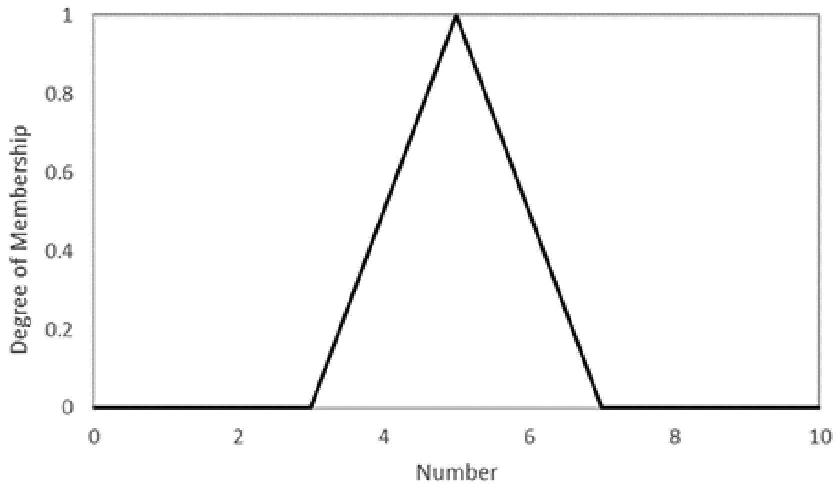


Figure 2.17: Membership function of fuzzy set "real number near 5"

In traditional crisp sets, the membership function χ_A maps elements in universal set X to either 0 or 1. i.e. it either belongs to the set or it does not.

$$\chi_A : X \rightarrow \{0, 1\} \tag{2.3}$$

In fuzzy sets, each element is mapped to [0,1] by the membership function

$$\mu_A : X \rightarrow [0, 1] \tag{2.4}$$

Where [0,1] means real numbers between 0 and 1 [118]. This implies that an element is permitted to have a partial membership in a set, as opposed to traditional sets where an element is either a member or not. For example, in a fuzzy set the membership function of fuzzy set "real number near 5" could be represented graphically as in Figure 2.17. Note that the word 'near' is subjective, and different people will come to different conclusions regarding what constitutes 'near' five. In this example, five is given a membership of 1, with membership linearly decreasing to zero as we move further away from 5.

Operations can be performed on fuzzy sets in the form of fuzzy rules. A fuzzy rule assumes the general form "*If x is A, then y is B*". "*If x is A*" is known as the antecedent and "*y is B*" is the consequent. For example, a heating, ventilation and air conditioning (HVAC) system may have rules like 'If the room is the right temperature and temperature is increasing then cool' or 'if room is just right and temperature is constant, then do nothing'. AND is generally applied as the minimum operator, and OR is the maximum. α is sometimes called the firing strength of the rule, which is calculated by Equations 2.6 and 2.5.

$$\alpha_i = \mu_{A_i} \wedge \mu_{B_i} \tag{2.5}$$

$$\alpha_i = \mu_{A_i} \vee \mu_{B_i} \tag{2.6}$$

Where $\wedge$ is the minimum operator and $\vee$ is the maximum operator. There are multiple methods for performing fuzzy implication. The two most common methods are the Mamdani and Larsen implications, both of which are considered suitable for engineering applications [117]. Multiple rules are generally combined using the maximum operator, and the output of fuzzy inference is a fuzzy set. Mamdani's method was first proposed in 1975 [119], which is the most widely used. It interprets the fuzzy implication as the minimum operation: inference result is the minimum of the consequence ($\mu_{C_i}(w)$) and antecedent. This truncates the consequents membership function. Equation 2.7 shows how the inference result ($\mu_{C_i'}(w)$) is calculated.

$$\mu_{C_i'}(w) = \bigvee_{i=1}^{n} [\alpha_i \wedge \mu_{C_i}(w)] \tag{2.7}$$

The Larsen Method is another well known function [118] which applies the algebraic product operator, rather than minimum, as shown in Equation 2.8. This scales the consequent's membership function rather than truncating it. Additional methods have also been proposed for fuzzy inference, for example, the Sugeno [120] and Tsuakamoto methods [118].

$$\mu_{C_i'}(w) = \bigvee_{i=1}^{n} [\alpha_i \bullet \mu_{C_i}(w)] \tag{2.8}$$

Multiple methods are available to create a crisp output, the most common being taking the centre of mass of the output fuzzy set.

In agriculture, fuzzy logic inference systems have been used on a number of applications including grading produce such as dates [121] and cabbages [122], monitoring seed germination [123] and classification of date trees [124]. These studies have identified fuzzy logic as a feasible replacement for decision making during the grading process, typically achieving 86-89 % agreement with experts [121][124][125]. However, it was identified that further research should be undertaken to better tune the membership parameters, even though it can be very time consuming. A number of methods have been investigated for tuning membership functions and fuzzy inference rules. By far the most common method is using experts and manually setting parameters. Learning techniques for fuzzy systems include artificial neural networks and genetic algorithms [126].

An example application of fuzzy logic in agriculture is for grading fruit [125]. Features such as colour, defect, shape, weight and size of apples were measured manually and used as grading criteria. 181 apples were graded by an expert, and then by the fuzzy logic system. The fuzzy logic system was implemented using MATLAB. The apples were graded into three quality groups: good, bad, and medium. Rules were formulated such as "If the colour is greenish, there is no defect, and if it is a well formed, large apple, then quality is very good". The maximum operator was used to combine rules, to determine membership degree to each class. Defuzzication was achieved using the centre of mass method. Decisions made using fuzzy logic showed 89% general agreement with the decisions of a human expert. Misclassification was a result of classifying an apple into an adjacent class, which is to be expected.

This research could potentially utilise fuzzy logic to deal with ambiguity. Firstly, for grading tree stock into 'good' and 'bad' categories based on language of the experts. For example, the nursery manager may say something like "the stem is a little thin, but the roots are strong and it is a good height, therefore I will accept it". Fuzzy sets can be used to deal with these subjective terms. In addition to grading purposes, it could be used for identification of roots. There is much ambiguity on what is classed as a root or not.

2.6.2 Artificial Neural Networks

Artificial neural networks (ANNs) are computational modelling tools that can be applied to solving complex real-world problems. Humans are capable of dealing with complex problems due to a biological neural architecture, while computers struggle at the same task. ANNs try to use some of the organisation principles believed to be used in the human brain [127]. ANNs consist of a number of simple highly interconnected nodes which can process information and provide outputs in response to inputs. They are self learning; after providing training data, an ANN is able to process further information without being given explicit rules to follow. A simple ANN network is illustrated in Figure 2.18. Data is entered through the input layer. Nodes in the input layer are connected to one or more hidden layers. Processing is achieved via weighted connections between nodes. Weightings are calculated for connections between nodes to fit the training data. These hidden layers then connect to the output layer to provide the output.

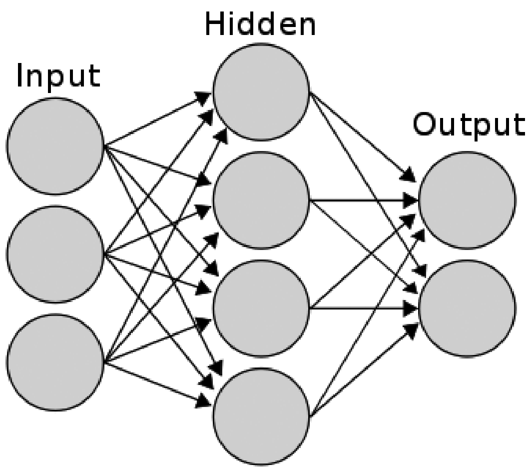


Figure 2.18: Architecture of a simple neural network

ANNs have been used for forecasting, control, data and image compression, and pattern recognition [129]. Back-propagation ANNs are the most widely used type of networks and very versatile, however, there are over 50 different architectures for neural networks [128]. Back-propagation refers to the learning method where the error is calculated at the output side and propagated backward to the hidden layer, and finally to the input layer. ANNs are 'black boxes': data is input and information is output without exact knowledge to the user of what is happening in the hidden layers.

In agriculture, ANNs have been used for a variety of applications, including grading eggs [130], classifying pot plants [131], weed detection and colour grading of apples [132].

An ANN has been used, for example, to grade apples by colour [132]. The study used two neural networks. One classified pixels into different categories: normal colour, injured, poor, or non-apple (vine, upper background, lower background). The other was used to grade the apple into five classes: superior, excellent, good, poor colour, and injured. Seven inputs were used in the first network: six were based on colour information, the other based on pixel location. The hidden layer had five nodes and the output had six, corresponding to the different pixel classes. Supervised learning was performed on every pixel of an entire image of an apple. The output of this network was used to calculate the 'colour ratio' and whether or not the apple was injured. These outputs were used as inputs into the second network, along with nine other inputs based on the RGB channels. The second network graded into the correct class 70% of the time. Most cases of misclassification graded the apple into an adjacent class, for example, 'excellent' apples are most likely to be misclassified as 'superior' or 'good', rather than 'poor colour' or 'injured'. Apples were correctly classified from between 33.3% for the 'excellent' class up to 92.5% for the 'superior' class.

Such techniques could be applied to the classification of forestry tree stock into 'good' and 'bad', however, it may not be necessary as a comprehensive specification is already available. Additionally, different customers have different requirements for the quality of tree stock, and the ANN would need to be retrained for each customer.

2.7 Research Objectives

The review identified areas where there is a need for additional research in the area of automated lifting and grading of forestry tree stock. It is well recognised that field robotics is a very difficult area and improved integration of all subsystems is required to enable commercialisation [133] [134]. Research with forestry tree stock is segmented; no researcher has looked at the lifting and grading processes as a whole. While there has been work on individual aspects there have been no attempts found to combine these into one solution. In summary, the literature review identified the following:

- No integrated forestry tree stock lifter/grader exists.
- No research has analysed the root structure or straightness of forestry tree stock.
- Research has not attempted to apply techniques to simulate the human decision making process for grading forestry tree stock.
- Grading work of seedlings undertaken by other researchers lacks accuracy and speed.

The purpose of the research can be summarised by the following question: Is it feasible to reduce reliance on manual labour by producing a *field factory* capable of processing forestry tree stock, and replace the human decision making process of grading with an automated system?

The research question can be broken down into three areas:

1. The performance of algorithms in identifying and measuring morphological tree features: can new or improved image processing algorithms accurately identify and measure morphological tree stock features?

2. The performance of grading logic when compared to nursery experts: is fuzzy logic, or similar, capable of replicating the human decision making process to an extent that it can replace seasonal labour for grading forestry tree stock?

3. The performance of the handling system: is an integrated *field factory* feasible, that is capable of handling and processing forestry tree stock reliably from point of lifting to sorting without damage?

The hypothesis can be stated as follows:

Automatic handling of grading of forestry tree stock could be achieved in the field using an integrated *field factory* with a machine vision system coupled with fuzzy logic to replicate the human thought process.

The objectives of the research were to:

- Investigate algorithms for obtaining seedling characteristics via machine vision at harvesting speed and high accuracy. This must be done more accurately than previous work and measure attributes not yet investigated such as tree straightness and root structure.
- Investigate techniques, such as fuzzy logic, for simulating the human decision making process.
- Determine whether it is feasible to replace seasonal workers for lifting and grading trees with an automated system.
- Evaluate the performance of the system in an outdoor nursery environment in terms of accuracy, reliability and speed.
- Integrate many features into one holistic design.

Challenges associated with the research include:

- Designing algorithms capable of accurately measuring morphological features of tree stock.
- Simulating the complex thought processes of a human.
- Customisable grading to the 95% accuracy required by the nursery.

- Dealing with organic material which is subject to much variation from tree to tree.
- Handling of trees for automation and sorting without damage to trees.
- Operating at harvesting speed of up to 5 trees per second.
- Cutting roots to the correct length at high speed when they are growing at a variety of orientations from the base of the stem.
- Navigating to high accuracy down narrow rows which are not perfectly straight.
- Integrating different technologies seamlessly into one *field factory*. Figure 2.19 shows the tasks the machine must perform. If any of the main tasks are not completed satisfactorily, then the machine becomes redundant and manual labour must be used.

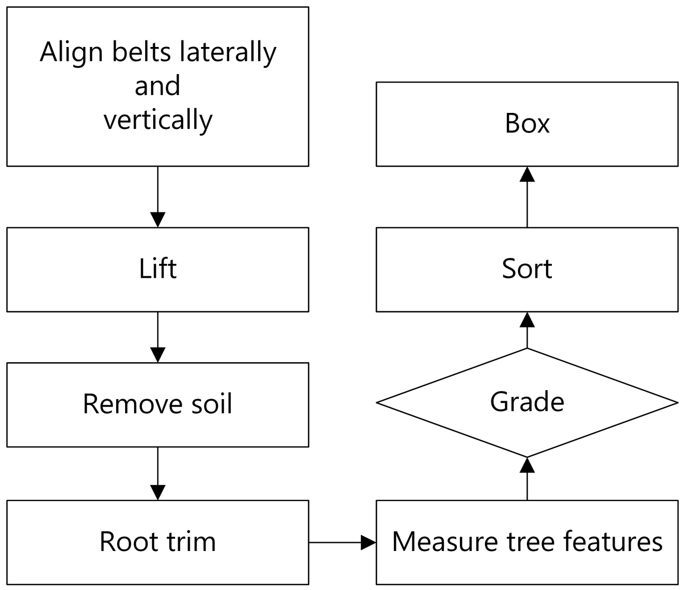


Figure 2.19: Tasks the *field factory* must perform

2.8 Methodology

The aim was to assess the feasibility of integrating the lifting and grading processes, combining them both into a *field factory*. The research was applied and experimental. Machinery needed to be developed to answer the research questions due to the applied nature of the work. This required design and manufacture of various prototypes and development of an integrated machine. Several stages were necessary to determine if it is possible to lift and grade tree stock in one integrated *field factory*.

Grading Feasibility

Firstly, it was necessary to investigate algorithms for machine vision grading of forestry tree stock, particularly whether analysis of root structure is possible and whether more robust algorithms can be developed for identification and measurement of RCD. A number of images were captured of typical pine seedlings and cuttings, and image processing techniques applied. OpenCV and C# were used to process the images, using the Visual Studio integrated development environment (IDE). OpenCV is open source, and capable of applying many common image processing techniques with built in functions, which simplified and accelerated the development process. Similarly, C# allows fast development as it is a high level language, automatically handling memory allocation and garbage collection without compromising performance. Also, graphical user interfaces (GUIs) are fast and easy to produce. Subsequently, a rig was produced where the tree is conveyed along lifting belts, to identify challenges and physical requirements to maximise success of real time grading.

Research prototype

A standard engineering design process was used to develop the machinery. Morphological analysis was used to break the problem down into parts which were initially addressed individually. Solutions to individual problems were then combined into a holistic concept which addressed the entire problem. A review of literature provided a starting point for the design of the machine. The machine was designed based on the belt lifter principle with additional features incorporated including soil removal, root trimming, machine vision grading. It was designed to be drawn behind a tractor and not autonomously navigate as there was already sufficient complexity in other areas of the machine. Concepts were generated for the mechanical tasks of the machine. Computer aided design (CAD) was used to model the various components to produce designs ready for manufacture. Various manufacturing methods were used including laser cutting and folding, welding, 3D printing and machining. A flexible research rig was produced which allowed different components and concepts to be attached, removed, and adjusted as necessary. Testing was performed in field at the Tokoroa nursery under real conditions in winter. Effectiveness of lifting, soil removal and root trimming was evaluated. It had been identified that reorientating the seedlings into a horizontal position is beneficial for grading and handling. Two methods for reorientating the tree were trialled in the lab. A design for an integrated *field factory* was developed. A research prototype was detailed and manufactured which was tested both in laboratory and field environments.

Algorithm accuracy

Repeatability of manual measurements were first determined by randomly choosing a small sample of tree stock and manually measuring various features multiple times. A random sample of 200 trees was then lifted, the soil removed, and the roots cut to the correct length manually. RCD, height, sweep and root angle of the trees were measured manually by an expert. The same sample was then measured by the machine vision equipment. Some researchers have evaluated RCD measurements by using dowel instead of actual trees, due to its regularity in cross section. This study used actual trees to give a more accurate indication of the real situation. Statistical comparison between the machine vision values and the manual measurements determined the accuracy of the algorithms.

Grading capability

An expert knowledge approach was used to determine the accuracy of the grading algorithms. The grading process of a group of experts was studied. Ambiguity in grading was investigated by gathering 3 experts and asking them to grade the same sample of a raw lift of 200 trees, with no knowledge of the others' decisions. This provided a base line for what an acceptable performance of the machine vision system would be. It was proposed fuzzy logic or ANNs could improve the accuracy of decisions made by the system. Fuzzy memberships were determined based on repeatability of measurements and grading criteria. Rules where formulated based on discussion with experts, for example, "if the stem is slightly thin, but the tree is a good height and the roots are strong, then accept". A fuzzy logic system was implemented. The decisions made by the machine vision system were compared to the decisions made by the experts. An ANN was also investigated, where tree stock was graded into an additional grade, which was somewhere between 'good' and 'bad'.

Evaluation of Mechanical Processing

Finally, the mechanical processing steps were evaluated by testing the *field factory* in real conditions in the Tokoroa nursery in winter. Video was taken of the *field factory* so that each function required of the machine could be analysed.

Chapter 3

Techniques for Machine Vision Measurement of Morphological Features of Forestry Tree Stock

The literature review identified that machine vision is the most suitable candidate for automatically grading forestry tree stock. Work by other researchers has reliability issues and roots have not been analysed in the way required for this study. This chapter investigates algorithms for processing images of tree stock and measuring various morphological features. A prototype real time system was designed, built and tested.

3.1 Software

There are many options available when considering what operating system, software and programming language to use for image processing. The OpenCV image processing library was selected for use in this study as it is open-source, and widely used by researchers. OpenCV was designed for computational efficiency and use in real-time applications. Commercial software packages are available, for example RoboRealm, but these are typically expensive.

Several options were investigated for the programming language and environment including MATLAB, Robot Operating System (ROS), C++, C#

.NET, and Python. MATLAB is easy to use, and comes with an extensive library of predefined functions. Toolboxes are available for a variety of tasks including neural networks, fuzzy logic, and image processing. MATLAB has two main disadvantages: it can execute more slowly than compiled languages and it is expensive [135].

Many researchers are turning to ROS for robotics applications. ROS is an open-source robotics platform for Linux. ROS provides a structured communications layer above the host operating systems of a heterogenous compute cluster. The goals of ROS are peer-to-peer, multi-lingual, tools-based, thin, and free and open-source. The fundamental concepts of the ROS implementation are nodes, messages, services and topics. Nodes are processes which perform computation, and they communicate with each other by sending messages. Messages are published to a given topic, which nodes may subscribe to if the information is relevant. Topic based publish-subscribe is not suitable for synchronous transactions, which is instead handled by services [136].

The framework and interface for a custom machine vision software package has been developed using C# and the .NET framework. Emgu CV has been used to wrap the C++ OpenCV libraries to C#. Although OpenCV is written in C++, C# .NET was ultimately chosen for the following reasons:

- Ease and speed of creating user interfaces on Windows Forms using the Visual Studio IDE. The end product will be used by nursery staff who require a simple interface.
- Automatic garbage collection and managed code means less time spent developing and dealing with things such as memory management, freeing up more time to focus on image processing.
- Structure is already there for dealing with events. Code can be organised and managed easily.
- Although a high level language, C# is comparable in performance to C++ and other languages in terms of processing speed.

3.2 Image Acquisition

A preliminary study was conducted into machine vision techniques based on a small sample of images captured from a standard digital camera, before purchasing expensive machine vision components. Images were acquired with a Sony Cybershot DSC-W180 10.1MP digital camera with a focal length of 6 mm, F-stop f/5.4 and exposure time 1/320 s. Original resolution was 3648x2736 pixels. The trees were photographed outside on a sunny day from two perpendicular planes: one provided a side profile of the tree, and the other showed the roots from underneath.

To facilitate image segmentation from the background, trees were placed onto a white board and the side profile of the tree was imaged. The original images were cropped and resized to 1500x700 pixels. Imaging the roots required more thought, as needles are visible when viewing the tree roots from underneath. A slot was cut into a white board to screen the needles and prevent them from appearing in the image. The tree stem was inserted into the slot, and the roots were imaged with the tree upside down. These images were cropped and resized to 1000x1000 pixels, making sure the root ball was centred in the image. This does not represent a real-life situation, which will be addressed in the Section 3.8. Figure 3.1 shows an example of the images captured from the digital camera. Although this method introduces shadows into the image, cast by the tree against the background the images were still useful for investigative purposes. 16 images were taken: 12 of acceptable cuttings, and 4 of rejects. These images were used to test various image processing algorithms and techniques.

3.3 Noise Removal

Noise removal is often the first step of image processing. Blurring and smoothing operations are common techniques to deal with noise, but they result in loss of detail. The simplest smoothing technique is applying a normalised box

Figure 3.1: Side profile (left) and roots (right) captured using standard digital camera

filter where the output pixel is the average of its neighbouring pixels. For example, a 5x5 box filter is shown in Equation 3.1.

$$K = \frac{1}{25}\begin{bmatrix} 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \end{bmatrix} \tag{3.1}$$

Gaussian smoothing can be more useful. An approximation of a 5x5 Gaussian kernel is given in Equation 3.2. The images in this study were blurred using this kernel.

$$K = \frac{1}{256}\begin{bmatrix} 1 & 4 & 6 & 4 & 1 \\ 4 & 16 & 24 & 16 & 4 \\ 6 & 24 & 36 & 24 & 6 \\ 4 & 16 & 24 & 16 & 4 \\ 1 & 4 & 6 & 4 & 1 \end{bmatrix} \tag{3.2}$$

3.4 RCD Measurement

Several techniques were investigated for measurement of RCD. Measurement of the RCD requires processing of the image to remove obstructions in the region, and subsequent location and measurement of the RCD.

3.4.1 Removal of Needles

Figure 3.2 shows images of trees with RCD regions obstructed by both roots and needles. Selecting an appropriate threshold aids the removal of obstructions from the RCD region [65], but it is not very effective. This was the only method found in the literature. Two additional methods are proposed: removal of needles based on colour information, and removal based on size.

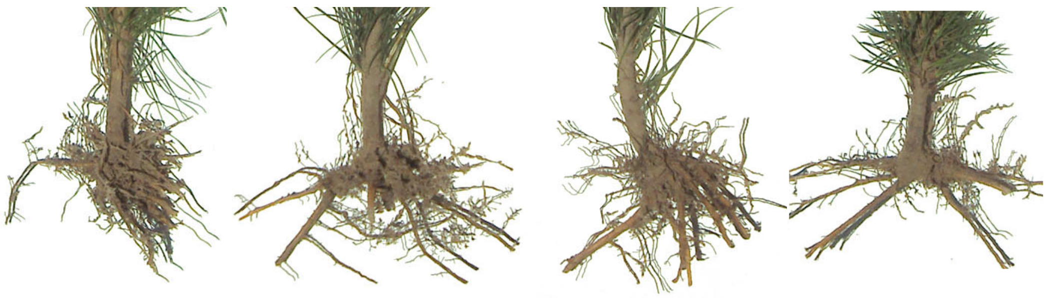


Figure 3.2: Images showing obstructed RCD region

Needles could potentially be removed based on colour information as the needles are green, which are a different colour to the stem which is brown. Non-green items such as soil and roots are not removed from the root collar region using this method. There are many colour spaces available, including RGB, HSV, YCbCr and Lab. Both the HSV and RGB colour spaces were investigated.

The HSV colour space is useful for selecting a colour range as the hue is separated into a single channel. The other two channels represent saturation (the amount of grey), and value (brightness). This colour space is defined in a way which is similar to how humans perceive colour. Figure 3.3 shows the histogram of the hue channel for the tree pictured in the left of Figure 3.2.

The histogram is bimodal, with two maxima: one occurs in the red/orange region, the other near the start of the green region. It was suggested that the best value for segmentation will be the minima which lies at a hue value of 23. If the hue channel for the pixel was over the threshold, it was converted to white. The effect of an increasing threshold level is shown in Figure 3.3. The threshold increases from 18 in the left image, in increments of 5, to 33 in the right image. These points are indicated by the vertical lines in the histogram. Lower values result in more needles being removed, but a portion of the stem information is lost. While the bulk of the needles are removed, it does not produce a 'clean' root collar. It is worth noting that at higher thresholds a 'skeleton' of the tree becomes visible, i.e. portions of branches and stem are left while the needles are removed. A threshold of 28 is pictured in the bottom of Figure 3.3 which shows a disconnected skeleton of the tree. This could be useful for determining whether a tree has multi-leaders.

In addition to the HSV colour space, the rg chromaticity coordinate was investigated. Researchers have used the rg chromaticity coordinate for segmentation when identifying fruits such as citrus [89] and apples [137]. The rg chromaticity space is a 2 dimensional system based on three channel RGB colour, which is independent of brightness. Equations 3.3 and 3.4 provide colour 'quality' of red and green channels. A third equation describing blue is not necessary because the sum of r, g and b always equals one, meaning b can be calculated if required.

$$r = \frac{R}{R+G+B} \tag{3.3}$$

$$g = \frac{G}{R+G+B} \tag{3.4}$$

The rg plane for the same image as in Figure 3.3 is shown in Figure 3.4. Green occupies the upper region of the rg chromaticity plot. A transition line from green to blue appears from (0, 1/2) to the white point (1/3, 1/3). Additionally, another transitional line appears from (1/2, 1/2) to (1/3, 1/3).

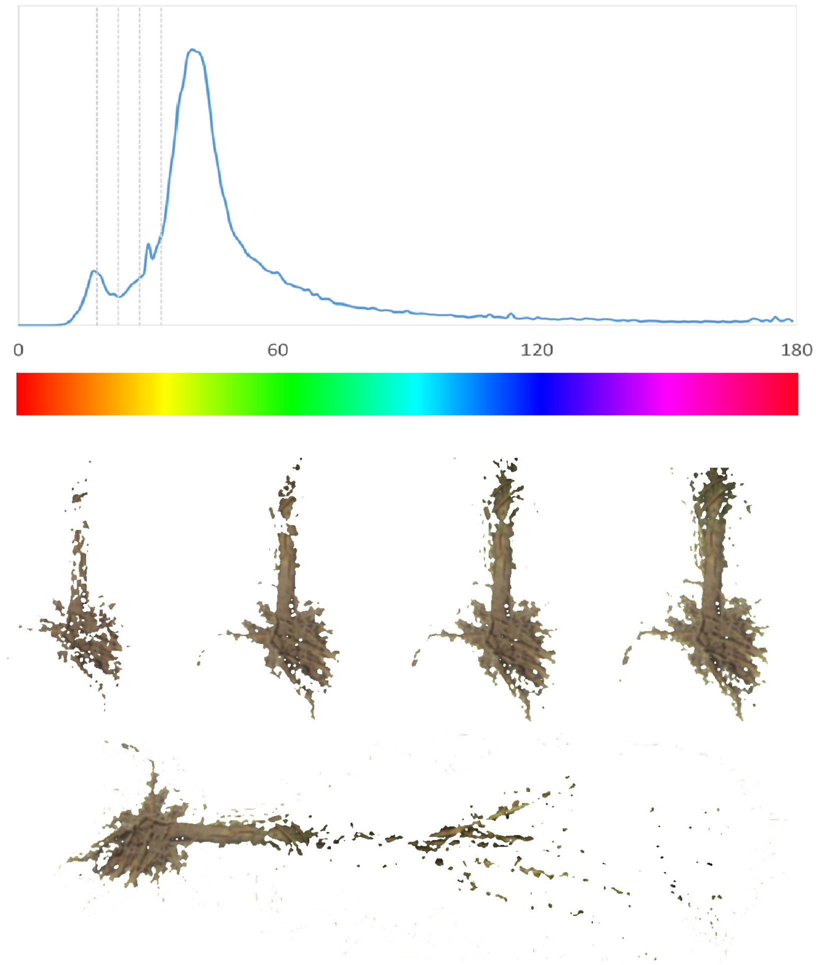


Figure 3.3: Histogram and effect of different hue threshold levels - 18 (left), up to 33 (right), in increments of 5

Therefore, these lines were used as the cut off point to remove green pixels from the image. If the pixels met the criteria in Equation 3.5, they were converted to white. This produced the image in the bottom of Figure 3.4, which was very similar to the result obtained using the HSV colour space.

$$(g > 0.5 - 0.5r \text{ and } r < 1/3) \text{ or } (g > r \text{ and } r \geq 1/3) \tag{3.5}$$

The colour methods did not produce good results, therefore another method was investigated. The needles and roots are significantly thinner than the RCD, which can be utilised to clean up the root collar region. The image was first converted to greyscale, as for RCD measurement no colour information is necessary. An appropriate threshold was chosen to reduce the image to binary.

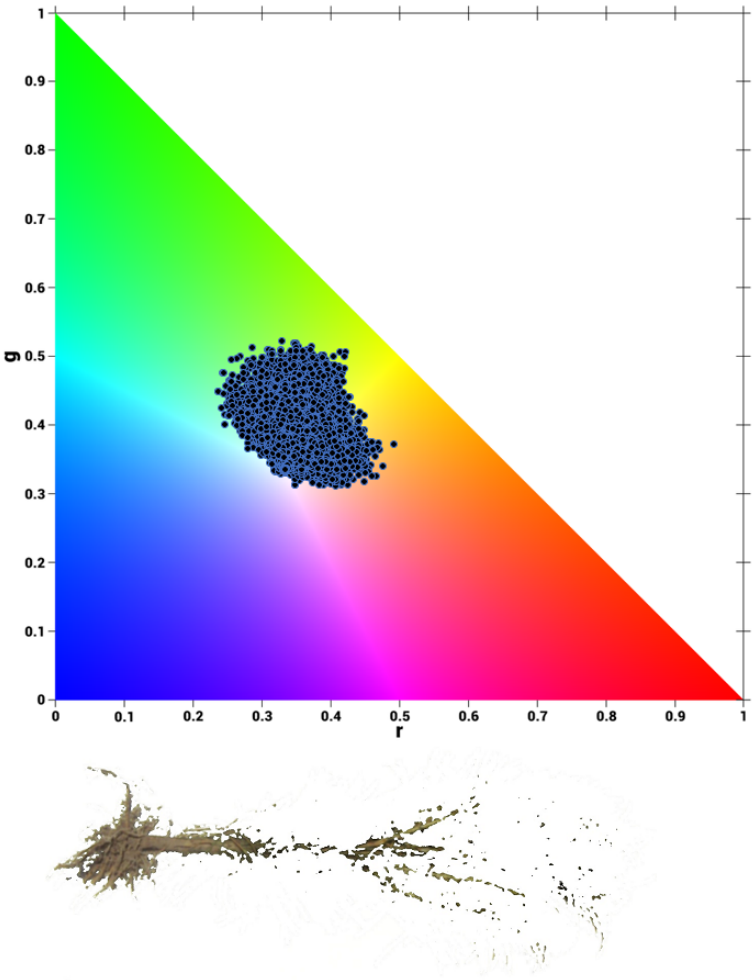


Figure 3.4: rg chromaticity plot of pine cutting (top) and needles removed (bottom)

Dilation and erosion are morphological operations which can grow and shrink white and black regions in a binary image. Dilation grows the white region, while erosion grows the black region. This can be useful for removing noise, or separating or joining disparate regions in an image. Dilation convolves a kernel over the image, and takes the maximum pixel value. Erosion does the opposite, taking the minimum. This could be used to remove fine needles and roots which obstruct the root collar region.

