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Neural network design and feature selection using principal component analysis and Taguchi method for identifying wood veneer defects

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and increase the response speed during the quality control stage so that veneers with defects do not pass through the whole production cycle but are rejected at the beginning.

 Keywords:

 ANN
 PCA
 feature extraction
 Taguchi analysis

1. Introduction

In recent years, quality concept has become very crucial not just for the products themselves, but as a competitiveness factor for the companies. Nowadays, the concept of quality for companies is synonymous with efficiency. The companies which reach high levels of quality are more efficient because they produce better products with lower costs. Companies whose organization or processes do not exhibit acceptable levels of quality are characterized by a number of internal errors such as dead times, poor coordination for numerous activities which are overlapping and disjointed, waste of resources, and a lack of tools and procedures for collecting feedback to a process of



the ANN takes the 17 features as input and assigns it to one of the 13 classes, and during recall it receives the 17 features and indicates the class to which it belongs to.

In order to improve the quality control and reduce the processing time, it is necessary to identify the critical variables and eliminate the redundant and the noisy features. A useful tool for this is the principal component analysis (PCA) (Pearson, <u>1901</u>); this multivariate statistical technique, employed in many fields uses orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components (PCs). In this way, it is possible to reduce an original space R^p by representing the variables in a new space R^k with k < p.

The aim of this paper is to improve the quality control for the identification of wood veneers defects through the integration of the PCA and ANN. The procedure consists of identifying the PCs in the 17 features in order to reduce the number of inputs to be given to the ANN necessary to detect the defects in real time with minimal error, whereby reducing the whole quality control process time.

This paper is organized as follows: Section $\underline{2}$ surveys the literature on the identification of wood veneer defects; the experimental procedure is given in Section $\underline{3}$; the PCA preprocessing is given in Section $\underline{4}$; neural network design is given in Section $\underline{5}$; the results

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in contrast to clear wood giving 13 classes. For each data sample, a classifier takes the 17-dimensional vector of image feature and decides to which of the 13 classes the pattern belongs to.

Among several algorithms, ANN has given the best results regarding the ability to recognize wood veneers defects. A three-layered multi-layer perceptron (MLP) gave 85% identification rates (Packianather, <u>1997</u>; Packianather, Drake, & Rowlands, <u>2000</u>; Pham & Liu, <u>1995</u>). Learning vector quantization networks have been applied to perform the classification of wood defects with high accuracy (Pham & Sagiroglu, <u>2000</u>). In order to improve the classification accuracy of a single network, a decision tree of smaller and more specialized modular neural networks were introduced to achieve classification by successive refinements (Packianather & Drake, <u>2000</u>).

In Packianather and Drake (2004), Response surface methodology was used to design a MLP network for classifying surface defects on wood veneer. The results showed that although the performance of the neural network could be improved by this method extrapolation outside the tested parameter range should be avoided.

A comparison between the minimum distance classifier (MDC) and neural networks to identify wood veneer defects was performed showing that the MDC does not perform as well as a neural network (Packianather & Drake, 2005).



(Ahmadzadeh & Lundberg, 2013; Charytoniuk & Chen, 2000; Mohamed-Saleh & Hoyle, 2008; Rajput, Das, Mishra, Singh, & Dwivedi, 2010; Sratthaphut, Jamrus Woothianusorn, & Toyama, 2013; Tabe, Simons, Savery, West, & Williams, 1999). In this paper, PCA is used to reduce the number of input features for the wood veneer defects identification problem.

2.1. Case study: wood veneer defects identification problem

Plywood is made of thin layers of wood, called veneers, joined together using an adhesive. The quality of a board is determined by the types and number of defects in the constituent sheets. In any case, high-quality boards should be made up of sheets containing as few defects as possible or preferably no defects. To ensure this, careful inspection of the sheets is required as part of the quality control process. Defects of the veneer are identified by human inspectors as the sheets are transported to an assembly on a conveyor. This task is extremely stressful and demanding and a short disturbance or loss of attention results in misclassifications. A study conducted on human inspectors on wood mills reported that they could only obtain up to 55% accuracy in wood sheet inspection (Pölzleitner & Schwingshakl, 1992). Hence, an automatic visual inspection system was developed in order to increase the accuracy in wood sheet inspection (Drake & Packianather, 1998; Pham & Alcock, 1996, 1998,

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3. Experimental procedure

For each defect shown in Figure 1, a 20×17 matrix was available except for the defects

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neurons in the hidden layers, different values of the Pearson coefficient, and different numbers of input for the network. Finally, Taguchi analysis (Roy, <u>1990</u>) has been performed in order to analyze the results and identify the best configuration of the ANN.

4. The PCA based feature selection

The PCA is a multivariate statistical tool that uses orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called PCs. The procedure starts calculating the covariance matrix of the variables if they were expressed in the same unit. In our case the original variables show different units and orders of magnitude. For this reason, the original variables had to be expressed in terms of standardized deviations using the correlation matrix instead of the covariance one.

