# A Fast and Continuous CT scanner for the optimization of logs in a sawmill

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**Abstract**
CT Log is a CT scanner used in an industrial process at very high speed in order to optimize the production of wood boards and other wood products. The scanner can reach 160 m/min, the typical speed at which wood logs are sawn in the sawmills. After the logs pass though the scanner, the images are reconstructed and processed in order to allow the automatic optimization of the cutting pattern according to the constraints set by wood defects and the value of the different products.
Building a a buffer between the scanner and the sawing line is expensive and often not possible because of constraints on the plant layout The time available for the entire processing is therefore very short, because it must be completed before the log reaches the breakdown equipment. In this paper, we present the structure of the scanner and the way we implemented the different stages of processing in order maximize the speed of the elaboration.

**Keywords: CT scanning, X-ray scanning, Virtual cut, Industrial CT scanner, Sawmill industry, Cone beam tomography, Convolutional neural network**

## 1 Introduction

The process of extracting wood products from logs is one of the oldest tasks performed by men, but it is still a complex procedure due to the natural variation of wood. Every log contains a high number of characteristics that can become a defect after sawing. Knots, resin pockets, pith, compression wood and many other features can degrade the quality of a board or a veneer and it is usually impossible to detect them before cutting the log. A real optimization of the sawing process requires necessarily a scanner able to detect in advance all the internal characteristics. Many studies were done to demonstrate the possibility of detecting the features of a log with a CT scanner since the '80s [1], but the feasibility and the cost of a scanner working at the required speed deemed this approach as not applicable to the industry.
In 2008 Microtec, an industry leader in scanners for the sawmill industry, began a project with the goal of building a CT scanner with the characteristics required for the industrial process and the ability to optimize the sawing process of each single log based on its internal features [2]. One of the aims was a system that could be installed just before a sawing line in order to optimize the cut of the logs at a typical speed of 160m/min. In this paper we will report the solutions we adopted at every step of the process in order to obtain a fully automated optimization system that works even positioning the scanner at small distance from the sawing line.

## 2. The scanner: material and methods

The speed of a big sawmill for softwood can often reach 160m/min and most of the logs are smaller than 70cm in diameter, but sometimes they are not straight so the tunnel of transportation must be even bigger. For these reasons the main geometrical constraints required for this kind of scanner are a field of view of 90cm and a transportation speed of 160 m/min.
To achieve this speed we have realized a cylindrical array of sensors with length of 752mm and width of 1670mm. One advantage of the application is the relatively low resolution needed, especially in the longitudinal direction. Most of the internal features of a log are, in fact, built along its longitudinal axis, meaning that a high resolution in that direction is not strictly needed. Our design goal was to build an array of sensors with a pitch of 2.2mm in transversal direction and 16mm in longitudinal direction.
The solution was found in building single modules with 32 x-ray sensors each with lead collimators mounted. Every module of 32 X-ray sensors is made of a crystal scintillator array for x-ray to light conversion, a photodiodes array for light to current conversion and 24-bit ADCs for the digitalization of the analogue signals. The maximum sampling frequency is 3000 Hz. The digital data are collected by a two-levels hierarchy of electronic boards and transmitted by a contactless data transmission link to the stationary part. The sensor boards and collector boards were all developed in house. The sensor matrix is constituted of 1081 modules with 32 sensors each. The sensors are mounted on a gantry rotating at 240rpm.

| | |
|---|---|
| Scan speed | 60-160 m/minute (1-2.7 m/sec) |
| Operating times | 24/7 |
| Maximal scan diameter of the log | 70cm(depending on wood density) |
| X-ray tube voltage and current | 200kV 14mA |
| Field of view | 90cm |
| Transversal resolution | 1 mm |
| Longitudinal resolution | 1 cm |
| Cone beam angle | 25° |
| Centrifugal force at the x-ray tube | 64g |
| Maximal rpm of the gantry | 240 |

Table 1: technical specification of CT Log.

