Building Industrial Applications with Neural Networks

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Abstract

This paper provides a short overview of neural networks (NNs) in real world industrial applications. We first outline some of the most important features of NNs affecting for the developing of industrial applications. We also provide lists of application areas and industrial sectors of neural networks within the Europe. Finally, some real world NN applications are reviewed, with discussion of the role of the neural networks in each application.

1 Introduction

Artificial neural networks (NNs) have been studied almost from the beginning of the computer era. In the beginning the NN research was strongly motivated by biological considerations and the developed NN models were too weak to solve complex information processing tasks typically found in many industrial applications. New innovations in 1980s lead to the emerge of more powerful NN models, and many successfull case studies aimed at demonstrating NN concepts and benefits to various categories in a number of industrial application sectors caused the industry to look the NNs as a serious tools. Nowadays NNs have popular appeal, and a wide application sector within the industry.

The research and application sectors of NNs are constantly working towards a more comprehensive understanding of NN models and their strengths and shortcomings in a wide range of applications. It seems that the past overexaggerated claims of the capabilities of NNs have become more sensible and realistic, i.e., the field of NN has evolved to correct direction and matured. Realistic expectations combined with positive feedback from the applications have also reduced the danger of NN interest to collapse due to overrealistic and unfulfilled promises. Nowadays it is known quite well what NNs are and what they are capable to do. When this knowledge is combined with industrial expertise needed in building a successful application, the results should be at the level of the NN capabilities and also objective.

This paper provides a short overview of NNs in real world industrial applications. Much of the material is based on authors' own research, especially in the section reviewing some real world industrial applications. However, we will also try to shortly review the basic features of neural networks concentrating to the topics to be addressed in developing NN applications. Also a short review of the application areas and industrial sectors of NNs within the Europe is provided based on the results of SIENA project [1].

2 Neural networks in industrial applications

From the engineering point of view NNs can be seen as highly parallel dynamical systems that can perform transformations by means of their state response to their input information. How the transformation is carried out depends on the NN model and its way of learning the transformation. The most natural application areas for the NNs are obviously tasks in which appropriate transformations from certain inputs to certain outputs should be established, but the transformations cannot be discovered analytically due to a variety of reasons. Therefore it is no wonder that the most successful applications of the NNs can be found in the areas of machine vision, pattern recognition, motor control, signal processing, etc., where such "inputs to outputs" transformations dominate the problem solving (see e.g. [1, 10, 2]).

Much of the current research in NNs is centered on individual network models, whereas in typical industrial applications, a system level view of NNs is more desirable. Individual NNs are then seen as components in a broader system which also contains many other data processing techniques, such as filtering of signals. This kind of use of NNs leads to a hybrid architecture in which some of the processing modules are based on NNs. The problem is then to decide what benefits NNs may provide for the given industrial application (if any at all) and what kinds of NN models should be used.

Up till now many different NN models have been proposed to a broad range of applications. Also a lot of effort has been done in laying the theoretical foundations of NNs and the links between statistical and neural methodologies (see e.g. [1, 10]). Many NNs models, such as multilayer perceptron (MLP) [11]) or Principal component analysis (PCA) [9] networks are similar or identical to popular statistical techniques like generalized linear models, polynomial regression, nonparametric regression and discriminant analysis, principal components and clustering. There are also some NN models, e.g. the Self-Organizing Map [3], that have no precise statistical equivalent, but are useful in data analysis. However, NNs should be inherently treated as statistical devices and used accordingly.

There are at least the following four main aspects that should be considered in any NN application:

1) Preparing the data: The training data should contain all the relevant information needed in building the NN model for the task. Also any a priori knowledge relevant for the problem must be considered.

2) Selecting the network model: The NN model affects crucially to the results obtained. Generalization ability, which is a measure of how well the network performs on the problem once training is complete, judges how good the network model is for the actual task. There are different types of NN models that can be divided to the following three broad categories according to their learning procedures: supervised, unsupervised and reinforcement models.