A 3x3 dilation matrix followed by an 3x3 erosion matrix was applied to the binary image of the tree to remove thin detail. Different shaped kernels can be used, typically rectangular, cross and elliptical. These have different effects on the shape of the outcome. Rectangular had the greatest positive effect on reducing the root collar to a consistent thickness. The other two produced 'bumps' in the stem: the elliptical kernel rounded the edges slightly, while the cross left diamond shaped edges. Figure 3.5 shows an increasing number of iterations using a rectangular kernel, from left to right (0, 1, 3, 7, and 15). The image progressively loses fine detail and ends up looking more like a 'blob', however, the stem becomes increasingly regular as the number of iterations increases. Any additional iterations cause the stem to disappear completely in this particular image. This method had a far more positive effect on 'cleaning' the root collar region, rather than attempting to remove by colour.

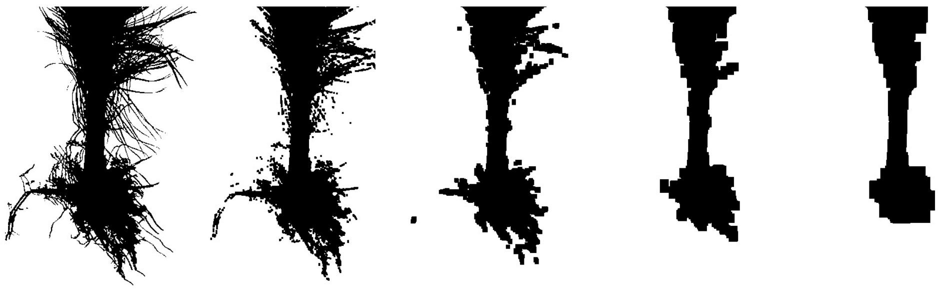


Figure 3.5: Effect of different levels of dilation and erosion

To remove as much unnecessary information as possible, the stem should be thinned back as close to a 'line' of single pixels. For example, if the thinnest part of the stem is 13 pixels wide, performing a 3x3 dilation 6 times will thin it to a single pixel. The number of iterations required can easily be calculated based on the smallest tree expected, by Equation 3.6.

$$n = \frac{s}{2r} \tag{3.6}$$

Where s is the minimum diameter in mm, and r is resolution in mm per pixels.

A custom algorithm was also tested for removing the small lines from the image. The process was as follows:

1. Loop through rows.

2. Count consecutive black pixels in each row.

3. If less than a threshold, convert to white.
4. Loop through columns.
5. Count consecutive black pixels in each column.
6. If less than a threshold, convert to white.

Figure 3.6 shows the effect of applying this algorithm. While this method was effective, it was not as fast as the previous method. Both methods were run 100 times, and the average time calculated. This method averaged 31 ms to perform it in the horizontal and vertical directions, removing lines up to 30 pixels long, while dilation and erosion only took 22 ms for 15 iterations of a 3x3 kernel. This time could be reduced significantly as this is being applied to the entire image which is not necessary. Also, the image is relatively large, at 1500x700 pixels, which increases processing time.

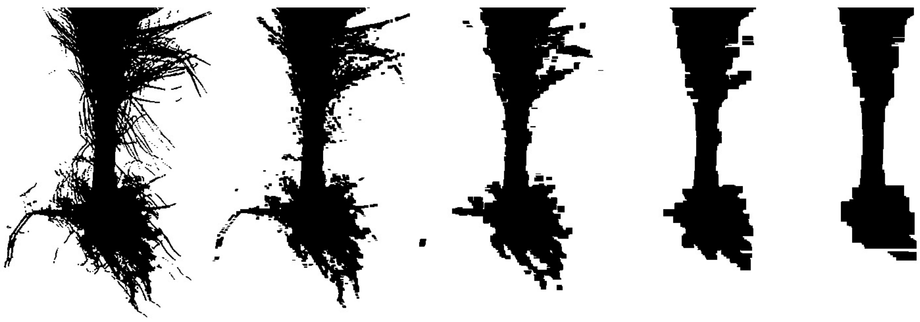


Figure 3.6: Effect of algorithm to remove small lines

These methods may leave blobs of black pixels disconnected from the bulk of the tree. The main contour can be isolated using the inbuilt *FindContours* function in Emgu. Contours can be easily looped through and inspected to find the largest contour which can then be drawn onto a new image.

3.4.2 Location and Measurement of RCD

Although the root collar region has already been 'cleaned' using the above dilation and erosion methods, the stem can still be irregular, especially if there are large chunks of soil stuck to the stem. Other researchers have searched for an area which is consistent in thickness and that falls within a certain range, but this can be prone to error due to irregularities. A more robust method is proposed: simply take the row in the region with the smallest number of pixels. This does not require a consistent clean area of stem, and means an area which has no mud build up or other items obstructing the RCD will be selected. The root collar can be located and measured using prior knowledge of the size of the root ball in relation to the size of the stem.

1. Moving up from the bottom of the image, the software checks for the root ball by looking for a block of pixels of a certain size (the root ball is larger and thicker than the stem).
2. Continuing upward for a certain distance (e.g, 100 pixels), the software checks for the RCD by picking the thinnest line in this region.
3. The pixel count for the RCD is converted to a measurement in mm.

The threshold levels for identifying the root ball were selected by counting the black pixels in each row of the 16 images. These were then manually inspected and the minimum width of the root ball was selected. The software was able to successfully locate and measure the RCD on all 16 trees in the sample. Algorithms by previous researchers failed to locate the RCD when there were roots or needles protruding into the root collar zone. This work does not suffer from the same limitations as it has addressed the issue by removing unneeded detail from the images before attempting to locate the root collar. Also, it does not rely on multiple lines to be consistent. Accuracy could be increased by taking the RCD as the average over multiple lines in the root collar region, e.g. taking averages of two lines, if one is 20 pixels wide and another 21, averaging these gives 20.5 pixels which provides sub-pixel resolution. Averaging more lines will get a better result, but this is unnecessary as the stem of the tree is not a perfect circle which introduces significant uncertainty into the measurement.

The previous method requires tuning and may not be robust when applied to a larger sample of trees. An artificial neural network could potentially classify each line into different features of the tree, for example, roots or foliage. An ANN was developed in MATLAB. The ANN took 3 inputs related to information about each line, i.e. the number of black pixels, line number and number of transitions from black to white or vice versa. The ANN consisted of five outputs: background, foliage, root collar, root ball, or roots. The layout of the ANN is shown in Figure 3.7. Three nodes were used in the hidden layer.

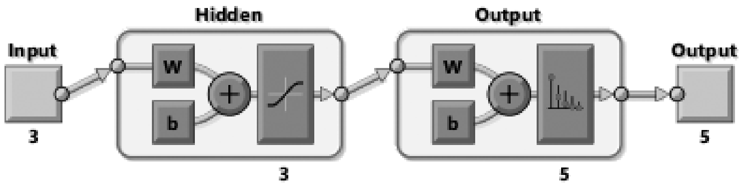


Figure 3.7: Artificial neural network for classification of tree features

Each line in each of 12 images were classified into one of the above categories by inspection. The data was randomly divided into training (70%), validation (15%), and test (15%) sets, for a total of 18,000 lines. A binary image was used which had been dilated and eroded three times with a 3x3 kernel. The network performed very well, with an overall classification accuracy of 97.8%, as shown in the confusion matrix in Figure 3.8. The confusion matrix consists of four separate matrices: training, validation, test and overall matrices. Each shows how the data was classified by the network. Green diagonal boxes indicate correct classifications, and red boxes indicate misclassification. For example, during testing, the network correctly classified the root collar (output class 3) 149 times. 16 lines were classified as the root collar, when they should have been foliage (class 2) or the root ball (class 4). Similarly to work by other researchers, misclassifications typically classed lines into adjacent classes.

Figure 3.9 shows an example image of a tree classified in this way. The chart at the bottom of the figure shows how each line was classified by the network. The network provides the probability of each line belonging to each

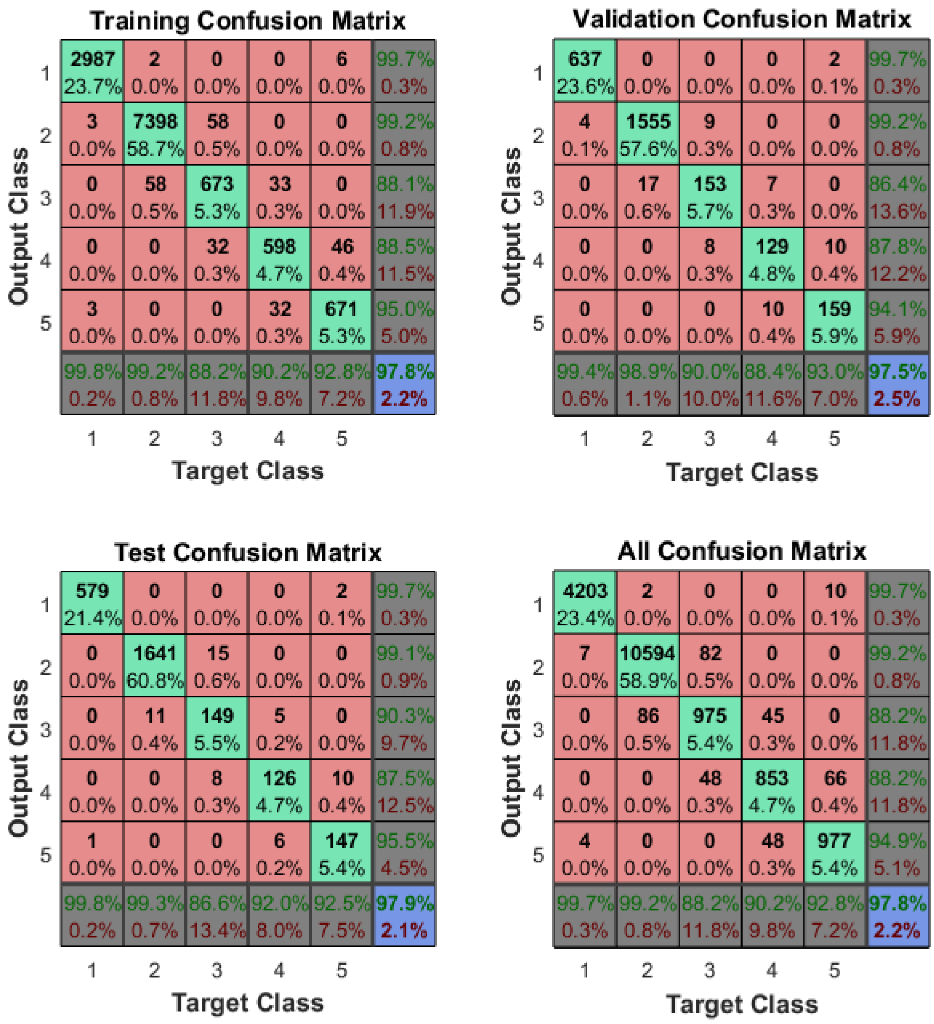


Figure 3.8: Confusion matrix for tree stock feature classification

class, from 0 to 1. The boundaries between regions were calculated at the point where the probability of the line belonging to the next class exceeded 0.5 for the first time, shown in red in Figure 3.9.

Alternatively, if systems are designed adequately and the tree is handled in an appropriate manner, location of the root collar may not be necessary. Controlled handling would mean the root collar is in a known region of interest (ROI) in the image, and could be measured easily without having to hunt for correct region.

Figure 3.9: Example tree showing transition points between different regions of a pine cutting

3.5 Height

Height is measured from the root collar to the top apical meristem. Height could be calculated using the ANN described in the preceding section, by subtracting the root collar row from the row corresponding to the top of the tree. Alternatively, height can be measured in the following way:

1. Threshold operation to convert image to black and white.
2. Dilate to remove thin needles protruding above the top apical meristem. This simplifies detection of the terminal bud.
3. Start at the row corresponding to average height, for example, the root collar location plus 350 mm. If this row contains at least one black pixel, jump halfway up the upper limit, else jump backwards the same distance towards lower limit.
4. If jumping higher, set lower limit to the last column inspected, else set upper limit to last column.
5. Repeat until upper and lower limits are within a range of 20 pixels.
6. Convert height of tree in pixels to mm.

A graphic depicting the sequence in which rows are inspected is shown in Figure 3.10. This is an improvement in performance on methods employed by other researchers, as it does not need to search every row to locate the top of the tree. The algorithm was run 1000 times, taking 25 ms, compared to searching from the top down which took 1716 ms. It is important to note that in this particular case, there were 306 rows before the top of the tree. This will be affected by camera resolution and the height of the tree. Alternatively, every xth row (corresponding to around 5 mm) could be checked, instead of every row. Checking every 20th row (the same tolerance as the faster algorithm) reduces the processing required by 20 times, which would reduce the time to 86 ms.

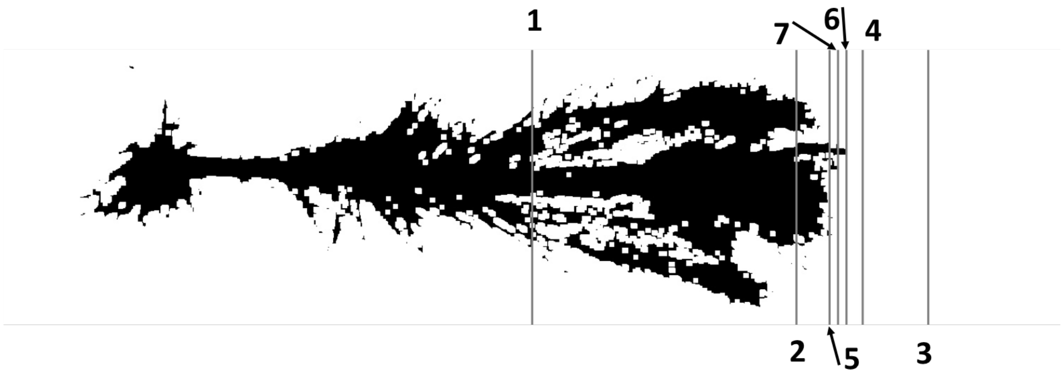


Figure 3.10: Sequence of lines inspected to determine height of tree

3.6 Root Structure

When a human grades roots, they inspect the tree from underneath, and cast their vision around the stem identifying roots. Typically, the manager will train staff by saying 'if there are roots from 12 o'clock to 6 o'clock, then the roots are good'. An algorithm is proposed which attempts to replicate this process, by rotating around the stem, identifying roots, and calculating the largest region void of roots. Firstly, a threshold operation is applied to reduce the image to a binary image. Small, insignificant roots are removed by dilating the image a few times. Note that what are considered 'insignificant' is subjective. The roots are then identified and angles between them measured as follows:

1. Inspect pixel at a certain radial distance to the right of the centre of the root ball.
2. If pixel is black, flag as the starting point, else calculate pixel 1 degree anticlockwise.
3. Repeat until 'starting point' is found.
4. From starting point, continue around another 360°, checking for black pixels. A black pixel is associated with a root being present. Potentially, instead of inspecting a single pixel, a block of pixels could be inspected.
5. Calculate largest angle void of roots.

Figure 3.11 shows an example of root identification using the custom software. The starting point described above was determined to simplify calculation of the empty root region, as the starting point will always be a root. The top left image is the raw image taken by the camera. The top right shows the binary image after the threshold operation. The bottom right image is taken after the small roots have been removed. The bottom left image shows where the largest angle between adjacent roots has been identified.

This method relies on having prior knowledge on the location of the centre of the root ball. The effect of having the stem not centred in the image is pictured in Figure 3.12. Measured angle can vary significantly depending on the centre point location. For example, the small shifts shown in Figure 3.12 can reduce the measured angle to as small as 95°(or potentially smaller), as opposed to the original 131°.

This method will require tuning. The radial distance from the root ball at which the roots are searched for will need to be optimised, and the size of the kernel passed over the image adjusted. This will depend on optics of the system, and is addressed in Section 5.2.6.

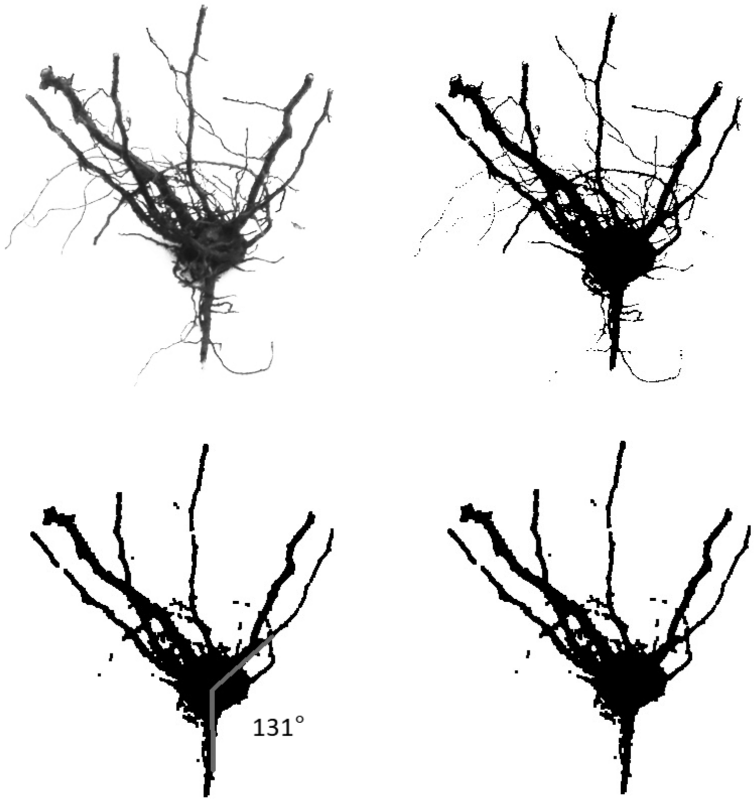


Figure 3.11: Steps in processing root images. Clockwise, from top-left: 1 - Raw image; 2 - After threshold operation; 3 - Small roots removed; 4 - Roots identified and angles measured

A neural network could potentially make tuning easier. For example, a network could be trained by having an expert identify whether regions of the image contain a root or not. Specific features about the root could be used as inputs into the network, for example, thickness of root, and radial distance from root ball. This will require a larger sample of images, and is investigated in Section 5.2.6.

Classification of Root Quadrants

Root quadrants, as determined by Figure 1.4, are used by the nursery for grading and statistical purposes. The angle void of roots calculated in the previous section could be used to classify root quadrants. It is relatively simple to classify into most classes, but more thought is required to identify the two opposite quadrants class. This requires knowledge of the two largest regions void of roots, and the angle at which these regions start. Both of these must

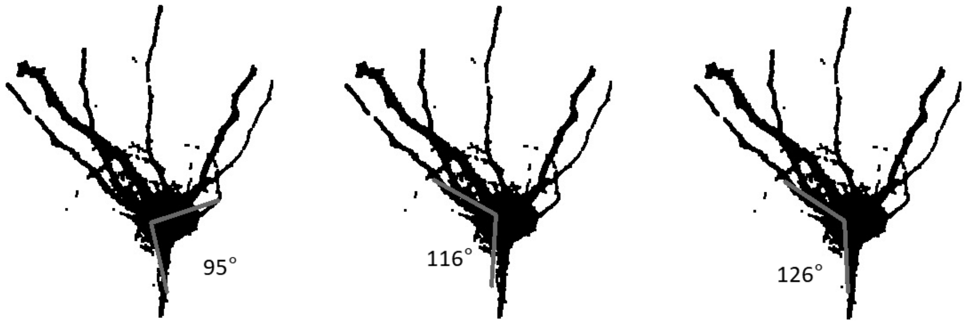


Figure 3.12: Effect of shifts in assumed centre of root ball on root angle measurement

be over 90 degrees, and there must be roots present at 180 degrees to each other. The diagram in Figure 3.13 shows the decision making process to be followed when classifying root quadrants. $Angle$ is the largest area void of roots, followed by the $Angle2$, the second largest. $AngleStart$ is the angle at which $Angle$ starts, and $Angle2Start$ is the angle at which $Angle2$ starts. Similarly, $AngleEnd = AngleStart + Angle$ and $Angle2End = Angle2Start + Angle2$.

3.7 Location of the Root Ball

It is necessary to locate the centre of the root ball when analysing roots. Two methods are suggested: one based on dilating images to isolate and locate the root ball, and the other based on tracing the stem down to the root ball.

After measuring the RCD, the root collar can potentially be dilated away, leaving blobs representing the root ball and foliage. This works because the root collar is smaller than the root ball and needles. As the RCD has already been calculated, dilation can be performed with a 3x3 kernel and iterated a number of times equal to just over half of the RCD. This will completely disconnect the root ball from the remainder of the tree. The roots would also be dilated away as they are much thinner than the stem, leaving the root ball as the lowest blob in the image. OpenCV has routines available to find blobs

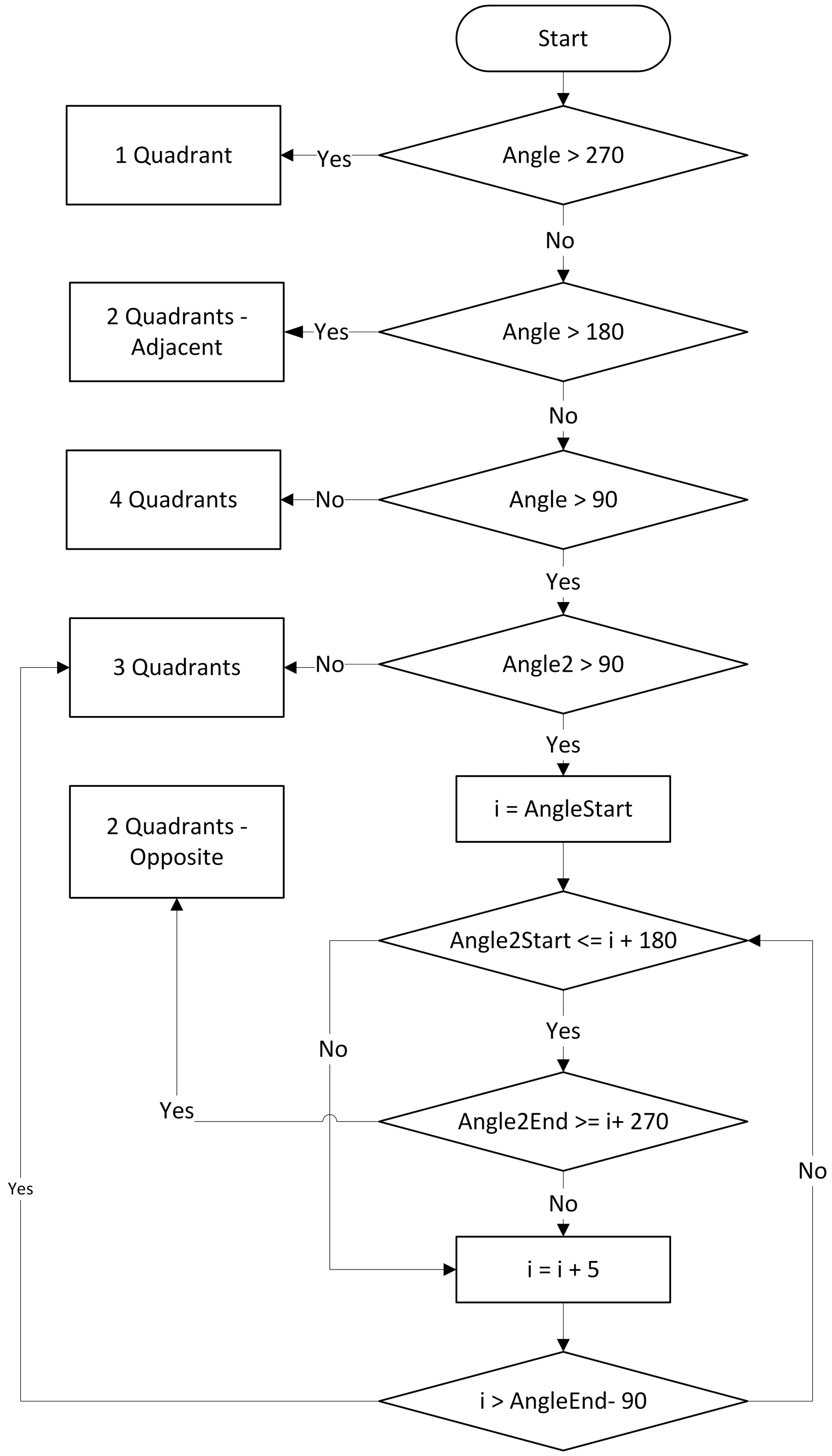


Figure 3.13: Flow chart to determine root quadrants

and their centre of mass. The contours can be inspected to identify which has the lowest centre of mass, as pictured in Figure 3.14. This locates the root ball in one plane only, another perpendicular image of the side profile would be required to locate it in 3D space.

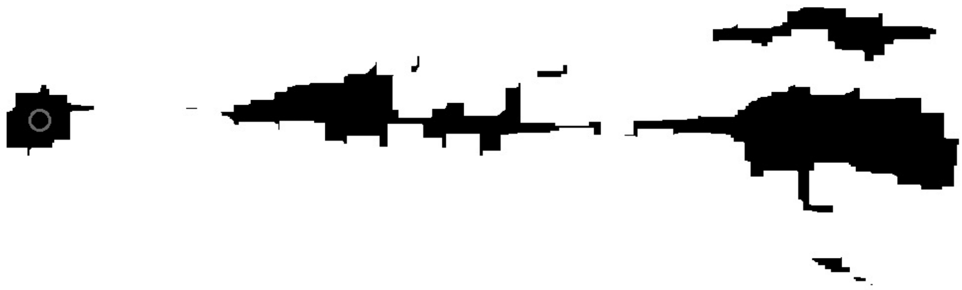


Figure 3.14: Centre of root ball identified with grey circle

Alternatively, the image of the roots could be dilated away to a small blob (approaching a single pixel), to identify the centre of the root ball. This method is pictured in Figure 3.15, applied to a particularly unbalanced root system. Some images suffered from shadowing from the roots, as such the threshold operation was not ideal on some trees. The image was continually dilated while there were more than 20 black pixels remaining in the image.

Figure 3.15: Centre of root ball identified with circle

This method will likely have issues handling very unbalanced root systems, for example, tree stock with only one quadrant. Tracing the stem down should more reliably locate the root ball and also provide a strong indicator of sweep. Bends are typically concentrated near the bottom of the tree, as cuttings are short when they are set, protruding only around 60 mm from the soil surface. The tree then tries to correct this angle by growing upwards, causing sweep in the tree. It is proposed that the stem can be traced by breaking it down into regions equivalent to about 5 mm in length. In each region, the row containing the least amount of black pixels is identified. These are joined together to trace the stem down. The horizontal offset from the start of tracing to the end can be used as an indicator of sweep. Figure 3.16 shows an example of this method on a tree exhibiting a significant degree of sweep. The tracing can stop when the larger root ball area is detected. In addition to being an indicator of sweep, this can also be an indicator of a weak stem, which can sag under its own weight. This method was more robust than the previous, but it was only able to locate the root ball in one direction.

Figure 3.16: Tracing the stem for possible location of root ball, and calculation of sweep

3.8 Real Time Grading Prototype

To gain experience grading in real time, an experimental rig was built that handles the tree using rubber belts in the same manner as commercially implemented lifting machines. A general arrangement of the rig is shown in Figure 3.17.

Used rubber lifting belts were acquired from a forestry nursery in the United States, and driven by a 1/4 HP AC electric motor. A 2000 CPR quadrature encoder was mounted to the drive shaft so that the speed and position of the belts could be calculated. A mechanism was designed to trip the trees onto a

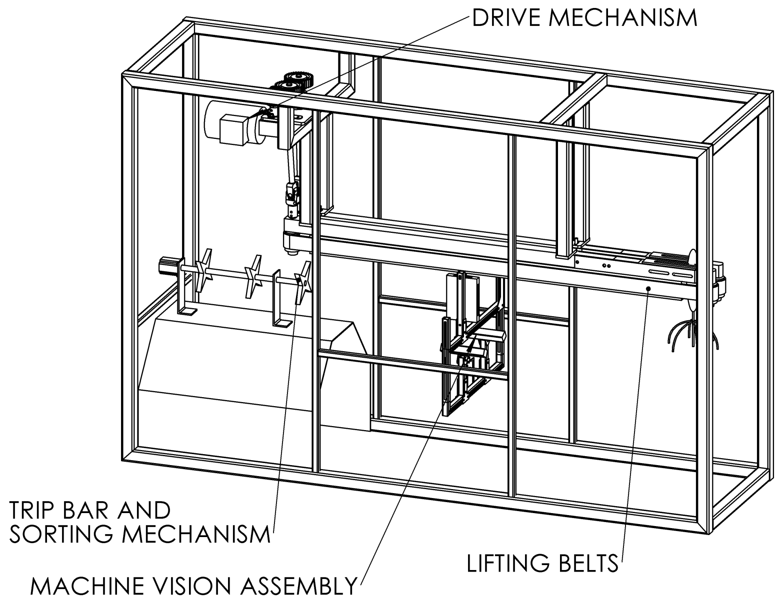


Figure 3.17: Proof of concept grading rig

horizontal cradle as they exit the belts. The cradle was mounted to a shaft powered by a stepper motor, in order to sort the trees clockwise for 'good' and anticlockwise for 'bad'. An Arduino Uno was used to interface with the stepper motor and encoder. It communicated with a Lenovo Thinkpad W530 laptop via serial, which was used to perform image processing. Two cameras were used in this study: one to measure the RCD, and one to analyse the root structure.

