The fingerprint approach: Using data generated by a 3D log scanner on debarked logs to accomplish traceability in the sawmill's log yard

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Abstract

Technological advances in the area of optical scanning have made sophisticated equipment such as three-dimensional (3D) log scanners available to the sawmill industry. In a typical Swedish sawmill, the measurements obtained from the 3D log scanner placed at the log sorting station is used exclusively for scaling and sorting the sawlogs. In the same way, the information obtained from the 3D log scanner placed at the saw intake is used exclusively for optimal positioning of the sawlog into the headrig. Meanwhile, large knowledge gaps regarding the flow and the origin of the sawlogs persist in the sawmill's daily routine. For the Swedish sawmills performing presorting of sawlogs, the most critical information gap exists between the log sorting station and the saw intake, where the forest log batch identity disappears, and the logs are mixed according to various sorting criteria. This study attempts to use the data generated by 3D log scanners together with advanced recognition algorithms to develop a traceability system, marking/reading free, between the log sorting station and the saw intake when working with debarked logs. The originality of the fingerprint approach rests on the hypothesis that logs are separate entities with individual features. Measuring these features with the same type of measuring device at both the log sorting station and at the saw intake and then connecting the data to a common database will permit each individual sawlog to be tracked within the sawmill and will thus make it possible to develop an advanced raw material flow control.

Traceability is defined as the ability to trace the history and the usage of a product and to locate it by using documented identification (Töyrälä 1999, Lindvall and Sandahl 1996). Automatic traceability of products and information is present in our daily life, e.g., in the food chain, in car manufacture, in the supermarket, in the library, etc. Currently, multiple technologies exist for automatic identification (Töyrälä 1999), including bar codes, optical character recognition, vision systems, voice recognition, RFID (radio frequency identification), and magnetic strips. Automatic identification is used to support material flow control and quality control applications as well as on-line business-to-business applications (Wall 1995). The primary benefits of automatic identification systems are accurate information (origin, history), timeliness of data availability through the possibility of on-line data collection, and cost reduction through automation of manual data entry when doing checkouts and inventory (Cheng and Simmons 1994, Maness 1993).

In the forestry-wood chain, the concept and technologies of traceability are in a mature phase of development. Important advancements in marking and reading techniques have been made in different areas along the forestry-wood chain (Lycken et al. 1994). The need for log inventory control and the environmental chain of custody requirement for the raw material (Jordan 1996) have led to the development of different marking and reading techniques for logs (Uusijärvi 2000, Sorensen 1992, Stirling 1992). So far, all development efforts have focused on traceability systems based on the marking/reading technique, in which each log is physically marked and then followed. This is a very costly operation and requires extra equipment.

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and competence at different points along the forestry-wood chain. There is also a risk that these physical identifiers (optical marks, bar codes, RFID transponders, etc.) can be destroyed or lost, thus negatively affecting the security and the precision of the log traceability system. An original and interesting alternative for accomplishing log traceability within the sawmill at a substantially lower cost is to use the data generated by the log measurement equipment already in place (Astrand 1996, Aune 1995, Hagman 1993) to develop a marking/reading-free log traceability system, i.e., the fingerprint approach. Research regarding the potential application of the fingerprint approach on sawn boards is underway (Baetty et al. 1999).

The fingerprint approach for sawlogs

The originality of this nondestructive and inexpensive approach is based on the biological variability of the raw material (wood) and rests on the hypothesis that each sawlog is a unique individual with unique features (Bahar 1991, Fronius 1989). Measuring these features accurately at different locations within the sawmill and connecting them to a common database will permit logs to be followed within the sawmill and thus enable development of an advanced raw material flow control. This is an inexpensive operation and requires no extra industrial equipment.

The fingerprint approach applied to sawlogs has very good potential for implementation in the Swedish sawmill industry, as almost 95 percent of the sawmills practice presorting of logs (Nylinde et al. 1997). From the sawmill's point of view, the most important gap is located between the log sorting station and the saw intake, where the forest batch identity disappears and logs are mixed according to varying sorting criteria.

A previous study (Chiorescu et al. 2003), which attempted to use the data generated by two-axis log scanners, showed promising potential of the fingerprint approach for sawlogs and pinpointed the fact that the “unique log fingerprint” notion is strongly related to the equipment’s measurement accuracy, as well as to the type of recognition algorithm employed.