[1]Stimulation Initiative for European Neural Applications, Esprit Project 9811

3) Estimating the parameters, i.e., training a network for a given problem: The task of a learning process is to construct a required transformation from the input space to the output space of the network. Any transformation of given inputs to outputs is a function approximation problem where the difficulties come from a common origin: The finite size of the training samples which easily leads to multiple possible solutions. In order to obtain usefull results one must restrict the eligible solutions to a smaller set. Coping with the constraints imposed by the data is one of the central points in the NN methodology. In addition, the effective number of parameters of the model, i.e. the NN complexity, should be matched to the problem complexity and the number of available training examples. If the network is too complex, it will perfectly learn the training set (low bias) while generalizing very poorly (high variance). Controlling the complexity is therefore a necessity to ensure good generalization. It is specially a key issue when the training set is small, noisy and even partially incorrect.

The practical methods for controlling the model complexity include, e.g., early-stopped training, committees of early-stopped networks, weight decay or other regulararization methods (see [4]), and Bayesian techniques for choosing the appropriate regularization level, such as the evidence framework [7] and Markov chain Monte Carlo based methods [8].

4) Assessing the performances of the network: The general way to determine how well a network has captured the nature of a function is to validate the network with additional test set examples that were not used during the learning steps. The results obtained with the test samples can be used as indicators of the generalization ability of the network. The aim should be to determine the level of confidence in the estimated generalization abilities of the model. For this task a few useful statistical techniques can be used, e.g., bootstrap, cross validation or Bayesian treatment. Of course, the final judgement about the success of the built NN model comes in operational use.

3 Application areas and industrial sectors

The material of this section is based on the SIENA (Stimulation Initiative for European Neural Applications, Esprit Project 9811) project. The objectives of the SIENA project were set in order to examine the current state of commercial ANN usage across the Europe. A detailed description of the outcomes of the project can be found at the WWW address: http://www.mbfys.kun.nl/SNN/siena . Here we only list the most important application areas and industrial sectors of the NNs within the Europe.

Table 1 shows the most typical application areas of NNs across the Europe, whereas Table 2 lists the most important industrial sectors. These figures are a couple of years old, but they should still quite well reflect the current situation. As can be noticed NNs have a widespread application domain across a broad spectrum of industries.

4 Examples of industrial applications

4.1 Quality Inspection of Wood Surfaces

In this section we shortly review a quality inspection system for wood surfaces that is largely based on neural information processing principles. As a natural material wood

Control, monitoring and modelling	31%
Recognition, detection and pattern matching	14%
Forecasting and prediction	14%
Image processing	10%
Optimization	4%
Signal processing (incl. speech and languages)	3%
Generic	23%

Table 1: Application areas of neural networks in Europe.

Production (manufacturing, agric., forest, etc.)	39%
Business services and marketing	19%
Banking, finance and insurance	12%
Medicine, health, pharmaceutic	3 %
Transportation	3 %
Utilities and energy	3%
Wholesale and retail trade	1%
Other	20%

Table 2: Industry sectors of neural networks in Europe.

has significant variation both within and between species, making it a difficult material for automatic grading. In principle, the inspection and quality classification of wood is straightforward: the quality class of each board depends on its defects and their distribution, as dictated by the quality standard. However, the definitions of the defects are based on their biological origin, appearance, or cause, so that the visual appearance of defects in the same class has substantial variation. The Finnish standards alone define 30 different defect classes, such as sound, dry, encased, and decayed knots, resin pockets, splits, bark, wane, mould, etc., each with various degrees of seriousnesses.

Figs. 1 and 2 show examples of defects to be recognized. Fig. 1 shows knot classes on spruce boards (from laboratory experiments during development of the system) and Fig. 2 shows actual production line images of defects in veneer sheets.

A schematic of the defect recognition system is shown in Fig. 3. The shape related information from the defect is encoded by a Gabor-filters and self-organizing feature construction system into a "local shape histogram". Information from the defect color is encoded as color histogram, and global features from the defect are encoded as logarithmically sampled spatial frequency spectrum over the defect. Suitable classifiers for the feature space are, e.g., subspace methods and MLP neural networks.

The approach gives knot recognition rate of about 85 %, yielding about 90 % correctness in the final grading of the boards, which is clearly better than the sustained performance of manual grading (about 70-80 %).

Based on these results, an industrial machine vision based system for automatic wood surface inspection has been developed by Mecano Group Ltd, Finland, and is reported in [6]. The system is implemented on signal processors, with processing capacity of about 70 2 by 2 meter veneer sheets per minute. The imaging resolution is about 1×1 mm, and the sheets may contain over 20 defects on average.