## Tomographic reconstruction

The data is sent to a computer, which applies to the projections the beam hardening compensation, adaptive filters to reduce the noise when needed and the reconstruction algorithm. The beam hardening compensation is easier when scanning wood with respect to other applications thanks to the fact that wood is mainly made of carbon and water, which have a very similar absorption spectrum in the used range of energies.

Due to the high amount of data, a compression schema was required in order to cope with the limited bandwidth of the contactless data link. The control board firmware does the dark compensation on the attenuation signal, computes the logarithm and then send the value encoded as 12 bit floating point number. This simple algorithm achieves a compression factor of 40% without any visible artifact on the reconstructed image.

Since the main requirement was the implementation of a reconstruction algorithm sufficiently accurate and fast, the Katsevich algorithm [3] has been chosen for this. In the specific case it is not possible to expect a perfect spiral trajectory of the scanner, the first reason is that the speed of the conveyor can not be assumed constant (due to, for example, log accumulation in the final part of the production line), while the speed of the gantry cannot change quickly due to the inertia. A second reason is that sometimes the logs are not sufficiently stable on the conveyor and sideway movements are possible during the scan.

For this reasons we chose to implement the version proposed in [10], where different trajectories of the scanner can be applied. In particular, the trajectory can be modeled as a standard spiral movement plus a rigid body motion with 6 degrees of freedom. The computational complexity of the reconstruction is very similar to the standard helix if the rigid body motion is limited to 4 degrees of freedom, assuming that the only possible rotations are along the axis of the scanner. Since this is the typical situation for a wood log moving on a belt conveyor, we implemented a reconstruction algorithm considering only translation in the 3 possible directions and rotation along one axis.

Usually a CT scanner acquires all the data of a scan and does the reconstruction of the whole volume when all the data is available. In order to reduce the space needed between the scanner and the sawing line this was not an optimal solution because it required to wait for the whole log to pass through the scanner before starting the reconstruction. In our implementation we preferred to create a continuous reconstruction scheme where the projections enter in the system, are filtered and back-projected. As soon as a new slice of reconstructed volume is ready (i.e. does not need any more back-projections), it is passed to the next stage of the system for the elaboration. In this way, we have a continuous stream of projections that are received from the sensors and a continuous stream of reconstructed slices that is sent to the image processing stage. In such a way, logs can be continuously processed even if they only have a small gap between them in the conveyor.

The filtration and back-projection of each new projection requires the knowledge of the past and future trajectories of the scanner/object system. In a simple helical trajectory, this can be assumed as known but in the general case the filtration of one projection cannot start until the acquisition of the future positions is complete. The amount of rotation needed is between half revolution and a full revolution: more precisely the minimal rotation is $\boldsymbol{\pi + 2 \cdot \mathrm{asin}\left(\frac{r}{R}\right)}$ where r is the radius of the field of view and R is the distance between the source and the axis of rotation. One slice of volume is complete when all the needed projections are backprojected, i.e. all the voxels with a certain z coordinate do not project any more in the Tam-Daniellson window (we assume the z axis parallel to the axis of rotation). This requires always less than one revolution from the moment when the voxels had the same z coordinate of the source. Therefore we can then always be sure that one slice of reconstructed volume is ready after 2 revolutions of the gantry from the moment when the slice passed the center of the gantry.

We implemented the algorithm on a computer with 3 Nvidia GTX1080 GPUs in order to do the filtered back-projection at 1600 projections per second. At the translational speed of 160m/min and rotational speed of 240rpm the helical pitch is 666mm, which means that each slice of the volume is reconstructed about 1.3 m after it passes the center of the scanner, equivalent to 0.5sec.