Study objective

The aim of this work was to study the premise of using the data generated by three-dimensional (3D) log scanners on debarked logs together with two different advanced search/recognition algorithms to develop a fingerprint approach-based traceability system for sawlogs between the log sorting station and the saw intake. Several issues were investigated in the study:

- evaluation of which and how many features are needed for separation of individual logs when using 3D log scanners;
- requirements for measurement accuracy for the 3D log scanner;
- evaluation of two different searching algorithms (tree-based searching and multivariate calibration combined with the nearest neighbor method); and
- the robustness of the fingerprint method with regard to influences such as rain, snow, ice, handling damage, and long storage time affecting the sawlogs.

Material and methods

The sawmill

The sawmill involved in this study is a large-sized mill located in the northern part of Sweden. The log supply consists of Scots pine and is rather stable from year to year in terms of both quality and size distribution. The logs come from a narrow area around the sawmill (approximately 150 km).

There are three main reasons for involving this sawmill in the study. The first one is that the sawlogs are measured under bark at both the log sorting station and the saw intake, which completely eliminates the measurement accuracy error due to bark thickness and bark damage. The sequence of log handling within the sawmill is:

1. The logs are unloaded from the truck and laid on a conveyor that passes them through the debarking machine;
2. The debarked logs are then measured with a 3D log scanner and the data are used for the sorting procedure of the sawlogs according to various criteria, e.g., diameter, length, and quality;
3. The logs are picked up from the different log bins from the log yard and laid on a conveyor that passes them through the 3D log scanner at the saw intake, and the data are used for optimal positioning of the sawlog into the headrig.

The second reason for conducting this study at this mill is that the debarked sawlogs are measured with the same type of measurement equipment, i.e., a 3D log scanner, at both the log sorting station and the saw intake. In this way, problems with measurement accuracy related to differences between measuring equipment and measuring and filtering procedures are eliminated.

The third reason is that the sawmill already has in place a well-functioning database system for recording and storing log measurement data from both the log sorting station and the saw intake. In the case that the fingerprint approach proves to be a successful concept, the three reasons described above qualify this sawmill as an industrial environment well suited for testing and on-line implementation of the fingerprint method.

The 3D log scanner

The sawmill involved in this study is equipped with two 3D log scanners of the same type (one at the log sorting station and another at the saw intake). The 3D log scanner is an optical system used for measuring log dimensions during longitudinal movement. The scanner is based on the infrared laser point triangulation technique and incorporates four measurement heads placed at 90° intervals. Each measurement head embodies several measurement units, thus providing a maximum of 230 measurement points/coordinates (for a log diameter of 500 mm) around each sawlog cross section. The relationship between the diameter of the log and the number of the measurement points/coordinates on the log mantle is shown in Figure 1. The resolution along the length of the sawlog is linked to the scanning rate, which is partly dependent on the speed of the feed conveyor, and varies between 10 and 30 mm (in this investigation, resolution was 10 mm).

The output from the scanner measurement is a full 3D dimensional profile of the outer shape and surface of the sawlog. Based on the log raw data, 27 different log parameters are generated and used for dimension or quality sorting and for scaling purposes.

Variables describing the log external shape

In this study, only nine log parameters were used to characterize each log individually. The nine parameters were chosen based on their robustness with re-
Figure 1. — The 3D log scanner’s inner relationship between the diameter of the log and the number of the measurement points/coordinates on the log mantle.

**Log database to be searched**

![Schematic representation of the TreeSearch engine, a tree decision-based recognition algorithm.](image)

Figure 2. — Schematic representation of the TreeSearch engine, a tree decision-based recognition algorithm.

gards to measurement. They are described below; the abbreviation for each variable, as used further in the tables, is given in parentheses:

- **Volume (V)** = the volume of the log calculated using the log’s scanned shape. Measurement unit is dm³.
- **Length (L)** = the length of the log measured during the longitudinal movement with the aid of an independent laser sensor which is fixed on the scaling frame. The length measurements are strictly synchronized with the diameter measurements performed by the scanner. Measurement unit is cm.
- **Area minimum diameter (amD)** = the area of the cross section which has the smallest diameter along the scanned shape. Measurement unit is mm².
- **Middle diameter (midD)** = the average diameter in the middle of the log. Measurement unit is mm.
- **Log taper (ITaper)** = value calculated by subtracting the butt diameter from the top diameter of the log and dividing by the log length. Measurement unit is mm/m.
- **Top taper (iTaper)** = value calculated by subtracting the top-end diameter of the log from the diameter 1 m from the top end and dividing by 1 m. Measurement unit is mm/m.
- **Bumpiness (Bump.)** = description of the surface roughness of a log expressed by the total number of bumps per meter. A bump starts when the actual diameter exceeds the filtered diameter by a certain threshold value. Measurement unit is bumps/m.
- **Relative taper (relTaper)** = value calculated by dividing the total log taper by the smallest diameter of the log. Measurement unit is %/m.
- **Bow** = parameter defined as the distance between the highest point of the log curvature and the line joining the centers of the log ends. Measurement unit is mm.

**Tree decision-based search algorithm (TreeSearch™)**

A special tree decision-based search algorithm, named TreeSearch™, was conceived and developed in order to conduct this study. The core code is written in the SQL (Simple Query Language) programming environment and represents a further development of the LogSearch code conceived in an earlier study (Chiorescu et al. 2003). A schematic representation of TreeSearch is given in Figure 2.

The search algorithm has a modular structure and encompasses four main phases (A, B, C, D) and 36 different steps (I...IX, I’...IX’, I”...IX”, and I”’...IX”’), i.e., each phase comprises nine steps. Each step runs a searching/sorting procedure by using one of the log variables at a time. The coupling between the step number and the log variable is given in Table 1, where each log variable is assigned a ranking number (I...IX) as given by the measurement accuracy test. First, the search is based on the most robust parameter (I) from a measurement accuracy point of view and continues with the other parameters in the order indicated in the robustness ranking list (Table 1). The first nine steps (I...IX) within Phase A successively execute the searching procedure based on the value of the searched parameter/variable (as measured at the log sorting station) and the corresponding interval of ± (4 x
The identification procedure starts with the TreeSearch identification algorithm as described in Phase A, Step I, the variable with the highest measurement accuracy (V) is used to narrow the search domain. In Step II, the variable with the next highest measurement accuracy (L) is used to narrow the results from Step I. In Step III, the results from Step II are further trimmed, and so on until Step IX. The same procedure is repeated in Phase B, whose starting base for the search is the results from the final step of Phase A, i.e., Step IX. The algorithm works in the same way through Phases C and D, after which the final search result is delivered.

Multivariate calibration nearest neighbor algorithm (MultivarSearch™)

In contrast to the TreeSearch identification algorithm that works with one log parameter at a time, the MultivarSearch™ algorithm works with all the log parameters simultaneously. The algorithm is built using the multivariate method called PCA (principal component analysis). Multivariate data analysis was used, as the PCA method can cope with nonindependent variables and with noise in the data, which is frequently the case when working with biological materials such as wood, with measurement processes, and with large data sets (Eriksson et al. 1999). For carrying out the PCA analysis, the software program SIMCA-P-9.01 was used.

SIMCA uses the unit variance (UV) scaling technique, which ensures that each scaled variable is given equal variance.

<table>
<thead>
<tr>
<th>Log diameter class limits</th>
<th>Number of study logs</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Small = 142 to 147 mm</td>
<td>254</td>
<td>32.8</td>
</tr>
<tr>
<td>Medium = 222 to 243 mm</td>
<td>256</td>
<td>33.2</td>
</tr>
<tr>
<td>Large = 299 to 540 mm</td>
<td>263</td>
<td>34.0</td>
</tr>
</tbody>
</table>

