Neural Networks for color image segmentation:

Application to sapwood assessment

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***Abstract*— This paper presents a method for detecting sapwood in hard wood such as cherry and maple. In the wood industry most applications need aesthetical boards. Thus the sapwood area on the board has to be detected as a defect region and be removed. To achieve this process, we classify the regions of the wood into two groups, by using neural networks techniques: sapwood is classified as a defect region while heartwood is considered as a good region. The use of neural networks by properly tuning the input vector provides a high defect detection rate with a low false positive rate.**

Keywords-component; color image; neural network; segmentation; classification; sapwood; heartwood

I. INTRODUCTION

To improve the quality of wood in the wood industry, many inspection techniques are employed such as Automated Visual Inspection Systems (AVIS). A review of these AVIS shows that image segmentation is the most important task in the entire process of inspection, in order to properly identify defects [1-4]. In this process an image is divided into homogeneous regions with respect to certain features. Image segmentation can be achieved in various ways such as: histogram thresholding, region-based approaches, edge detection, hybrid methods and neural networks learning [5-10].

The evaluation of the performance of AVIS is based on the percentage of good detection and false detection. Moreover a good AVIS must have a high percentage of good detection and a low percentage of false detection while offering robustness over the change of color and texture and dirty stain (false defects) on the board under inspection. In addition, this AVIS has to minimize the time allocated to the process: in the factory the detection must be done in real time and this is not usually possible because image processing software takes time.

Our approach is to show how we obtained an AVIS that minimizes the limitations presented above and gives a good result for sapwood detection with a low percentage of false detection. The proposed architecture and the training of the neural networks over various samples of cherry boards showed a very good rate of sapwood detection.

This paper is organized as follows: section 2 describes the Image acquisition system, section 3 presents an overview on neural networks, section 4 describes material and methods used, section 5 presents experimental results and finally, the conclusion is provided in section 6.

II. IMAGE ACQUISITION

Various methods of image acquisition have been proposed to enhance the contrast between sapwood and heartwood. Arnerup [11] used an Infra Red camera to enhance this contrast but his excellent work was conducted under ideal conditions and focused only on Scots pine trees. Kaestner [12] tried to polarize the microwave radar in order to produce similar images since the dielectric properties of wood depend on moisture content. However this method was found to be suitable for detecting wood defects rather than contrast enhancement and was not implemented in practice.

For our acquisition system we first tried to measure the heartwood and sapwood reflectivity according to the wavelength in order to choose a camera that responds better to the corresponding suitable wavelength to enhance the contrast. As this approach was very costly we chose to use a three CCD camera and illuminate the piece of wood with a fluorescent lamp Fig. 1. The use of a three CCD camera leads to good quality RGB channels and avoids blurry image contours.

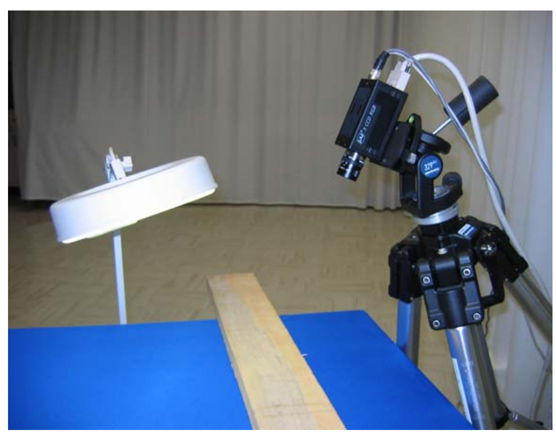

Figure 1. Camera setup.

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III. NEURAL NETWORKS OVERVIEW

Various techniques of color image segmentation on plants have been proposed: Arnerup [11] used a Hopfield neural network adaptive thresholding combined with edge detection algorithms to measure the heartwood content on Scots pine trees. Foucher, Revellon and Vigouroux [13] used a neural network called Multilayer perceptron (MLP) to detect plants from the ground, by considering the neighboring of the RGB value of pixel as an input layer vector. As the neural networks are widely used with plants, they were found to be good candidates for our color image segmentation problem. We first explored the MLP that uses the backpropagation algorithm to minimize the learning error and we compared it to another algorithm called Learning Vector Quantization (LVQ).

A. Multilayer Perceptron

The MLP is a parametric technique to approximate a vector function of some input with a series of layers [14]. Each layer has a weight matrix W, a bias vector b and an output vector a. The output equation of every layer is described in (1).

$$a^k = f^k\left(W^k a^{k-1} + b^k\right) \text{ for } k = 1 \ldots M \qquad (1)$$

Where M is the number of layers. To approximate the function, the network must be trained in order to adjust its weights.

B. Learning Vector Quantization

The LVQ is a hybrid neural network for training competitive layers in a supervised manner; it is a variant of Kohonen's networks: the Self-Organizing Map (SOM). The competitive layer consists of a neural map where neurons are spread out according to the form of data. This network is called competitive because the classification is done according to the distance (neighbors) between input vectors [15].