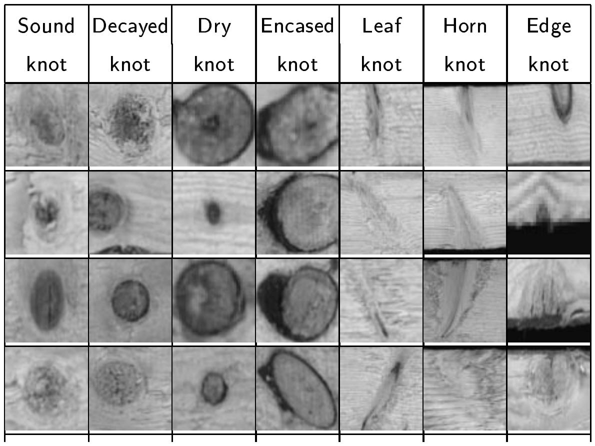

Figure 1: Examples of various knot types in spruce boards (aboratory experiments.)

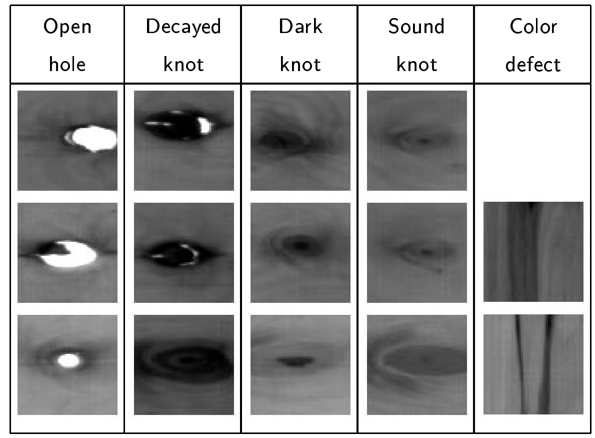

Figure 2: Examples of defect classes in veneer (production line images.)

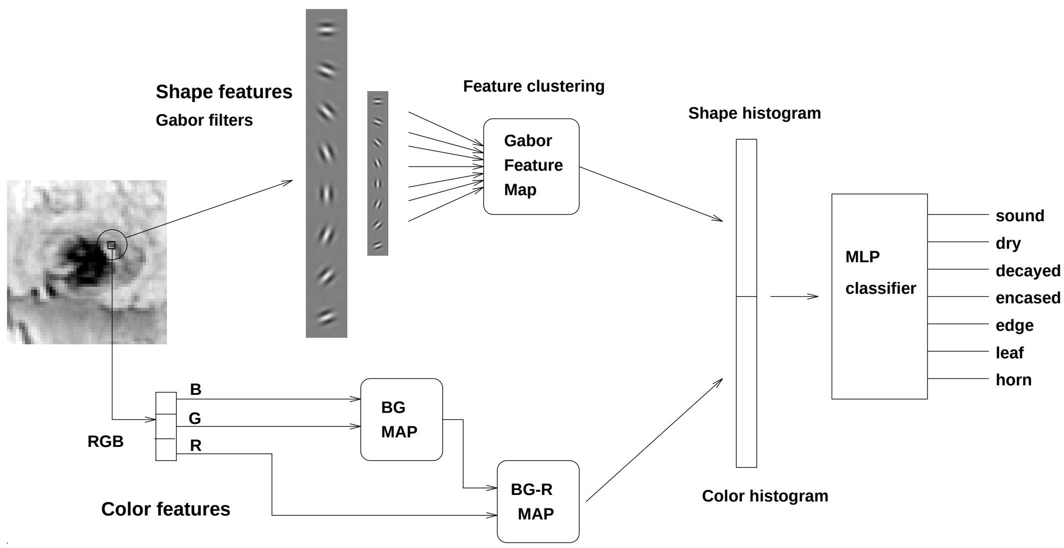

Figure 3: A schematic of the classification system combining shape based and color based information.

