# Modular Structure of Neural Networks for Classification of Wooden Surfaces with PLC Industrial Implementation

Irina Topalova
Automation of Discrete Production Engineering
Technical University of Sofia
Sofia, Bulgaria
itopalova@tu-sofia.bg

Alexander Tzokev
Automation of Discrete Production Engineering
Technical University of Sofia
Sofia, Bulgaria
alextz@tu-sofia.bg

***Abstract*—This paper presents development and research results, applying new approaches and means to the design of Modular Structure of Neural Network for classification of wooden balks (MSNN). It is based on machine vision, unified recognition algorithm and modular neural network structure for real time operation in a standard Programmable Logic Controller (PLC). MSNN is modular, which provides possibility for constructing different structures using in parallel many neural network function blocks with different topologies. It includes development of decision making method for obtaining high recognition accuracy in texture classification using histograms as input data. The method simplicity combined with the modular performance contributes to fast computations and high flexibility of the proposed system. The modular MSNN, containing standard functional blocks, can find application in different applied science fields.**

***Keywords – texture classification; machine vision; automation; PLC.***

## I. INTRODUCTION

The main disadvantage of the processes at the enterprises for production of high quality wooden items is the lack of objective quality control on the textures of the used wooden balks before any further treatment process. The identification of the type and quality of the balks is accomplished through subjective assessment, which leads to a lower material utilization factor and lower the quality of the produced items. There is a demand for automated visual control, which should include the recognition of defects within the whole range of produced surface structures and their classification. This will result in optimized cutting up and fitting of the produced parts. The international state-of-the-art shows that the company “Michael Weining-Technowood” Ltd, Germany [1] is the leading producer that has introduced in the woodwork a method for texture quality automated control applying optical scanning of the surface and cutting optimization with defects elimination. The firm has not developed automated selection of wood balks with different textures in the process of wedge-shaped splicing, as well as it offers complete technological equipment at a very high market price. In this case, the use of different visual sensors does not contribute to the unification of the used methods for recognition. The system is developed in accordance with the specific equipment, available at the company.

### A. *Current state of similar approaches*

Most research in the wood product industry has been applied in the development of automatic visual inspection systems for the purpose of grading and edging based on the quality of the wood and the presence of defects. These technologies use devices such as ultrasound, microwave, laser ranging, cameras and spectrometers, which are rather expensive. Another wood classification system based on several multi - layered - perceptron (MLP) neural network models has been developed [2]. The MLP structure has been trained by the authors, using 20 input features (Angular Second Moment, Contrast, Correlation, Inverse Difference Moment, Entropy, etc., for five different image rotations), extracted from the texture. In this case, the authors have obtained 1sec overall computation time and 95% accuracy. The main difference considering our approach is the obtained 679 ms computation time and the implementation of the method in standard industrial PLC. Another method [3,4] for defect detection in textured wood surfaces relies on the analysis and fusion of image series with variable illumination. This method can be considered as filter-based, where the filters or feature detectors are learned from a set of training surfaces. It spends 0.5 to 1.6 seconds to process an image of 256x256 pixels and is tested in MatLab.

### B. *Motivation for the research*

Considering the existing texture classification methods [2, 3, 4] and technologies, we came to the conclusion that they are not effective for textures having identical structures, they need significant computational time, and in the most cases cannot obtain high recognition accuracy. The existing neural network software for texture recognition is applicable for simulating and testing the methods but is not intended for implementation in standard modules as PLCs widely used for control of different automated technological processes in industry.

The paper structure consists of MSNN and functioning modes description, definition of image processing and texture feature extraction. As next training of the neural network structure is described and the results of the recognition of seven wood textures are represented and discussed. The results are compared to these obtained by

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similar approaches. The main benefits of the developed system, together with the applied method are discussed.

## II. SYSTEM STRUCTURE

The designed system for texture recognition of wooden surfaces with a modular recognition structure of neural networks (NN) is implemented in a PLC for real-time operation as shown in Fig. 1. The system uses only standard devices and interfaces such as a high resolution (Charged Coupled Device) CCD camera, standard personal computer (PC), Siemens PLC model S317 and technological terminal (TT), Siemens Operational Panel (OP) 73 with liquid crystal (LC) display. The Siemens proprietary Multi Point Interface (MPI) - (based on the standard EIA-485) is used for connecting the PC to the PLC. The system functionality is described in the next section.