The PCA model was built on the data from the first measurement (M1) at the log sorting station. A matrix with \( x_{np} \) observations (in this case \( n_p = 773 \times 9 = 6,957 \)) structured in \( n \) lines and \( p \) columns forms the input data to the model. The \( n \) lines denote the number of logs (in this case \( n = 773 \)), and \( p \) denotes the number of variables describing each log (in this case \( p = 9 \)). The PCA technique looks for a few linear combinations that can be used to best summarize the input data matrix by losing as little information as possible in the process. These new linear combinations are described by new noncorrelated indices called principal components (PC), further abbreviated as \( t \). Thus, each PC is the linear combination of the variables \( x_{1p}, \ldots, x_{np} \), where \( t = t_1 x_1 + t_2 x_2 + \ldots + t_p x_p \), and thus a certain degree of economy is achieved because the variation in the \( p \) original variables is now accounted for by a smaller number of \( t \) variables, i.e., principal components. When a new observation/log, i.e., a log from a saw intake measurement (M2 or M3), is generated, then the log receives its own coordinates in the multi-dimensional space defined by the existing PCA model. Once this step is accomplished, another algorithm is built in order to find the nearest log neighbor to the new observation within the multi-dimensional space. This nearest neighbor algorithm is based on the Euclidean method; it calculates the Euclidean distance from each repeated observation (M2 or M3) to all the other 773 (M1) observations and automatically finds the so-called "nearest neighbor", which is in fact the final search result of the MultivarSearch algorithm.

Study approach

Altogether, 773 Scots pine (Pinus sylvestris L.) sawlogs were included in the study. The logs were chosen from three different log diameter classes, small, medium, and large (Table 2), in such a way that their external features extended over large intervals (Table 3). Each of the 773 logs was manually marked with a unique ID number on both ends using an industrial printer and special ink that withstands water and sun. On each log end, the unique ID number was applied two or three times, depending on the diameter of the log, in
order to increase reading accuracy, especially because of the mud present in the log yard.

During the period September–November, three different on-line measurements (M1, M2, and M3) were made on the study logs with the help of the 3D log scanner placed at the log sorting station. The measurement data generated by the log scanner was retrieved from the sawmill's database. During each measurement, the sequence of the logs through the scanner has been recorded manually, as well as tape-recorded, thus securing the accurate matching between the unique log ID number and the corresponding log measurement data retrieved from the sawmill's database.

The first measurement (M1) occurred after the debarking procedure, thus simulating the first two steps (S1 + S2) of the log-handling sequence described above. After the first measurement, the 773 logs were stored in the log yard for two weeks, which is the normal storage time for the sawmill involved in the study. At the end of the two-week period, the logs were measured for the second time (M2) thus simulating the third step (S3) of the log-handling sequence described. After the second measurement, the 773 logs were stored in the log yard again for another two months and then measured again (M3). The third measurement (M3) was intended to assess the potential of the fingerprint method when factors such as long storage time, rain, snow, ice, and handling damage affect the sawlogs.

Once the log data generated by the three measurements (M1, M2, M3) described were retrieved from the database and matched with the individual log ID numbers, the second phase of the study began. This phase focused on measurement accuracy and on the development of two different advanced search/recognition algorithms for the fingerprint method. The structure of both recognition algorithms was partly based on the results from the measurement accuracy test when factors such as long storage time, rain, snow, ice, and handling damage affect the sawlogs.

The approach used to conduct this study made workable three important things. Firstly, the two searching engines together with the measurement accuracy test were used to screen among the 27 log parameters generated by the 3D log scanner and to tackle the question of which and how many features are needed in order to achieve separation of logs at the individual level. The requirement for the measurement accuracy of these parameters was also tackled. Secondly, the study made possible the evaluation of two different searching/recognition methods: the tree-based searching algorithm (TreeSearch) and the multivariate calibration combined with the nearest neighbor method (MultivarSearch). Thirdly, owing to the measurement scenarios that were tested (M1-M2 and M1-M3), the robustness of the fingerprint method with regard to influences such as rain, snow, ice, handling damage, and long storage time affecting the sawlogs was tested.