IV. MATERIAL AND METHODS

The wood images were captured in RGB format by using a three CCD camera. Therefore every single image had 256 levels (8 bit) of light intensity. In addition the camera was adjusted for white balance and the resolution was set to 1024 X 775 for the best quality.

To build the input vector for our neural network we divided our image into a customizable square grid. Traditional methods use histograms (HIST) to feed the network for example every grid of a 24 bit image has 3 histograms, each for a 8 bit color space channel. The other method involves a vector of pixels (PIX) in the grid; by way of illustration an input vector of a 5 x 5 square grid has 125 values (25 x 3). The first attempt was to use pixels of the grid to build our input vector. It is obvious that as the grid becomes larger and larger the input becomes so large that the training becomes impossible.

The alternative attempt arose after noting that the peak of every color channel histogram, whether it was Hue Saturation Value color space (HSV) or Red Green Blue (RGB) color space, moved according to the type of wood region (sapwood, heartwood or dirty strain). We chose to feed our network with the histogram peak values on the abscissa and ordinate axis. For instance in Fig. 2a, the input vector would be a vector of six elements [70 200 105 150 118 176].

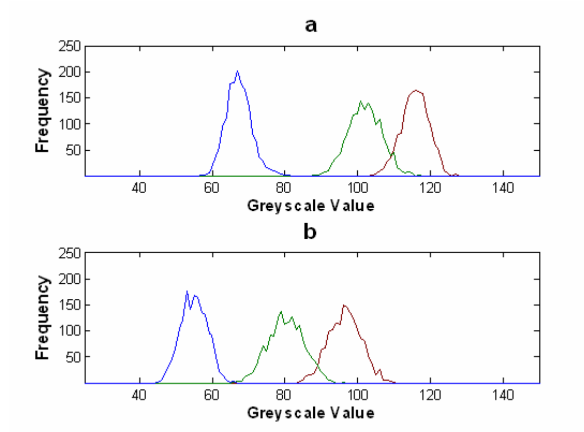

Figure 2. Histogram peak mouvement a) Sapwood b) Hearwood.

Although the input vector was simplified, it became evident that the neural networks must be able to distinguish more clearly between the different regions. Inspired by a human eye that uses neighboring tiny grids to grow and classify regions, we improved the input vector by drawing a circle around every grid Fig. 3. After choosing the radius of the circle in terms of the grid and the number of neighbors wanted, the input vector was created. For example if the radius is equal to 2 grids by considering 4 neighbors, then the input vector will have five grids (4 neighbors + current grid). This leads to a vector with 30 elements.

Yet a problem remains on the image contour neighboring grids cannot be used. To solve this problem, every image is extended according to the radius of the circle in terms of the grid. The new grids are then filled with the pixels of the grids on the contour and finally the grids on the four corners are filled with the pixel values of the image intensity average.

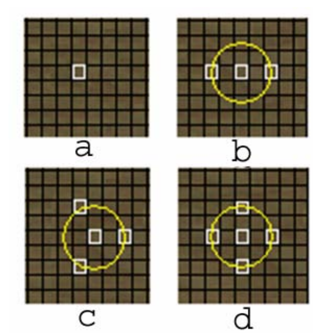

Figure 3. Neighbouring grids:
a) 0 neighbour and 0 as radius b) 2 neighbours and 2 as radius
c) 3 neighbours and 2 as radius d) 4 neighbours and 2 as radius.

Consequently with this tuned input vector we proceeded with the training, and the image database was divided into 2 sets: 70% for the training set and 30% for the testing set. Furthermore, to determine the numbers of hidden layers and the corresponding neurons, different simulations were ran to choose a network that responds best. But the simulations did not show a big difference between networks with one hidden layer or more. After that, the threshold was set to classify results from the output layer into two groups: the sapwood and the heartwood.

V. EXPERIMENTAL RESULTS

The two neural networks MLP and LVQ were simulated on a 3.4 GHz Pentium IV with 1 GB of RAM and both training and testing phases were considered to evaluate the results.

During the training phase, the network accuracy was defined by the percentage of the trained data that met the classification according to the target out of all trained data as presented in (2).

$$\text{Accuracy}_{\text{learning}} = \frac{\text{Trained data corresponding to the target}}{\text{All trained data}} \quad (2)$$

During the testing phase we summed up all the regions presented in the testing images and evaluated the network according to the region detection response. The final results are summarized in Tab. I after gathering all possible neural network topologies and all three network responses: correct detection (CD), false detection (FD) and partial detection (PD) as pictured in Fig. 5-7.