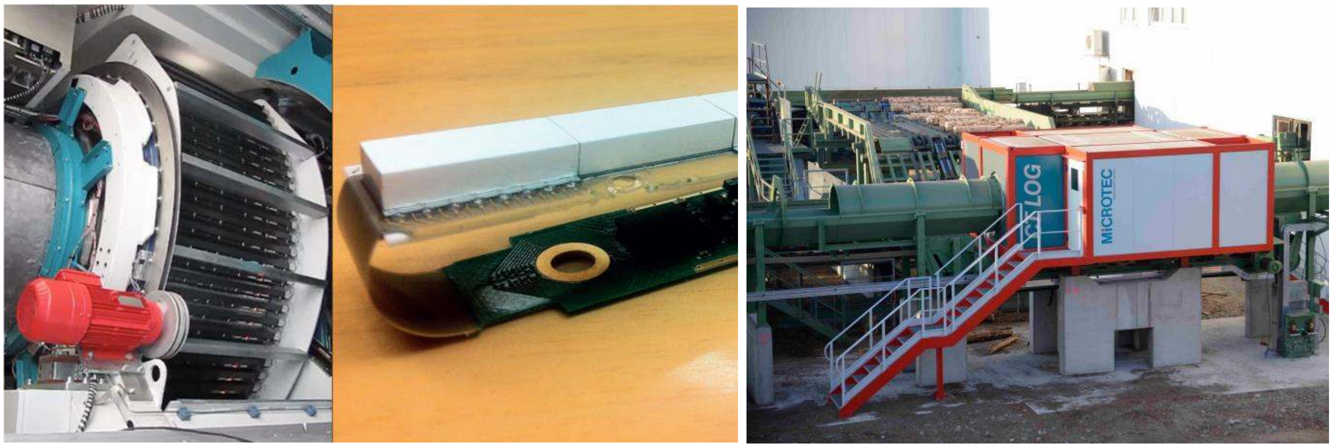


Figure 1 - Internal view of the scanner, with the sensors mounted on the black bars in the gantry (left); one of the sensor modules developed by Microtec (center); one of the sawmill installations of the scanner (right).

## Image processing

Typically a sawmill processes about 10 logs per minute: it is therefore impossible for an operator to analyze manually the CT images and decide the best solution. For this reason, algorithms for the automatic detection of the main features of a log where developed by exploiting state-of-the art approaches [4,5,6,7] and by customizing many of them in strict collaboration with the authors themselves.

Most of the structure of a log is built around the pith, the center of the year ring. For example, the knots and most of the cracks start from the pith and are oriented in radial direction, while the year rings, the ring shakes, and the resin pockets are oriented along circles around the pith. The detection of the pith position is done by applying a Hough transform on each slice (see Figure 2). Additional regularization filters forcing the continuity along the axial direction of the log are applied in order to consider that the pith is usually a regular curve with the exception of specific points where the top of the tree was broken [12].