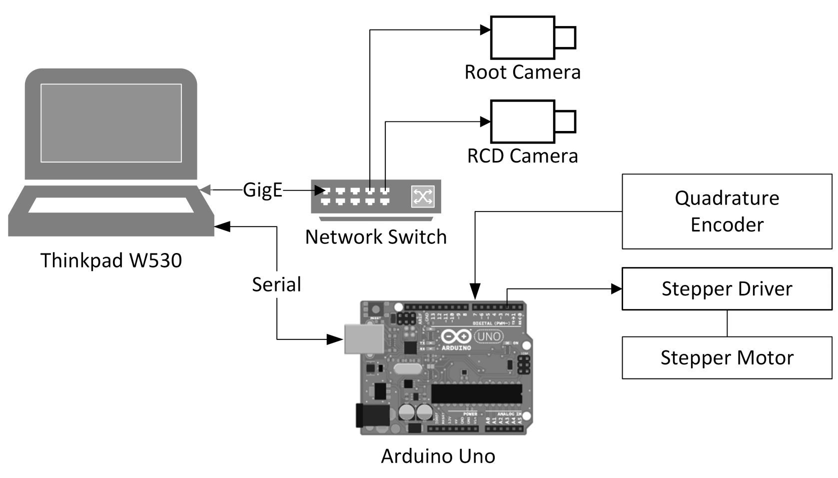


Figure 3.18: Communication diagram of Grading rig

Later studies by other researchers used line scan cameras, however, these were all performed on conveyors in controlled environments. Area scan cameras were chosen for this study as additional processing is not required to reconstruct lines into an image, accurate knowledge of the speed of the tree is not required, and line scan can introduce distortion and motion artifacts if the tree was to move slightly during image acquisition. The previous section identified that colour cameras are not required for RCD, root structure or height measurement. Monochrome is acceptable unless there is the need to inspect for disease or something which requires colour. Assuming the camera images a window width of 150 mm, a low resolution camera of 640 x 480 pixels gives a pixel resolution of approximately 0.23 mm, which is well within the nursery's required precision of 0.5 mm. As identified in Section 2.5.3, GigE and USB 3.0 are the most popular interfaces. Basler's Ace camera range was selected as they are reasonably priced and compact. GigE was chosen as the interface due to the longer and low cost cables available. The specifications of the selected camera are listed in Table 3.1. The camera is programmable via an application programming interface (API), so parameters such as exposure time and ROI can be controlled via software.

Table 3.1: Camera specifications

Model Number	acA640-120gm
Interface	GigE
Resolution	659 x 494
Shutter	Global
Frame Rate	120 FPS
Mono/Colour	Mono

The machine vision system needs to be compact due to required portability and lack of space. A wide angle lens may be necessary to give a large angle of view and allow the camera to be close to the subject. Alternatively, more thought could go into camera placement, or design of lifting belt assemblies.

The camera could look at the tree from an angle, or perhaps more simply the heights of the lifting belts could be staggered so that the trees are conveyed at different heights, without interference between neighbouring rows. Camera lenses with focal lengths of 4 to 75 mm are commonly available. A shorter focal length provides a larger angle of view and means the camera can be closer to the subject, however, distortion is increased and backlighting will need to be larger. The longest focal length should be chosen which meets the space constraint. A 6 mm lens will require a working distance of approximately 250 mm for the RCD camera, as calculated from Equations 2.1 and 2.2.

Only an outline or silhouette of the tree and roots is necessary to extract information on the features required. Backlighting was chosen where possible as it is the most reliable way to separate the subject from the background. The subject (tree) appears as a silhouette on a white background, making image segmentation easy. A red 150x100 mm LED backlight was selected from Advanced Illumination to light the root collar. Red was selected as it is the most common, and therefore least expensive option. Additionally, for monochrome applications, the red colour corresponds with the peak sensitivity of the CCD sensor. It is difficult to apply the same technique to light the roots, while removing other features such as foliage. The easiest way to achieve this is to have the roots much lighter than the rest of the image. As such, diffuse lighting was selected for this application. The belts help screen the foliage from the image of the roots. The underside of the belt frame was painted matte black in order to reduce reflections in the image. The configuration of the cameras and lighting is shown in Figure 3.19.

The software continuously captures images from the two cameras. The Arduino is polled every time an image is captured to get the current encoder count. A minimum number of black pixels was searched for in the centre of a certain row in order to detect the presence of a tree. If this threshold was met, a flag was set to indicate that a tree is present in the centre of the frame. The images were then processed, locating and measuring the root collar as

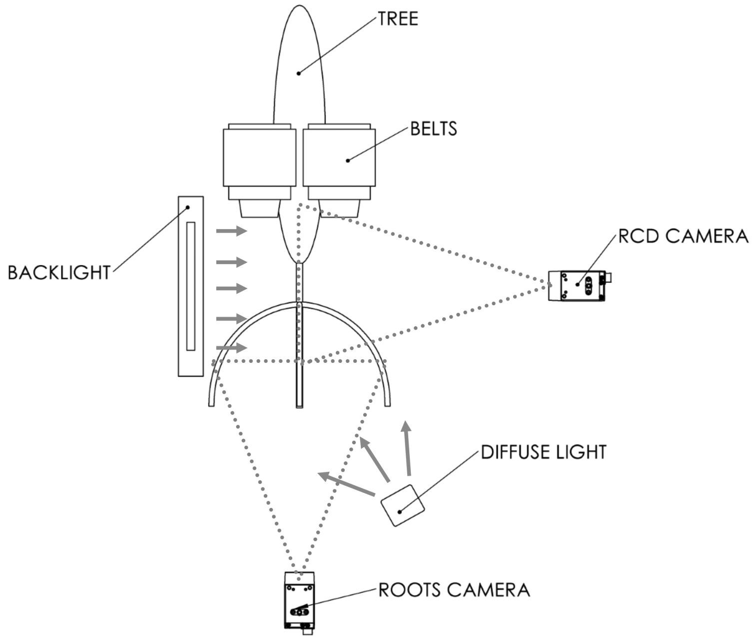


Figure 3.19: Camera configuration

in Section 3.4, and measuring the roots as in Section 3.6. A simple decision was made on the quality of the trees: if the RCD measured over 6.0 mm, and the maximum angle void of roots was less than 180 degrees, then the tree was accepted. This decision was sent to the Arduino over serial, along with the count of the encoder when sorting would be necessary, i.e the encoder count when the image was taken, plus an offset corresponding to the distance between the cameras and the sorting mechanism. A slight delay is incorporated into the software to ensure the tree has time to leave the frame before image capture restarts.

This study did not hunt for the centre of the root ball when measuring roots and assumed that the tree was straight and centred in the belts. Calibration of the location of the root ball was achieved by manually locating the position of the root ball in the image. It was assumed that further images would have the root ball located in the same position.

Figure 3.20 shows the grading rig on display at Fieldays 2015, the Southern Hemisphere's largest agricultural event.

The following was learnt from the grading rig:

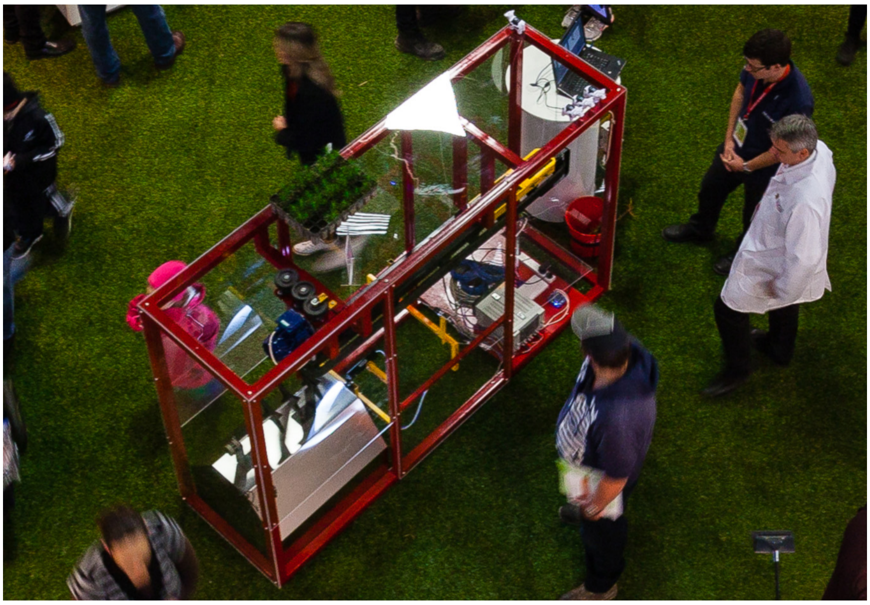


Figure 3.20: Grading rig on display at Fieldays 2015

- Identification of trees was successful and no trees were missed.
- Difficulties were encountered taking images with the camera directly under the roots, due to the amount of soil which falls onto the camera over time. There are potentially systems which could be put in place to address this, for example, a lens cleaning system. Alternatively, the tree could be transitioned into a different orientation, e.g. on its side, or upside down. Both methods will require additional complexity.
- Much of the middle of the tree is obscured by the belts, however, the top and bottom is still visible, so RCD, roots and height can be measured.
- The lifter aims to extract trees as controlled as possible so that the belts are always the same height above the ground. This means the RCD will always be in approximately the same location relative to the belt. In this case image processing is simplified as it not necessary to iterate up and down the image hunting for the RCD because its location is known.
- The 'trip' mechanism will not be capable of keeping trees singulated due to how closely the trees are planted together. There is interference between neighbouring trees when they are too close together. Therefore, an alternative mechanism will need to be investigated for the *field factory*.

- Colour cameras are not necessary for measurement of tree stock features required by this study.
- Needles and roots protruding in the RCD region can be removed, the best method being dilation and erosion.
- Controlled handling from point of lifting will simplify grading algorithms.
- Location of the centre of the root ball is important for analysing roots.
- A faster height algorithm has been developed.
- The tree should be presented on its side so that the roots can be graded and handling is easier.
- Real time grading of forestry tree stock using machine vision is feasible.
- There is much ambiguity in measurement of roots.

Chapter 4

Processing Tree Stock

Chapter 3 investigated techniques to measure forestry tree stock features using machine vision and concluded it is feasible to measure the morphological features required for this study. However, the question remains whether tree stock can be handled in such a way from the point of lifting through to sorting, without human intervention. This chapter describes the development of mechanical processing systems for handling tree stock and provides a pathway for an integrated *field factory*.

4.1 Scope

There are certain tasks the *field factory* must perform if it is to add value to the nursery. It is not necessary to automate every aspect of lifting and grading tree stock in order to realise considerable gains. At a minimum, the *field factory* needs to lift, clean roots, root trim, handle, grade and sort without human intervention. Achieving this will dramatically reduce the labour requirement and will add value as long as machinery and development cost is reasonable. If the machine is unable to perform any one of these tasks there will be no reduction in the number of labour units required. If at any time a human is required to perform a non-bulk task on tree stock, i.e. something which must be applied individually to every tree, then automation becomes fruitless as the worker may as well perform all tasks from lifting through to sorting.

Although full autonomy is the goal for robotics, partial autonomy can still add significant value to a machine if the cost is low and performance is high [138].

The non-critical tasks which are beyond the scope of automating in this research are motive power, steering and alignment, undercutting, lateral root pruning and boxing.

Motive Power

The *field factory* will be tractor-drawn, and will not self-navigate. This will require one skilled labour unit to drive the tractor and navigate down the beds. A John Deere 6210 tractor with a creeper box is available at the nursery.

Steering and Alignment

Steering will be mechanically assisted, but manually controlled. One labour unit will be required to align the machine to the rows of tree stock, and set the height of the belts above the ground. This will be aided by hydraulics.

Undercutting and Lateral Root Pruning

Lateral root pruning should take place immediately before, or at the time of lifting. This is because roots become intertwined with neighbouring rows. The nursery already has established equipment for this, therefore it will not be addressed. However, integrating lateral pruning into the design in future would be beneficial as it would save labour and tractor running costs. The nursery also has equipment for undercutting under the bed. This study will not investigate integrating an undercutter in the machine, instead rely on the existing equipment.

Boxing

Manual labour will be required for placing accepted trees into boxes. It is not feasible for trees to be presented singularly, as the boxer will not be able to keep up. As such, trees should be presented in bulk, at around 20-50 at a time. In Edendale, tree stock is placed onto a conveyor in bundles of ten. The boxer lets these accumulate, frequently picking up 50 trees at a time.

4.2 Rig Overview

A versatile research rig was produced to investigate lifting tree stock in the field, and to test various concepts for each function required of the *field factory*. One version of the prototype is pictured in Figure 4.1. It was designed to allow ease of changing configurations and mounting various equipment for lifting, removing soil, root trimming, and tree stock handling. It consisted of a single axle mounted to a frame. The frame had a drawbar so it could be drawn by a tractor. The nursery has a suitable tractor available with creeper box and hydraulics (John Deere 6210). The frame housed a pivoting subframe which the belts and other implements were mounted to. The pivot point allows the belts to be raised and lowered relative to the ground as necessary.

Figure 4.1: Prototype for lifting tree stock

4.3 Steering and Alignment

The first step to lifting is alignment of the machine to the trees. Lifting requires precise alignment of the belts to the rows of trees, as a small lateral deviation can cause the lifting mechanism to miss the trees. Steering is necessary to reduce the turning radius of the *field factory*, so it is capable of turning in the limited space at the end of the rows. Automated steering is preferable, but not critical to the success of the machine, and would only save one labour unit. As such, automated steering will not be implemented into the design.

The *field factory* will essentially be a trailer drawn by a tractor. A simple steering mechanism was considered, which has been implemented by machines such as the Love Harvester [139]. The entire trailer is steered by adjusting the draw bar angle with a hydraulic cylinder. The trailer becomes offset laterally from the tractor depending on the extension of the cylinder position from the tractor. The trailer will self-correct in order to keep the wheels pointing straight. The principle and geometry is pictured in Figure 4.2. The lateral offset of the machine to the tractor can be calculated from Equations 4.1 and 4.2.

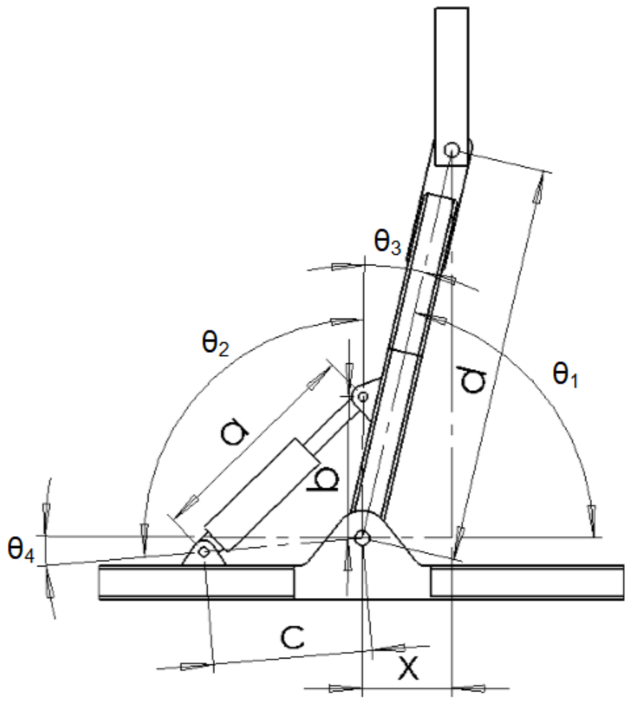


Figure 4.2: Steering principle of lifter

$$x = d \sin \theta_1 \tag{4.1}$$

$$\theta_1 = \pi - \theta_3 + \theta_4 - \cos^{-1} \frac{b^2 + c^2 - a^2}{2bc} \tag{4.2}$$

For non-slip steering when turning at the end of the nursery beds, the trailer should follow the same turning radius as the tractor, i.e. the axis through the axle should be coincident with the centre of the turning circle of the tractor. Ackermann steering geometry on the tractor ensures the axis for all four tractor wheels meet at a single point. The pivoting draw bar will be capable of producing this type of motion. However, as it will be manually actuated it will depend on the experience of the driver. Automating this requires knowledge of the angle of one of the front wheels of the tractor, and the angle between the tractor and the draw bar.

4.4 Tree Extraction and Conveying

Once aligned, trees must be lifted from the ground. Mechanical lifting is already implemented commercially in foreign markets, but is yet to be realised in New Zealand. Lifting of forestry tree stock is achieved by two counter-rotating inclined rubber belts, by machines such as the Love Seedling Harvester, as detailed in Section 2.3. Existing machinery could be applied here, although it is likely to perform significantly differently as there are many factors which impact the lifting operation. Tree stock in New Zealand is significantly larger and the soil is more clay-like [58], which makes lifting more difficult as the soil has more of a tendency to clump together, which will be removed with the tree. This significant added weight increases the force required to lift the tree from the ground. At the time of harvest the roots are also more developed when compared to the US [58], making entanglement between adjacent trees an issue. This further increases the required lifting force as more roots means more soil, and intertwined roots can mean that when a tree is lifted, the neighbouring tree may also be raised also, resisting the lifting motion. Lifting additional weight will require that a larger force is applied between the belts and the tree to prevent slippage.

The force required to lift tree stock from the ground was investigated. A sample of 33 trees was lifted using a digital fish scale. One end of a bungy cord was tied to the top of the tree, and the other attached to the fish scale. The average lifting force required was 65N, with a standard deviation of 25N, as listed in Table 4.1. Using a 99.9% confidence interval, this suggests the maximum lifting force required will be around 148N.

Table 4.1: Force required to lift tree stock (N)

Average	65
Standard Deviation	25
Maximum	140
Minimum	26

Used lifting belts were acquired from a nursery in the United States and mounted to the research rig. The belts were approximately 50 mm wide, and 50 durometer. 50 durometer is a good compromise to provide greater belt life, while still handling tree stock gently. Softer belts tend to wear quickly, while harder belts can damage tree stock [140]. They consist of a number of 3VX rubber belt strands glued to a neoprene backing and are available in lengths up to 140”. The belt assemblies were cleaned with ethanol to kill any diseases that may threaten the domestic forestry industry. The belts were powered with a hydraulic motor and geared together at a ratio of 1:1 using glass reinforced nylon gears. Two universal joints per belt allowed misalignment of the belts and drive gears, and provided lateral movement in the belts. Due to geometry, a single universal joint suffers from fluctuating output speed when a constant input is given. This can be overcome by using a double cardan shaft, which consists of two U-joints joined by an intermediate shaft. The driving and driven shafts must be at equal angles to the intermediate shaft for the output to match the input. A manual flow controller was used to control the speed of the belts. The belts were mounted on a pivoting subframe so that the height of the belts above the ground could be adjusted.

In order to lift the trees vertically from the beds with no relative movement between the tree and the length of the bed, the horizontal component of the belt velocity should be matched to the speed of the tractor, but opposite in magnitude. Alternatively, the horizontal component of the belt speed can exceed that of the tractor, which results in the tree being pulled up and backwards at the same time. This effectively spaces the trees out further and may make it easier to separate entangled roots and keep trees singulated down the line. The caveat of this is that more grip will be required due to intertwining of roots, therefore, the risk of slippage is increased. Also, the adjacent tree may be upset due to intertwining roots.

Lifting should be performed as controlled and smooth as possible so that other operations are easier as tree stock is gripped at a known reference point. Depth of tracks in between the beds is approximately 150 mm, but is not exact, and over time high tractor traffic can cause this to differ, even from one side of the bed to the other. Initially, the height of the belts above the nursery beds was manually adjusted. This worked relatively well but relied on operator skill to maintain a consistent height above the bed. Later trials implemented an automated system based on a modified scissor jack with a DC electric motor, as pictured in Figure 4.3. A pivoting wheel was attached to the lifting end of the belts, which rested against the nursery bed and a linear resistive position transducer (essentially a voltage divider) provided feedback on the height of the belts relative to the ground. An Arduino Uno was used to measure the voltage, and an H bridge configuration switched the motor to run either clockwise or anticlockwise. Simple on-off control was used with a dead band of approximately $\pm 5mm$ around the set point. PID control could be implemented in future if accuracy of the dead-band system is insufficient.

Trials were performed early in the season with good success, with minimal slippage in the belts. Figure 4.4 shows tree stock travelling relatively consistently up the belts. At this point trees were not mature and weather conditions were optimal, making lifting easier.

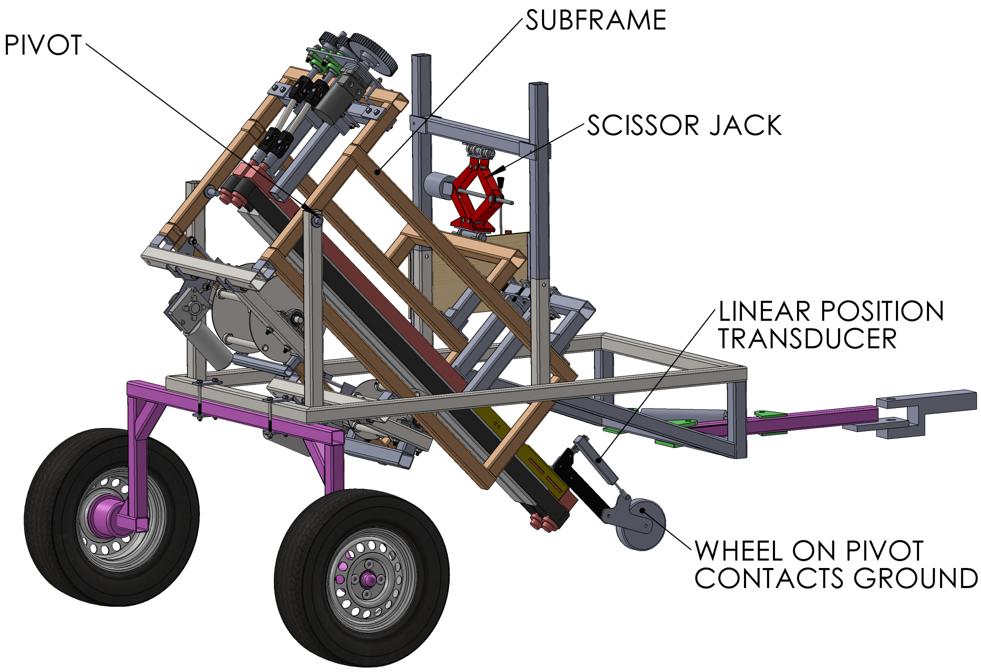


Figure 4.3: Motorised scissor jack for height control

One significant concern expressed by the New Zealand nurseries manager regarding the standard lifter design was pinch points in the system. Damage to tree stock is a major concern as they are very fragile and must survive transplanting out into the forests. Typically, lifters have a mechanism which 'squeezes' all the belts together. Belt tension is maintained by a telescoping end, and the use of pulleys and/or guide bars in the belts, as pictured in Figure 4.5. The pulleys and guides create pinch points when they are pressed together, which can cause damage to the fragile stem. Additionally, needles can be crushed which can cause them to fall off [58]. If the machine is incorrectly configured, tree stock can potentially be left behind and not lifted (inadequate force), or damaged (extreme force). Damaged trees are no longer saleable. Damage may not be noticed immediately, and a significant amount of tree stock could potentially end up needing to be discarded before the problem is found.

Due to the additional difficulty lifting tree stock in New Zealand when compared to nurseries in the United States, belt width was increased. This

Figure 4.4: Tree stock being lifted with early prototype

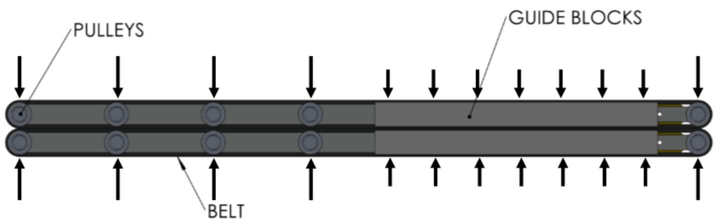


Figure 4.5: Pinch points created by pulleys and guide bars

permits a larger force to be imparted on the tree, thereby reducing chance of slippage. Doubling the width will permit twice the force to be applied to the tree while maintaining the same pressure, without increasing risk of damaging tree stock. Anything which results in less pressure being applied or less damage to the tree is beneficial. Wider belts were simulated by stacking two sets of belts on top of each other. This reduced the slippage problem.

The single row lifters used in NZ used idler pulleys sprung loaded against the belts to attempt to address the pinching issue [57]. The lifting end and drive pulleys were fixed, and the idler pulleys were staggered to remove the pinching issue along the length of the belts, as pictured in Figure 4.6.

Implementing this would require significant work. To easily address the pinching issue, belts were sprung using the principle shown in Figure 4.7. One

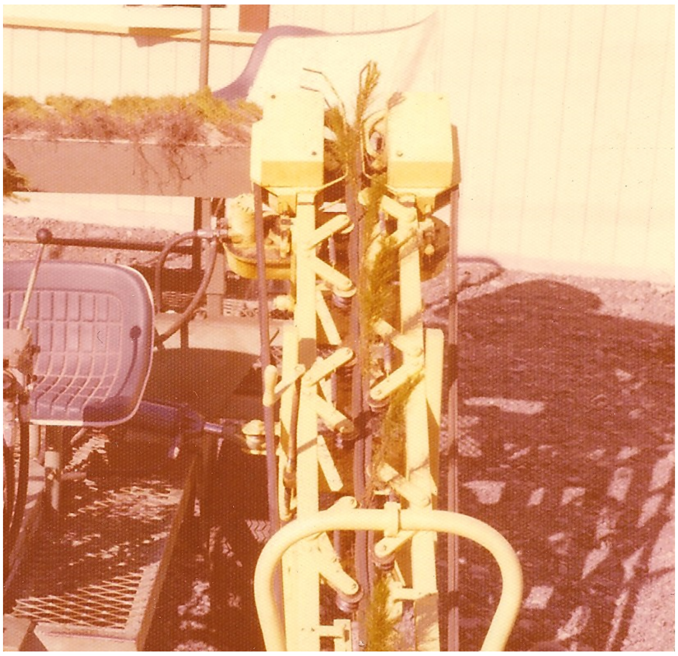


Figure 4.6: Lifter with sprung loaded idler pulleys [57]

belt remained fixed, while the other was hinged and sprung against it. Tension was adjusted by tightening or loosening a nut sitting against a compression spring. Slippage increased when compared to earlier trials, which can partially be attributed to the larger trees with larger root systems. Furthermore, the soil was significantly wetter, meaning large chunks of soil were lifted. The main reason for increased slippage is likely attributed to the method of springing. As belts moved further apart, they were no longer perfectly parallel due to the pivoting action, therefore an even pressure was no longer being applied to the belts, and consequently the tree stock. Also, if a large tree is lifted the belts may separate slightly, reducing force applied to smaller trees. This solution was non-ideal, as such, was discarded.

A different configuration was proposed to remove all pinch points: staggering adjacent pulleys and mounting them slightly closer together laterally. The force on the trees can be controlled by adjusting the tension on the belts. Commercial machines use telescoping ends to tension belts which are compact, but difficult to adjust. This type of system will be difficult to implement in this study as more than one belt will be required. As such, the location of all

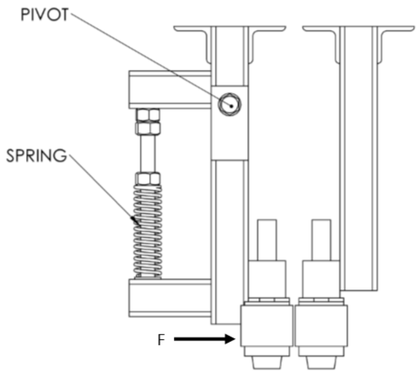


Figure 4.7: Concept for sprung loaded belts

the pulleys was fixed, and the belts were tensioned from the sides as shown in Figure 4.8. Multiple tensioners were used per belt as a single tensioner provides little movement in this configuration. Placing tensioners on the flat outer face of the belt means expensive machining is not required to match the profile of the v-belt. This design simplifies the system by reducing the number of parts required.

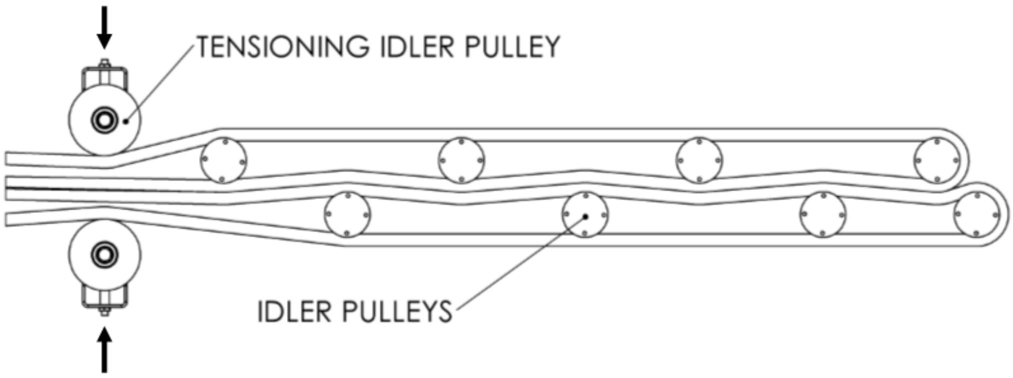


Figure 4.8: Staggered belts and offset pulleys

Belts for this machine will need to be much longer than on the US machines so that additional operations can be undertaken, i.e. root trimming and tree rotation. Unfortunately, such belts are only available in specific lengths, as they are moulded in one piece, and multiple belts must be used together to produce the length required. Belts could be butted up against each other (left of Figure 4.9), however, this may provide a brief period where control of the tree is lost, and it may be upset slightly. Alternatively, belts can be overlapped, as pictured in Figure 4.9 (centre). Overlapping will require longer belt length, but it will mean the belts are always in strong contact with the tree. This will cause the tree to be gripped higher up along the stem. A third option is to butt them together and have a short transitional belt above the join, as in Figure 4.9 (right), adding additional parts and complexity. The 3VX profile is used by commercial machines as it is flexible enough to use pulley diameters as small as 75 mm, which can fit between rows. Two or three lengths will be required for this study, depending on the final design, as belts are only available in lengths up to 140". The alternative to multiple belts is to transition the tree into a secondary system where root trimming and grading can take place, but this comes with added complexity.