Table 3. — External features of the 773 Scots pine sawlogs used in the study.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Volume</th>
<th>Length</th>
<th>anD</th>
<th>midD</th>
<th>fTaper</th>
<th>Bump.</th>
<th>rTaper</th>
<th>Bow</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(dm³)</td>
<td>(cm)</td>
<td>(mm²)</td>
<td>(mm)</td>
<td>(mm/m)</td>
<td>(bumps/m)</td>
<td>(mm/m)</td>
<td>(mm)</td>
</tr>
<tr>
<td>Minimum</td>
<td>0.07</td>
<td>335</td>
<td>131.00</td>
<td>155</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>5</td>
</tr>
<tr>
<td>Maximum</td>
<td>0.76</td>
<td>588</td>
<td>417.00</td>
<td>428</td>
<td>30</td>
<td>24</td>
<td>30</td>
<td>162</td>
</tr>
<tr>
<td>Min./Max.</td>
<td>0.09</td>
<td>0.57</td>
<td>0.31</td>
<td>0.36</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Mean</td>
<td>0.28</td>
<td>475</td>
<td>240.64</td>
<td>260</td>
<td>11</td>
<td>14</td>
<td>11</td>
<td>55</td>
</tr>
<tr>
<td>Median</td>
<td>0.26</td>
<td>478</td>
<td>239.00</td>
<td>257</td>
<td>10</td>
<td>15</td>
<td>10</td>
<td>50</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>0.16</td>
<td>43.32</td>
<td>74.58</td>
<td>73.38</td>
<td>5</td>
<td>4</td>
<td>5</td>
<td>26</td>
</tr>
<tr>
<td>Skewness</td>
<td>0.45</td>
<td>-0.33</td>
<td>0.05</td>
<td>0.08</td>
<td>0.73</td>
<td>-0.48</td>
<td>0.73</td>
<td>0.92</td>
</tr>
</tbody>
</table>

Table 4. — External features of the 51 Scots pine sawlogs used in the measurement accuracy study.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Volume</th>
<th>Length</th>
<th>anD</th>
<th>midD</th>
<th>fTaper</th>
<th>Bump.</th>
<th>fTaper</th>
<th>Bow</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(dm³)</td>
<td>(cm)</td>
<td>(mm²)</td>
<td>(mm)</td>
<td>(mm/m)</td>
<td>(bumps/m)</td>
<td>(mm/m)</td>
<td>(mm)</td>
</tr>
<tr>
<td>Minimum</td>
<td>0.08</td>
<td>370</td>
<td>46.00</td>
<td>157</td>
<td>4</td>
<td>4</td>
<td>4</td>
<td>18</td>
</tr>
<tr>
<td>Maximum</td>
<td>0.55</td>
<td>529</td>
<td>361.00</td>
<td>381</td>
<td>25</td>
<td>23</td>
<td>21</td>
<td>115</td>
</tr>
<tr>
<td>Min./Max.</td>
<td>0.15</td>
<td>0.70</td>
<td>0.40</td>
<td>0.41</td>
<td>0.16</td>
<td>0</td>
<td>0</td>
<td>0.16</td>
</tr>
<tr>
<td>Mean</td>
<td>0.26</td>
<td>477</td>
<td>226.03</td>
<td>245</td>
<td>11</td>
<td>15</td>
<td>9</td>
<td>54</td>
</tr>
<tr>
<td>Median</td>
<td>0.21</td>
<td>491</td>
<td>232.50</td>
<td>243</td>
<td>10</td>
<td>16</td>
<td>9</td>
<td>52</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>0.17</td>
<td>41.78</td>
<td>78.53</td>
<td>76.31</td>
<td>5</td>
<td>4</td>
<td>4</td>
<td>22</td>
</tr>
<tr>
<td>Skewness</td>
<td>0.58</td>
<td>-0.45</td>
<td>0.38</td>
<td>0.40</td>
<td>0.70</td>
<td>0.68</td>
<td>0.15</td>
<td>0.78</td>
</tr>
</tbody>
</table>

Results and discussion

The approach used to conduct this study made workable three important things. Firstly, the two searching engines together with the measurement accuracy test were used to screen among the 27 log parameters generated by the 3D log scanner and to tackle the question of which and how many features are needed in order to achieve separation of logs at the individual level. The requirement for the measurement accuracy of these parameters was also tackled. Secondly, the study made possible the evaluation of two different searching/recognition methods: the tree-based searching algorithm (TreeSearch) and the multivariate calibration combined with the nearest neighbor method (MultivarSearch). Thirdly, owing to the measurement scenarios that were tested (M1-M2 and M1-M3), the robustness of the fingerprint method with regard to influences such as rain, snow, ice, handling damage, and long storage time affecting the sawlogs was tested.