Each PC is expressed as linear combination of the standardized deviations of the p variables. The first PC is:



y1=Za1

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Alternatively, it is possible to obtain the scores of the PCs with mean equal to zero but variance equal to one, dividing each score by the root of the respective eigenvalue.

Another way is by considering a_{vs} satisfying the following expression:

The a_{vs} coefficients are the correlation coefficients between components of each of the p variables:

4.1. Number of PCs

There are several criteria to choose the right number k of the PCs. Considering a PCA using the correlation matrix, the first criterion suggests choosing a number of PCs which contain a high percentage (at least 80%) of the total variance. This criterion can be modified considering a percentage threshold changing as a function of the starting number of variables.



available for each variable have been reported, while in Table 3 the correlation matrix between the variables is reported.

Table 2. Statistical measures calculated for each variable. Download CSV Display Table	
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The Bartlett's test of sphericity has been applied on the correlation matrix, and the null hypothesis of absence of correlation between the variables indicates the safe use of PCA on this data. Table 4 shows the percentages of variance related with the extracted PCs. This indicates that all the variables except 11th, are well explained by the extracted PCs having percentages of variance higher than 50%, between 58.8 and 98.4%. Table 5 contains the amount of total variance contributed by each component and the percentage of cumulative variance. Considering just the first four components, the percentage of cumulative variance was equal to 81.876%.

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Since the first four components are responsible for 81.876% of the total variance, which is clearly higher than the 46.329% suggested for p = 15, and have eigenvalues higher than 1, and the scree plot shows a pronounced bend between 4 and 5, the three criteria agree to choose 4 as the optimum number of PCs.

In Table 6 the correlation coefficients between each PC and each variable are reported.



be considered, while when $\alpha \ge .7$, indicating a strong relation between the variables, just 9 variables should be considered.

Table 7. Critical variables related with Pearson coefficient.Download CSVDisplay Table

The above results have found four PCs. Based on the results in Table 7 and $\alpha \ge .6$, features 4, 5, 6, 15, and 16 are merged under one component which means they have something in common. These features are standard deviation, skewness, kurtosis, number of edge pixels for the pixels after thresholding at $\mu - 2\sigma$, and number of edge pixel for the pixels after thresholding at $\mu + 2\sigma$, respectively. These features are statistical features which illustrate the characteristics of the image data distributions, according to the Gaussian distribution. Therefore, these features merged under one PC represent the Gaussian characteristics of the image.

The features 1, 2, 3, 9, and 10 are mean gray level, median gray level, mode gray level, gray level p for which there are 20 pixels below, and gray level s for which there are 20 pixels above, respectively. What is common in these features is that they are calculated from the average gray level.



In this section the ANN, based on the results of the PCA, was designed in order to identify wood veneer defects.

A feed-forward ANN with a Back-Propagation learning algorithm has been chosen using 75% of the data-set for training and 25% for testing. The hidden layer has a tansigmoid transfer function because the data are normalized between -1 and +1, while the output layer has a logsigmoid transfer function because the output of the network should be 0 (for defect free) or 1 (for defect).

Figure 3 shows a network with an input layer of nine neurons representing the critical features considered, two hidden layers with 10 and 10 neurons, respectively, and finally the output layer with 10 neurons, one for each defect and clear wood. Figure 4 shows the classification results in terms of training curves in the case of reduced number of features according to the PCA and using all the features. It is clear how the performance of the network improves when the PCA is applied. The average results in terms of training time improved by 56.6%.

Figure 3. A feed-forward artificial neural network 9-10-10-10.







the ANN in order to produce near-optimal expected results.

The first factor is the number of hidden layers for which two levels were considered, low and high. The low level denotes one hidden layer and high level denotes more than one hidden layer (in this case two hidden layers). In order to use an L9 Orthogonal Array a dummy level was used for level 3 which was set to level 1. The second factor was the number of neurons in the hidden layer and three levels were chosen, low, medium, and high. For single hidden layer, these levels varied from 5 to 15 neurons, whereas in the case of two hidden layers, levels were presented as lower than 10, 10, and higher than 10 neurons. Finally, the third factor considered was Pearson coefficient and three levels were chosen: complete correlation (level 1), moderate correlated features (a \geq .6, a \leq -.6) (level 2), and highly correlated features (a \geq .7, a \leq -.7) (level 3), respectively.

Table 9 shows the results using one hidden layer, changing the number of neurons in the hidden layer from 5 to 15 using three levels of the Pearson coefficient.

Table 9. Results of the ANN training and test using one hi layer. Download CSV Display Table	dden
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When training ANNs with all features available (more input to the network), then the number of neurons does not influence the mean performance. Moderate neurons per layer (10, i.e. level 2) reduce training variance and time simultaneously maintaining percentage of training success around 92%. The fact that the performance during the training does not change mean and S/N value much indicates that it is better to use lesser inputs to the network in order to reduce the computational time.