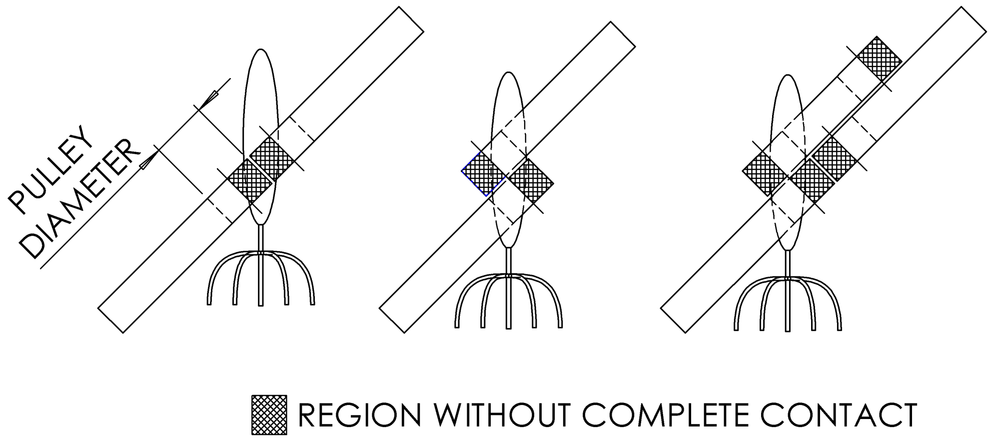


Figure 4.9: Potential configurations for compounding belts

4.5 Soil Removal

Before roots can be trimmed, soil should be removed from the roots. Two concepts for soil removal were considered: a rotary bar system and oscillating paddles, as implemented on commercial machines. An oscillating rubber paddle was trialled first, and mounted to the prototype machine. A four bar mechanism was designed to produce the oscillating motion and powered by a

DC motor with a worm and wheel gearbox. The mechanism was effective at removing soil from the roots, however, it did cause visible damage to the root collar and roots. The oscillating rubber paddle is shown contacting the roots of tree stock in Figure 4.10. Damage was predominantly caused by the sharp edge on the rubber paddle. More gentle handling could be implemented by modifications such as tuning the speed, contact area and the type of rubber paddle. Also, a thinner piece of rubber could be used which is folded in half to remove the sharp edge. The oscillating motion causes much vibration which raises reliability concerns.

Figure 4.10: Oscillating rubber soil remover contacting roots

Rotary soil removers were also trialled as they have a simpler geometry and less vibration. A two stage system was trialled with two different diameter beaters, as pictured in Figure 4.11. This system performed similarly to the oscillating system in terms of soil removal, however, several benefits were realised: vibration was minimised due to the smooth rotational motion; manufacture was simplified; and reduced damage to roots as there were no sharp edges.

The design could be improved by using a hard wearing roller which could rotate on the bars, made from Ultra High Molecular Weight Polyethylene (UHMWPE), or similar. Speed control should also be implemented which could be adjusted depending on the conditions on the day. The rotary system

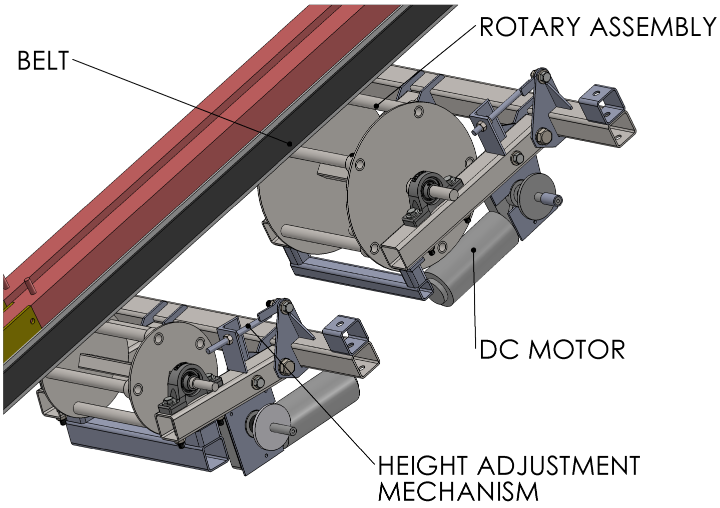


Figure 4.11: Rotary mechanism for removing excess soil from roots

was selected to be implemented due to the advantages listed. The system was simplified, mounting both assemblies to a single frame. Mounting points were designed to allow the unit to easily be attached and removed. The height and angle of the assembly could also be adjusted.

4.6 Root Trimming

Root trimming should be performed while trees are still held in the belts, as it is already gripped, and the tree is in a known position. There are many challenges associated with root trimming:

- Roots protrude in all directions. All must be trimmed to within specification, typically 50-100 mm. Specifically the leading and trailing roots when compared to the direction of travel are problematic.
- Trees are closely spaced, typically around 80 mm, dependent on tree type.
- Roots can be intertwined between neighbouring trees.
- Trimming must be performed at the same rate as lifting.
- Handling must be very gentle as roots and trees are easily damaged.

- Some roots can be relatively stiff, while others are very flexible.

The most difficult issue to address was trimming the leading and trailing roots. When humans trim roots, both in the field and in pack houses, they 'funnel' the roots down with their hand and grasp them as they make one cut with the blade close to their hand. A concept was proposed which attempts to replicate the human process, and is suited to a continuous production line. The stem is surrounded with a 'ring', and moves down relative to the tree, pulling the roots down. This pulls all roots down to the same point, regardless of their orientation around the root ball. A blade then cuts the roots close to the ring.

The ring is formed by a chain with pin attachments, which slot around the stems as they travel up the belts, as pictured in Figure 4.12. Each tree becomes located in its own 'cell'. The horizontal speed of the chain is matched to the horizontal speed of the belts so that trees do not tilt. The root trimming assembly is fitted at a slight angle relative to the belt assembly. The net result is that roots are pulled down by the pins as the trees are conveyed up the belts, as shown in Figure 4.12. The intra-row spacing of the trees is not exact, as such it may be difficult to ensure that trees are located in individual cells. However, as long as the cell spacing is less than the minimum tree spacing, trees will always be in their own cell. Some cells will be empty, which is not an issue.

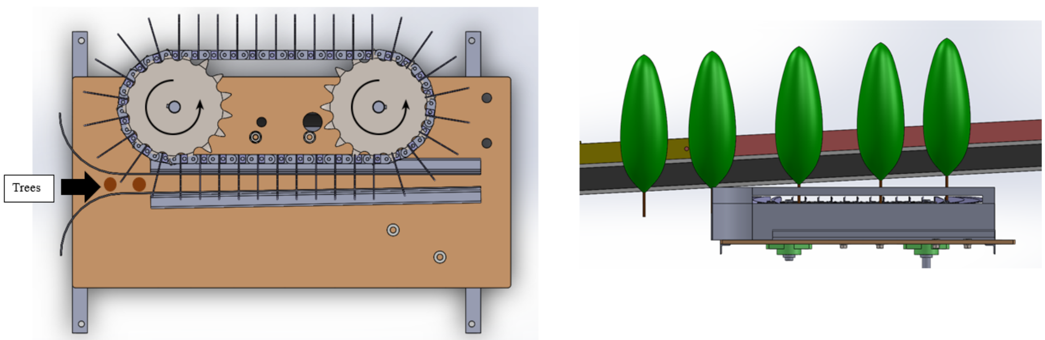


Figure 4.12: Root puller in preparation for root trimming.

This concept was prototyped using laser cut and folded pins welded to chain links. Shearing motion of the roots was required by the nursery as alternatives such as serrated blades will damage the delicate roots. A battery powered rotary shearing tool was used in the prototype. The blade was hexagon shaped which produces a scissor-like shearing motion when combined with an additional shearing edge.

The first trial of the root cutter showed that concept was feasible, but further development is required to produce an adequately functioning device. The pins successfully located the trees in individual cells, but there were issues. Tree stock was toppled due to the chain horizontal speed not perfectly matched to the belts, and some stems were missed due to misalignment of the belt and the root trimming assembly. Trimmer height was adjusted, the chain was re-aligned and chain speed was automatically matched to the belt by introducing an encoder and control circuit. A 2000 PPR encoder was mounted to the top of the drive shaft. Speed was calculated every 50 ms by counting encoder pulses during that interval and converting to a linear speed based on the radius of the belts as they wrap around the drive pulley. The cutter assembly shown in Figure 4.13 (right) did work but jammed frequently. Modifications such as a larger blade and stiffer assembly are necessary to produce a reliable root cutter. Additionally, a duller edge is required on the pins to not damage the roots.

Figure 4.13: Root trimming prototype

The speed matching problem can also be solved by mechanically gearing the chain to the belt drive. This will be more difficult mechanically, but will not require additional control and will always be perfectly matched. Two universal joints can be used to gear the trimmer to the belts at the required angle, and ensure the speed of the input shaft matches the output.

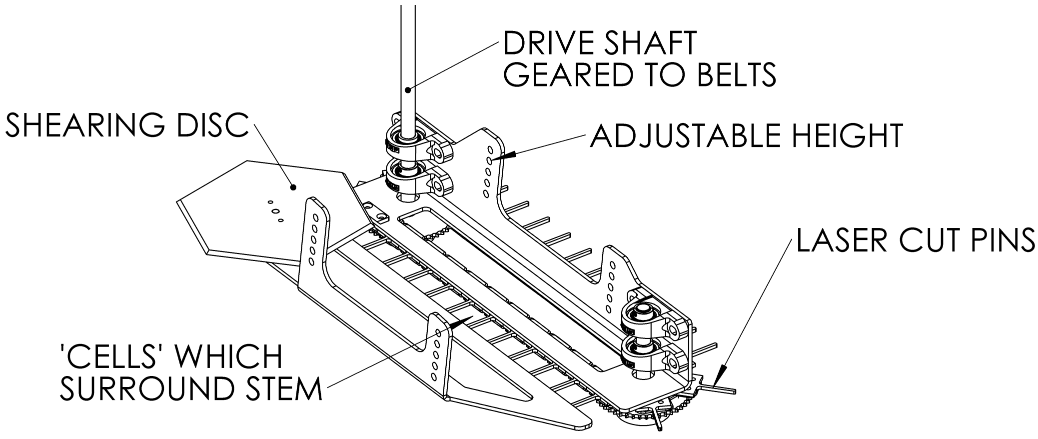


Figure 4.14: Drawing of root trimming prototype

4.7 Re-orientation of Tree Stock

The preceding chapter identified that reorientation of the seedlings horizontally will be beneficial to prevent soil from falling from the roots onto the camera and ease handling. Concepts were generated to rotate the tree without stripping needles or damaging tree stock. Two concepts considered worth investigating were twisting the belts 90 degrees, and putting belts at a 45 degree angle and rotating tree stock around a large pulley.

Twisting the belts provides a smooth rotation of the tree, but mounting points are complex and belts are not intended to twist in that orientation, rather it is intended that all pulleys lie in the same plane. The concept is shown in Figure 4.15. It has been implemented before in packaging lines, but it takes up a lot of room. Mounting points were designed so that the belts would twist symmetrically to minimise the stress on the belts. Rather than attempting to bend tube to the complex shape required, the bars holding the belts were made in multiple straight pieces which were laser cut, and welded together to form the approximate shape required. This method ensured that pulley mounting locations were in the correct location. There was difficulty trying to manufacture the correct shape due to distortions when welding, and accumulation of tolerances along the length.

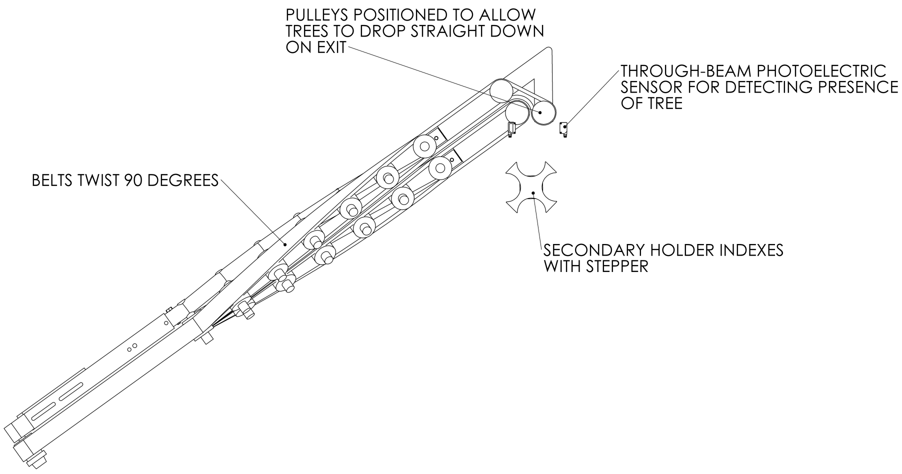


Figure 4.15: Twisted belts for tree re-orientation

The twisted belts successfully rotated trees during trials in the lab. Figure 4.16 shows the rig. There were some issues keeping the belts running on the pulleys, as they tended to track off due to belts not being intended to twisted in that way.

Figure 4.16: Reorientation of tree using twisted belts

The second method for reorientating tree stock relies on the tree being vertical as it enters a large pulley, which is at a 45 degree angle to the tree. Tree stock is gradually reorientated horizontally as it rotates around the pulley as pictured in Figure 4.17.

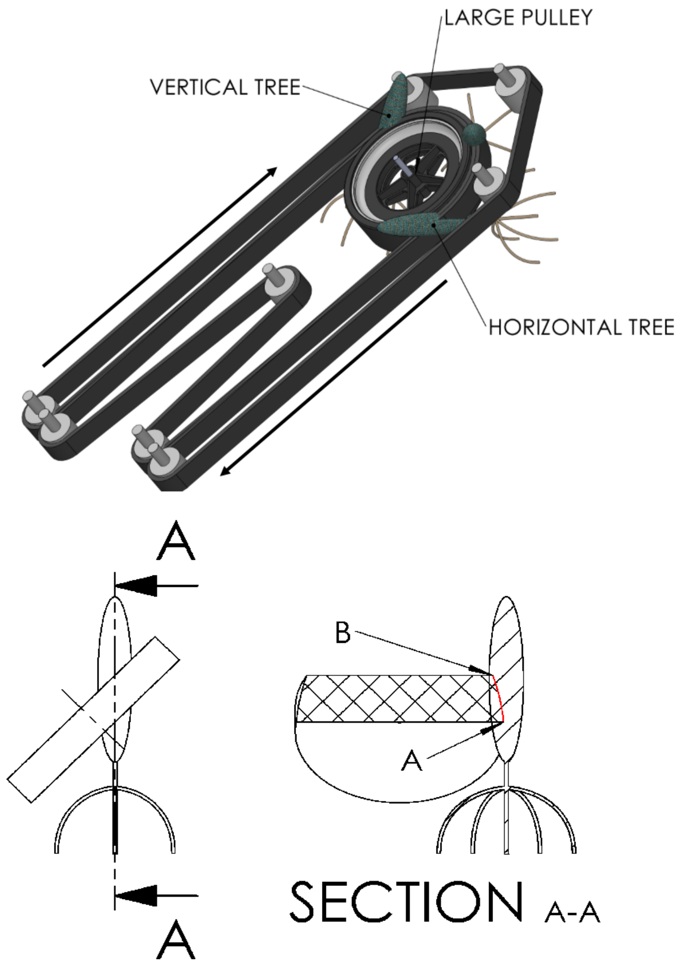


Figure 4.17: Reorientation of tree around pulley

This concept requires slight flexing of the tree as it travels around the pulley. As tree stock reaches the centre of the pulley, it will start rotating around it. However, at this time, the bottom of the tree will still be travelling linearly up the belts as it has not yet reached the pulley due to the 45 degree belt inclination. All points of the tree will have the same linear speed, but the direction of the velocity will differ slightly. When the entire tree begins to rotate around the pulley, the tree will remain at this curvature until it leaves the pulley. It was assumed that the tree remained in a single plane while rotating around the pulley, which is true if the pulley height is much smaller than the pulley radius. Slicing the pulley at a 45 degree angle gives an ellipse, described by Equation 4.3. The outer belt will force the tree to follow this curve, which is shown in red in the bottom of Figure 4.17. The maximum radius of curvature is at point A, while the minimum is at point B.

$$\frac{x^2}{r^2} + \frac{y^2}{2r^2} = 1 \tag{4.3}$$

The radius of curvature can be calculated from Equation 4.4. The maximum radius of curvature is approximately $2r$ for $t << r$. Figure 4.18 shows hows the minimum radius of curvature (at point B in Figure 4.17) changes as the pulley width increases for a given pulley radius. The minimum radius of curvature should be as large as possible to reduce likelihood of damage to tree stock.

$$\frac{(r^2 \sin^2(t) + 2r^2 \cos^2(t))^{\frac{3}{2}}}{\sqrt{2}r^2} \tag{4.4}$$

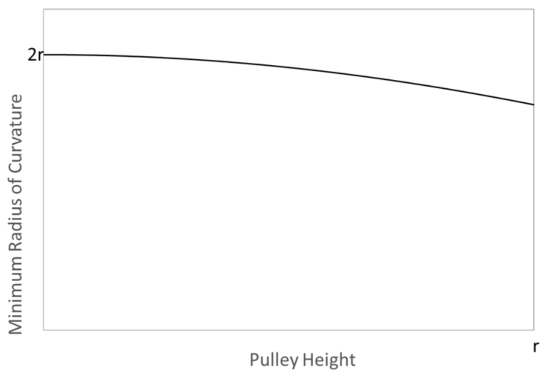


Figure 4.18: Minimum radius of curvature for tree in terms of pulley radius, based on pulley height

The concept was prototyped and was effective at reorientating tree stock, but it depended on the straightness of the tree as it entered the pulley. Keeping the pulleys in a single plane makes manufacture significantly easier, and it is more compact. Therefore, this option was chosen to be integrated into the *field factory*.

4.8 Grading and Sorting

With the tree stock lifted, soil removed, root trimmed and reorientated, it can now be graded and sorted. The tree can either be graded on the belts or transitioned. It makes sense to grade the tree while it is already gripped, however, trials with the twisted belts showed it is possible to transition to a secondary holder and sort. A system was proposed where the tree would fall a short distance once it leaves the lifting belts and rest into a cradle. Image capture can be performed while the tree is in this position and it can then turn clockwise or anticlockwise to sort into 'good' and 'bad'. Image processing could potentially take place while on this holder, as it is relatively fast. Additionally, the design of the holder could help locate the tree in an appropriate manner. This would mean less time would be needed for tree and feature recognition. A grading unit was developed based on this principle as pictured in Figure 4.19. 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, root collar 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.

The design relies on the centre of mass of the tree being relatively high so the tree does not topple. This is reasonable to assume as soil has been removed from roots, and they have been trimmed. The centre of mass on a sample of 20 trees was measured from the root ball by balancing the tree on its side, and measuring from the top of the root ball to the balancing point with a ruler. Table 4.8 shows the results. The lower limit dictates how far the roots are able to protrude past the holder before the tree will topple. 99.9 % of the data lies within 3.291 SDs of the mean, which gives a lower limit of approximately 48

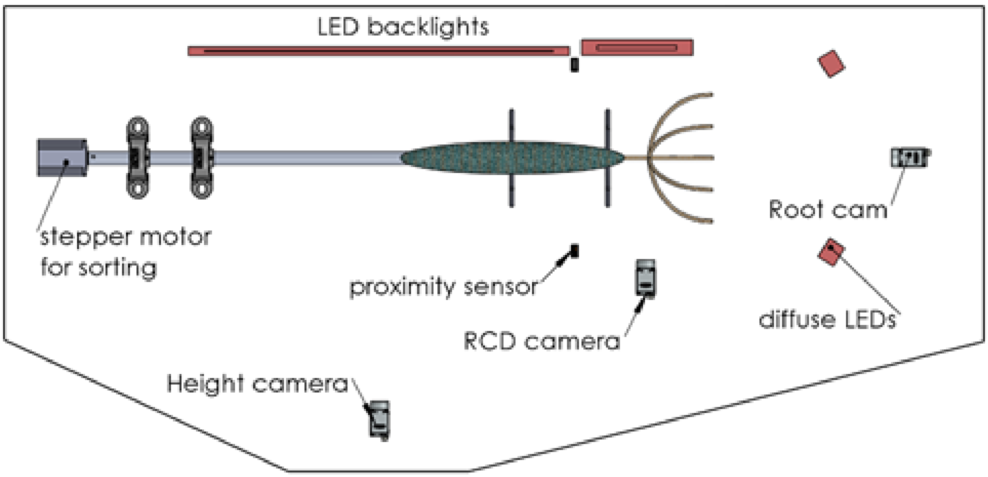


Figure 4.19: Top view of grading unit

mm. As long as no more than 48 mm stem protrudes out past the holder, the tree should not topple.

Table 4.2: Lifting force required for small sample

Average	132 mm
Standard Deviation	26
Maximum	170
Minimum	70

Once sorted, tree stock can then fall onto a conveyor. These should not be delivered to the worker one at a time as it will not be possible to keep up with boxing them individually. Additionally, keeping track of when there are 100 trees in the box will be difficult. Therefore, 25 trees will be accumulated before the conveyor increments. The operator can then grab a bundle and box them all at the same time, similar to how it is performed at the Edendale nursery. Manual labour will be utilized for handling boxes.

Chapter 5

Field Factory

Chapters 3 and 4 laid the ground work for an integrated *field factory* capable of lifting and grading forestry tree stock in the field. This chapter investigates the system as a whole. Firstly, an overview of the integrated machine is given. Next, the performance of the machine vision measurement and grading system is analysed under controlled conditions. Finally, the performance of the *field factory* in the field is evaluated.

5.1 Integrated Design

The previous chapter proved it was feasible to mechanise each of the functions required of the machine. These components have been integrated into a *field factory* capable of lifting through to grading and sorting of forestry tree stock. A general arrangement drawing of the *field factory* is shown in Figure 5.1. An operator sits at the front of the machine near the lifting belts, steering the machine and aligning the belts to the rows of trees. The belts are wider at the point of lifting where a strong grip on tree stock is required. A two stage rotary system then removes the majority of the soil from the roots. As tree stock continues upwards along the belts, it enters the root trimming unit which pulls the roots down and trims them with a rotary cutting disc. Tree stock is reorientated horizontally as it rotates around the large upper pulley, before it transitions from the belt system, falling a short distance into the grading unit where image processing and sorting is performed. 'Good' trees are deposited onto a conveyor which is indexed periodically, delivering 25 trees at a time to a worker who boxes tree stock by the hundred.

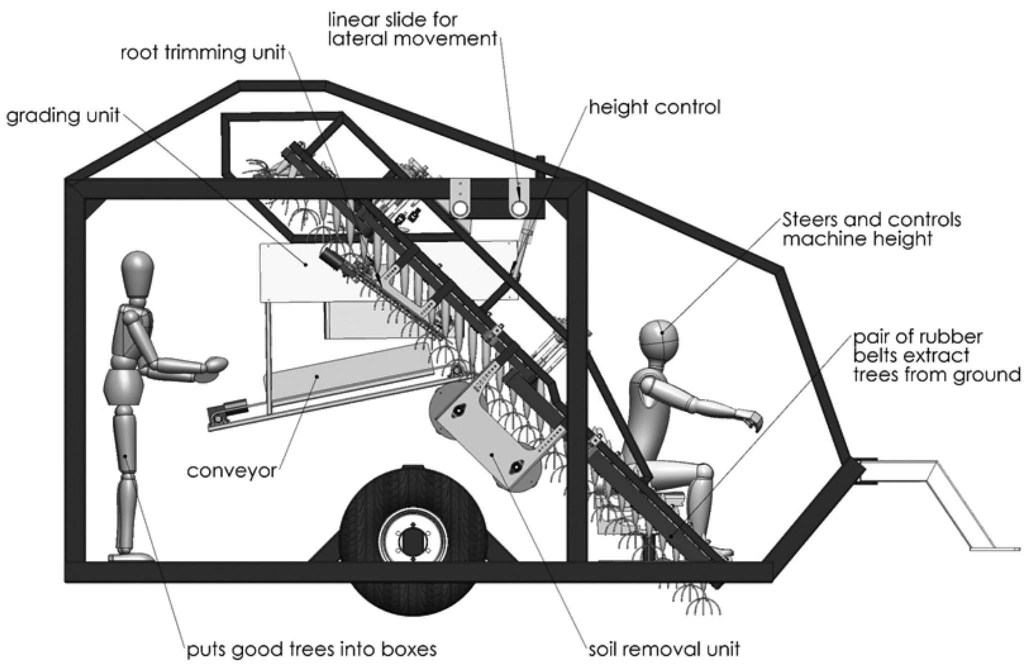


Figure 5.1: General arrangement drawing of the prototype *field factory*

A system diagram is shown in Figure 5.2. Undercutting and lateral root pruning is performed using existing nursery equipment drawn behind a tractor before the *field factory* lifts tree stock. Manual input is required for aligning the belts to tree stock, and boxing. The remaining task are autonomous, requiring no human intervention.

Commercial lifting machines lift the entire bed of 8 to 10 rows at a time. This is the most efficient configuration as only one pass over the beds is required, maximising lifting rate, and reducing time and cost required. While this is the ideal solution, this research has constraints imposed which limit the space available for additional processing. Two rows per pass is the practical limit with the proposed design. The system was designed to be modular, with initially only a single row lifter being produced. Once the single row lifter has been developed and operating to an acceptable standard, a second module can be added. A single module will take 8 passes to lift the entire bed, while two

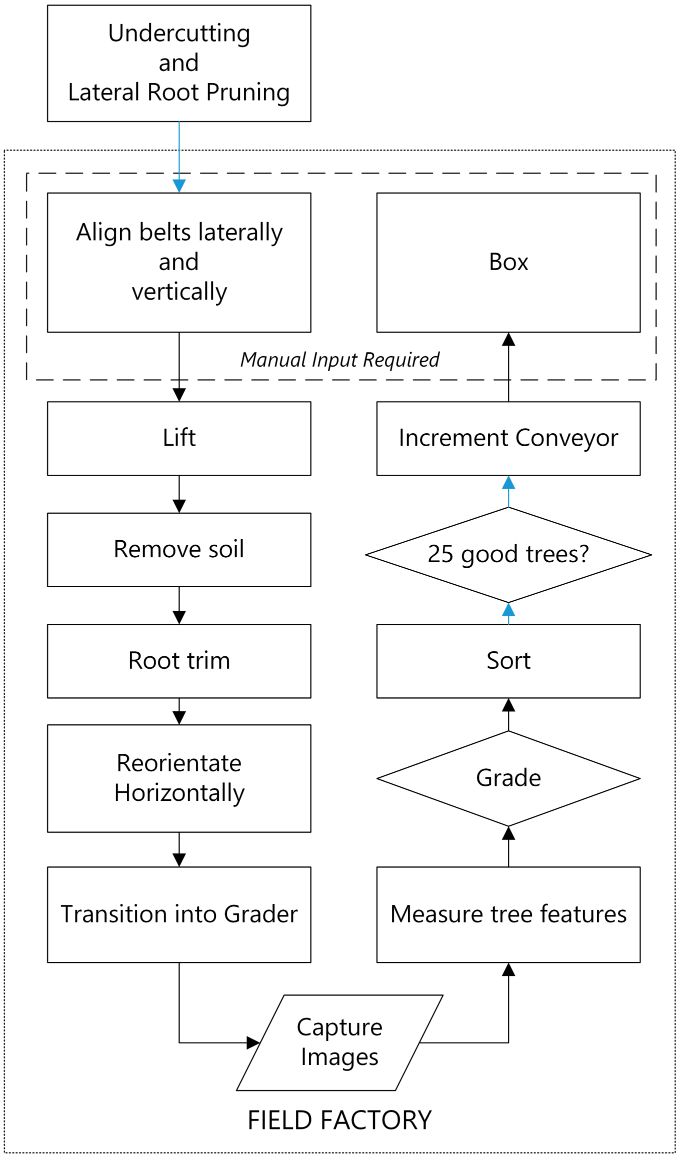


Figure 5.2: System diagram

modules will half the number of passes required to 4. The lifting sequence with two modules is as follows:

1. Module one begins by lifting row 1, and module two will collect row 5.
2. When returning the opposite way for a second pass along the bed, rows 8 and 4 on the other side of the bed will be lifted.
3. On the third pass, the modules are incremented laterally a single row, allowing them to lift rows 2 and 6.
4. The final fourth pass will lift the remaining two rows, 7 and 3.

The sequence of lifting is pictured in Figure 5.3. Lifting tree stock four rows apart separates the modules and provides room for mechanisms and handling equipment.

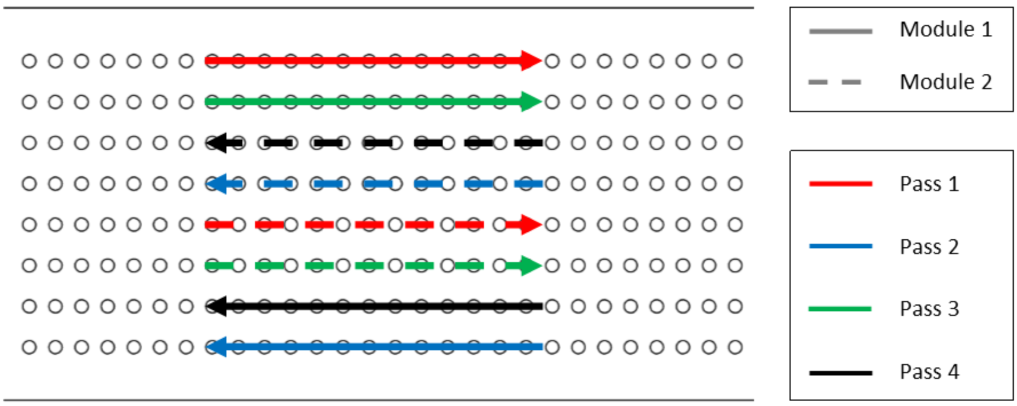


Figure 5.3: Sequence of lifting to lift entire bed

It is estimated that a significant reduction in labour units will be realised once the *field factory* is commissioned, from approximately 30-40 units, down to about 8. One person will be required to drive the tractor. Five people will be required on the machine: one to steer, two boxing (one per lifting unit), and another two handling the boxes. It is estimated an additional two staff will be required to transport boxes back to storage while lifting continues. A significant number of boxes will be lifted per pass. For example, lifting two rows at a time from a 300 m long bed, with tree spacing of 80 mm and an acceptance rate of 80%, around 60 boxes are filled per pass. Based on the target raw lift rate of 5.2 trees per second, and if two rows are lifted at once, 2.6 trees will be lifted per second, equivalent to 2.1 *accepted* trees per second, per lifting line. On average, this is a box every 24s for the machine, giving each boxer 48s per box, as there are two lines. If trees are delivered in bundle of 25, this gives the boxer 12s to collect a bundle of trees and place it in the box.