Table 4 presents a description of the 51 sawlogs used in the measurement ac-
accuracy test. The logs were chosen in such a way that their external features (volume, diameter, length, bumpiness, taper, and bow) extended as much as possible over very large intervals. Thus, the measurement accuracy results can mirror a realistic way the scanner’s ability to measure those parameters. Measurement accuracy (SD) for each of the nine log features (calculated on the log-level basis and between the five runs) is presented in Table 1. The ranking of the relative robustness of measurement is obtained after weighting the standard deviations within the five measurements (SD5) with the standard deviations among all 51 logs involved in the measurement accuracy test (SD51) (see Table 4). In this way, the measurement accuracy for each parameter is related to the variation of the parameter within the test. The ratio SD5/SD51 expresses, in fact, the measurement robustness for each parameter and is compatible in comparison with the other parameters, thus making possible the parameter ranking.

The robustness of each parameter is a way to quantify the potential role of a certain log feature within the fingerprint method. Earlier research work on the fingerprint method (Chiorescu et al. 2003) has shown that the notion of “unique log” is strictly related to the ability to measure accurately. Thus, in this study, the nine log features considered for future work with the fingerprint method were chosen based on the criteria of relatively high measurement robustness (SD5/SD51 was less than 38% for eight of the parameters and less than 65% for just one parameter). The two conceived search/recognition algorithms, TreeSearch and the MultivarSearch, were based on all nine log parameters (Fig. 2).

The most robust parameter from a measurement stability point of view is the volume of the log (rank 1), while the highest uncertainty occurs when measuring the bumpiness of the log (rank IX). The reason that the bumpiness parameter was kept for further work in the study despite a low robustness (SD5/SD51 = 62.5%) was that when running the searching/recognition algorithms together with the bumpiness parameter (additionally to the other eight log features), the individual separation rate could be increased by approximately 2 percent. One explanation for this might be that among the other eight parameters, bumpiness is the only feature that describes the unevenness of the log’s mantle. Furthermore, as a log’s mantle unevenness is very strongly influenced by the internal knot whorls, this further strengthens the hypothesis that the bumpiness parameter should be an important part of the “fingerprint equation”, and thus it was kept for this study. One reason for the low robustness of the bumpiness parameters could be that the filtering procedure that aims at sorting knot bumps from bark flakes, wood sticks, dirt, etc., has not been very successful. Another explanation might be that the log handling damage occurring during the measurement accuracy test primarily affects the bumpy parts of the logs.

Table 5 shows the fingerprint recognition results at individual log level, i.e., “unique logs” which could be correctly identified after running the two search/recognition engines (TreeSearch and the MultivarSearch) and for both measurement scenarios, i.e., M1-M2 and M1-M3. The values represent the average of the individual recognition rates from the three log diameter classes.

When using the first searching engine (TreeSearch), which works with one log parameter at a time, the percentage of correctly identified logs for the first measurement scenario (M1-M2) was as high as 87 percent. This means that with the given measurement accuracy of the 3D log scanner and the chosen searching engine, the rest of the logs (13%) could not be correctly identified. In the measurement scenario with influences such as rain, snow, ice, handling damage, and long storage time affecting the sawlogs (M1-M3), the percentage of individually separated logs decreased to 82 percent.

When using the second searching engine (MultivarSearch), which works with all log parameters simultaneously, the percentage of correctly identified logs for the first measurement scenario (M1-M2) was as high as 89 percent. In the second measurement scenario (M1-M3), the percentage of correctly identified logs decreased to only 86 percent.

An important aspect of the TreeSearch algorithm is that it has a tree decision-based structure. The risk with such a search strategy is that it works with only one criterion/parameter at a time, and thus, if one of the steps fails, then the whole search procedure will be negatively affected. Thus, the 2 percent superior recognition rate obtained using the MultivarSearch method was to be expected. It also seems that the multivariate approach is more robust with regard to climatic influences, handling damage, and long storage time than the tree-decision approach. The drop in recognition rate between M1-M2 and M1-M3 is only 3 percent when using the MultivarSearch engine, compared to a 5 percent drop when using the TreeSearch engine. From a practical point of view, the MultivarSearch algorithm could also be better suited to sawmill implementation, as it results in shorter search times, which is a crucial criterion for online applications.

