Multi-Sensor Fusion Model for On-line Surface Roughness Prediction

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NOMENCLATURE

d_y	Depth of cut, [mm]
fl_X	Feed/revolution, [mm/rev]
F_Z	Cutting force, [Newton]
F_X	Feed force, [Newton]
I_S	Spindle current, [mA]
P_C	Power in cut, [Watts]
R_a	Surface roughness, [ìm]
r_e	Cutting tool nose radius, [mm]
T_C	Cutting torque, [Nm]
T_t	Mean temperature in cutting tool tip, [^{0}C]
S_C	Cutting sound, [mV]
V_C	Cutting speed, [m/min]
V_y	Cutting tool-work piece vibration, [mV]

Introduction

The on-line measurement of surface roughness in machine turning implies assessing the conditions of a work piece just behind the cutting edge of the tool. A stylus can be used, but it often results in destruction of the sensor head due to high surface speeds of the work piece. Optical reflection methods have been restricted to measurement of relatively smooth surfaces, but due to this limitations are not applicable for use on production floors.

A laser measuring system, which employs a linear charge-coupled device sensor and a neural network to process captured light patterns scattered from the work piece surface, was developed to predict the maximum peak to-valley roughness[1]. However, rather than using direct measurement, several researchers have derived surface roughness indirectly using vibration signals between tool and work piece generated during the turning process[2]. It is clear from recent literature that superior performance through neural networks (NN) may be achieved if information from multiple sensors is fused[3]. An individual sensor only senses partially as it contributes to the measurement of surface roughness. However, a combination of sensors or sensor fusion data may classify it with greater accuracy. Research in sensor fusion has a relatively short history in machining. However, recently more attention has been directed at using and improving sensor fusion techniques[4]. Two major difficulties are encountered when applying the fusion of sensors. These are the adequate selection of input sensors and the establishment of effective fusion modeling. This paper describes a statistical method to identify relevant sensors and the neuro-fuzzy (NF) modeling technique to predict surface roughness on-line for a machining process.

Neuro-Fuzzy

In most sensor fusion applications classification criteria are often expressed using sample data. Although NN has exciting possibilities, it does not use structured knowledge with symbols as used by humans to express reasoning processes[5]. NF technology allows for the automated generation of fuzzy logic (FL) systems based on neural network trained data. NF combines the advantages of fuzzy systems, the transparent repre-

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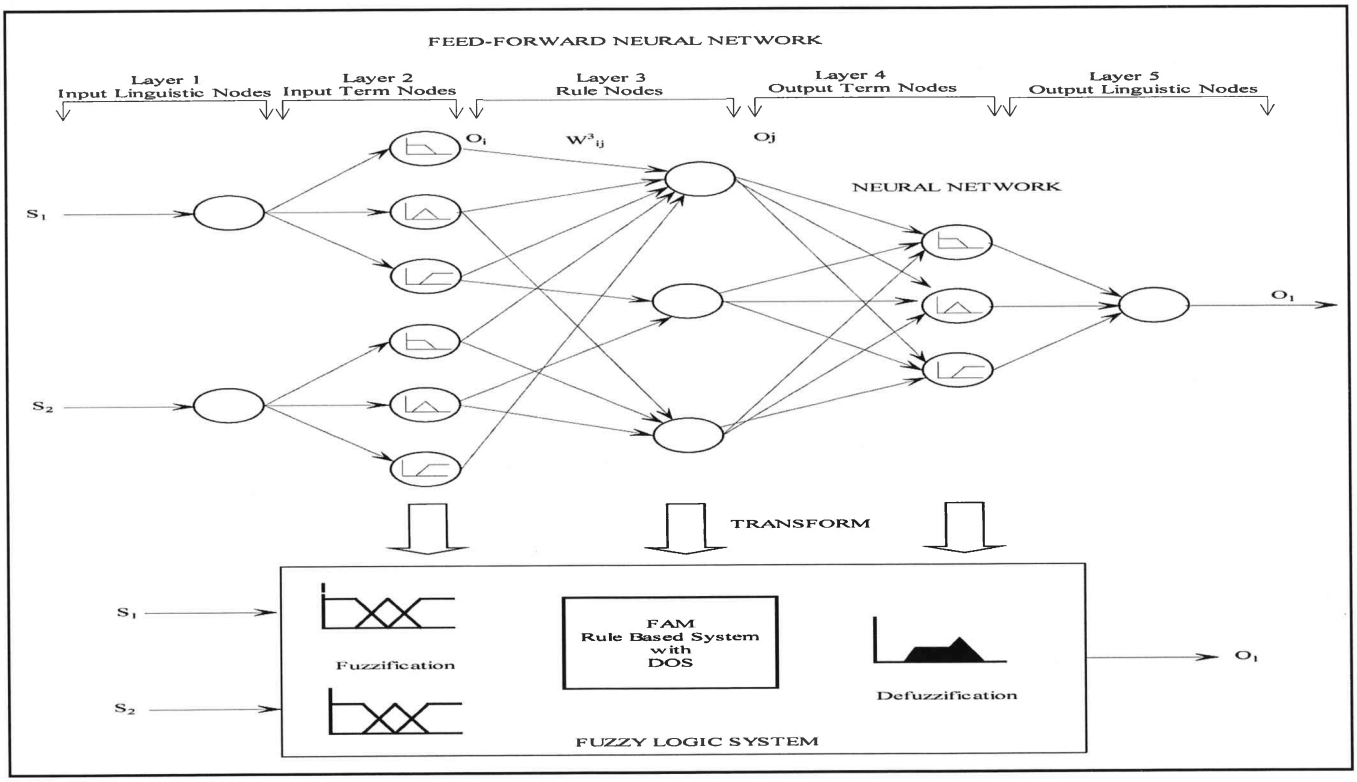