Software

A solid state Sony Vaio Ultrabook was used to perform image processing and to display an interface to the user. Solid state devices are less susceptible to fatigue by vibration compared to other drives, and they have faster data access, consume less power usage and are more durable. IO is handled by an Arduino Mega. Communication between the Arduino and PC is via serial. Firstly, the PC polls available COM Ports and waits for a response from the Arduino. A connection between the two is then established and the process begins. Once in run mode, the Arduino waits for a tree to be detected (i.e. the through sensor is tripped) and messages the PC to begin processing. Images are then captured from each of the three cameras. The RCD is measured and the offset calculated for the root ball. Height and roots are measured, and a decision is made which is communicated to the Arduino. During image processing, the Arduino waits for a decision to be returned from the PC, at which point sorting is performed by actuating the sorting stepper motor 120 degrees either clockwise or counter-clockwise, depending on the decision. A simplified flow diagram of the process is pictured in Figure 5.4.

Human Machine Interface

Most interfaces for fully and semi-autonomous systems are designed by robotics experts for themselves. They are not intended to be operated by untrained users, which often results in poorly designed interfaces. Interfaces should be designed with migration into non-research tasks in mind to be operated by people who are not robotic experts [141]. A simple interface was designed as the machine is to be operated by nursery staff who are not robotics experts. Large industrial push buttons were selected to interface between human and machine as they are easy to press and can be operated with gloves or dirty fingers. Only three buttons were used for simplification to navigate the on screen menu: up, down and confirm. These were wired into digital inputs in the Arduino. When the Arduino detects a button press, a message is sent to the PC indicating which button is pushed. The PC then executes the corresponding

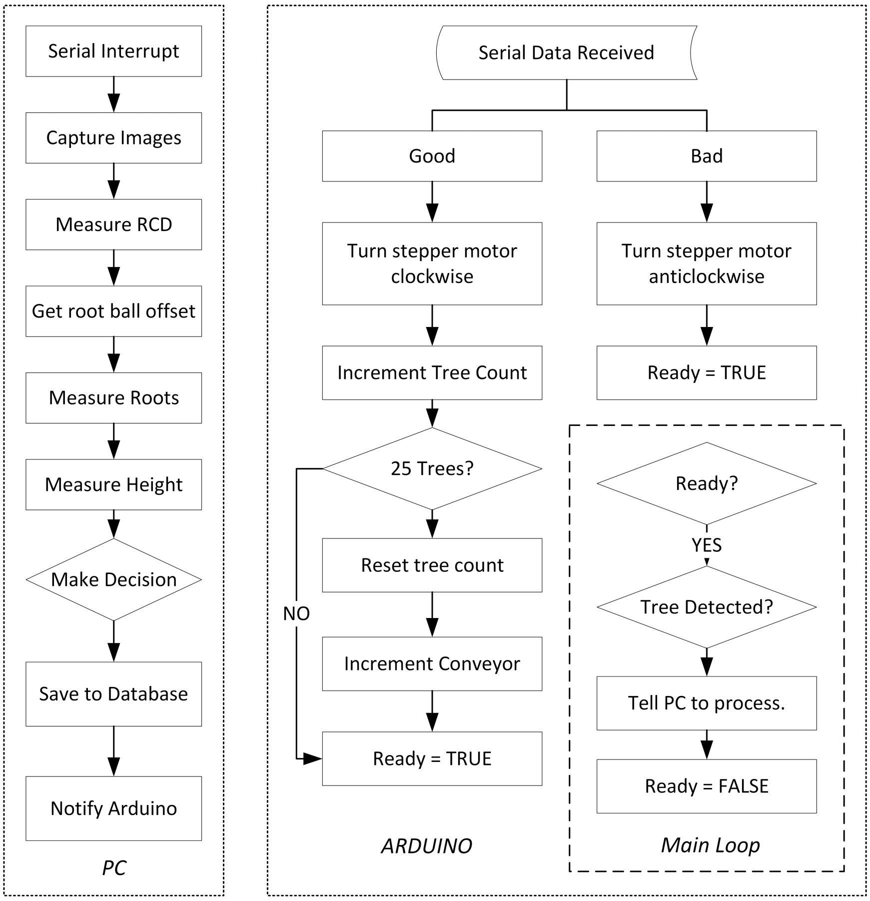


Figure 5.4: Software flow diagram

command, depending on what screen is currently active. The Arduino also alerts the PC when the button is unpressed. Debouncing is achieved in the Arduino using a debounce delay of 25 ms. If there is a change of button state that persists for 25 ms, then a button press, or depress, is registered. Debouncing is necessary on mechanical switches as when pressed there is often not a single transition from LOW to HIGH (or vice versa), i.e. the signal can bounce several times between states before it latches. Alternatively, this can be performed in hardware using an RC circuit, but this requires additional circuitry.

As soon as the PC is switched on, the *field factory* software is loaded. Icons indicate whether the Arduino and cameras have been successfully initialised. The menu system was deliberately kept simple to facilitate ease of use. The opening screen had options to begin a lift, or export data. The export option allows users to save lift data to a USB drive as an Excel spreadsheet. When the lifting option is chosen, the software checks if an order for a previous lift is incomplete, and if so, it asks the user if they would like to continue where they left off. If a new order, the user is prompted for settings such as number of trees to lift, minimum RCD, minimum height, and maximum root angle. The screen is fast to use as it is initially populated with a typical profile. The screen is pictured in Figure 5.5. A yellow box surrounds the currently selected button for clarity. Although there are limited inputs, users can quickly change parameters, even if significant changes are required. For example, if wanting to change the number lifted from 10,000 to 100,000, the value will continue to increment increasingly faster the longer the button is held.

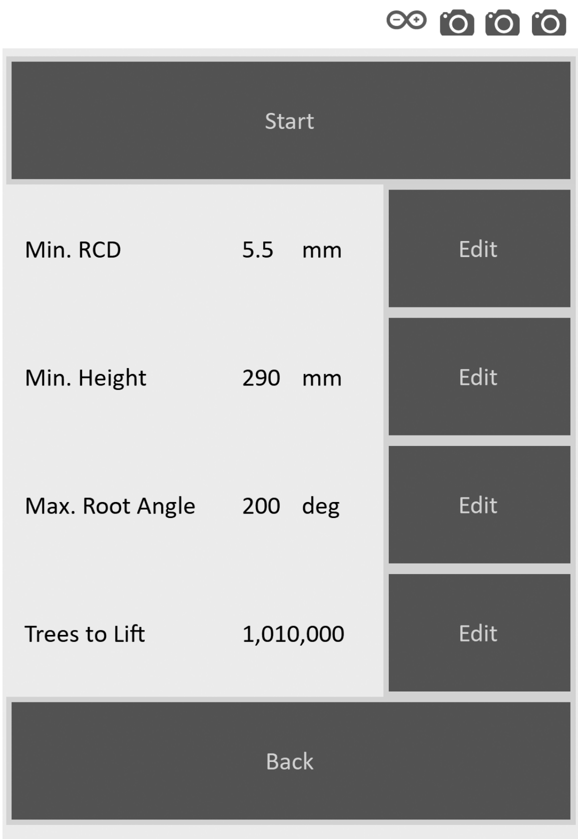


Figure 5.5: Example screen of human-machine interface (HMI)

While the machine is running, the screen in Figure 5.6 is displayed. It provides basic information to the user, such as the selected grading criteria, i.e, minimum RCD, maximum void root angle, and minimum height. It also shows how many trees are to be lifted to fill the order, how many trees have been accepted, and how many more trees remaining to fill the order. Images of the last tree graded are displayed, along with the measurements and decision made, so the operator can easily see whether it is functioning correctly.

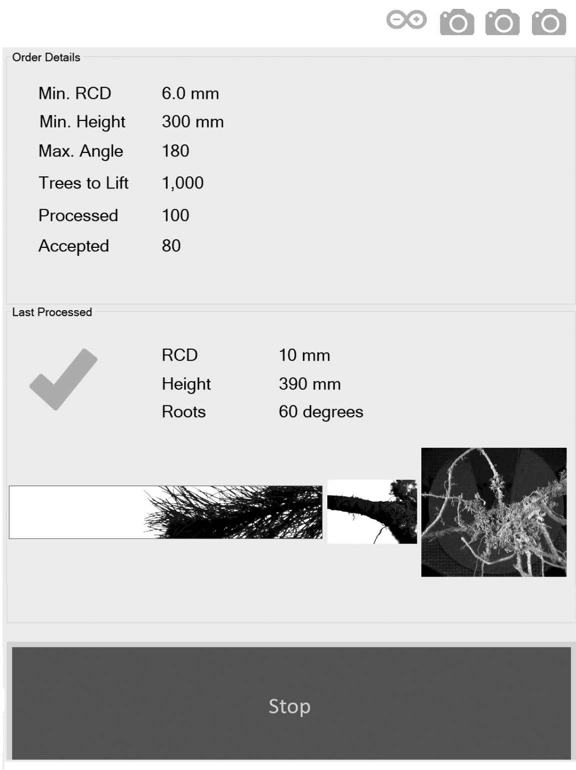


Figure 5.6: Screen shown while grader is running

Arduino IO

An Arduino Mega was chosen to handle IO as they are low cost, and a large number of inputs and outputs are available. The Arduino is responsible for monitoring button inputs, such as the hydraulic control box and buttons for the interface, detecting a tree is present, sorting, incrementing the conveyor, and switching solenoids and relays. A diagram of the components connected to the Arduino is shown in Figure 5.7.

Power

The system was designed to run on 12V DC where possible, as this is the voltage of the electrics in the tractor. It is intended that the electrics will run and be charged from the tractor, so that additional complexity and cost

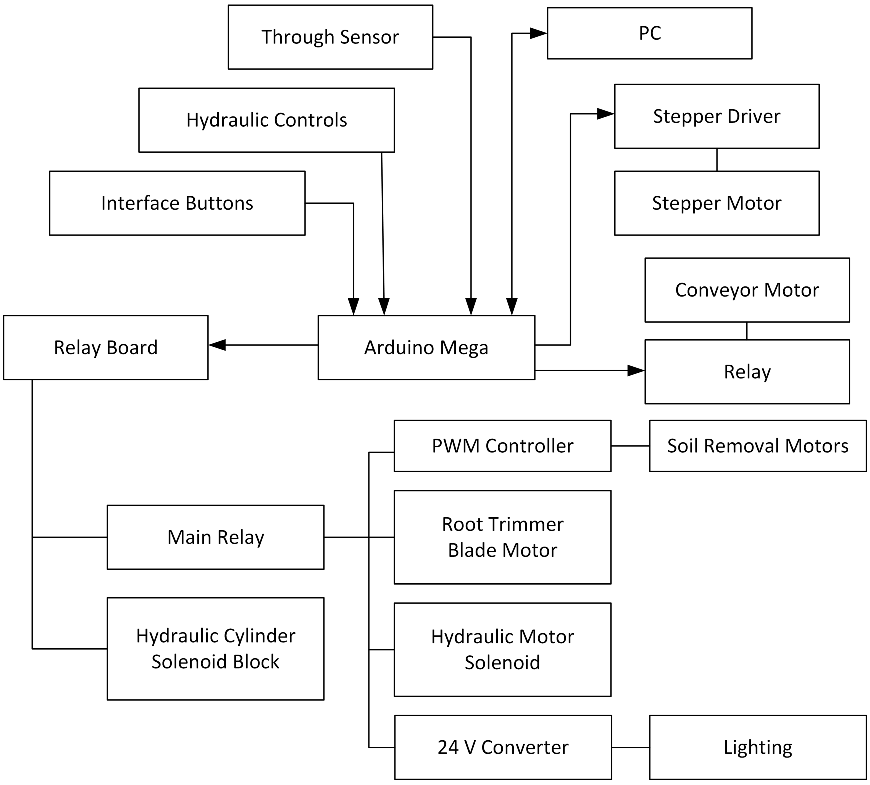


Figure 5.7: Components connected to Arduino

of a separate power system such as a generator is avoided. However, for the trials the electrics were powered solely from a 50Ah 12V deep cycle battery. At an estimated average 10A, it could run for up to 5 hours before a recharge is required which is more than sufficient for testing purposes. A split charging system is intended to be used in future. This will isolate the machine battery from the tractor, but still allow it to be charged by the alternator. This can be achieved using a pair of diodes to ensure current only flows from the alternator to the batteries, and not from battery to battery. More sophisticated systems use voltage sensitive relays to connect the batteries with a high power relay only when charge is available.

Hydraulics

Hydraulics were used where appropriate as a hydraulic power source was readily available from the tractor. Hydraulics were used to power the belts, steer the machine, raise and lower the belts, and to move the lifting unit laterally so other rows could be lifted. A solenoid valve block was used to actuate the

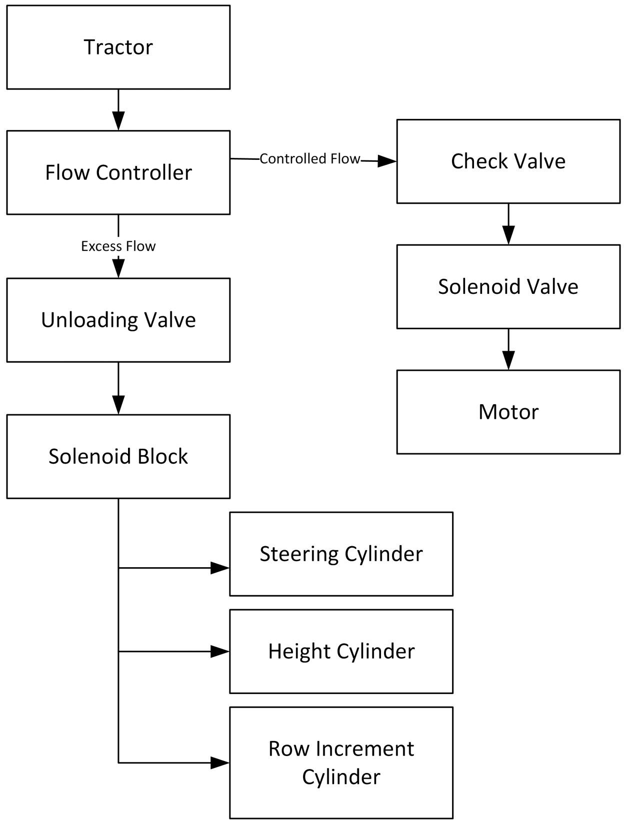


Figure 5.8: Hydraulics schematic

cylinders. The motor driving the belts was given priority flow from a manually adjusted flow controller to ensure the speed of the belts was consistent. The Arduino switched a solenoid valve to turn the motor on and off. Cylinders were controlled by a control panel operated by a user near the lifting end of the belts. Switches on the control panel were sensed by the Arduino, which then controlled relays to switch the solenoids. As cylinders are electrically controlled it will be easier to automate in the future. Excess flow from the controller was used to power the cylinders. A schematic of the hydraulic system is shown in Figure 5.8.

When new, the tractor was capable of outputting flow of 71.5 LPM. Due to its age, it was assumed that only 75% of the original flow was available when designing the system. 15 LPM was allocated to the cylinders, with the remainder available to the motor. The required speed of the motor was calculated from Equation 5.1.

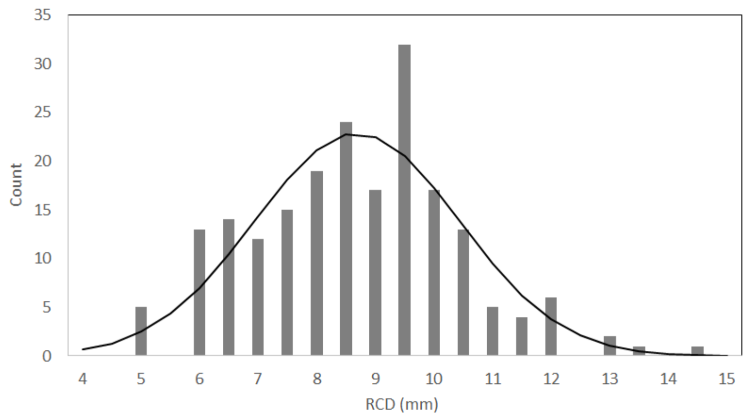


Figure 5.9: Histogram of RCD of sample

$$RPM = \frac{60ts}{\sqrt{2}2\pi r} \tag{5.1}$$

Where t is the maximum number of trees to be lifted per second, s is the tree spacing and r is outer radius of the belt around the drive pulley. This was used to select an appropriate motor.

5.2 Measurement of Bare-Root Seedling Morphological Features using Machine Vision

This section applies the machine vision measurement techniques described in Chapter 3 and evaluates the accuracy of machine versus manual measurements.

5.2.1 Method

A raw lift of 200 trees was taken from a bed of typical cuttings. Cuttings were selected as they are the most difficult to grade due to variable root structures. Although the sample was lifted from a single block, the variation in sizes of trees is indicative of the population. RCD ranged from 5 mm to over 13 mm, compared with the larger sample described in Appendix B, which varied from 4 mm to over 13 mm. The distribution of the sample is illustrated in Figure 5.9.

Each tree was labelled, and RCD, height, maximum root angle and sweep were measured manually. RCD and height were measured as per standard nursery practice. Vernier calipers were used to measure the RCD ten mm above the root ball, rounded to the nearest 0.5 mm, and height was measured from the root collar to the top apical meristem and rounded to the nearest 5 mm. A protractor was used to measure the largest region void of roots to the nearest 5 degrees. The grading unit from the *field factory* was set up on a table in the nursery workshop. Tree stock was dropped into the grading unit by hand, one at a time. The machine vision system captured images and measured RCD, sweep, height, and root structure. Raw images and measurements were saved to disk.

5.2.2 Repeatability of Manual Measurements

It is not possible to obtain an exact, or 'correct' reading as measurements are imperfect. This is in part due to the accuracy of the measuring equipment, but more so due to the variability in the product due to its organic nature. For example, the stem is not perfectly round, and different measurements can be obtained depending where the stem is the measured. Also, there may be bumps or dirt build up on the stem. Differences in height come from different interpretation of the top of the bud, taking the lower reference point slightly differently, and the natural flex in the tree. Roots measurements are even more subjective. Small or short roots may be ignored by one person, but classified as a root by another. Inaccurate location of the root ball affects measurements. Roots do not protrude perfectly radially out from the root ball, so it can be difficult to determine which segment the root originates from. Roots can be bent, starting in one quadrant, and protruding into another.

To provide an indication of the repeatability of manual measurements, the RCD, height and maximum void root angle were measured manually on a sample of 9 trees. Each of the three features were measured 32 times for each tree, for a total of 864 measurements. The standard deviation was calculated for each of the three features measured for each tree. The largest standard deviations for each feature from the sample of trees are shown in Table 5.1, along with the width of a 95% confidence interval. The RCD had a maximum standard deviation (SD) of 0.25 mm. This suggests that on average, 95% of the RCD measurements will be within ±0.49 mm of the average. The height had a SD of 2.6 mm, or a 95% confidence interval width of approximately 10.3 mm. Roots had a SD of 7.2 degrees, and a 95% confidence interval width of 28.2 degrees. These values were used as uncertainties in data when comparing machine vision measurements to manual measurements.

Table 5.1: Repeatability in manual measurements

Feature	Max. SD	95 % interval
RCD (mm)	0.25	0.98
Height (mm)	2.6	10.3
Roots (°)	7.2	28.2

5.2.3 RCD

The *field factory* has been developed in such a way that handling of tree stock is well controlled, which constrains the position of features during processing. Techniques for locating the root collar were investigated in Section 3.4, however, for this research it was not necessary to inspect the entire tree to locate the root collar as it was located in a region of interest captured by the RCD camera. A ROI was selected based on the positioning of the camera relative to the backlight. An example of an image used to measure the RCD is pictured in Figure 5.10. The root collar and part of the roots are present in the image.

Measurement steps

An example of the steps performed to measure the RCD is pictured in Figure 5.11. The raw image (top-left) is converted to binary (top-right), then dilation and erosion is applied as described in Section 3.4 (bottom). Equation 3.6 was

Figure 5.10: Example image captured by RCD camera

used to calculate the number of dilations and erosion required, using 4 mm as the minimum expected RCD. The RCD was measured on every column of the image, and the smallest value was selected. Taking the smallest value errs on the side of caution as there can be obstructions remaining in the RCD region, most commonly dirt, after the algorithm has been applied to clean up the image.

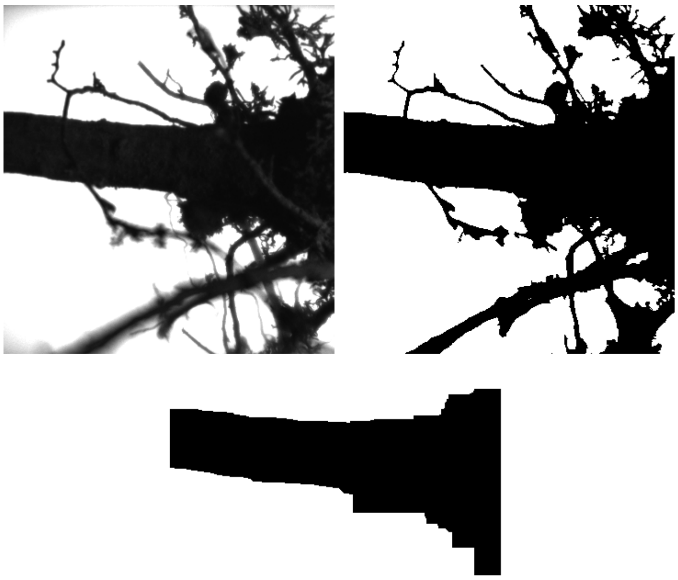


Figure 5.11: RCD measurement example

Regression based on the least squares method was used to relate the number of pixels to the manually measured RCD, with the intercept constrained to 0. A pixel to measurement ratio of 0.125 was determined, i.e, each pixel was

0.125 mm wide, which was used to calculate the actual RCD. Figure 5.12 compares the manual to machine measurements and shows the line of equality.

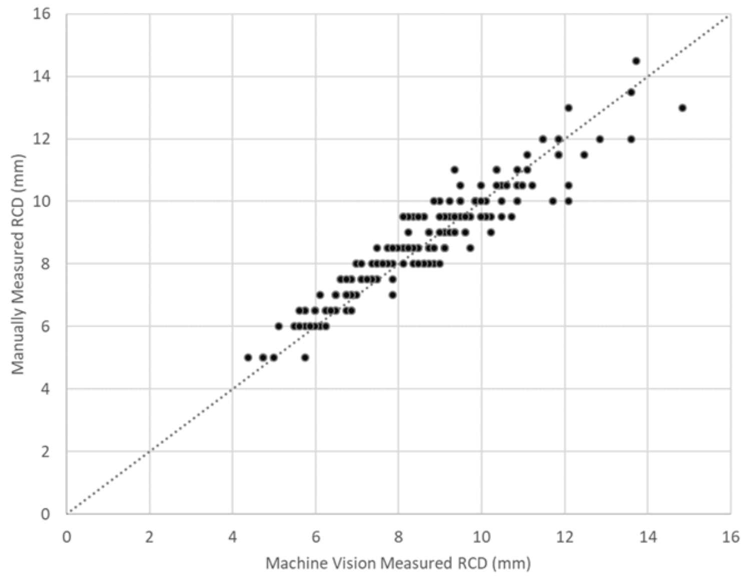


Figure 5.12: Count of difference between MV and manually measured RCD

A Bland-Altman plot of the differences between the machine and manual measurements is pictured in Figure 5.13. The dotted lines indicate $\pm 2s$ around the mean of the difference between manual and machine measurements. 95% of machine measurements can be expected to be within 1.3 mm lower, and 1.2 mm higher than manual measurements.

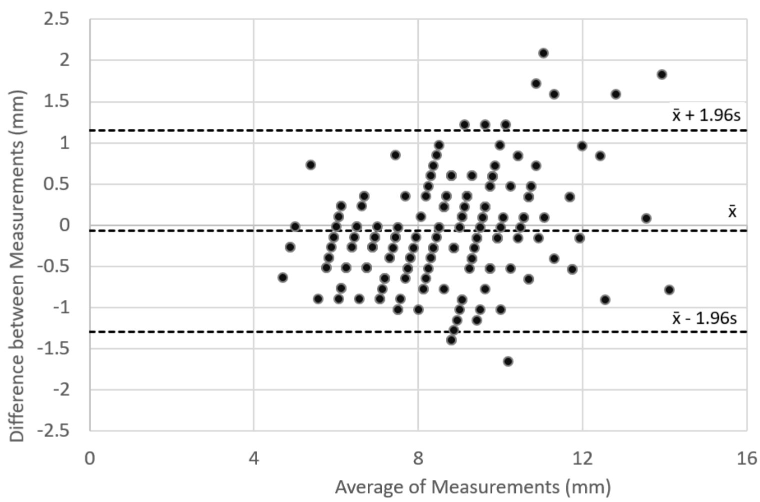


Figure 5.13: Bland-Altman Plot for RCD measurements

5.2.4 Tracing Stem and Sweep

Tree stems were traced to the root ball using the method described in Section 3.7. The most extreme example is pictured in Figure 5.14.

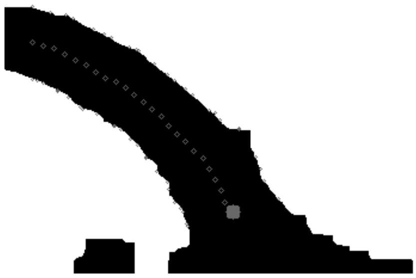


Figure 5.14: Example of tracing stem to root ball

A threshold was applied based on the offset to identify which trees may have sweep present. Figure 5.15 shows the effect of varying the threshold on the proportion of trees correctly identified to contain sweep, when compared to the manual decision. The maximum lies at a threshold of 260, where all trees were correctly classified.

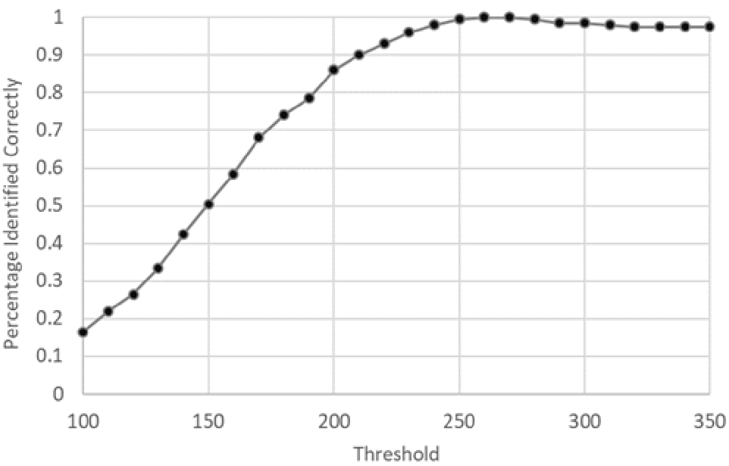


Figure 5.15: Sweep threshold

5.2.5 Height

Height measurement was performed using the algorithm as described in Section 3.5. The minimum height able to be measured was approximately 240 mm due to the design of the grading unit. Trees shorter than this were recorded as 240 mm and have been excluded from this analysis. The column corresponding to the top of the tree was identified. Regression based on the least squares method was used to fit the machine measured column number to the manually measured height. Figure 5.16 shows the manual height measurements plotted against those measured by machine, along with the line of equality.

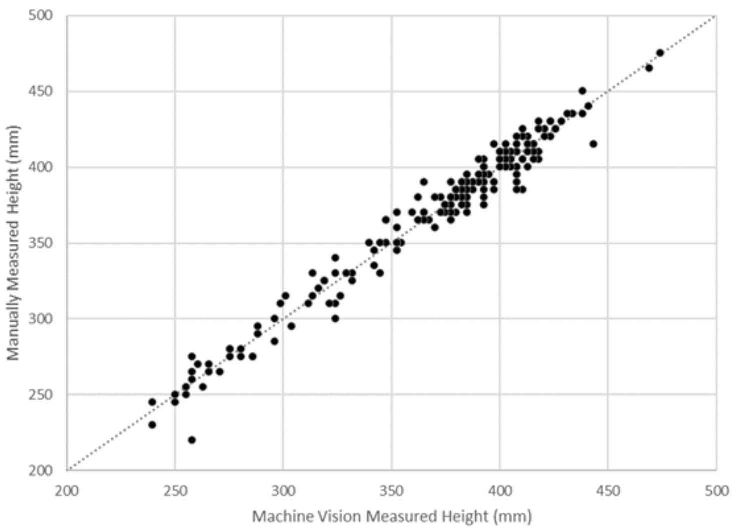


Figure 5.16: Difference between machine vision and manually measured height

The error between machine vision and manually measured height was calculated. The Bland-Altman plot is shown in Figure 5.17. 95% of machine measurements can be expected to be within $\pm 18mm$ of manual measurements.

5.2.6 Roots

Two methods for analysing root structure were investigated, as described Section 3.6: rotating around the root ball inspecting pixels at a certain radial distance, and using an ANN to classify roots, based on expert opinion.

Segmentation of the roots from the remainder of the image was challenging. Although the tree holder was designed to block the majority of the background, needles could be seen through the slot in the tree holder, and were difficult to remove using common threshold operations as they were similar in brightness to the roots. An example of when needles could not be removed from the

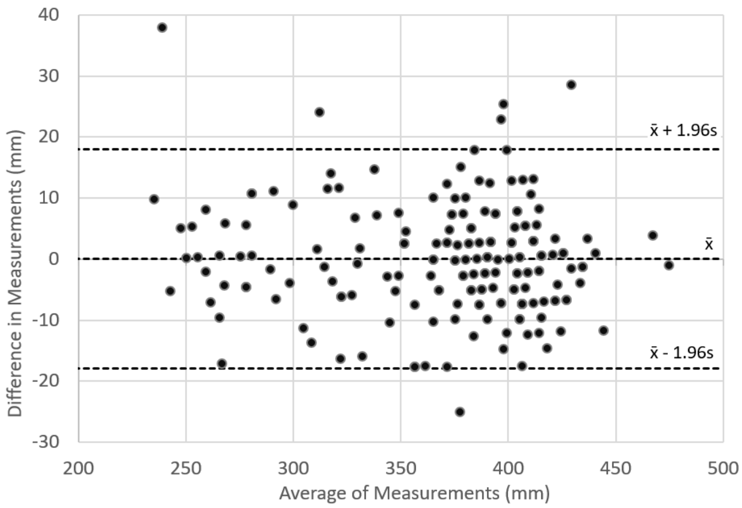


Figure 5.17: Bland-Altman plot of difference between manual and machine height measurements

image using a simple threshold operation on a greyscale image is pictured in Figure 5.18.