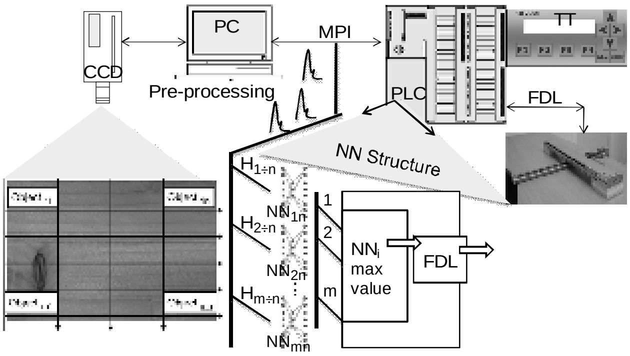



Figure 1. Experimental MSNN with PLC implementation

## III. FUNCTIONAL MODES

The system works in two modes – Off line or pre-processing and training mode; On-line or recognition and classification mode.

In “off-line” mode, after image acquisition of a large wooden surface, MxN dimensional grid with M rows and N columns is applied on the image. The histogram of each MxN cell is calculated and defined as a different class parametrical description. The correlation coefficients $r_{ij}$ between each two classes are calculated according to [5]. All classes with $r_{ij}$ greater than 0.75 (i.e., they are high correlated having almost the same histograms) are attributed to one and the same new class. Thus, the cells containing some defects will be separated in a different class because of a small correlation with the dominant surface background - Fig. 3. The class definition is performed with different samples of the same texture some of which with different defect inclusions. Next step in this mode is training of M different neural networks (NNs) with the obtained histograms, corresponding to each defined class. The “off-line” mode operation takes place completely in the PC. After finishing this mode, the trained NNs are downloaded to the PLC in different function blocks.

In “on-line” mode the chosen MxN grid is applied to the current CCD camera acquisition and the histograms are calculated for each cell. Each histogram column (1÷n) of the same raw (M) is used consecutively as input data to the corresponding NNmn in the PLC (Fig. 1). The recognized class results in a maximal value at one of the outputs in the corresponding NN. Additional logic for the assessment of the NN output values and for the finding the maximum one is developed in the PLC using ladder diagram technique. In case of good homogeneous surface, all NNs give the same output with maximum value i.e., one and the same recognized class. If a defect or other inhomogeneous area exists, the corresponding NNmn recognizes one of its input samples as another class. The defected region is defined as a cell that is a cross-point between raw (NN number) and column (number of the current NN input sample) in the MxN grid. A Final Decision Logic (FDL) in the PLC is developed to combine grid cell regions, recognized as one and the same class and to announce them as corresponding homogeneous areas. Finally, the FDL classifies the grid cells with some homogeneity variations and all the rest homogeneous areas. A technological terminal is used to assign the two system modes and display the classification results. FDL results are directly usable for the purpose of connecting to the control logic, actuating the physical outputs of the PLC. Next step is to analyze the feasible combinations between structural ranges for wedge-shaped splicing of wooden balks and to develop logic for any technological process control.

## IV. IMAGE PROCESSING

The image preprocessing algorithms are executed on a separate PC after acquiring the image from the camera. The generalized block scheme of these algorithms is presented on Fig. 2. These algorithms are very important since the recognition of the objects depends on their results, as well as on the overall system performance.

The first step after receiving the image from the camera, is to extract the region, which contains only the inspected object by applying edge detection algorithms (and calculating the rotation angle if required). The second step is to segment the image into M rows and N columns. The values N and M are user defined and they depend on the size of the object and the required texture analysis accuracy. After segmenting the image into objects (O), a parallel execution of histogram calculation for each object is performed. The number of the parallel processes is N. Following the parallel calculation of the histograms, each of the results form an input data vector, that is send in serial order ($O_{X,0}$ – $O_{X,N}$) to the neural network for further analyses.

## V. NN TRAINING – EXPERIMENTS AND RESULTS

Each NN in the MSNN is of type multi-layer perceptron. Each NN topology was optimized applying the method given in [6]. The method is based on changing the number of hidden layers, number of neurons in each layer and reducing the mean square error (MSE) till all NN outputs have regions, where the output stays near to “1” or “-1” as shown in Fig. 4b. Finally, all NNs were trained with MSE between 0.05 and 0.1 and different

