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Articles

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

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nhstract
Nowadays, ensuring high quality can be considered the main strength for a company's success. Especially, in a period of economic recession, quality control is crucial from the operatio
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defects do not pass through the whole production cycle but are rejected at the beginning.

Q 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 continuous improvement.

Quality control may generally be defined as a system that maintains a desired level of quality, through feedback on product/service characteristics and implementation of remedial actions in case of a deviation of such characteristics from a specified standard (Mitra, 2012). Several tools stemming from statistics, computer science, and other similar fields are used to perform and improve the process of quality control. For instance, artificial neural networks (ANNs) (McCulloch \& Pitts, 1943) have been used in many real-world applications related to quality control and in particular an ANN classifier has been proven to give the best results to correctly recognize wood veneer defects (D'Addona \& Teti, 2013; Pham \& Liu, 1995). The ANN takes as input 17 statistic coupled histogra extrag betw the ANN during $r$

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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, 1997; Packianather, Drake, \& Rowlands, 2000; Pham \& Liu, 1995). Learning vector quantization networks have been applied to perform the classification of wood defects with high accuracy (Pham \& Sagiroglu, 2000). 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, 2000).

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).

Further, the Bees Algorithm (BA) was employed in place of the Back Propagation (BP) algorithm to optimize the weights of neural network for identification of wood defects (Pham, Ghanbarzadeh, Koc, Otri, \& Packianather, 2006). Both the algorithms showed the same accuracy and in addition the BA proved to be considerably faster.

Lastly, the evolutionary ANN Generation and Training algorithm was used in the design and training of MLP classifier for identification of wood veneer defects (Castellani \& Rowlands, 2009). The algorithm enabled the neural network topology and the weights to evolve over time. Compared to the approach based on the Taguchi method for the manual optimization of the MLP structure and the control parameters of the BP rule for tuning the connection weights, this algorithm performed equally well to the ANN solutions works or from wo ident been (Ahmad: 2008; R

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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, 1999c). Wood sheets were presented to a CCD camera which captured their images. These were segmented to separate clear wood and defective areas. Features were then extracted from the segmented images. The feature vectors obtained were finally presented to the defect classification module that performed the task of grouping them into one of 12 types. Seventeen statistical features (Table 1) of the local gray-level distribution were identified as relevant for defect identification (Lappalainen et al., 1994; Pham \& Alcock 1999c). Twelve possible defects of the veneer can be distinguished in contrast to clear wood giving 13 possible classes shown in Figure 1. For each data sample, a classifier takes the 17-dimensional vector of image features and decides to which of the 13 classes the pattern belongs. The experimental procedure for training the ANN classifier is described in the following section.

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## 3. Experimental procedure

For each defect shown in Figure 1, a $20 \times 17$ matrix was available except for the defects of curly grain, holes, and worm holes where their matrix dimensions were lower. In order to avoid any imbalance in the training data these three defects were excluded in this study. The number of rows in the matrix dimension indicates the number of exemplars available for each class and the number of columns indicates the total number of features extracted as given in Table 1. An initial examination of features 7 and 8 showed that a considerable number of feature values were zero and for this reason they were excluded from this study.

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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, 1990) 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:

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The score for the i-th statistical unit is:

$$
\text { yi1=a11zi1+ }+\cdots+\text { alszis }+\cdots+\text { alpz1pfori }=1, \ldots, n
$$

where $a_{1 s}$ is the coefficient of the first PC and s-th variable. The sign of this coefficient reveals the relationship between the first PC and the s-th variable and its value shows how much this variable contributes to the scores of the first PC. In general, considering the first

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\operatorname{Var}(Y 1)=y 1^{\prime} y 1 n=a 1^{\prime} Z Z^{\prime} n a 1=a 1^{\prime} R a 1=a 1^{\prime} \lambda 1 a 1=\lambda 1 a 1^{\prime} a 1=\lambda 1
$$

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 $a_{v s}$ satisfying the following expression:

$$
a v s^{\prime} a v s=\lambda v
$$

The $a_{v s}$ coefficients are the correlation coefficients between components of each of the p variables:

$$
r(Y v, X s)=a v s=a v s \lambda v
$$

### 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.

The second criterion suggests considering all the PCs having eigenvalue higher than one. In this way, each PC explains a percentage of the total variance higher than that of a single variable.

The third criterion suggests making a graphic called scree plot of the eigenvalues $\lambda_{\nu}$ as a function of the number $v$ of PCs $(v=1,2 \ldots \mathrm{p})$. Since the eigenvalues are obtained in a decreasing order, this plot is descending; the criterion suggests choosing $k$ as the number

Usually,

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between the variables is reported.

Table 2. Statistical measures calculated for each variable.


Table 3. Correlation matrix between the variables.
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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 $81.876 \%$.

Table 4. Amount of variance of each variable related with the extracted PCs.

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Table 5. Eigenvalues and percentage of variance.

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available for each variable have been reported, while in Table 3 the correlation matrix
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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. The sign of the coefficients indicates if the relation between the coefficient and the variable is direct or inverse, while the numeric value indicates the correlation strength between the variables.

Table 6. Correlation coefficient - moderate correlation in bold and high correlation in italics - between the variables and the four extracted PCs.

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The first secon has relation \(\alpha \geq .7\) h cufficien
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be considered, while when \(\alpha \geq .7\), indicating a strong relation between the variables, just 9 variables should be considered.

Table 7. Critical variables related with Pearson coefficient.


The above results have found four PCs. Based on the results in Table 7 and \(\alpha \geq .6\), 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.

The third PC contains features 11 and 17 , where feature 11 is related with the histogram tail length on the dark side and feature 17 is the number of the edge pixels after thresholding at \(\mu+2 \sigma\). There is a link between the edge pixels and histogram of both dark and bright side, where it is expected to have brighter image on the edge after threshold which changes the histogram of both bright and dark pixels. However, PC has only found the direct relationship between dark side and thresholded edges.
Therefore, this PC is sensitive to the histogram changes at the edge.
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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

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 performance of the network improves when the PCA is applied. The average results in

Figure 4. (a) Training curve without feature reduction; (b) training curve with reduction
In this section the ANN, based on the results of the PCA, was designed in order to .號
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6. Results and Taguchi analysis

Several network configurations have been tested in order to improve the performance. Moreover, Taguchi method has been applied on the training and test results in order to evaluate the effects of the three factors on the performance of the network. The Taguchi orthogonal array (design set) used is given in Table 8. The signal-to-noise ratio according to the criteria 'Larger is better' is expressed by the following expression

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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 hidden layer.


Table 10 shows the results when two hidden layers are used, changing the number of neurons in a way that their values are always included between the number of input and output neurons.

Table 10. Results of the ANN training and test using two hidden layer.
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the ANN in order to produce near-optimal expected results.

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\(40 \%\). 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

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moderate correlated variables is \(80 \%\), which reduces testing process time by around
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which reduces testing process time by around

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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.

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