In summary, the benefits of neural processing in this application are:

- **Robustness**: All stages of processing are suitable for generic recognition of defects. The features are not manually taylored for any particular set of target classes, and the fine tuning is carried out by unsupervized self-organizing procedure.
- **Adaptability**: The system can be easily trained for any classification criteria (quality standards) or for changes in imaging environment or tree species. For example, exporting the system to North-America required only minor changes, even though the trees are much larger and different appearance of the defects would require different manually selected classification features.

4.2 Generic modeling tool based on neural network

Common use of neural networks is modeling of industrial processes at system level. Here we shortly describe a modeling tool, Q-OPT, developed for building statistical quality control models. The product, commercialized by Taipale Engineering Ltd, Finland, supports modular building of the models and training the network with measured data and background knowledge:

1. Modular network design.

Subprocesses of the whole process are encapsulated into modules that can be trained on the data, expert rules and simulation models.

The modules are connected with adaptive layers and then the whole model can be trained together, so that the interconnection layers compensate the errors of the individual modules. This facilitates use of inaccurate simplified models for the subprocesses.

2. Training background knowledge on the network

The training data base consists of data samples and additional set of rule data. The rules are similar to those in fuzzy expert systems, such as *"Adding chemical A to the process causes strong increase in target variable Y"*, with fuzzy-like definitions for the terms and quantities.

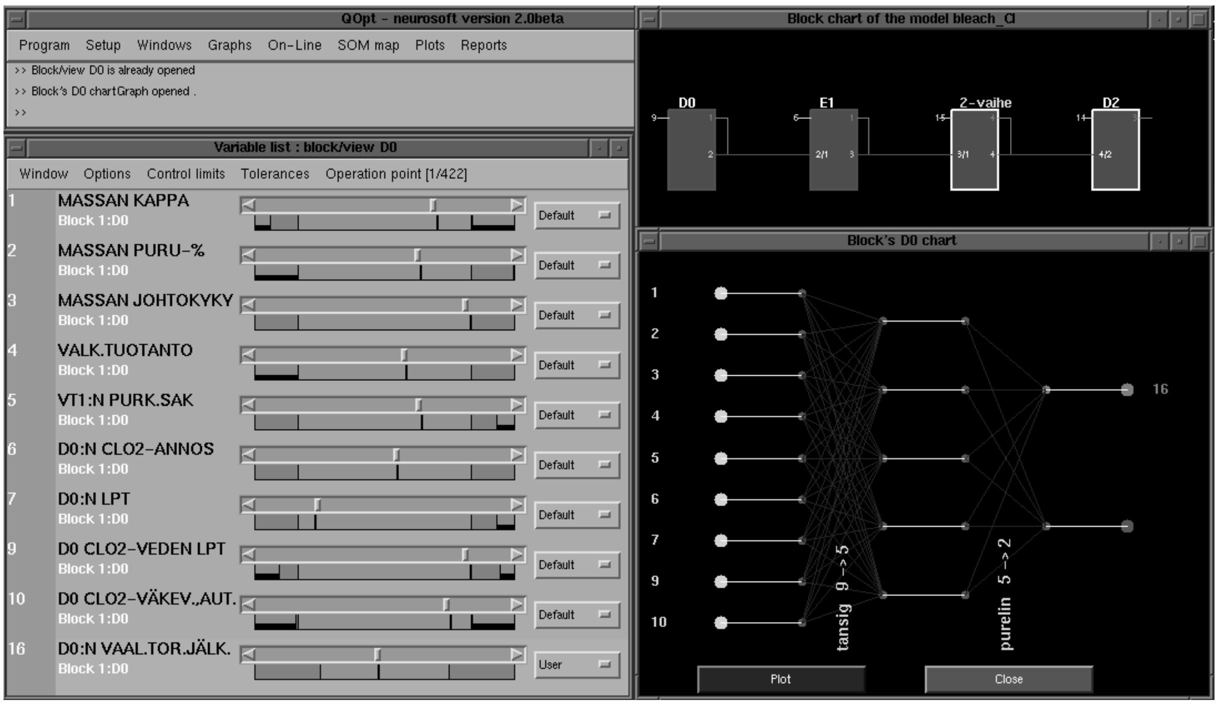

Figure 4: Overview of the neural modeling tool Q-OPT 2, with main menu, variable control window and network display window.

The theoretical background of the system, together with results on real process data are reported in [12] and [5].