TABLE I. TRAINING AND TESTING RESULTS FOR DIFFERENT NEURAL NETWORK TOPOLOGIES

Topology	Algorithm	Color Space	Input Structure	Input Radius	Input Neighbors	Training Accuracy	Correct Detection	Positive Detection	False Detection
1	MLP	HSV	HIST	0	0	90.6%	74.1%	18.5%	7.4%
2	MLP	HSV	HIST	3	3	95.1%	74.1%	22.2%	3.7%
3	MLP	HSV	HIST	3	4	94.6%	74.1%	22.2%	3.7%
4	MLP	RGB	HIST	0	0	90.0%	70.4%	22.2%	7.4%
5	MLP	RGB	HIST	3	3	94.7%	70.4%	25.9%	3.7%
6[a]	MLP	RGB	HIST	3	4	95.0%	77.8%	22.2%	0.0%
7	MLP	V	HIST	0	0	59.3%	59.3%	40.7%	0.0%
8	MLP	V	HIST	0	0	83.4%	55.6%	37.0%	7.4%
9	LVQ	HSV	HIST	3	3	39.1%	66.7%	33.3%	0.0%
10	LVQ	HSV	HIST	3	4	37.6%	63.0%	37.0%	0.0%
11	LVQ	RGB	HIST	3	3	34.8%	66.7%	33.3%	0.0%
12	LVQ	RGB	HIST	3	4	36.1%	63.0%	37.0%	0.0%

a. The best topology

The results above lead to the following observations:

- Both training and testing accuracies increase when all three channels of RGB or HSV space are used while using the same algorithm as shown in Tab. I with topology 1,4 and 7.
- Both training and testing accuracies increase when the input vector by considering neighbors as shown in Fig. 4.

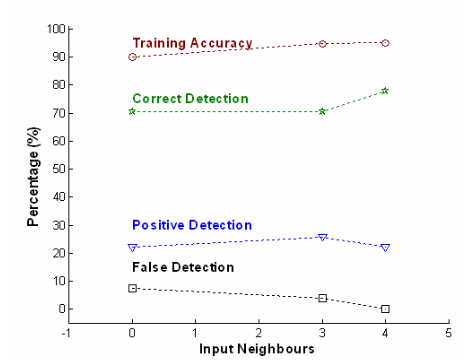

Figure 4. Input neighbours effect on the neural networks topology 4,5 and 6 in Tab. I.

- The MLP algorithm has both better training and testing accuracies over the LVQ algorithm as it is shown in Tab. I.
- The LVQ algorithm was able to solve some problems a MLP could not solve, for some testing wood; it did not lead to any false detection at all.
- The best and proposed topology as shown in Table 1 is the topology 6 using the MLP algorithm, while the input vector is built using the histogram of the grid of all three RGB channels, with 4 neighbors and 0 as a radius.
- As has been noted, the number of neurons for hidden layers did not change the training accuracy significantly. For example for a MLP network with 3 neighbors and radius 3 as input vector the mean was 93.9% and the variance of 0.9% while changing the number of neurons of the first two layers. With LVQ of the same input vector structure, the mean was 35.2% and the variance of 0.7%.

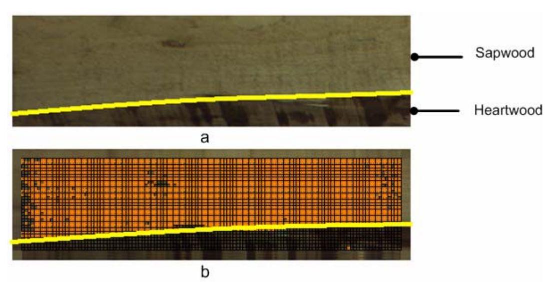

Figure 5. Correct detection example: a) Original picture with 2 regions b) Sapwood detected. In this example RGB colour space.

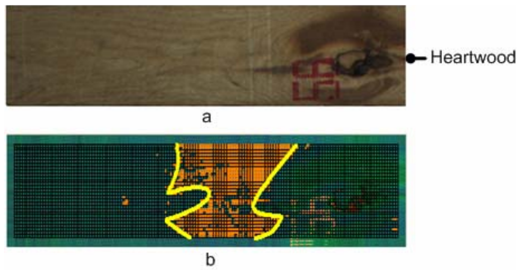

Figure 6. False detection example: a) Original picture with 1 region b) Sapwood detected while absent. In this example HSV color space is used.

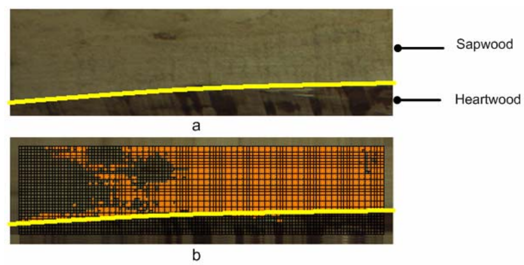

Figure 7. Partial detection example: a) Original picture with 2 regions b) Sapwood detected partially. In example RGB colour space is used.

VI. CONCLUSION

In this paper a new method for color image classification based on neural networks is proposed. The algorithm is tested on cherry board for detecting the sapwood as a defect region in the wood in the factory. The result of the proposed method is achieved with an average percentage of good detections of over 73 % and an average percentage of false detections of around 4 %. This represents a significant improvement in comparison to previous primary tests conducted by the company Ixode Technologies.

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