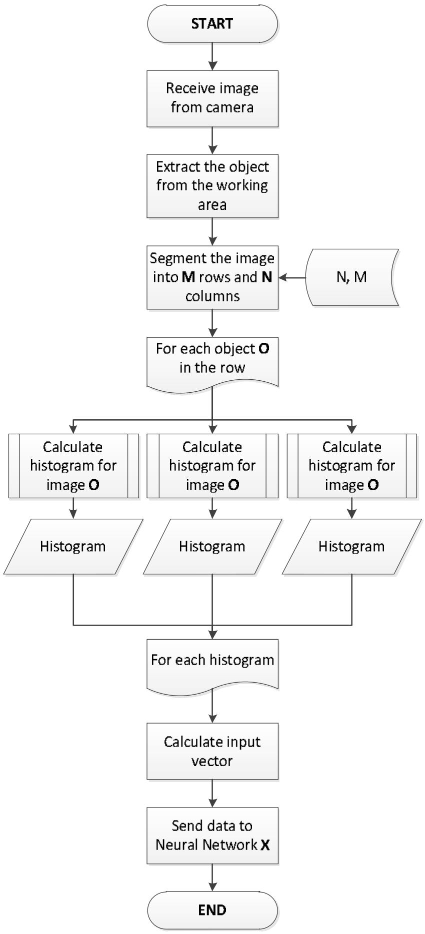
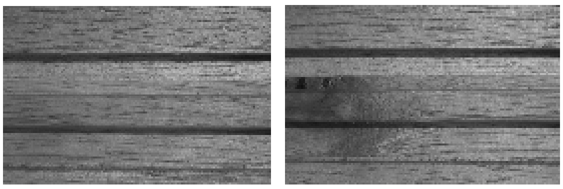
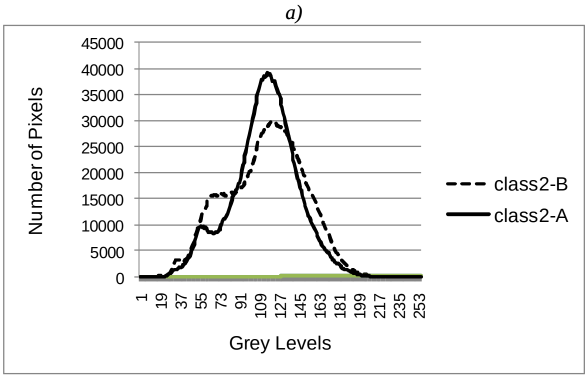



Figure 2. Image preprocessing algorithm



*Class2-A* *Class2-B*

*a)*

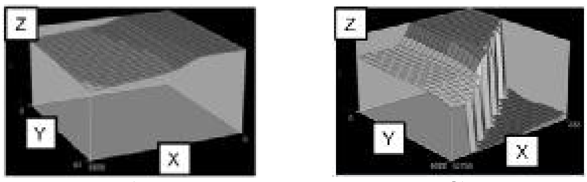



*b)*

Figure 3. a) Two cells defined as class2-A and class2-B
b) The calculated histograms of class2-A and class2-B

topologies: 42-20-10, 42-50-10, 42-80-10 where 42 (input neurons) is the number of sampled histogram values, 80 is the chosen optimal number of hidden layer neurons, and 10 (output neurons) is the number of recognized wooden surface classes. Tangent hyperbolic was used as NNs transfer function. Each trained NN is downloaded to the PLC in a different Function Block (FB) using NeuroSystem Run-time tool [7]. When calling the FBs, the NN inputs must be provided with the desired values, i.e., the addresses of where the inputs are stored should be stated. After being processed by the FB, the values written to the outputs are read out from the instance Data Block (DB).

The maximal number of different NNs is 256. The classification performance was validated with a histogram dataset different from the training dataset. 1100 training samples and 100 test samples were used. Fig. 5 shows the recognized classes given in Fig. 3, 6 and 7. Each $NN_{1n} \div NN_{5n}$ recognizes (x) the corresponding sample (column in the MxN grid) as a predefined class in the training phase. For example the defected texture given in Fig. 3a will be recognized as class 2-A in the outputs of $NN_{1n} \div NN_{2n}$ for all *n* samples (in our experimental grid n=4) and also for samples 3, 4 of $NN_{3n} \div NN_{5n}$. Samples 1, 2 of $NN_{3n} \div NN_{5n}$ are recognized as class 2-B. The recognition accuracy given in % (Fig. 5) is calculated as the overall number of correct classifications, divided by the number of samples in the testing dataset for each class.