Figure 5. (a) Taguchi analysis results during the training; (b) Interaction between factors during the training.



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moderate correlated variables is 80%, which reduces testing process time by around 40%. This performance has been found with more than one hidden layer and 10 neurons in each layer. The worst performance is found with less number of inputs to the network and less number of neurons. The best performance is found with highly correlated features of the minimum level of hidden layers with more than 10 neurons per layer.

Figure 6. (a) Taguchi analysis results during the test; (b) Interaction between factors during the test.



This paper has introduced ANN-based intelligent quality control for the detection of wood veneer defects with lower inspection criteria. To reduce the training time and increase the testing performance, a principal component analysis (PCA) based dimension reduction stage has been proposed. The proposed PCA method is based on the determination of the critical features for the inspection process. The proposed method has been applied on a case study for identifying defects on wood veneer. The reduced feature set has been used as inputs to train the ANN classifier which successfully identified the defects and clear wood. The best performance with one hidden layer was found to be with more than 10 neurons. The reduction of features reduces the number of epochs. According to the best performance, a reduction of 61 epochs increased the quality of outputs in testing stage by 18%. Different ANN designs have been studied by running some experiments with three control factors and carrying out Taguchi analysis on the results to determine the best-performing ANN topology.

References



1. Ahmadzadeh, F., & Lundberg, J. (2013). Remaining useful life prediction of grinding

4. D'Addona, D. M., & Teti, R. (2013). Image data processing via neural networks for tool wear prediction. Procedia CIRP, 12, 252–267.10.1016/j.procir.2013.09.044

Google Scholar

 Drake, P. R., & Packianather, M. S. (1998). A decision tree of neural networks for classifying images of wood veneer. The International Journal of Advanced Manufacturing Technology, 14, 280–285.10.1007/BF01199883

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 Lappalainen, T., Alcock, R. J., & Wani, M. A. (1994). Plywood feature definition and extraction (Report 3.1.2, QUAINT, BRITE/EURAM project 5560). Cardiff: Intelligent Systems Laboratory, School of Engineering, University of Wales.

Google Scholar

 McCulloch, W., & Pitts, W. (1943). A logical calculus of ideas immanent in nervous activity. Bulletin of Mathematical Biophysics, 5, 115–133. doi:10.1007/BF0247825910.1007/BF02478259



 Packianather, M. S., & Drake, P. R. (2004). Modelling neural network performance through response surface methodology for classifying wood veneer defects. Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture, 218, 459–466.10.1243/095440504323055588

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.2. Packianather, M. S., & Drake, P. R. (2005). Comparison of neural and minimum distance classifiers in wood veneer defect identification. Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture, 219, 831–841.10.1243/095440505X32823

Web of Science ® Google Scholar

.3. Packianather, M. S., Drake, P. R., & Rowlands, H. (2000). Optimizing the parameters of multilayered feedforward neural networks through Taguchi design of experiments. Quality and Reliability Engineering International, 16, 461–473.10.1002/(ISSN)1099-1638



.7. Pham, D. T., & Alcock, R. J. (1999a). Recent developments in automated visual inspection of wood boards. In S. G. Tzafestas (Ed.), Advances in manufacturingdecision control and information technology (pp. 79–88). London: Springer.

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.8. Pham, D. T., & Alcock, R. J. (1999b). Plywood image segmentation using hardwarebased image processing functions. Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture, 213, 431– 434.10.1243/0954405991516903

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.9. Pham, D. T., & Alcock, R. J. (1999c). Automated visual inspection of wood boards: Selection of features for defect classification by a neural network. Proceedings of the Institution of Mechanical Engineers, Part E: Journal of Process Mechanical Engineering, 213, 231–245.10.1243/0954408991529852

Web of Science ® Google Scholar

20. Pham, D. T., Ghanbarzadeh, A., Koc, E., Otri, S., & Packianather, M. (2006). Optimising



23. Pölzleitner, W., & Schwingshakl, G. (1992). Real-time surface grading of profiled wooden boards. Industrial Metrology, 2, 283–298.10.1016/0921-5956(92)80008-H

Google Scholar

24. Rajput, N. S., Das, R. R., Mishra, V. N., Singh, K. P., & Dwivedi, R. (2010). A neural net implementation of SPCA pre-processor for gas/odor classification using the responses of thick film gas sensor array. Sensors and Actuators B: Chemical, 148, 550– 558.10.1016/j.snb.2010.05.051

Web of Science ® Google Scholar

- 5. Roy, R. (1990). A primer on Taguchi method. New York, NY: Van Nostrand Reinhold. Google Scholar
- 26. Sratthaphut, L., Jamrus, S., Woothianusorn, S., & Toyama, O. (2013). Principal component analysis coupled with artificial neural networks for therapeutic indication prediction of thai herbal formulae. Silpakorn University Science and Technology Journal, 7, 41–48.



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