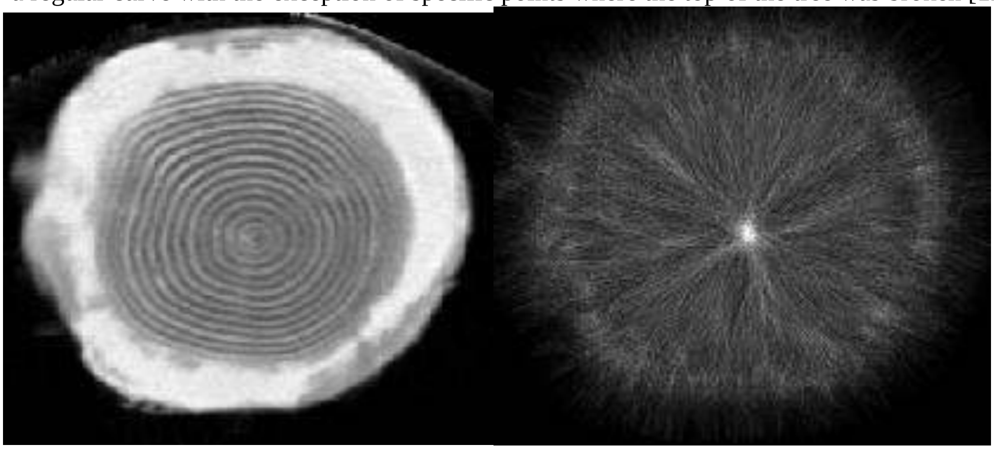

Figure 2 – Example of Hough transform used to estimate the position of the pith. On the original image (left), the gradient is calculated around each pixel. Along the direction of the gradient, a line is plotted on the map with an intensity proportional to the magnitude of the gradient. The accumulation of all the lines creates the map on the right, where the pith position is easily detectable.

The most important feature in each log is the knots detection, localization and estimation. The knots can be roughly described as cones with the top on the pith extending radially toward the outer surface of the log. In the central part of the log (heartwood), the density of the knots is higher than the sound wood. In the external part of the log (sapwood), the density of knots and sound wood is very similar but the texture of the image is often different.

We divide the knots detection in two steps. The first step creates concentric surfaces around the pith [7]: in the concentric surface extracted from the heartwood, the knots appear as white circles. By detecting and connecting the intersection of the knots with the concentric surfaces, we define a starting point and a main direction for each knot.
For the second step of detection, we extract a volume around each knot of size 128x64x8 pixels, where the third dimension is parallel to the axis of the log and the second dimension is orthogonal to the axis of the knot. The pixel size is 1mm in the first two dimensions and 10mm in the third. The images are processed with a Convolutional neural network (CNN) (e.g. [11]) that have the advantage of being suitable for parallel implementation. By iteratively convolving the input image with different learned filters and i rescaling the feature maps (i.e. result of each convolution), the network produces an output with the same size as the input, with the scaled probability indicating the presence of a knot as value.

In order to train the CNN, more than 5000 knots (and their respective volumes) were manually marked on available CT images. The scaled probability volumes from the CNN are processed in order to extract the parameters describing each knot, using a parametrization similar to [5]. In Figure 3, we show an example of images of knots with the knot manually defined by an expert and the automatic detection of the CNN.

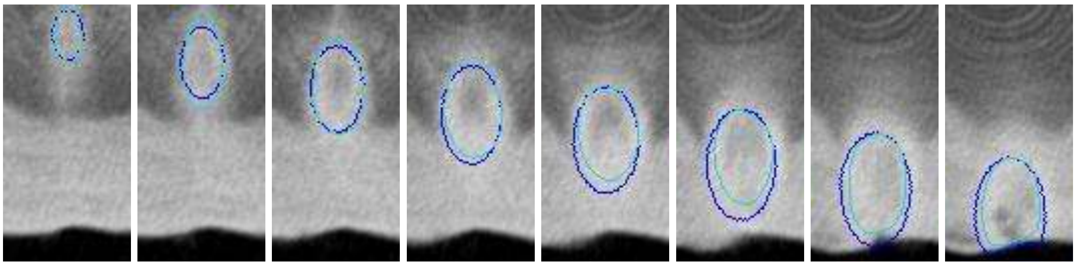

Figure 3. Eight layers of the image of a knot with superimposed in dark blue the manual ground truth and in light blue the thresholded output of the neural network.

The processing of a log of 6m length in a computer with one GPU requires about 25 seconds, during which the log would cover almost 70 meters. To reduce the required time of at least a factor of 10, the algorithm had to be parallelized on multiple computers. It is not possible to divide the log in ten pieces and process each independently because many features (like long knots or cracks) can cover a long part of the log and having the possibility to analyze each feature completely is important to obtain a good result. For this reason we pass the whole log to 10 computers in parallel, each one calculate the pith position and identifies all the knots (step 1), which is a fast computation. For the volume extraction and parameters computation (step 2), each computer analyze only a predefined set of knots and the results are merged. Two additional computers are devoted to the detection of the other minor features (sapwood border, resin pockets, cracks, ring width, blue stain, metal inclusions and bark). With this solution, it is possible to process a log 6 meters long in about 2.3 seconds.