*a)* *b)*

Figure 4. a) Undesirable change of a NN output Z depending on two inputs X, Y of the corresponding histograms in training phase
b) Desirable change of a NN output Z depending on two inputs X, Y of the corresponding histograms in training phase

| class / NN | $NN_{1n}$ | $NN_{2n}$ | $NN_{3n}$ | $NN_{4n}$ | $NN_{5n}$ | recognition accuracy [%] |
|---|---|---|---|---|---|---|
| class1-A | xxxx | xxxx | x xx | xxxx | xxxx | 88 |
| class1-B | | | x | | | 93 |
| class2-A | xxxx | xxxx | xx | xx | xx | 98 |
| class2-B | | | xx | xx | xx | 98 |
| class 3 | xxxx | xxxx | xxxx | xxxx | xxxx | 100 |
| class 4 | xxxx | xxxx | xxxx | xxxx | xxxx | 100 |
| class 5 | xxxx | xxxx | xxxx | xxxx | xxxx | 100 |

Figure 5. Recognition (x) of a corresponding sample (column in the MxN grid) for classes given in Fig. 3,6,7.

Fig. 7a) and b) shows the output values of all NNs (m=1÷5) for columns 1 and 3 respectively when recognizing texture surface in Fig. 1. For column 3 all NNs give the same result, till for column 1, $NN_{31}$ and $NN_{41}$ recognize a different class. The maximal value of the time needed for image acquisition, histogram calculation, and providing the values to the PLC NN Function Block, recognition through the trained NN, and sending the result to the text display OP73 takes 579 ms on the average with a Siemens PLC model S317. The obtained recognition accuracy is between 93% and 100% for real-time performance in the PLC.A complete model for the inspection system is shown on Fig.

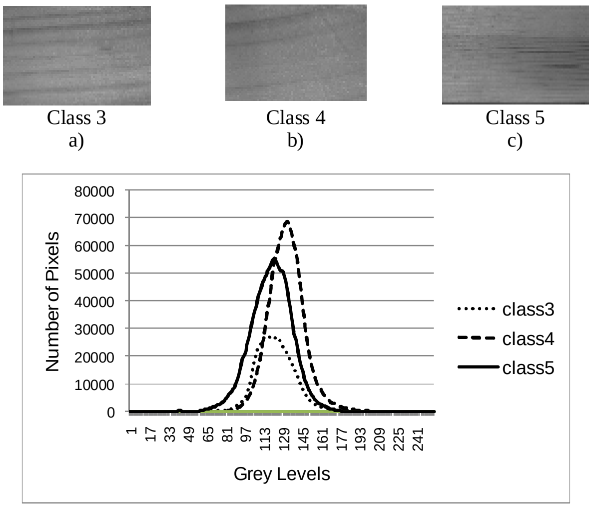
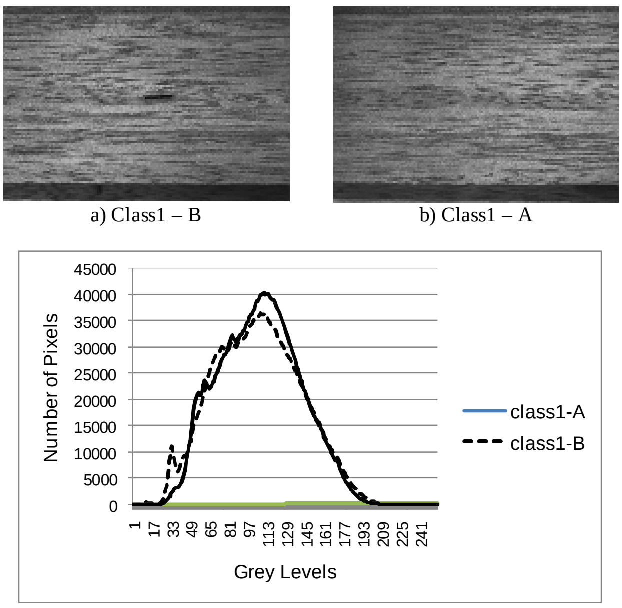



Figure 6. a), b) and c) Three cells defined as classes 3,4,5
d) The calculated histograms of classes 3,4,5

A system prototype has been built in the laboratory “Intelligent Manufacturing Systems” at the Technical University of Sofia, Bulgaria.




c)
Figure 7. a) and b) Two cells defined as class1-A and class1-B
c) The calculated histograms of classes 1-A and 1-B

The system functioning is quasi-parallel because after the texture acquisition and image segmentation in mxn cells, the histogram calculation goes in parallel, but the histogram downloading as input parametrical vectors to the NNs in the PLC is accomplished as a serial communication.