Figure 3 illustrates the log recognition rates per log diameter class and the two measurement scenarios when using the MultivarSearch engine. The PCA model from the MultivarSearch engine was calibrated on all 773 logs, but the separation rates were now calculated separately for each diameter class. The results show that recognition rates are very different for different diameter classes: in the M1-M2 scenario, as many as 93 percent of the large logs were correctly identified, while the separation rate was just 81 percent for the small logs. Based on these values, it becomes clear that small logs are more difficult to separate than large logs. These results are in agreement with a previous study (Chiorescu et al. 2003) which also focused on the fingerprint approach. One reason for this might be the scanner’s ability to measure different logs based on their diameter (Fig. 1); the accuracy of the 3D-log reconstruction is linked to the number of laser beams “hitting” the log, which in turn depends on the log diameter. The larger the log, the more laser beams will “hit” the log, and thus, a more accurate description of the log shape will be obtained. Another explanation might be that for large logs,

Table 5. — The identification rate for the two searching algorithm and for each measurement scenario.

<table>
<thead>
<tr>
<th>Measurement scenario</th>
<th>TreeSearch</th>
<th>MultivarSearch</th>
</tr>
</thead>
<tbody>
<tr>
<td>M1-M2</td>
<td>87</td>
<td>89</td>
</tr>
<tr>
<td>M1-M3</td>
<td>82</td>
<td>86</td>
</tr>
</tbody>
</table>

*Identification rate obtained as an average for the identification rates in all three log class diameters.
which generally are butt logs, some feature(s) might be more distinctive than for small logs. Such a feature might be butt taper or ovality, but it is still quite difficult to say exactly if there is one, two, or a specific combination of parameters that make large logs easier to identify than small logs.

Figure 3 also shows that the recognition rate in the M1-M3 scenario decreased by only 1 percent (to 80%) for the small logs, compared with a decrease rate of 3 percent (from 93% to 90%) for the large logs. In other words, the recognition rate for small logs was less affected by climatic conditions, handling damage, and long storage period than it was for large logs.

When considering the results of this work, the reader should be aware of the limited number of sawlogs (773) used in the study. This puts a certain limitation upon the results, despite the fact that the logs studied were chosen in such a way that their external features extended over large intervals as much as possible (Table 3). Thus, further studies on the fingerprint approach should work with a larger number of logs and spruce logs should also be studied. The biggest problem when conducting such studies is that the individual log ID-marking and the reading of the log sequence through the scanner has to be done manually. This is a very time and money consuming operation, very susceptible to errors, which also limits the number of logs that can be used in the study. Thus, further studies should try to take full advantage of other kinds of marking techniques and even automation of the reading process (Uusijärvi 2000).

Relative to the fingerprint method's implementation possibilities, the reader should also be aware of the measurement scenario that characterizes the sawmill involved in this study: the sawlogs were measured both at the log sorting station and the saw intake under bark. This means that the negative influences of bark thickness and bark damage on log measurement with the 3D log scanner (Chiorescu and Grundberg 2001) were not covered in this study. However, almost 99 percent of the Swedish sawmills (Nylander et al. 1997) practice a measurement scenario that involves the negative influences of the bark on the measurement procedure. Therefore, further work should also include the measurement scenario of sawmills where the sawlogs are measured over bark at the log sorting station and debarked at the saw intake.

Conclusions

The results of this study are in line with earlier research results and emphasize the promising potential of the fingerprint approach for tracing logs within the sawmill with the aid of the measurement data generated by 3D log scanners. The notion of "unique log" is highly dependent on the equipment's measurement accuracy and the type of recognition algorithm employed. The results also pinpoint the robustness of the fingerprint approach with regard to the influence of climatic factors such as rain, snow, ice, handling damage, and long storage period.

The approach employed in this study made it possible to compare two different recognition algorithms. It was shown that the searching engine based on multivariate calibration and the nearest neighbor method (MultivarSearch) gave a 2 percent better recognition rate than the tree decision-based searching engine (TreeSearch). When running the MultivarSearch engine, the average recognition rate for the 773 studied logs was 89 percent. It appears that large logs are easier to recognize (93%) than small logs (81%). However, small logs appear not to be as sensitive as large logs to climatic influences, handling damage, and long storage.

Future work should study the robustness of the fingerprint approach within a sawmill measurement scenario where the negative influences of bark (thickness and damage) are reflected on the 3D log measurement. Future work should also test how the results from this study would be influenced if a larger number of logs were taken into consideration. In order to do so, advantage must be taken of more automated marking/reading techniques for individuals logs.

Literature cited