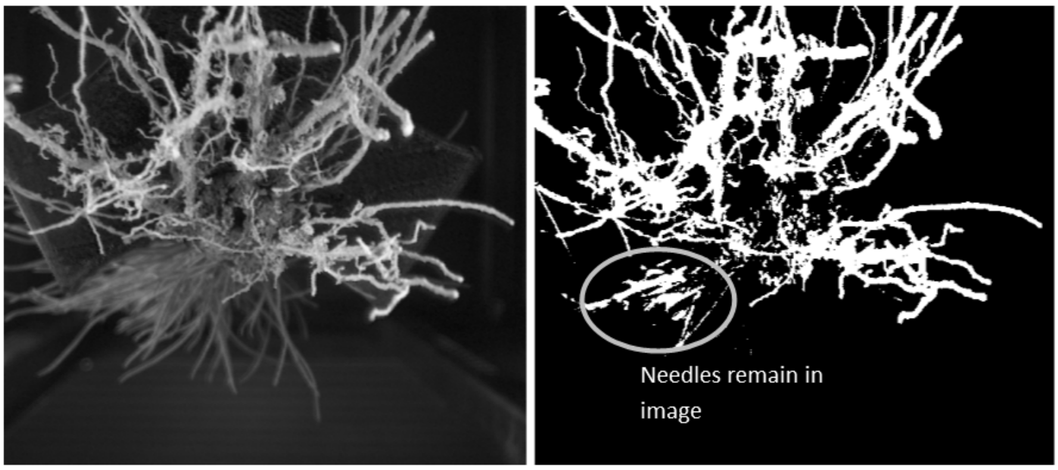


Figure 5.18: Needles unable to be removed from greyscale image

A few methods were investigated to remove the needles from the image. Firstly, the HSV method described in Section 3.4.1 was used to remove green needles from the image, but this was not very successful as hue values of the needles were very similar to the roots in many regions.

Secondly, a method based on the variance of pixels was investigated. Roots are in the foreground and are more focussed than the needles in the background. Blur occurs in regions where pixels are similar in value, whereas in

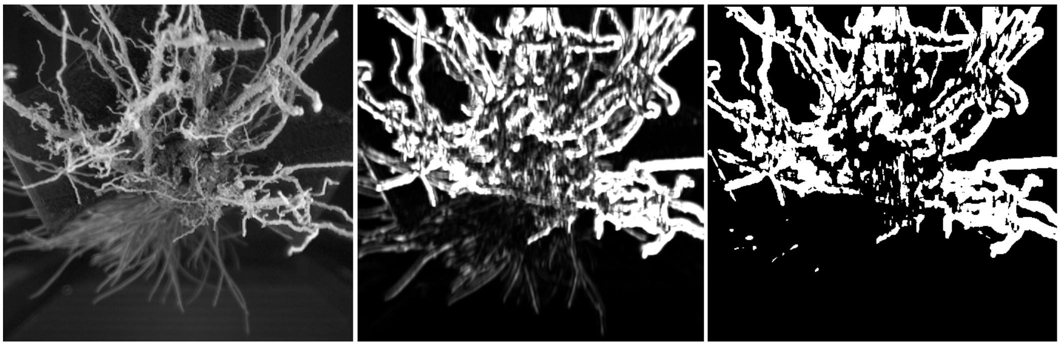


Figure 5.19: Example of removing needles based on variance of pixels

focus regions tend to have pixels which differ greatly. A 5x5 window was slid over the image, and the variance of pixels were calculated at each pixel location. There was greater success removing needles from the image using this method. The mean for each window was first calculated using Equation 5.2. The variance was calculated using Equation 5.3. Figure 5.19 shows an example of removing needles based on the variance of the pixels. The left image is the raw image, centre is the variance of pixels, and right is after a threshold operation has been applied.

$$\mu = \frac{\sum X}{N} \tag{5.2}$$

$$\sigma^2 = \sum \frac{(X-\mu)^2}{N} \tag{5.3}$$

Ultimately the issue was resolved by adjusting the lighting. The backlight which illuminated the bulk of the tree was dimmed to reduce the brightness of the needles. Additionally, the orientation and location of the diffuse lights were adjusted so that more light fell on the roots, and less on the needles. A threshold operation was now more reliably able to produce a binary image, showing only the roots.

The vertical offset calculated in the preceding section was used to locate the root ball in the vertical direction, and it was assumed to be centred horizontally. Roots were searched for by rotating around the root ball at a certain radial distance, inspecting blocks of pixels. The size of the kernel inspected was varied from 1x1 pixels to 9x9 pixels. If all pixels contained within this kernel were white, a root was identified in this region. The radial distance from the root ball at which roots were searched for was varied from 30 to 190 pixels. The maximum angle void of roots was calculated for each of the 200 trees, at each radius, and each kernel size. The RMSE was calculated when compared to the manual root angle measurement, as specified by Equation 5.4. This was plotted onto a surface plot shown in Figure 5.20 to identify the parameters where error is minimised. A minima occurs at a radius of 130, and a single pixel. These parameters were selected to be implemented in the machine vision system.

$$RMSE = \sqrt{\sum \frac{(Z_m - Z_c)^2}{N}} \tag{5.4}$$

Where N is the sample size, Z_m is the manually measured root angle, and Z_c is the root angle calculated by the machine vision system.

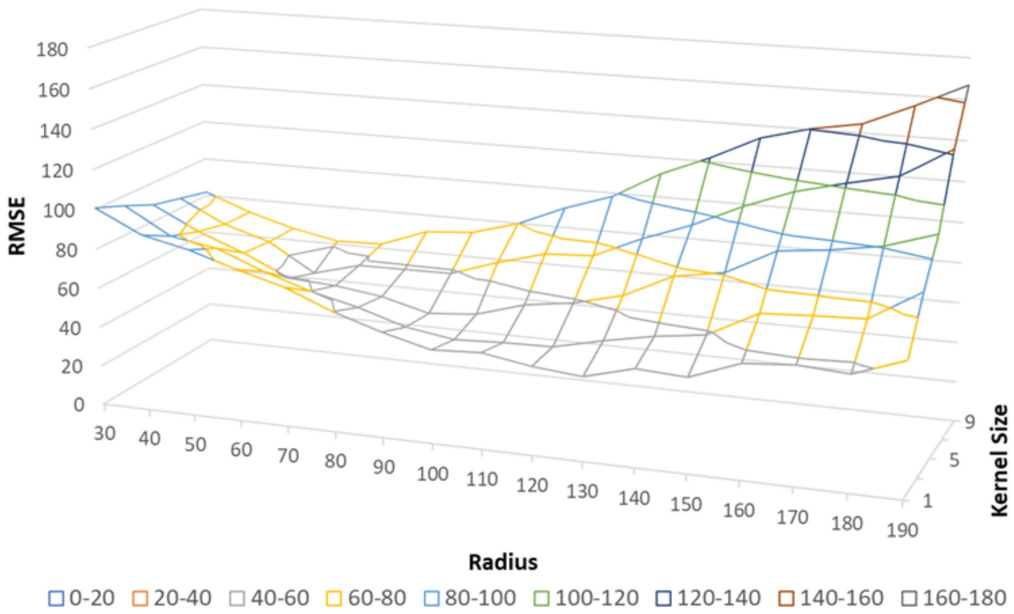


Figure 5.20: RMSE for different parameters used to detect roots

A comparison of measurements determined with manual versus machine methods is pictured in Figure 5.21, showing the line of equality.

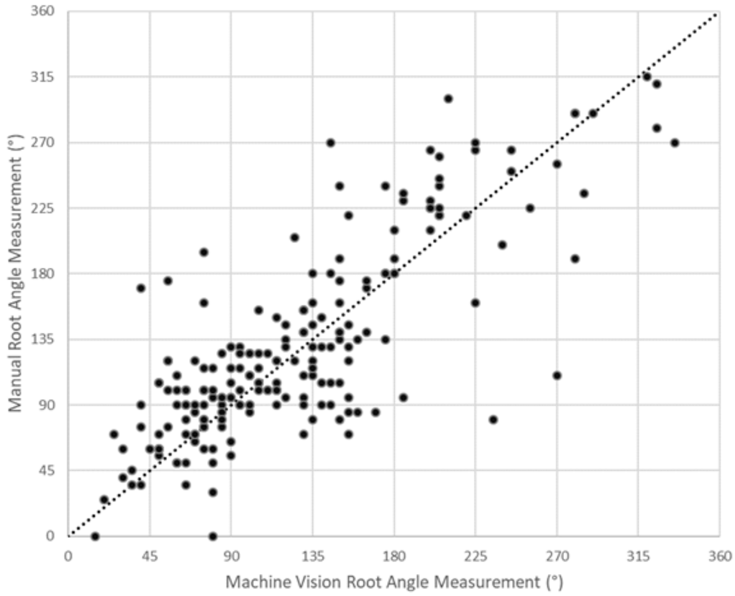


Figure 5.21: Comparison of machine vision vs manual measurements for root angle

The Bland-Altman plot for the machine and manual measurement of roots is pictured in Figure 5.22. 95% of measurements made by machine can be expected to be between 87 degrees less and 78 degrees more than the manual measurements.

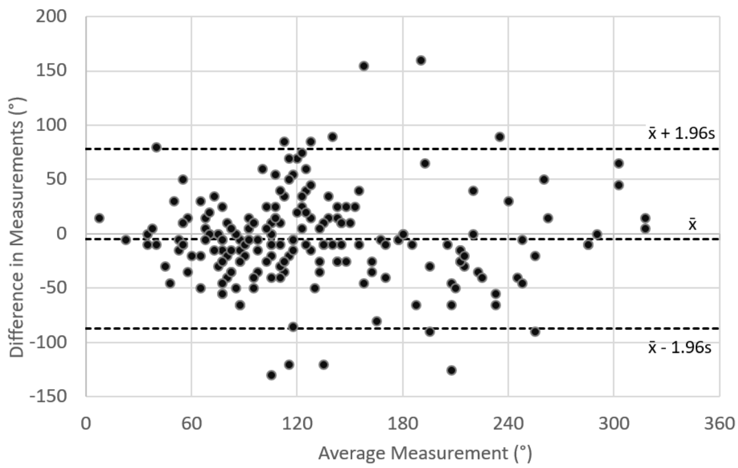


Figure 5.22: Bland-Altman plot of difference between manual and machine root measurements

Classification of Root Quadrants

Classification of root quadrants is not necessary for grading purposes as workers typically use the 'clock face' approach, however, it is still useful for reporting purposes. An expert classified each image into the appropriate category, as per the diagram in Figure 1.4. The machine vision system then classified the same images as per the flow chart in Figure 3.13.

66% were classified correctly as shown in Table 5.2. The rows represent the machine vision system classification, while the column indicates the classification determined by the expert. For example, the machine vision system classified three trees as one quadrant, when the expert classified them as two adjacent quadrants. There may appear to be a significant number of misclassifications, but it must be considered that the expert does not necessarily make the correct decision; in fact, in many cases there will be no 'correct' decision. Two opposite quadrants were commonly misclassified as three, which is not an issue for grading purposes as both are typically accepted. Of more concern is the 10 which would be rejected, but were classed as acceptable, and the 4 'good' trees which would have been rejected. Misclassifications typically classify trees into an adjacent class, for example, a number of 3 quadrants were misclassified as 4, and vice versa.

Table 5.2: Classification of root quadrants

	One	Two Adjacent	Two Opposite	Three	Four
One	**7**	3	0	1	0
Two Adjacent	2	**23**	0	2	1
Two Opposite	0	0	**1**	0	0
Three	1	8	10	**63**	10
Four	0	1	1	28	**38**

Classification of Roots using an ANN

Neural networks could potentially be used to classify roots based on an expert's decision, which would remove the need for manually tuning the algorithm parameters. A neural network was used to classify roots as follows:

1. Use offset to identify centre root ball calculated in Section 5.2.4.
2. Centre image around root ball.
3. Split image into segments of 15 degrees, isolating root region and ignoring centre of root ball.
4. Ask user whether it is a root or not.
5. Save an array of the count of white pixels in each row moving radially out from the root ball, along with the expert's decision.
6. Feed data into neural network, splitting into training, validation and test data.

Splitting the images this way produces 24 segments per image, for a total of 4800 segments over the 200 images. This investigation reinforced the ambiguity in measurement of roots as there was a significant difference between this and the manually measured angles, as pictured in Figure 5.23. It was frequently difficult for the expert to decide whether or not the segment should be considered to contain a root. The decisions by the expert in this case appeared to favour higher quality root structures.

The network had 161 inputs: one for each row moving radially out from the root ball, from a radius of 30 to 190 pixels. Two outputs were used: whether it was a root or not. The ANN was trained 10 times with nodes from 1 to 10, for a total of 100 times. The 10 results from each number of nodes were averaged. There did not appear to be a significant difference between using a different number of nodes. There was an overall correct classification of 92% using only 2 hidden nodes. This method would require more processing power than the other method. It was worth considering but will not be implemented in the final machine.

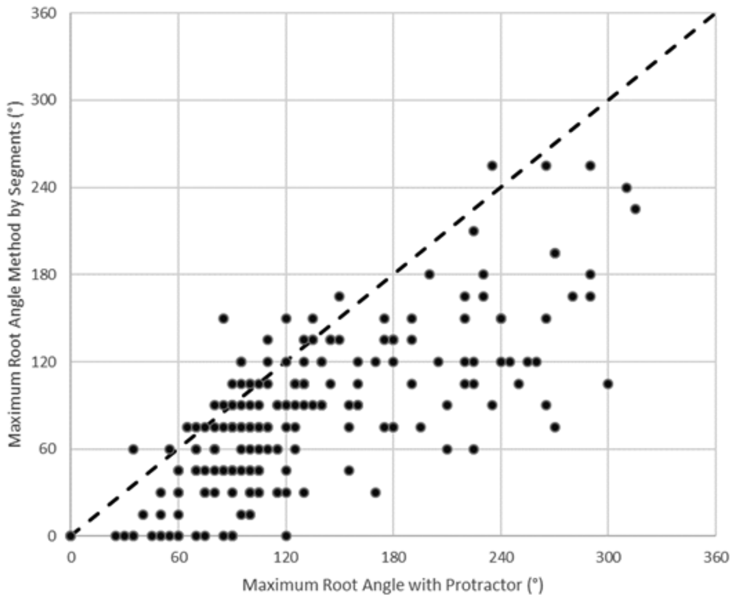


Figure 5.23: Comparison of maximum root angle measured with protractor and via the segment method

5.3 Grading of Bare-Root Forestry Seedlings

This section investigates techniques to classify tree stock as 'good' or 'bad' based on the machine vision measurements, and compares these decisions to those derived from both manual measurements and expert knowledge.

5.3.1 Method

Three experts from the pilot nursery were gathered and asked to independently grade the same raw lift of 200 trees measured in the previous section, with no knowledge of the other experts decisions. These experts were in senior positions, and far more trained than the seasonal workers performing the lifting. Firstly, grading decisions were determined based on the manual measurements. The three experts' decisions were then compared to each other, to determine how much disagreement there is between humans in the decision making process. This provides a benchmark for the repeatability of grading decisions. The machine vision measurements were then used to investigate three different classification methods:

1. Grading to specification, with a margin of error, based on the repeatability study performed in the previous section. i.e. assume uncertainties on each quantity, and grade accordingly. e.g. if RCD is greater than of equal to x AND RootAngle is smaller than or equal to y AND height is greater than or equal to z.

2. Fuzzy logic grading: this attempts to deal with ambiguity and translates human language into rules a computer can process, e.g. a statement such as the stem is a bit thin, but the rest is the tree is strong, so Ill accept it.

3. Using an ANN to recognize patterns between the input data (measurements) and output (experts' decisions).

The latter two options attempt to deal with ambiguity in the human decision making process. Bias between the various assessors (experts and machine) was then investigated when compared to the manual decisions.

5.3.2 Grading based on Manual Measurements

Grading decisions were determined based on the manual measurements, using the nursery's margins of error for both RCD and height, i.e. 0.5 mm and 5 mm respectively. If the specification stated a minimum 6.0 mm for the RCD, then tree stock at least 5.5 mm was accepted. Similarly, if the specification stated a minimum of 300 mm for height, the tree was accepted if it was 295 mm or over. Margin of error for the roots was determined to be twice the standard deviation calculated in the repeatability test, and rounded to 15 degrees. Equation 5.5 was used to make the grading decision.

$$\begin{aligned} \mathit{Accept} =& \mathit{RCD} \geq 5.5 \text{ AND } \mathit{RootAngle} \leq 195 \text{ AND } \mathit{Height} \geq 295 \\ & \text{AND } \mathit{Sweep}! = \mathit{TRUE} \end{aligned} \tag{5.5}$$

Figure 5.24 shows a Venn diagram with the reasons for rejection for the sample. Sweep has been ignored for clarity. The overall acceptance rate was

72.5%. Only 2.5% of trees were failed due to a small RCD, and of these, none were rejected solely because they were too thin. All of the trees that did not meet the RCD specification were less than 300 mm high, and would be rejected anyway due to height. This suggests that if a cutting is going to be too thin, it is also going to be too short. If there was no RCD grading at all, the trees would still be graded the same, however, it is still valuable for reporting purposes and as an aid in analysing the root structure. Out of the sample 18% trees were too short according to the specification and 18% were rejected for inadequate root structures. 28.5% of tree stock exceeded the maximum height of 400 mm, however, the experts did not reject any of these trees. Therefore, maximum height was ignored and not included in the grading criteria.

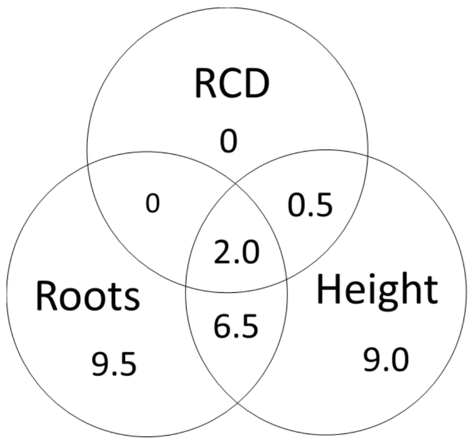


Figure 5.24: Rejection rate based on manual measurements

5.3.3 Grading by Experts

The grading specification for forestry tree stock 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. A group of experts will not necessarily all come to the same conclusion on the quality of a tree, particularly due to difference in opinions on the quality of the roots. Similarly, a grader may make slightly different decisions when presented with the same set of trees more than once. Trees which are clearly either in or out of specification will generally be agreed upon, however, a proportion of trees lie close to the rejection threshold and could potentially be either accepted or rejected.

The acceptance rate varied considerably between experts: Expert 2 only passed 62.0 %, Expert 1 passed 71.5% and Expert 3 passed 79.5%. A unanimous agreement was not reached between the experts on one in every four trees. This suggests 25% of the trees lie somewhere between good and bad and will potentially be classified differently depending on the person grading them. The variation in the number of trees passed by experts suggest there may be bias, with Expert 3 more likely to pass trees than Expert 1, who is more likely to pass trees than Expert 2.

The experts agreed between 77.5 and 86.5% amongst themselves when compared individually, and between 85.5 and 89.0% with the decisions derived from manual measurements.

5.3.4 Machine Vision Grading

5.3.4.1 Crisp Boundaries

Equation 5.5 was used as the grading criteria for the machine vision system. The machine decision agreed with the manual measurements 96.0% of the time. The agreement is high because they are following the same set of rules, and it is just the input data which may vary slightly. The machine agreed between 86.0 and 90.0% when compared individually with the experts.

The machine vision decisions were compared to the experts decisions again, however, on trees where there was not a consensus agreement between the experts, the machine vision decision was deemed to be correct no matter what the decision was. The quality of this subset of trees could be argued either way. The machine decisions agreed 97.5% of the time, i.e. five trees were disagreed upon, which are pictured in Figure 5.25. Four trees were accepted which the experts failed, i.e. false positives, and one tree was rejected which the experts accepted, i.e. false negatives.

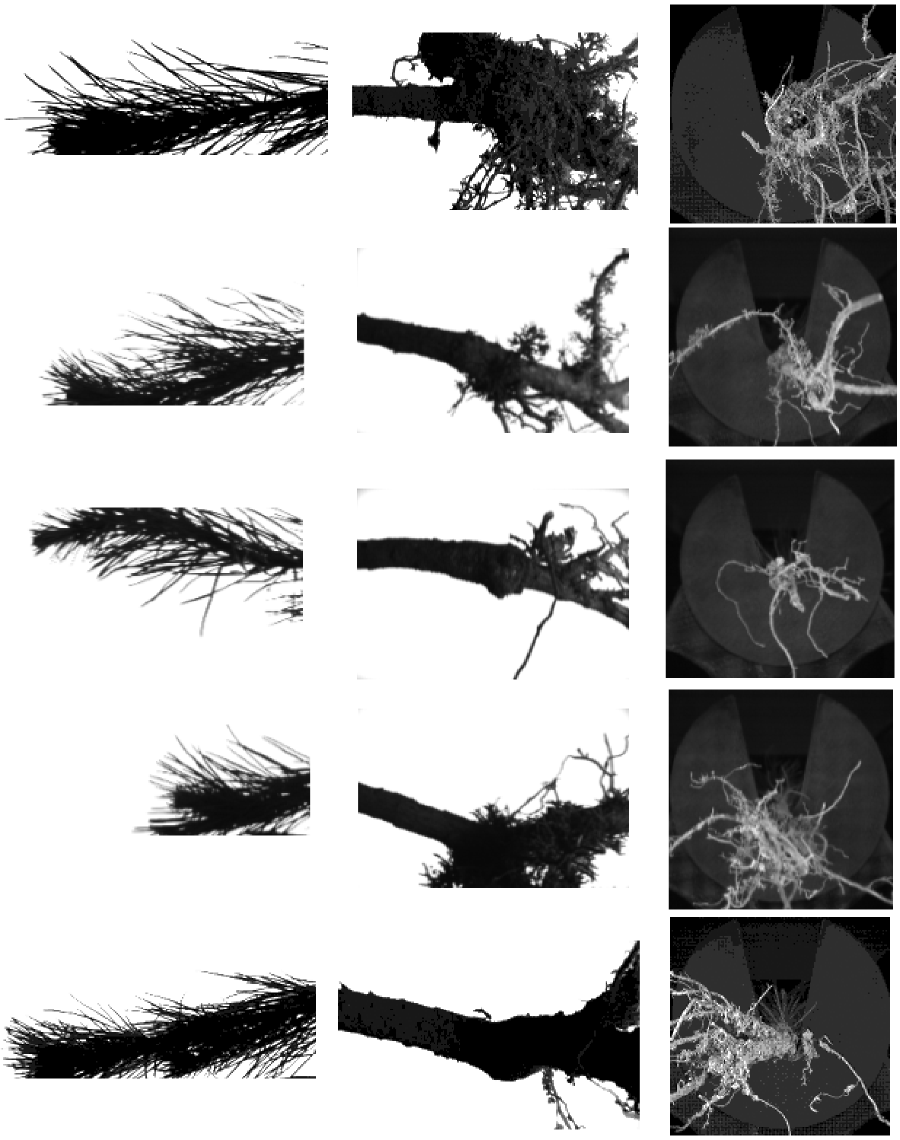


Figure 5.25: Trees where machine vision did not agree with the consensus

5.3.4.2 Fuzzy Grading

Fuzzy systems can be based on rules derived from human conversation, and do not have the same 'crisp' cut off as the previous grading method. It does not seem reasonable to accept a tree with a 6.00 mm RCD, and reject a tree with a 5.99mm stem. When talking about quality of trees, the nursery managers may say things like 'this tree is a bit thin, but its roots are strong and its a good height, so I'll accept it'. This language can be translated into fuzzy sets and rules. A fuzzy system was implemented and tested in C# using an open-source library.

Membership Functions

The three features used for grading were height, RCD, and maximum root angle. Membership functions were selected based on the grading criteria used in the preceding section. The kernels (membership value of one) of membership functions relating to 'strong' tree stock features, i.e. 'Thick', 'Good height' and 'Good roots' were located at the cut off level stated in the specification. The width of all membership functions between the kernel and support (membership value of 0) were based on the margin of errors determined earlier (0.5 mm, 5 mm and 15 degrees). Membership functions for 'bad' tree features were a mirror image about the support of the 'good' feature. This provides a transition between the classes with no overlap between a 'good' feature and 'bad' feature. The kernel for the 'borderline' membership functions were placed at the support of the 'strong' membership functions. Membership functions are pictured in Figure 5.26. There is a narrow transition between classes due to the well defined grading specification.

Fuzzy inference

Numerous conversations were held with nursery staff regarding their thought process when grading tree stock. Difficulties arise making a decision on tree stock near the rejection threshold. Fuzzy rules were formulated based on whether there was more than one grading feature which was near the threshold.

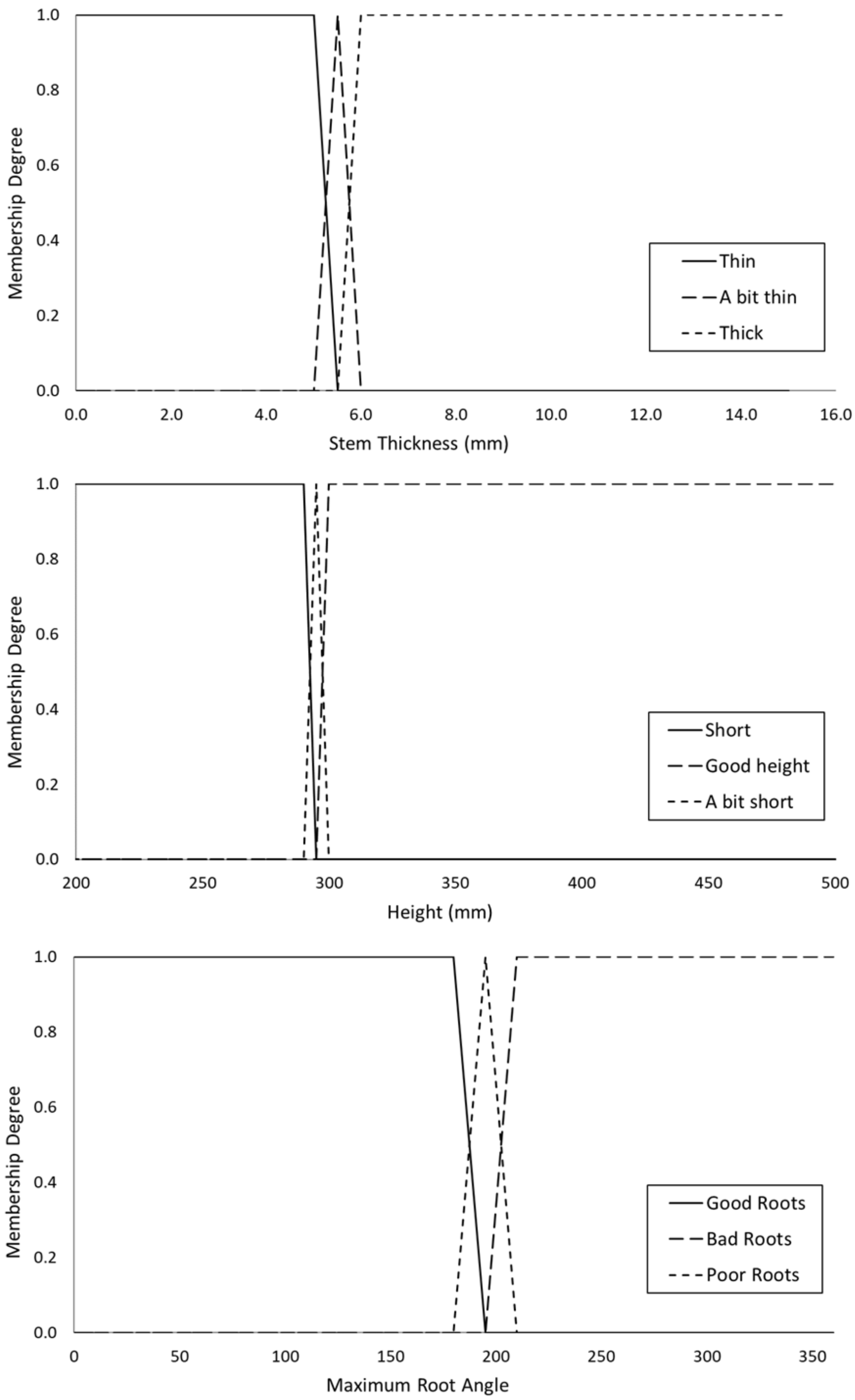


Figure 5.26: Membership functions

For example, if the tree was on the borderline of being rejected for being thin, it would only be accepted if all other features, such as root structure and height were strong. If more than one feature was near the threshold then it would be rejected, for example, the tree was slightly short and a little thin. The following fuzzy inference rules were used in this study:

1. If stem is thin then reject.
2. If roots are bad then reject.
3. If tree is short then reject.
4. If stem is thick and roots are good and tree is tall then accept.
5. If stem is a bit thin, but roots are good and tree is good height, then accept.
6. If stem is a bit thin and roots are poor, then reject.
7. If stem is a bit thin and height is a bit short, then reject.
8. If tree is a bit short and roots are poor, reject.
9. If roots are poor, but stem is thick and height is good, then accept.
10. If tree is a bit short but roots are good and stem is thick, then accept.

The Mamdani method was used for inference, and the centre of mass method was used to convert the fuzzy output set into a crisp output. This produced an agreement of 94.0% with the manual measurements, and between 83.5% and 88.0% with the experts. This performed comparably to the crisp' method; the added complexity of implementing a fuzzy system does not appear to be worth the effort.

5.3.4.3 Grading using Artificial Neural Networks

Artificial neural networks are capable of training themselves based on a set of input data. This could potentially lead to more consistent and accurate results when compared to the decisions of experts. In this case, no prior knowledge of the grading criteria is required. A clearly defined specification is available, however, whether or not the experts follow this closely is questionable. The disadvantage of using an ANN to perform the grading is that retraining is necessary for each customer as they all have a slightly different set of specifications.