## VI. COMPARISON OF THE RESULTS

Many similar approaches [8, 9, 10] have the common disadvantage that they are not intended for implementation in standard modules as PLCs widely used for control of different automated technological processes in industry. The results of our research can be compared to the neural network approach given in [2]. The proto-type PC-based wood recognition system is capable of classifying 30 different tropical Malaysian woods according to their species based on the macroscopic wood anatomy. Image processing is carried out using newly developed in-house image processing library referred to as “Visual System Development Platform”. The textural wood features are extracted using a co-occurrence matrix approach. A multi-layered neural network based on the popular back-propagation algorithm (BPG) is trained to learn the wood samples for the classification purposes. The system can provide wood identification within seconds. The results obtained show a high rate of recognition accuracy. Several MLP models (with different structures) are trained by the authors, using 20 input features (Angular Second Moment, Contrast, Correlation, Inverse Difference Moment, Entropy etc., for five different image rotations), extracted from the texture. In this case, the authors have obtained 1sec overall computation time and 95% recognition success of 20 different tropical wood species. But this system is not intended for implementing the recognition results in an automated system for further process control.

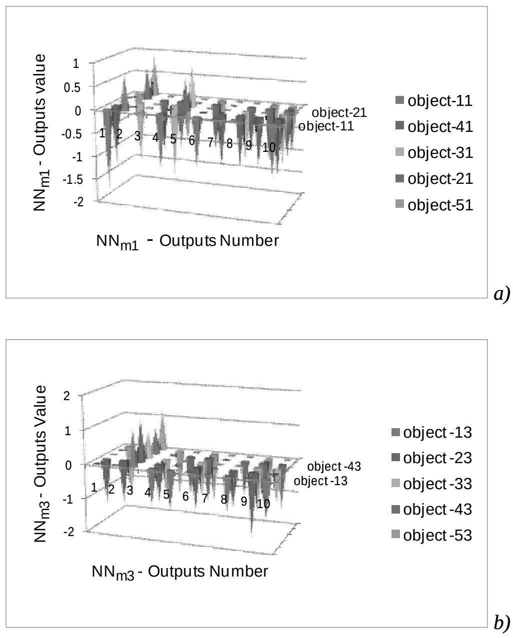



Figure 8. a) Output values of all NNs (m=1÷ 5) for column 1 when recognizing texture surface in Fig. 1
b) Output values of all NNs (m=1÷ 5) for column 3 when recognizing texture surface in Fig. 1

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In our case, the overall computation time is 579 ms and the obtained recognition accuracy is between 93% and 100% for real-time performance in a PLC S7-317. The proposed in this paper MSNN system provides that the techniques used is suitable to be implemented for industrial purposes. The development of additional FDL working in "on-line" mode is used for assessment and further logical interpretation of NNs outputs at the recognition stage. FDL results are directly usable for connecting to the control logic, actuating the physical outputs of the PLC.

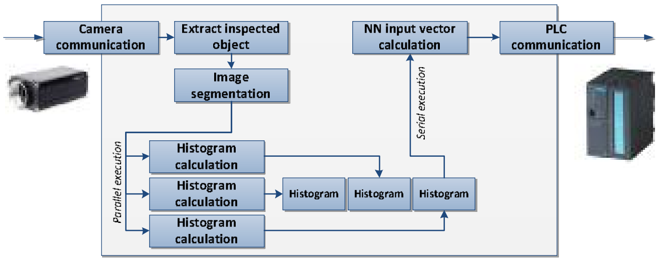


Figure 9. Model of the inspection system

## VII. CONCLUSION

- A MSNN is designed, implemented, and proved for real-time work on standard PLC SIMATIC S7-317 instead on FPGA, because PLCs are widely used as control devices in automated production.
- The parallel work of many different NNs, which number is practically limited to the PLC functionality (256 MLP NNs in our case), provides a good opportunity for using different texture (or objects) parametrical description data as input data for the NNs; Additional FDL is developed for assessment and further logical interpretation of NNs outputs at the recognition stage (in On-line mode);
- MSNN has been tested for classification of wooden textures. It shows high recognition rate and fast performance for the tested samples;
- FDL results are directly usable for connecting to the control logic, actuating the physical outputs of the PLC. The developed MSNN includes standard devices and interfaces and is easily stackable with already introduced different automated control systems in many automated productions at a low price, affordable for small and medium enterprises (SMEs).

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