In this application neural network forms the basis of the statistical process model. However, building non-linear statistical models requires inevitably more expertise from the users than building linear models, which also require non-trivial amount of statistical knowledge. Thus generic modeling tools, such as the Q-OPT, can only be used by domain experts, who can use discretion in selecting the variables in the models, and are able to analyse and validate the models before taking them to operational use.

4.3 Neural network in weight measuring product

In this secion we review a typical application of neural networks as part of a larger system, where the NN is used as a building block to solve some separate subproblem.

The case application is a weight measuring system manufactured by Omni Weight Control Ltd, Finland. The principle of the system is following: Weight or load causes strains to the supporting structure, and by measuring the strains the weight can be estimated. The strains are measured by a number of high resolution strain gauges that are welded to the locations in the structure which bear the weight most directly. Basically the estimation problem is linear, as the stretching of metal depends linearly on the force. However, several factors make the problem in practice non-linear. The framework may contain lever mechanisms designed to distribute the load evenly, as in trucks. Dynamical effects and elastic vibrations may be a problem, as found in conveyor belts or moving vehicles. Also moving parts in the system may change the distribution of weight. In beam lifter, for example, the wheel rail of the carriage may have slack, causing different torques depending on the carriage position.

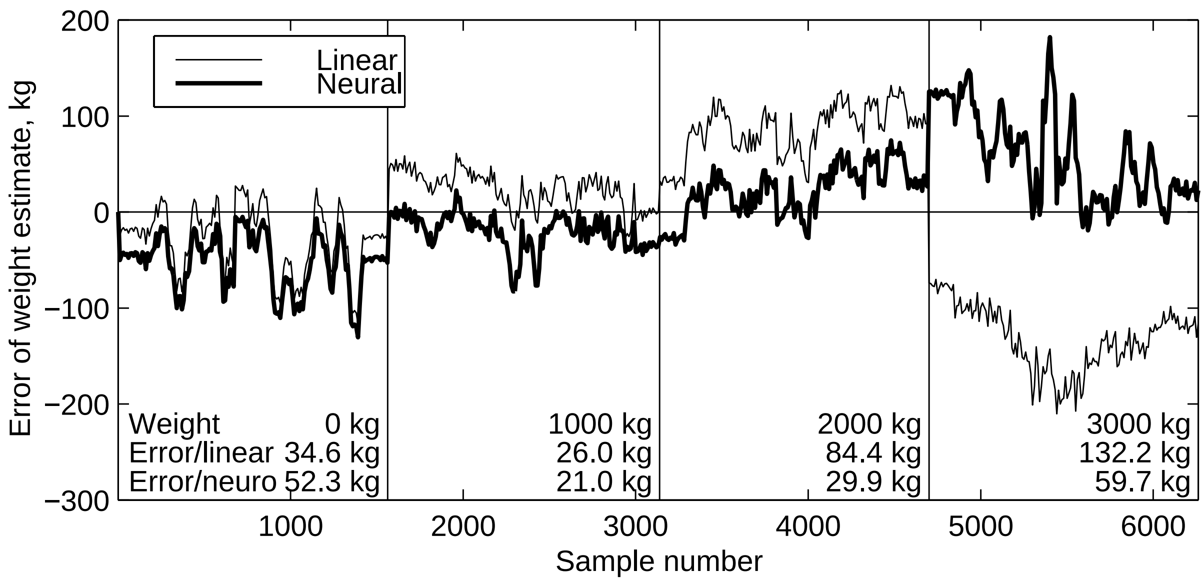

Figure 5: Weight estimation from strains in beam lifter with linear and neural model. The figure shows the weight estimate errors for four different loads when the carriage is run from one extreme position to the another. The mean absolute error for the linear estimate was 69.3 kg and for the neural 40.7 kg.

In the product, neural networks are used for compensating the slight non-linearities. Fig. 5 shows an example from a beam lifter. The linear weight estimate gives errors when the carriage is moving, which can be somewhat attenuated by the neural network estimator. In this application neural network is not a critical part; the success of the weight estimation depends mainly on the positioning of the strain gauges and filtering of the raw measurement signals. However, NN provides inexpensive method for improving the results, in some cases to reach the required accuracy of the weight measurement application.

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