## Cutting pattern optimization

The fact that all the logs have different characteristics is usually a problem, but can also be used as an advantage as long as the different wood products also have different quality standard requirements. For example, boards with big knots do not have good static properties if used as construction timber, but a board with one big sound knot can be sold at the maximal price in the flooring market . The problem is that different markets require different size of the boards: for example if a board for construction timber is sawn with a dimension of 2”x4”, it is then not possible to sell that board for flooring since that dimension is not required. With the optimization software developed for the scanner it is possible to define the quality, dimension and price of the different products of the market. The software proposes a high number of different combinations of boards and intersects their position with the outer shape of the log and the model of all the internal features extracted with the image processing steps. This process creates 3D “virtual boards”, i.e. models of boards with all the features that appear on their surfaces. The optimizer software can apply the quality rules to each virtual board, calculating its potential sell price. For each log, many thousand of virtual boards have to be simulated and evaluated in order to verify the different possible cutting pattern and choose the best one.
A first step of the optimization identifies the combination of boards that are compatible with the outer shape of the log, a second step calculates the value of the boards of the different combinations.
The parallelization of this process is easy since the main computational cost is the evaluation of the grade and value of each board. In the current solution 84 parallel threads are distributed in 12 computers with an Intel i7 processor in order to optimize a log in 1 second, processing about 10,000 virtual boards.
With such processing, value of the production can increase by 5% - 20% [8,9].

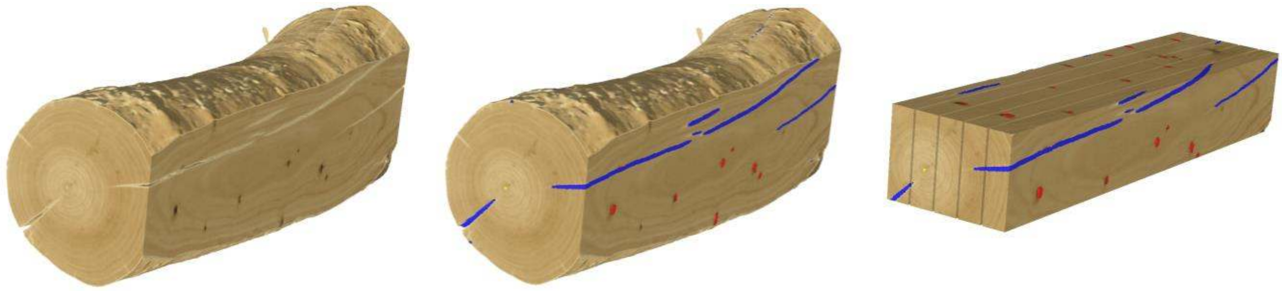

Figure 4 – Example of CT reconstruction (left) feature extraction (center) and creation of virtual boards (right)

## 3. Conclusions

We have described our implementation of a CT scanner able to process the data and to optimize the production at the speed of 160 m/min. Table 2 records the times needed by the different steps of the system. The first step considers the maximal length of the log, typically 6m, because we calculated the space from the moment where the whole log has passed the center of the scanner.

| Step | Time (s) | Space (m) |
|---|---|---|
| Passage of the log with maximal length | 2.25 | 6 |
| Tomographic reconstruction | 0.5 | 1.33 |
| Image processing | 2.3 | 6.13 |
| Cutting pattern optimization | 1 | 2.66 |
| Total | 6.05 | 16.1 |

Table 2: time and space needed between the scanner and the final optimization of a log at 160m/min.

Within the timespan of 3.8 seconds the system is able to reconstruct, process and optimize logs in an industrial process. This means that it is possible to install the sawing line at 16.1 meters from the center of the scanner.
Five installations of CT Log are already installed and working. One new installation, based in the framework presented in this paper, will be started in Sweden during January 2018.

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