MATLAB was used to produce a feed-forward network with one hidden layer. It is suggested that one layer is sufficient due to the simplicity of the input data in this case. The benefit of a neural network is that additional information can be used as inputs, without the need for manual tuning. For example, the number of pixels in the roots images, and the sweep offset were used in this study, in addition to the manual measurements of the tree features (RCD, height and roots). A third output category was introduced to deal with tree stock where experts did not reach a consensus. The tree can potentially be good, bad, or somewhere in between. It would have been very difficult to tune this using other methods, but the ANN is capable of training itself. It does not make sense to compare individually to the experts because the network will be different each time as it will have to be retrained for each person.

The network was trained and run 20 times for 1 to 10 nodes, and the maximum training performance at each number of nodes taken. This was performed multiple times because a randomised stream is used each time (i.e, different starting weights), which affects the result. There was not a significant difference between the different number of nodes, with the maximum validation between 86.7% and 90.0%. This is due to the simplicity of the input and output layers. 2 hidden nodes were selected as this was the minimum number of nodes that performed at 90.0%. The confusion matrix is pictured in Figure 5.27. Output class 1 is Accept, 2 is 'In-Between' and 3 is Reject. Misclassifications are almost certainly in the adjacent class, i.e. a reject is unlikely to be classed as acceptable, and vice versa. Even more classes could potentially be introduced in future. The network would not need to be retrained for each customer if enough grades were introduced. Customers could be charged premiums for higher quality tree stock. Additionally, tree stock rejected by one customer may be good enough for another. If multiple orders were completed at once, a portion of trees which were going to be rejected could potentially be sold to another customer. This method showed promise where additional grades may be a requirement, or no specification is available, but as there is only a pass/fail requirement it was not implemented in the final system.

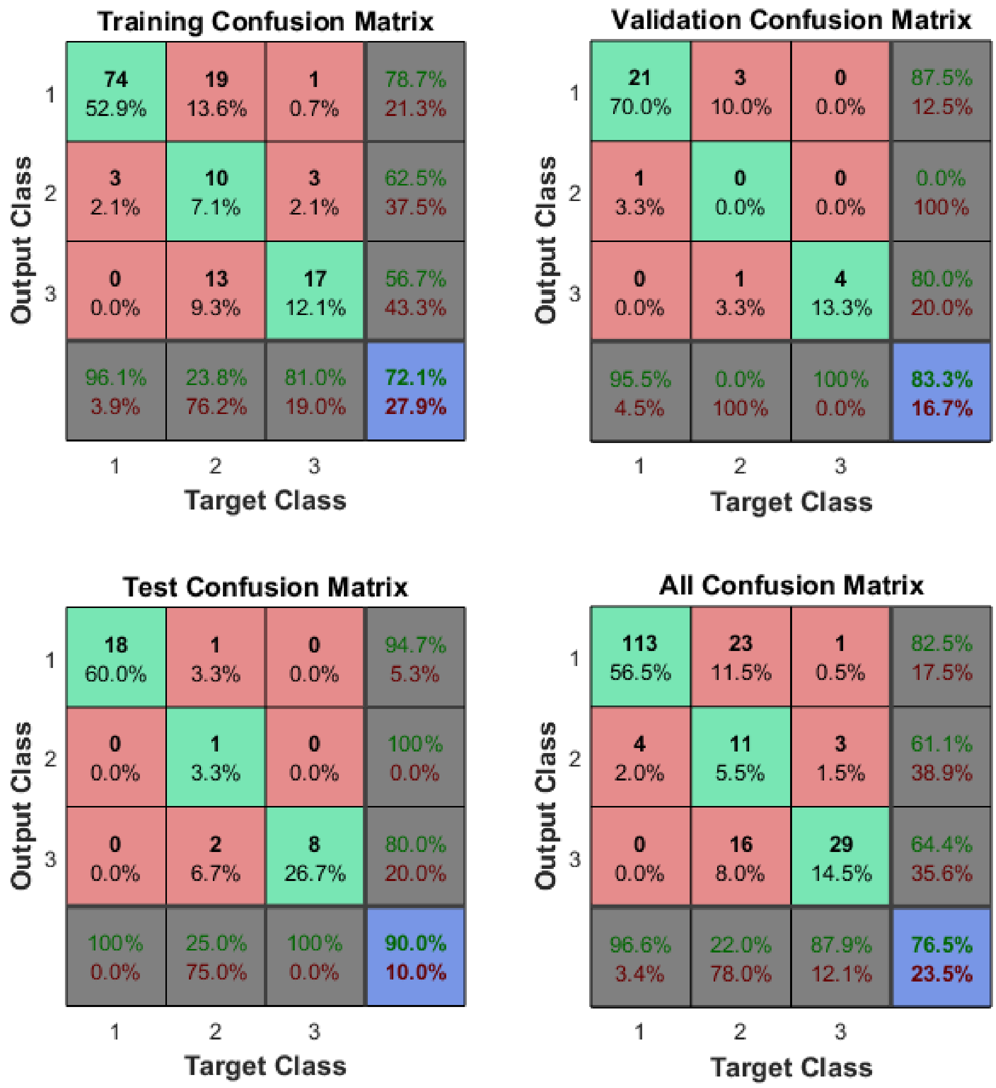


Figure 5.27: ANN confusion matrix for grading tree stock

5.3.5 Comparison of Assessors

The 'crisp' grading method was selected to be implemented and compared to both the manual measurements and human experts.

Table 5.3: Assessor pass rate

Assessor	**Accepted (%)**
Manual	72.5
Expert 1	71.5
Expert 2	62.0
Expert 3	79.5
Machine	73.5

Expert 1 appears to be the least bias of the three as his pass rate was very close to the specification, i.e. the decisions made based on the manual measurements. Expert 2 appeared more likely to fail tree stock than the other two, while Expert 3 was more likely to accept trees, as shown in Table 5.3.5. Expert 1, the machine vision and manual measurements all had a similar pass rate.

The assessment disagreement in Table 5.3.5 indicates the disagreement with the manual decisions for each assessor. It shows the percentage each assessor failed, that should have passed (false negatives), and the percentage each assessor passed, but should have failed (false positives). There is further evidence to support that Expert 3 is more lenient and more likely to pass trees than the others as he had a much higher false positive rate than anyone else. Expert 2 had a much higher false negative rate than anyone else, supporting the idea that Expert 2 is more likely to fail trees than the others. The machine vision system had a relatively low level of false positives and false negatives compared to the others.

Table 5.3.5 presents the chi-square scores from McNemar's test, which is used to compare paired proportions to determine whether there is a significant difference. A chi-square score of over 3.841 indicates a 5% significance level. Table 5.3.5 shows that there is no evidence to support that there is any difference in the decisions made between Expert 1, manual and machine. There is, however, a significant difference in all other cases, i.e. Expert 2 and 3 are both

Table 5.4: Assessment disagreement

Assessor	Passed that should fail (%)	Failed that should pass (%)
Expert 1	18.2	8.3
Expert 2	7.3	17.2
Expert 3	38.2	4.8
Machine	9.1	2.1

Table 5.5: Chi-square scores from McNemar's test

	Expert 2	Expert 3	Manual	Machine
Expert 1	13.4	9.1	0.2	0.8
Expert 2		27.2	15.2	19.6
Expert 3			7.0	5.1
Manual				0.5

making significantly different decisions to Expert 1, the machine, and manual decisions.

A subset of trees was taken which excluded trees which failed on roots, RCD or sweep, leaving trees which if they failed, should have only failed on height. These trees were re-graded based on the manual measurements, varying the acceptance threshold from 220 to 380 mm. At each measurement, these decisions were compared to the three experts and the machine vision system. If the assessors are accurately grading to the specification, there should be a peak agreement at the cut-off level in the specification of 300 mm. An earlier peak suggests a biased grader who is more likely to pass short trees, while a later peak suggests a harsher grader. There is no evidence of bias for Expert 1 and the machine as their decisions peak in line with the specification as shown in Figure 5.28. Expert 3 peaks earlier and Expert 2 peaks later, further reinforcing their bias.

Figure 5.29 shows the grading bias of the assessors based on root angle. Tree stock which failed due to RCD, sweep or height was excluded from this

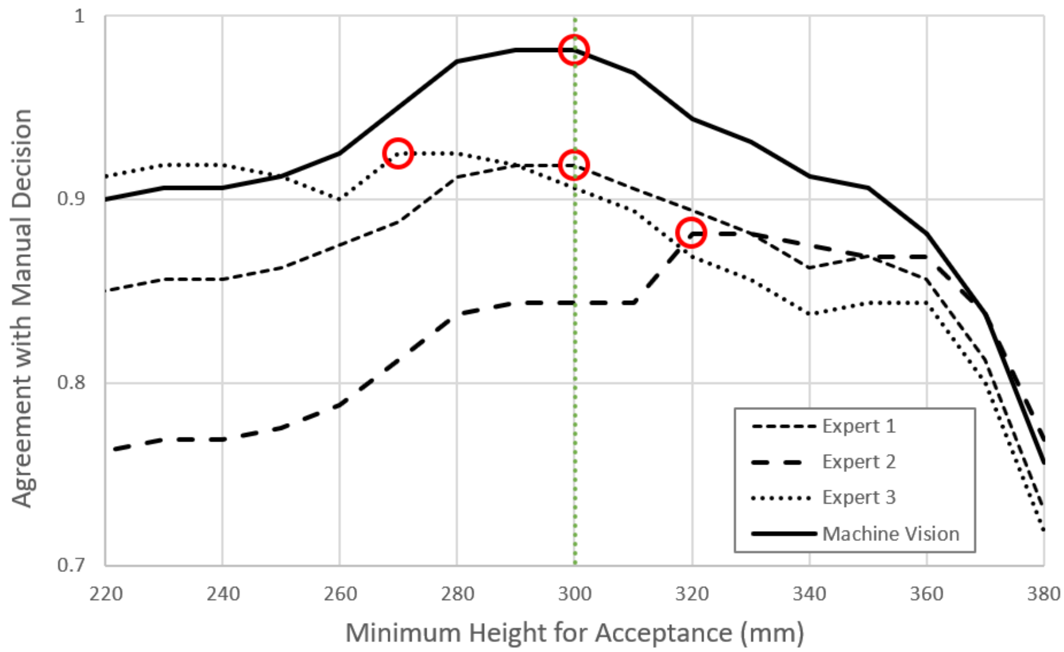


Figure 5.28: Bias of assessors when grading based on height

analysis. In this case, an early peak indicates a harsher grader, and a later peak indicates a more lenient grader. Once again, Expert 2 was shown to be bias towards failing trees, peaking far earlier than the others. There was no well defined peak for Expert 3 which suggests that his decision is not sensitive to the quality of the roots. The machine vision system showed the least bias, peaking closest to the specification.

5.3.6 Summary

All three grading methods produced good results, but there was no advantage using fuzzy grading over the crisp method. Crisp grading agreed strongly with the experts, attaining 87.2% agreement on average. Grading using an artificial neural network is able to use additional inputs and outputs easily, and could find application if multiple grades were introduced. This however, is not a requirement of the nursery at this stage. Therefore crisp grading will be implemented in the final *field factory*.

Ambiguity in the grading process was identified, with large variation on the proportion of trees passed. A consensus was only reached 75% of the time

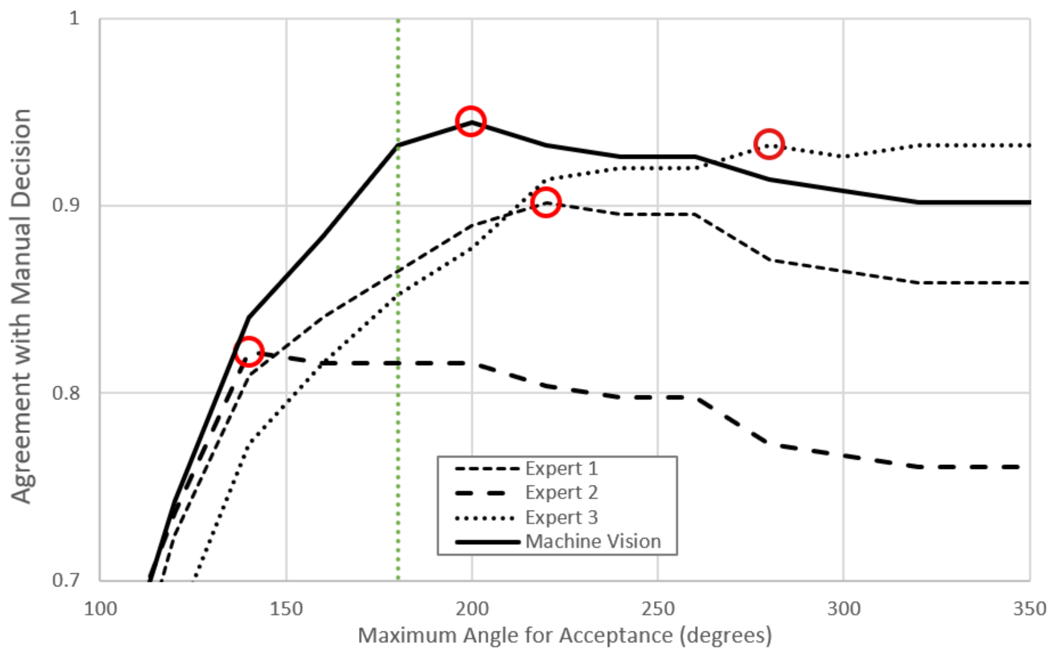


Figure 5.29: Bias of assessors when grading based on root angle

between the experts. The agreement of the experts and machine vision with the specification is shown in Figure 5.30, showing the margins of error. The machine agreed significantly higher with the specification than the experts did.

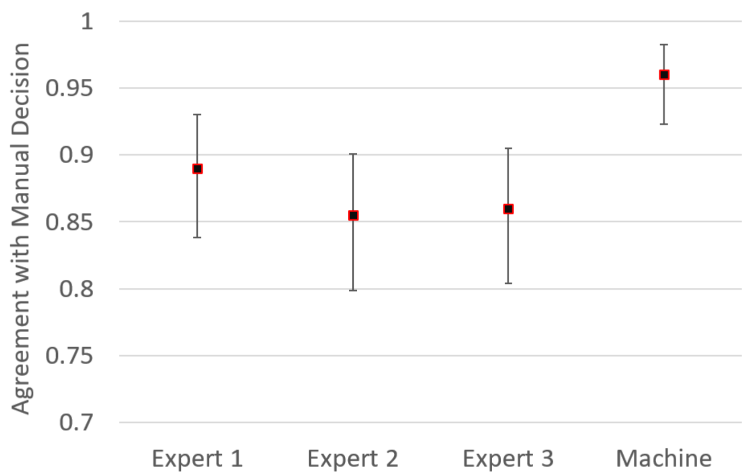


Figure 5.30: Agreement of assessors with the specification

Expert 2 was shown to be bias, and more likely to fail trees, while Expert 3 was more likely to pass trees. There was no evidence to suggest that either Expert 1 or the machine were biased, however, the machine agreed significantly higher with the specification than Expert 1.

The time taken to process the images of the 200 trees and make a decision was 985 ms, or around 5 ms per tree. This excludes image acquisition time, which would be approximately 25 ms to capture 3 frames at 120 FPS. This is more than fast enough to process trees. This was calculated just with the bare processing, without any updates to interface, for example displaying images to user.

5.4 Evaluation of Mechanical Processing

The *field factory* was tested during the 2017 lifting season, June through September. A video of the testing can be viewed at https://youtu.be/tpZqcbl7Bdw. The tractor was operated at speeds of between approximately 200 and 500 m per hour. It is necessary for each task to be performed satisfactorily, or else the entire machine will not work. Multiple modifications were required in order to get the machine functioning adequately. Due to the significant amount of work required, the number of field trials were limited. The *field factory* was only able to be tested in the field three times over the season. However, much testing was performed in the shed, manually feeding trees into the machine. Each aspect of the machine was investigated in the order of processing, i.e. lifting followed by soil removal, root trimming, tree reorientation, and finally grading and sorting. It was necessary to optimise each task in order, because if one task is performed inadequately, all subsequent processing can be affected. For example, if the lifting belts are too high, the soil remover may not contact trees properly. If the soil remover does not remove enough soil, the root trimmer can jam. If the tree is at the wrong height in the belts, roots will not be trimmed to the correct length. If the root trimmer is not set to the correct speed, the tree can be tilted and then rotation will not be performed correctly. If roots are not trimmed short enough, they can become entangled when trying to enter the grading unit. The *field factory* is pictured being transported to the beds in Figure 5.31.

Figure 5.31: Field factory being transported to beds

5.4.1 Alignment of Belts to Trees

Steering was manually controlled by an operator sitting near the lifting belts, constantly monitoring the alignment of the machine to the rows. This functioned adequately during the testing. This should be automated in future to reduce the dependency by an extra labour unit, however, would not be a priority, nor necessary. The value comes from the other functions of the *field factory*. An operator steering the machine is pictured in Figure 5.32.

Figure 5.32: Operator steering and aligning belts with tree stock

Of more importance would be maintaining a consistent height of the belts above the ground, in order to facilitate subsequent processing operations such as soil removal, but more importantly root trimming. It was relatively difficult to maintain a consistent height of belts above ground manually. Height control should be implemented in the final machine, as used in early prototypes. This consisted of a wheel mounted to the lifting end of the belts, which pivoted and rested against the nursery bed. A linear displacement transducer measured the relative position between the belts and the bed. The micro-controller can then switch the actuator to raise or lower the belts accordingly.

Better control on both hydraulic circuits is desired, or switch to an alternative system such as an electric screw. Ideally, hydraulics would be used as hydraulic power is readily available. The output from the tractor is not 100% consistent when operating under varying conditions, e.g. different loading and engine speed. The desired amount of flow was not always present for steering and raising the belts. Controlled flow is sent to the belts, and the excess is diverted to the other controls (steering, height control and row alignment). Cylinder speed was not consistent, suggesting the flow is not constant.

5.4.2 Lifting and Conveying Trees

Lifting is pictured in Figure 5.33. The rig was capable of lifting all trees it encountered. Adequate force was provided from the belts at point of lifting. Larger trees require more force to lift, and as these are larger, they are held more tightly in the belts, and therefore more force is provided by the belts. The belts are staggered due to limited lengths of the belts available. At the first transition between belts, small trees under approximately 200 mm fall out of belts at this point. This is not an issue, as the minimum tree height is 300 mm, and this acts as a 'pre-grading'. These trees need to be directed away from the bed, or into shredder or bin.

There was some movement of the tree within the belts at the soil remover, and particularly the root trimmer, sometimes significant. Additional pulleys

Figure 5.33: Lifting with the field factory

should be used to provide more tension. Reorientation of tree stock horizontally worked well when the tree was vertical when approaching the large pulley. However, if a tree had been upset in previous steps, it did not fully transition horizontally, entering the grading unit on an angle. The staggered pulleys effectively removed pinch points, removing the most significant potential for damaging trees. A sample of trees would need to be tested by an expert to prove that no damage had been sustained. This can potentially be done by slicing the tree open and checking for visual damage, but the best way would be to simply plant these trees out in the field and check the survival and growth rates after a year. There were some issues with the upper-inner belt, which slipped down off the large and smaller pulleys after running for approximately an hour.

5.4.3 Soil Removal

The soil removal system was effective. The height was manually set at the beginning of lifting. The speed was continuously adjusted using the PWM controller, until soil removal was adequate. This occurred at approximately 60 RPM. The machine was only tested in dry conditions; it may not function as well when soil is waterlogged. Figure 5.34 shows the soil removal unit from two different angles. The right image shows the typical result of soil removal. No visible damage was noticed on the roots.

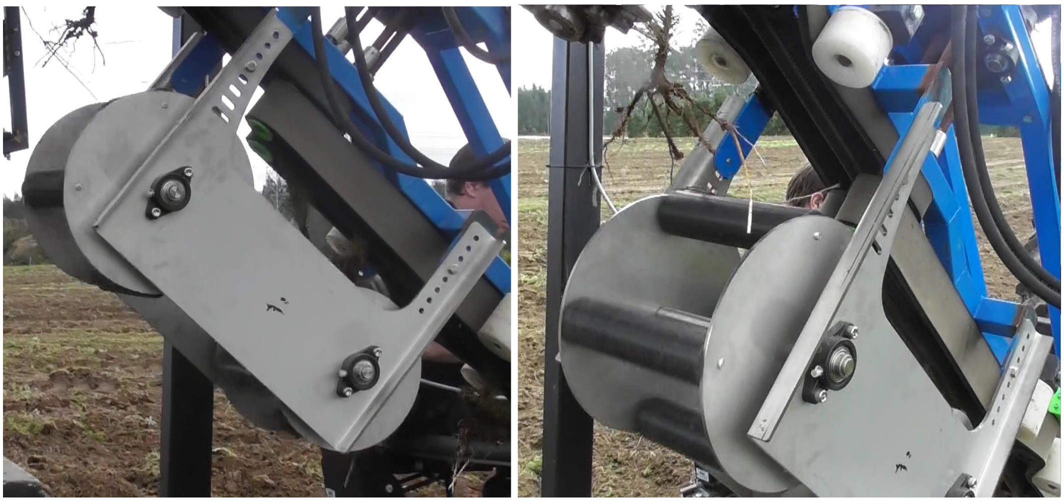


Figure 5.34: Soil Removal

5.4.4 Root Trimming

Even though the horizontal speed of the chain was matched to the belts through gearing, the tree was still upset slightly. This is due to the pin rotating around the sprocket. It moves relatively faster at this point than it does on the straight portion of the chain, as the velocity is proportional to the radial distance from the centre of rotation. This was not accounted for when calculating the gearing. The required gear ratio was recalculated. It was assumed the pin will contact the tree when the end of the pin is in the centre of the slot. Let t_1 be the time taken from the pin contacting the tree, to the point where the pin finishes rotating around the sprocket and begins to travel horizontally. t_2 is the time taken for the pin to travel from this point to the cutting blade. As the speed of the belts is constant, the horizontal component of the distance travelled can be calculated from Equation 5.6.

$$x = \dot{\theta}_1 r_1 \cos(\theta_3)(t_1 + t_2) \tag{5.6}$$

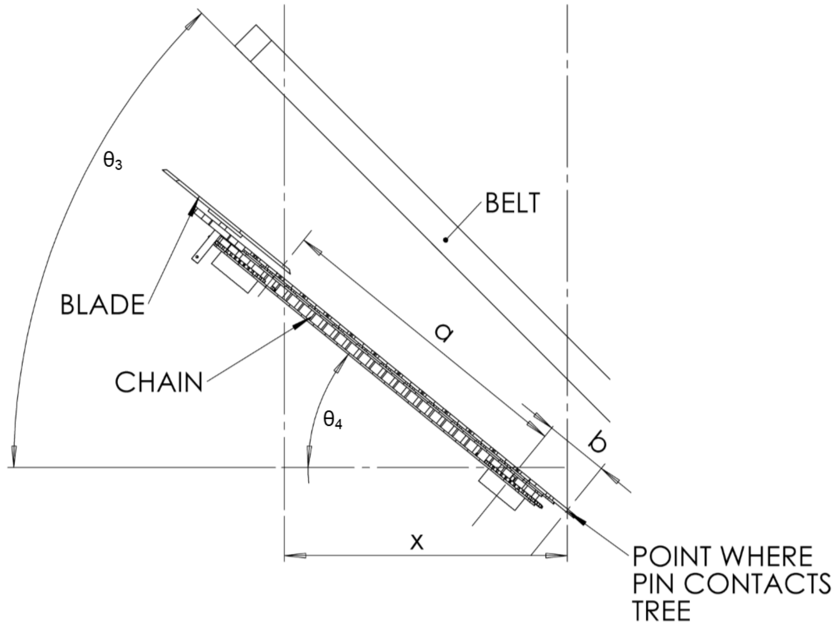


Figure 5.35: Schematic of the root trimmer

Where r_1 is the radius of the belt as it wraps around the pulley and $\dot{\theta}_1$ is the speed of rotation of the pulley driving the belts. θ_3 is the angle of the belts to the horizontal. This needs to be equated to the horizontal component of the distance travelled by the pin as it comes in contact with the stem of the tree, which is given by Equation 5.7.

$$x = \cos(\theta_4)(r_4 \sin(\theta_2) + a) \tag{5.7}$$

$$t_1 = \frac{\theta_2}{\dot{\theta}_2} \tag{5.8}$$

$$t_2 = \frac{a}{\dot{\theta}_2 r_2} \tag{5.9}$$

Where θ_2 is the angle between the pins travelling along the chain, and the pin rotating around the sprocket as it contacts the tree. a is the distance between the the cutting blade and the point where the pin stops rotating around the sprocket. θ_4 is the angle the chain is at to the horizontal. Finally, a ratio between the belts and the root trimmer can be derived by combining these equations and simplifying:

$$\frac{\dot{\theta}_2}{\dot{\theta}_1} = \frac{r_1 \cos(\theta_3)(\theta_2 + \frac{a}{r_2})}{\cos(\theta_4)(\sin(\theta_2)r_4 + a)} \tag{5.10}$$

It was difficult to adjust the speed of the root trimmer due to the fixed gearing. As such, the system was modified and a separate PWM controlled motor was used to control the speed of the root trimmer. Multiple conditions needed to be met for the assembly to effectively trim roots: there needed to be no slippage in the belts, trees had to be at the correct height, and the chain needed to be running at the correct speed. An example of when the root trimmer functioned well is pictured in Figure 5.36.

Figure 5.36: Root trimmer when functioning correctly

Unfortunately, it frequently did not perform adequately. Effects of having the tree enter the root trimming system at the incorrect height are shown in Figure 5.37. The left side of the figure shows what happens if tree stock is too low: the stem can be completely severed, making the tree a reject. This can also be caused by trees slipping in the belts. Belts at this location do not strongly grip trees, and stronger root systems can cause the tree to slip in the belts, rather than the roots deforming and being drawn down. This was a more significant issue than the tree entering the root trimmer too low. The right side of the figure shows the effect of the tree being too high: roots can missed, especially at the trailing end of the tree. Due to the angle on the root trimming unit, the trailing root can sometimes be missed by the pins.

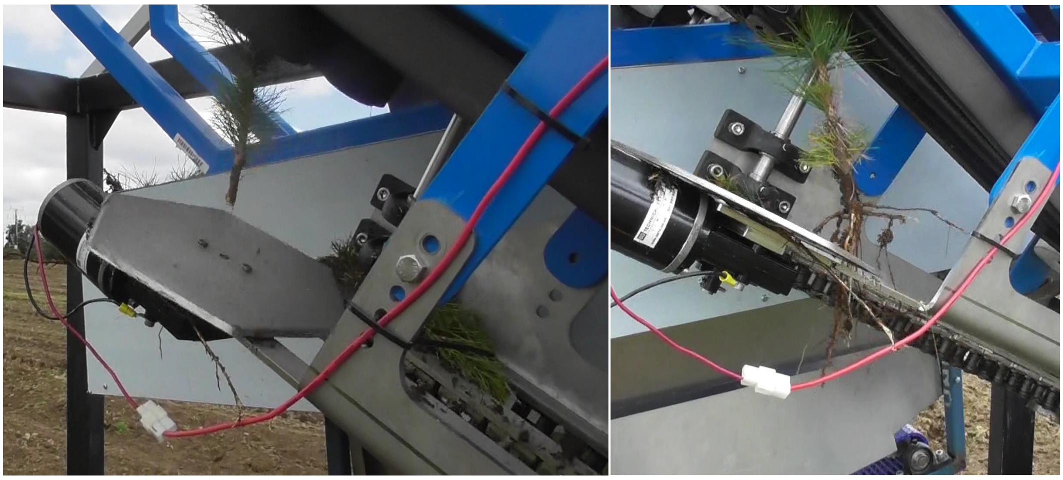


Figure 5.37: Effect of incorrect height of tree in root trimmer

Figure 5.38 (left) shows a tree entering the blade with roots correctly drawn down. However, the cutting blade does not function adequately in this case, and the roots are able to 'escape' out the side of the cutter, without being trimmed. This is mainly caused by the ability of the tree and roots to flex. This is due to a combination of factors: belts do not provide adequate force at this point, so the tree can slip; there is a large distance between the belts and the cutter, so the stem of the tree can flex; and the pins do not hold the roots well, especially as the cutter is on top of the pin. Having the cutter on top of the pins means that once a portion of the roots are cut, there is no longer a solid grip on the remaining roots. Additionally, the blade design could be improved, but if the other issues are addressed, it should function well.

5.4.5 Transition into Grader

At this point, the tree has been reorientated horizontally. It is now required to fall a short distance, approximately 100 mm into the grading unit. This proved to be far more problematic than initially thought. Trees do eventually fall, but often get caught up. Particularly, needles can get caught between the pulleys and the belts, and the tree attempts to rotate around with the

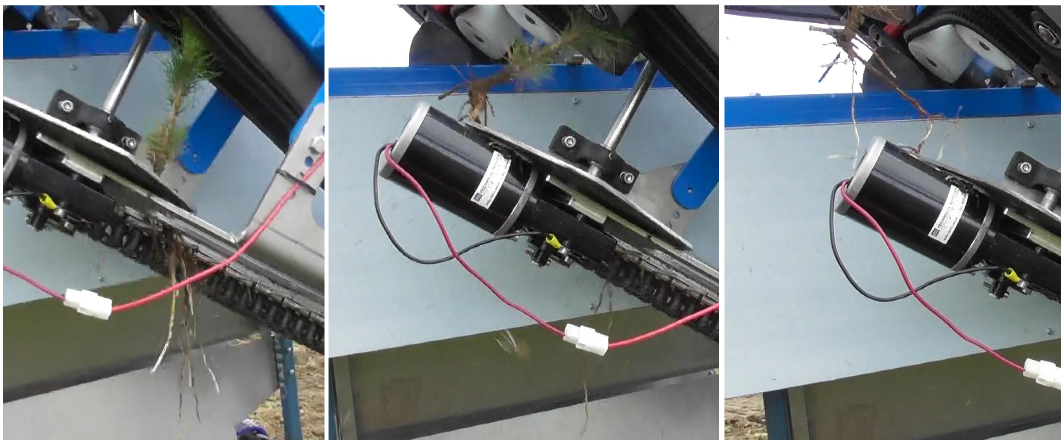


Figure 5.38: Root trimmer when functioning correctly

pulley as shown in Figure 5.39, rather than falling straight down out of the belts. Tests in Chapter 4 suggested this would not be much of a problem; however, that rig was not tested in the field, and stock was used which had been handled many times, had dried out, and many needles had already fallen off. In hindsight it turns out was not really representative of the real situation. Additionally, the field factory grips the tree higher up than in the trials, which means more needles are in the region near the bottom of the belt. As needles protrude upwards, they can get caught between the pulley and belt.