Figure 1: Neuro-fuzzy Structure [6]

sentation of knowledge and the ability to cope with uncertainties, with the advantages of neural nets and its ability to learn. Figure 1 shows a general 5 – layer structure of a NF model, as well as an indication of how to map a NN to a FL system[6].

The linguistic nodes in layers one and five represent the input (S_1-S_n) and output (O_1-O_m) linguistic variables respectively. Nodes in layers two and four are term nodes acting as membership functions (MBFs) to represent the terms of the given linguistic variable. Each neuron of the third layer represents one fuzzy rule (rule nodes). Layer three links define the precondition of the rule and layer-four links incorporate the rule consequences. Initially these layers are fully connected representing all possible rules. A fuzzy system uses different units of computation for the input, hidden and output layers. Rules may be represented by Fuzzy-Associative Maps (FAM), which is a fuzzy logic rule with an associated weight, known as the rule firing strength (or degree of support) for supervised learning.

The NF training employed combines error back propagation with the idea of competitive learning. After a system output is computed by forward propagation, an error is identified by comparing the system output with the sample data[7]. The error is then used to determine the fuzzy rules most suited for influencing system behavior. Using the selected rule, the plausibility of the fuzzy rule is modified before subsequent data sets are processed.

Experimental Setup

Numerous factors influence surface finish during turning operations. Accordingly, as shown by the cause-effect diagram in Figure 2, this study will be restricted to cutting parameters, namely: Feed, speed, depth of cut and a tool wear process condition.

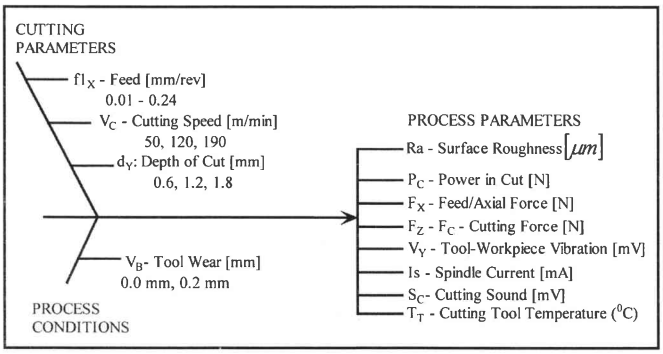

Figure 2: Process cause - effect diagram.

The effect of cutting parameters and tool wear on machining process parameters measured online include: Force in the direction of the feed (Fx), force in the direction of cut (Fz), tool-work piece vibration (Vy), cutting sound (Sc), spindle current (Is), cutting tool temperature (Tt) and power in the cut (Pc), which is calculated from Fz and Vc.

Statistical Data Analysis

The Spearman's rank correlation module of Statistica V6.0 was used to find the measure of association between surface finish and the machining cutting and process parameters derived from the experimental data. Statistical hypotheses testing used to indicate if there exists a relationship. The hypothesis for the Spearman's Rank test is:

Ho: $R_{Ra\text{-}Sensor_data} = 0$, indicates that the correlation equals zero and

H_A: $R_{Ra\text{-}Sensor_data} \neq 0$ indicates the alternate hypothesis.

The p-value, shown in Table 1, indicates the truth of the null hypothesis. Therefore a p-value of less than 0.05 indicates a correlation between surfacE roughness and the machining parameter, i.e. alternative hypothesis. It shows that Ra is correlated with Vz (0.3946), Is (0.5043), Fz (0.4999), dy (-0.6478) and strongly correlates to f1x (0.91770). The parameters are used as sensor inputs to an FL based model to predict surface roughness.

Sensor Machining Data	Spearman's R-value	p-value
Tt	-0.114	0.507947
Pc	0.086435	0.610983
Vz	0.394604	0.015654
Is	0.504253	0.001461
Fz	0.499943	0.001629
Fx	-0.30282	0.068486
Sc	-0.28023	0.102987
dy	-0.6478	1.46E-05
f1x	0.917731	1.34E-15
Vc	-0.00565	0.973535

Table 1: Resultant p-value of Spearman's rank hypothesis correlation test between surface roughness and machining parameters

Multi-Sensor Fusion Modeling

FuzzyTech NF module[8] was used to generate the FL model for surface roughness measurement. The surface roughness obtained experimentally with the predicted values determined using the FL model was compared with the theoretical model given as[9]:

$$R_a = \frac{1}{8r_e} f1_X^2 \quad [\mu m]$$

The comparative results indicate that the FL model represented an average error of at least three times lower than the theoretical model. In both cases the error increased as the feed increased. The FL model was able to measure Ra with an accuracy of 86.44%.

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