Figure 5.39: Tree failed to transition due to needles caught in pulley

Guards were fitted to the bottom of the pulleys, which rubbed against the bottom of the belts, as pictured in Figure 5.40. This was an attempt to remove the pinch points, so that needles could not get stuck in between the belt and the pulley. Additionally, an aluminium guide was fabricated to guide the tree into the grading unit. This was a significant improvement, but a more reliable solution will be necessary for a commercial machine.

Figure 5.40: Tree successfully transitioned into grading unit

The other issue with the transition is when the tree enters at the incorrect height, or at an angle, as pictured in Figure 5.41. The tree fails to locate correctly in the 'holder', and the roots end up in the wrong position. This happens when the tree is gripped at the incorrect height, or it enters the rotational unit at an angle. This can be solved by correct handling up to this point, mainly controlling the height of the belts better, and preventing slippage of tree stock in the belts.

5.4.6 Grading and Sorting

Grading and sorting works well when trees falls into correct location, and are not delivered too quickly. In the current configuration, just under half a second was needed to handle each tree. The sorting mechanism performed quite slowly, taking around 400 ms. Ambient lighting upset the root grading system when used in the field. Light was able to enter through the top of the grading unit, resulting in overexposed images. Examples of the overexposed images are in Figure 5.42. The enclosure should be redesigned to prevent ambient light from entering. This could include 'light curtains' and a larger

Figure 5.41: Tree failed transitioning into grading unit

enclosure. Exposure time could be reduced, but this would not produce a reliable system as ambient lighting is so variable. Lighting for RCD and height measurement was adequate as it was based on backlighting which is far more robust as it creates high contrast between the background and the subject.

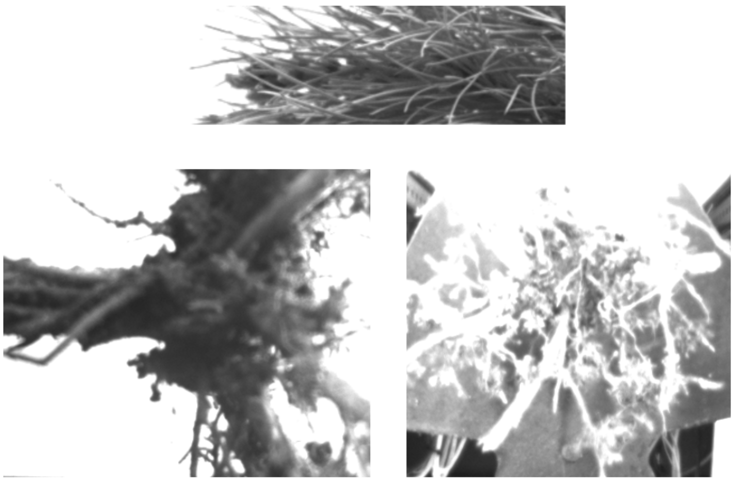


Figure 5.42: Overexposed images

The transitional step from the belts to the grading unit was the most problematic aspect of the machine. It is recommended that grading be performed while still held on the belts, and a faster sorting mechanism be implemented, based on a fast acting cylinder (e.g. electric, pneumatic or hydraulic).

Chapter 6

Discussion

Chapter two identified there was no existing work into automating lifting and grading forestry tree stock in the field. No researcher has analysed whether machine vision can be an adequate replacement for humans when grading forestry tree stock. The research question was broken down into three main questions. Can new or improved image processing algorithms accurately identify and measure morphological tree stock features? Is a machine vision system capable of replicating the human decision making process to an extent that it can replace seasonal labour for grading forestry tree stock? Is an integrated *field factory* feasible, that is capable of processing forestry tree stock reliably from point of lifting to sorting?

Measurement of Tree Stock Features

It was necessary to investigate mechanical handling of tree stock before the effectiveness of machine vision measurement could be evaluated, as the system needed to be integrated into machinery for processing tree stock in the field. It is of no benefit if the vision system can not be implemented in the real-life situation.

The grading unit was developed and integrated into the field factory. Complexity of algorithms were greatly reduced due to the controlled handling of tree stock from lifting through to grading, which confined tree features to known locations. For example, no hunting was necessary to locate the RCD region, which was the most time consuming process in studies by other researchers.

Algorithms by previous researchers failed to locate the RCD when there were roots or needles protruding into the RCD region. This work does not suffer from the same limitations as unneeded detail was removed before attempting to measure the RCD. Dilation and erosion was able to reliably remove fine detail such as needles and roots from the root collar region.

Exact measurements of tree features are not possible due to the variability of organic product. This differs from inspection of parts in a factory environment where dimensions of parts have tight tolerances. The stem of the tree, for example, is not perfectly cylindrical, nor smooth. The RCD can vary significantly depending on the point where it is measured.

The RCD measurement system performed well, with 95% of the machine vision measurements expected to be within 1.3 mm less than, and 1.2 mm higher than the manually measured values. Larger differences were on larger trees far from the rejection threshold, over 8 mm in RCD, which would not affect the grading decision.

This research introduced a faster algorithm for finding the top of the tree which performed well. 95% of machine vision measurements can be expected to be within 18 mm of the manual measurements. There were several potential sources for error when measuring height in this study. The top of the bud may not be accurately located if there are many needles protruding above it. Additionally, trees were dropped into the unit and may be positioned slightly differently each time. The algorithm did not hunt for the bottom of the tree as it was assumed to be in a known location. This could be accounted for, as the stem is traced down in order to locate the root ball.

It is important to locate the the centre of the stem to accurately analyse root structure. This is very difficult when only viewing the image of the roots; however, a vertical offset can be calculated from the RCD image by tracing the stem to the root ball. It was assumed that the stem is centred horizontally due to the design of tree holder. 95% of machine vision measurements for roots can be expected to be within 87 degrees less, and 78 degrees more than manual measurements. Different experts (field workers, managers, quality control, and customers) have varying opinions on the quality of roots and what should be classified as a root, and therefore there is significant ambiguity when measuring roots. Classification of root quadrants is not necessary for grading, but it is a commonly used tool by nursery management. The system was able to classify quadrants correctly 66% of the time. This performs well considering there are 5 different classes, and misclassifications typically occur into adjacent classes. Additionally, it is difficult to definitively class many root systems, so the 'correct' decision is not necessarily made in the first place.

The measurement system performed well, but the true measure of performance is how well it grades when compared to experts.

Grading

There is much ambiguity in grading by humans as it subjective, relying on opinion and experience. Three experts came to a consensus on the quality of tree stock only 75% of the time. This suggests that around 25% of tree stock lies somewhere between 'good' and 'bad'. Even if the grading system was to agree 100% with the majority decision of the experts, it would only agree an average of 87.5% when compared to the experts individually. Similarly, the experts only agreed with each other an average of 83.3% of the time. This suggests the limit of agreement lies around this range.

The crisp grading system achieved a high level of agreement with the experts, averaging 87.5%. It was proposed that a fuzzy logic system or artificial neural network may be necessary to replicate the human grading process due to the ambiguity in the grading process, however, no benefit was realised with fuzzy logic. The fuzzy system agreed on average 86.2% with the experts, similar to results obtained by other researchers when grading produce with fuzzy logic [121][124][125]. Membership functions could likely be tuned further to produce a slightly better result, but fuzzy logic did not have any advantage over basic crisp grading. Crisp grading provides the nursery with better control: the grading specification for different customers can easily be changed and produce predictable results.

Fuzzy logic may not be necessary, but an artificial neural network could potentially add benefit. Additional inputs and outputs can be easily introduced using this type of system as it is self-training. Obtaining the data for training need not be overly time consuming in this case. All that is necessary is for an expert to grade a tree stock sample, and process the tree through the machine vision system, noting the expert's decision. This study introduced an additional grade in order to deal with the indecision between experts: 'in-between'. An artificial neural network was able to classify tree stock correctly 90% of the time, and had only one false positive. Introducing an additional class can put a premium on the accepted trees, while the 'in-between' trees could be sold at a lower price point. Multiple orders could be filled at the same time to reduce wastage, and instead of discarding 'in-between' trees, they could be sold to customers willing to accept them.

There was significant difference in the grading decisions made between the three experts, with acceptance rates varying from 62.0 to 79.5%. There was evidence to suggest two of the experts were bias: one was more likely to pass trees, and one more likely to fail trees. There was not a significant difference between Expert 1 (who can be considered the most experienced, and therefore 'best' grader), the manual measurements and the machine vision system. The machine vision system had a higher agreement with the decisions based on manual measurements than any of the experts, suggesting the machine follows the specification more closely than humans. This study was compared against experts, but most of the staff performing the grading can not be considered experts as they are inexperienced. The machine vision system will therefore outperform the typical seasonal worker.

As predicted, the RCD, height, and root structure alone is enough to make valid judgements on the quality of forestry tree stock. This can be improved slightly by accounting for sweep. The specification lists additional grading criteria such as 'multi-leaders' and dead trees, however, this study suggests these are insignificant enough to not be concerned with.

Mechanical Handling

Prototypes were required to answer whether it is feasible to produce a *field factory* capable of lifting and grading forestry tree stock. Each aspect was investigated individually, both in the lab, and the field and it was proven that each mechanical processing function required of the machine is feasible on its own. These were then integrated into a single machine.

Integration of all processes into a single machine streamlines the entire process, removing the need for multiple handling steps as required in nurseries where tree stock is lifted in the field and processed in a pack house. Integration means that control of the tree can be achieved from the point of lifting to the point of sorting. Additional processing steps can be performed without the need for realignment or separation of trees. The moment these tasks are split up and performed in isolation, significantly more work is required.

A significant amount of work was required to get the various functions operating together correctly. The success of each component depended on the ability of the previous to perform its task. The importance of a strong grip on the tree throughout the entire process was identified. Minor slips of the tree in the belt can upset subsequent processing steps.

It was important to not lose control of tree stock at any point. Early trials indicated that it would be easy enough to let tree stock fall a short distance as it leaves the belts, transitioning into a holder where it can be sorted and graded. However, the real life situation proved to be much different as tree stock is so variable. Trees are bushy with lots of needles, which can be easily entangled in mechanisms, and therefore do not fall consistently. Future designs should move image processing so that it is performed when tree stock is still firmly gripped by the belts, and a high speed sorting mechanism should be introduced to sort the trees as they leave the belts.

The *field factory* did not function to a reliable standard required of a commercial machine, but it did show promise. There were three main areas for improvement. Pressure on tree stock was adequate at the point of lifting, however, at other points along the belts, it was insufficient. The root trimmer functioned adequately when all other processing steps functioned correctly, but another iteration on the design is necessary to produce a robust and reliable mechanism. The most problematic aspect of the machine was the transition of tree stock into the grading unit.

Pack House Implementation

Although the ultimate goal is to produce a small number of robust, fully operational *field factories* to be implemented at ArborGen's nurseries, this research could also be adapted to a pack house environment. ArborGen owns one nursery in New Zealand where tree stock is graded, root trimmed, and boxed in a pack house. Lifting is still performed with manual labour. The pack house minimises the amount of time staff need to be in the field in harsh winter conditions typical at Edendale.

The root trimming, grading, and sorting assemblies could be modified to suit the pack house environment. Even root trimming alone would add significant benefit, due to severe health and safety concerns: in particular, workers operate guillotines, which come dangerously close to their hands. Tree stock would still be manually loaded onto the modified conveyor, with holders designed to to individually grasp each tree. This locates tree stock in known locations, reducing complexity and making root trimming, image processing, and sorting easier.

This would only be feasible at the Edendale nursery, as the infrastructure is already in place; the capital cost of a pack house and associated equipment would be prohibitive to implement at other nurseries. It is not much more effort to trim the roots, grade, and box at the same time when trees have already been manually lifted.

If tree stock is mechanically lifted and taken back to a pack house, multiple handling steps are required for each tree, negating any benefit of reducing labour in the field. For example, at the Edendale nursery, tree stock is transported by a worker from a trailer to the sorting tables, where they are root trimmed and graded by a team of around 8 people. Another person performs quality control on tree stock travelling down the conveyor, before they are boxed by yet another worker.

Lifting without Grading

It is common practice in foreign markets such as the United States to not grade individual trees. Instead, the nursery manager will come to an agreement with the customer on the proportion of trees which will be saleable in a given block. Every tree is passed onto the customer; however, only the agreed portion of trees which are 'good' are paid for. The same does not apply in the New Zealand market, so grading cannot be avoided. The nursery and customer agree on a strict set of specifications which dictates what product the customer will accept, which varies between customers. It is agreed that at least 95% of trees sold must be deemed acceptable by the customer, i.e. up to 5% of stock out the gate are allowed to be 'rejects'.

Even more desirable than automating the grading process would be to improve cultural practices to the point that grading becomes unnecessary [142]. The nursery claims an overall acceptance rate for seedlings of approximately 95%, and 65% for cuttings. The typical acceptance rate for seedlings meets the 95% threshold required by customers. This suggests that grading is not necessary for seedlings, although it would still be valuable for statistical purposes. Mechanised bulk lifting could be performed on seedlings, with constitutes approximately 50% of tree stock, without the need for grading and sorting. Root trimming would still be required. Additionally, a sensor and actuator would be necessary so that tree stock could be separated in bundles of 100, and manually boxed as it is very difficult to separate tree stock once bulked together.

The same could not be applied to cuttings due to the high rejection rate, mainly attributed to poor root structures. Although the acceptance rate for cuttings is poor, data received from one block (Table B.2) showed a very high acceptance rate for cuttings when compared to all the others, to the point where grading would not be necessary. This suggests it is possible to improve consistency and quality of cuttings to the point where rejects are negligible. Replicating these conditions, however, would take significant research. There are numerous factors which affect the growth of a tree, which are beyond the scope of this research, including things such as soil type, proximity to wind breaks, amount of weeds, and fertiliser use.

There is limited literature regarding factors affecting the formation of roots in pine cuttings [143] [144], but none found that specifically relates to the formation of evenly distributed root structures. This could be an area of future research. Although there is an agreed upon specification with customers, it is not necessarily the best indicator of tree stock quality. For example, one study identified no significant difference in growth, or stability, over three years for cuttings with one through to three quadrants. There was however, a significant increase in growth for cuttings with four quadrants [6].

Despite the possibility of removing grading altogether, it still has numerous other benefits, and this study has shown that machine vision measurement is the least of the problems with the *field factory*.

Benefit of Automation

It is estimated that automation of the lifting and grading processes can reduce labour requirement down to around 10 units, instead of crews of 30-40. This is less than a third of the current labour demand, which reduces the labour bill immensely. Currently, tree stock is quality checked up to 3 times before it is shipped to the customer. Quality control checks samples and measures the RCD, height, sweep, root quadrants, disease and multi-leaders. This work load will be reduced dramatically, as it has been proven that the grading is comparable to an expert.

Although the labour cost would be significantly reduced, additional costs would be associated. The *field factory* will require regular maintenance, and running costs of the tractor would be incurred. Skilled workers will be required to operate the tractor and also maintain the machine. Adjustment of the machine will be necessary for differing conditions, for example, speed of soil removers may need to be adjusted if the soil is muddy compared to when it is dry.

Reducing the labour demand provides other benefits in addition to reduced cost of wages. The *field factory* reduces health and safety related issues: back strains are reduced as workers no longer need to bend over lifting short trees; cuts are reduced as shears are not needed; and repetitive movements are reduced significantly. Manual tasks have been separated into driving, steering, boxing, preparing boxes and dealing with full boxes. Staff can be regularly rotated and can perform multiple jobs, reducing fatigue and chance of OOS.

Although there are many health and safety benefits associated with automation, the machinery does introduce potential for serious injury. There are numerous hazards including injury potential from the sharp cutting disc; entanglement from chains, gears, and belts; and crush potential as the unit moves. The final machine will require appropriate guarding. The machine and components are generally slow moving, so that will minimise the issue. Each worker, i.e. driver, steerer, boxer, will be provided with an emergency stop so that the machine will come to a safe state when required. Noise is a concern, particularly from the tractor, which makes communication between team members difficult.

The machine allows data to be exported on every tree lifted. This is invaluable for reporting purposes. In future, tree quality data could be correlated to a number of factors such as location in nursery and fertiliser use. This can be used to optimise fertiliser use, or hardier stock can be planted in harsher blocks. Customers can have confidence in the product as they can be given a report based on the entire population, rather than just a sample. Reports can be automatically generated, reducing the work load of quality control.

Processing Time

The total time for the *field factory* to grade and sort a tree was just under half a second, as shown in Table 6.1. This equates to a maximum throughput of 2.2 trees per second, which is slightly lower than the target rate for a single row lifter of 2.6 trees per second.

Grading and sorting consisted of several steps: firstly, the tree falls a short distance after it trips the optical through sensor before it comes to rest in the grading unit; image capture and processing then takes place; finally, the tree is sorted. Running some tasks in parallel on different threads could reduce processing time, however, this is not necessary as image processing only consumes around 7% of the total processing time. By far, the are for greatest improvement was sorting, which took around 400 ms. The slow stepper motor could be replaced by a high speed actuator to significantly reduce this time. If necessary, the required throughput can be achieved by increasing working hours from 8 to 10 hours per day, or working an extra day per week.

Table 6.1: Grading and sorting time for a single tree

Process	**Time (ms)**
Delay after optical sensor	32
Image capture	25
Image processing	5
Sorting	400
Total	**462**

Commercial Viability

The proposed *field factory* shows promise for commercial viability, however, significant work is required to ensure reliability, particularly on mechanical processing. Table 6.2 shows the projected annual costs using the *field factory*, per 1000 trees sold. The greatest savings over the manual costs from Table 1.1 is on labour which is more than halved, however additional costs are incurred by the required tractor. It is estimated that the annual costs could be reduced by around a third from 79.92 to 53.93 NZD per 1000 trees by automating the lifting and grading processes.

Table 6.2: NZD per 1000 trees lifted with the *field factory*

	NZD per 1000 trees
Labour	
Workers	19.73
Supervisor	2.82
Tractor Drivers	5.64
Quality Control	3.10
Equipment	1.25
Tractor Expenses	18.75
Drug Testing	0.14
Machine Maintenance	2.50
Total	**53.93**

Although substantial annual savings are estimated, a significant capital outlay is required. It is predicted that an additional 150k NZD would need to be spent to develop the *field factory* to a commercial level. However, an estimated decrease in annual expenses of over 100k is expected, with a pay-back period of 2.5 years. Table 6.2 shows the estimated capital cost, annual expenses, and pay back period expected for the field factory.

Table 6.3: Annual savings and pay back of *field factory*

Capital Costs	
Spent to Date	
Components and Manufacture	70,000
Labour	35,000
Projected	
Components and Manufacture	60,000
Labour	90,000
Total	255,000
Annual Expenses	215,702.70
Annual Savings	103,964.60
Pay back (years)	2.5

Chapter 7

Conclusions and Recommendations

7.1 Conclusions

It is now possible to answer the questions posed at the end of the literature review.

There was good correlation between the measurements taken with the machine vision system and manual measurements. Exact measurements of tree stock features are not possible. There was the greatest ambiguity and variation when analysing root structure. Measurement of tree stock features was aided by the design of the mechanical handling system.

Crisp grading performed well enough for the system to be considered expert, without the need for fuzzy logic. The system performed well and was at least as good as the experts. The machine vision system was less biased than the human graders and agreed to a higher degree with the specification. It would be unproductive to try to improve the system further as there is a limit due to ambiguity. An artificial neural network could find application in grading into additional classes, besides 'good' and 'bad'.

It is feasible to produce a *field factory* capable of harvesting and grading forestry tree stock in the field, but significant development is required to produce a reliable machine. Care is required to ensure tree stock is handled consistently. Annual savings of around 100k NZD are estimated by automating the lifting and grading processes, with a pay back of approximately 2.5 years.

7.2 Recommendations

Further work is required to produce a reliable *field factory* capable of harvesting and grading forestry tree stock. The main recommendations relate to mechanical development of the machine:

- Automatic height control should be implemented to ensure tree stock is delivered to subsequent processing steps at a consistent height.
- Additional pulleys should be added along the length of the belts to provide greater gripping force and prevent slippage, particularly at the soil removal and root trimming assemblies.
- Another iteration on the design of the root trimmer is necessary for it to perform reliably:
  - The assembly should be positioned horizontally to remove the chance of trailing roots being missed by the mechanism.
  - Roots should be held more securely by using thicker pins which are guided to prevent deflection of the chain.
  - The cutting blade should be repositioned to cut at the bottom of the pins, rather than on top to reduce the chance of roots slipping from the mechanism during trimming.
  - Horizontal speed of the chain should be electronically matched to the belt using and encoder and PID control to stop trees tilting.
- The grading unit should be moved to the belts so that image processing occurs while the tree is still moving and gripped securely by the belts.

- A large enclosure around the grading unit is necessary to block ambient light.
- A high speed sorting mechanism is necessary to sort tree stock as it leaves the belts.

Once the *field factory* is operating reliably and consistently, further evaluation can take place. For example, the reliability and performance of the machine can be tested under varying weather conditions. The machine vision system can be evaluated for a larger sample of tree stock, and at various times during the lifting season. Damage to tree stock should be investigated. This could be performed by planting a sample of trees lifted by the *field factory*, and checking survival rates and tree health in a year.

A faster road to implementation would be to adapt the root trimming, grading and sorting system to a pack house environment, where trees could be manually placed into a unit by hand. This would remove much of the variability and uncertainty of working outdoors. Capital cost is prohibitive to implement this in most cases, however it is feasible in cases where infrastructure is already in place.

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Appendix A

Design Specifications

1. Performance

   (a) The *field factory* must lift forestry tree stock, remove excess soil from roots, trim roots to length, grade, sort and present trees in bundles to be boxed.

   (b) Should be easily configurable to allow lifting and grading of different tree types, including:

      i. P. radiata bare rooted cuttings
      ii. P. radiata bare root seedlings
      iii. Douglas Fir bare root seedlings

   (c) Speed should be sufficient to lift an average of 120,000 acceptable Pinus radiata per day. This equates to a raw lift of approximately 150,000 trees.

   (d) Maximum 10 hours operation per day.

   (e) Must not foul to the extent at which it hinders performance.

   (f) Tolerances

      i. Height - 10 mm
      ii. RCD - 0.5 mm

   (g) Ideally, the grader should meet as many of the grading criteria as possible; however, this may not be technically feasible. At a minimum RCD, height and root quadrants should be measured.

(h) Design should be modular, initially lifting only one row at a time.

(i) Handling must not incur damage to tree stock. Aim to handle at least as gently as a human.

(j) Tree stock is either accepted or rejected. There is no requirement to sort into additional grades.

2. Planting and bed specifications

    (a) Inter-row spacing is fixed at 125 mm for all tree types.

    (b) Planting beds are 1200 mm wide and between 160 - 340 m in length.

    (c) Pinus radiata are typically spaced at 77 mm, Plug plus 85 mm, Douglas Fir 120 mm.

3. Typical grading criteria for P. radiata bare rooted cuttings

    (a) Box weight: maximum 12 kg.

    (b) Tree condition: stem should be stiff and not bend over on its own when held vertically. No new or "soft" shoots longer than 3 cm on the foliage tips.

    (c) RCD: measure on the section of stem 10 mm above uppermost root development. Minimum of 6 mm.

    (d) Stem height: measured from the root collar to the top apical meristem. Minimum 30 cm. Maximum 40 cm.

    (e) Sturdiness ratio: Defined as height / RCD. Less than 60.

    (f) Tree form: single-leader preferred. Reject if multileaders originate below half of the foliage height and there must still be a central leader in place.

    (g) Root structure: must have well established roots. Roots to arise from a swelling at the base of the cutting, over at least two full quadrants, i.e. greater than or equal to 180 and not higher up the stem (with dieback on the base from damaged cambium).

While some stem swelling around the base of the cutting is acceptable, a complete solid ball of callus is unacceptable, being a sign of maturation and stress. Roots up, root bound and spiral roots are not acceptable.

Twisted: primary roots severely twisted and bent are unacceptable.

Sparse: very few roots present, or very little or no soil and mycorrhizae adhering to roots are unacceptable.

(h) Damaged: significant root damage (tearing, slicing, breakage, etc) from conditioning and lifting is unacceptable.

(i) Root trimming: measured from the first part of root initiation, in 2 opposite quadrants. Minimum 50 mm. Maximum 100 mm.

(j) Stem sweep. No greater than 3 cm deviation from the centre of the stem above nursery bed level.

4. Grading criteria for P.radiata bare root seedlings

   (a) Same as cuttings, except RCD to be measured 0-5 mm above soil level.

5. Grading criteria for Douglas fir bare root seedlings

   (a) Same as P. radiata cuttings except:
   RCD to be measured 0-5 mm above soil level, minimum of 7 mm
   Max height: 60 cm, min height: 30 cm
   Max root length: 12 cm
   Reject if there is any multi-leadering, one single straight stem only shall be accepted
   No new or "soft" shoots on the foliage tips.

6. Manufacturing

   (a) Manufacture of parts will be outsourced.

   (b) Assembly at University of Waikato.

   (c) Where possible, all material and components used should be readily available off the shelf.

7. Driving power

   (a) May be self-driven, or it may be pulled behind a John Deere 6210 tractor currently owned by ArborGen.
   (b) Must be able to be disengaged when required by the tractor operator.
   (c) Must be able to be transported easily from the shed to the nursery bed.
   (d) Nursery beds may be up to a kilometre from storage shed.

8. Environment

   (a) Lifter-grader must operate under typical New Zealand weather conditions including sleet on the planting beds, frozen, muddy, dry, hard and saturated ground.
   (b) The *field factory* will be stored in a shed when not in use.
   (c) Temperature ranges: -5 to 33 degrees Celsius.
   (d) The *field factory* will experience humid and wet conditions.
   (e) Any noise emitted from the machine must not exceed that deemed safe under New Zealand regulation.
   (f) Must be able to navigate muddy and uneven terrain.
   (g) Must be robust enough to withstand rough handling typical in an agricultural environment.

9. Target Cost

   (a) $100,000 for a fully operational and commissioned machine.

10. Quantity

   (a) One prototype will initially be built.
   (b) Machine will be modular: initially one row to be lifted.

   (c) Further machines may be built after verification of design; however, beyond the scope of this project.

11. Maintenance

   (a) Must undergo regular maintenance as prescribed by the manufacturer.

12. Operational

   (a) Dirt and other foreign objects must be removed at the end of each day.

   (b) An annual maintenance check done by ArborGen staff will be carried out at the start of the season.

   (c) Parts which are likely to need replacing over the course of the machines life should be readily available off the shelf components.

13. Interface

   (a) Standard Windows form interface should be simple and intuitive.

   (b) Ability to save settings for various seedling types.

   (c) Change configuration to different tree types quickly and easily.

14. Size and Weight Restrictions

   (a) Must fit inside a storage shed for protection from the weather.

   (b) Width must not exceed that at which interferes with the neighbouring beds.

   (c) Track width should be 1800 mm to fit between the beds.

   (d) Design is limited by row spacing of 125 mm. Lifting mechanisms must not interfere with tree stock in neighbouring row.

15. Aesthetics

   (a) Form is not important to the design, follows function.

16. Ergonomics

   (a) One semi-skilled person should be able to set up the machine.
   (b) All controls needed during lifting should be situated in an accessible position.
   (c) Motions required by operator must be consistent with accepted ergonomic practice.

17. Quality and Reliability
   (a) Should not fail over the course of its service life.
   (b) Grading should remain accurate for the lifespan of the machine.

18. Safety
   (a) Moving parts should be guarded where feasible.
   (b) Should not catastrophically fail under normal operating conditions.
   (c) Must follow regulations outlined in the Health & Safety document "Guidelines for Guarding Principals and General Safety for Machinery".
   (d) Minimum Safety Factor of 4.

19. Testing
   (a) Functional testing will be carried out.
   (b) Accuracy of grading will be determined by comparing to decisions made by experts.
   (c) Effectiveness of lifting, soil removal and root trimming will be analysed.
   (d) Modifications will be made where necessary.

20. Transport
   (a) The lifter-grader needs to be transported safely from Hamilton to Tokoroa once the build is completed and be easily transportable between ArborGen sites.

Appendix B

Tree Stock Profile

Data was obtained from the Tokoroa nursery for a raw lift of 7004 cuttings, taken in winter 2014, from 7 different blocks. This included RCD and height measurements, root quadrants, and how many trees contained sweep, multi-leaders, or were dead. This provides an indication of what features are the most important when grading. Data was also obtained for one block of seedlings, for a total of 1000 trees. Sweep, root quadrants, and dead trees were not considered for seedlings. This is due to the superior root structure of the seedling, and seedlings are generally not affected by sweep. Table B.1 shows the percentage of tree stock in specification based on the various grading criteria.

Table B.1: Tree stock profile

Feature	**Cuttings in Spec (%)**	**Seedlings in Spec (%)**
RCD $\geq$ 6.0 mm	92.6	88.9
Height $\geq$ 300 mm	96.4	98.7
Root Quadrants $\geq$ 2O	83.8	-
Sweep	97.8	-
Dead	96.4	-
Multi-leaders	97.2	94.9

RCD was rounded to the nearest 0.5 mm, while height was grouped in roughly 50 mm intervals, for example between 240 and 290 mm, 290 and 340 mm, etc. Root quadrants are clearly the most important grading criteria, with only 83.8% being in specification, which is typically a minimum of two opposite quadrants. The second most important grading feature appears to be RCD. This does not provide information on whether trees would have failed on more than one feature, as the information is not listed for individual trees.

Table B.2 shows the variation between planting sites for cuttings. One block considerably outperformed all the rest in every area. This suggests that tree stock quality is site dependent, and rejection rate can potentially be reduced far below the current level. If all blocks performed like block 7, grading may not even be necessary as such a high proportion of tree stock is within specification. Even assuming individual trees only failed on one feature, there would be a total rejection rate of 6.4%. This is the worst case, and some trees are likely to have failed on more than one feature.

Table B.2: Cuttings in specification by block

Feature	**1**	**2**	**3**	**4**	**5**	**6**	**7**
RCD	92.2	88.6	87.5	92.2	96.7	91.9	99.0
Height	93.8	95.3	97.8	93.8	98.1	96.5	99.7
Quadrants	77.8	82.7	83.7	77.8	84.9	84.2	95.5
Sweep	98.0	95.2	97.4	98.0	98.8	97.1	100.0
Dead	95.4	88.1	98.2	95.4	99.1	98.3	99.9
Multi-leaders	95.0	97.7	98.6	95.0	97.2	97.7	99.5