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Diagnostic Information Fusion for Manufacturing Processes

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Abstract - This paper addresses diagnostic information fusion for situations where several diagnostic tools are used to estimate a single system state. These estimates will always disagree to some extent and it is the task of the fusion module to provide an estimate which is more reliable than the best of the diagnostic tools. To that end, a fusion process was developed which performs a weighted average of individual tools using confidence values assigned dynamically to the individual diagnostic tools. These confidence values are derived from validation curves which are designed using individual a priori tool information and which are centered about the previous system estimate. In a further step, the fusion output is smoothed leading to additional performance improvement. In experiments, data were gathered from a high speed milling machine and fed through several developed diagnostic tools.

Key words: fusion, information fusion, diagnosis, soft computing, fuzzy fusion.

Introduction and Background

The need of manufacturers to produce inexpensive quality products has resulted in increasing demand for unattended and/or automated manufacturing systems. One problem in automating machining is how to deal with common malfunctions and disturbances such as tool wear, chatter, and tool breakage. Tool wear is a highly non-linear process which is hard to monitor and estimate. To avoid costly damage due to tool wear or breakage, manufacturers use conservative operating procedures to prevent these malfunctions [1]. However, these result in less efficient and more costly production. A number of diagnostic techniques attempt to deal with theses problems, including neural networks [2], clustering algorithms Burke [3], Kohonen’s Feature Map [4], fuzzy logic [5], and influence diagrams [6]. To achieve further performance improvement, hybrid systems were proposed to overcome shortcomings of individual systems, such as fuzzy-neural systems [7]. Hybrid use of above mentioned techniques and other soft computing principles for diagnostics and prognostics are given in Bonissone and Goebel [8]. In a similar spirit, fusion techniques combine different methods to overcome shortcomings of individual tools. This paper proposes one fusion method based on fuzzy validation gates.

Diagnostic Fusion via Validation Gates

The method developed is a two-level system consisting of a number of diagnostic classification systems on the first level and a managerial fusion unit on the second. The data are fed into each of the first level units, and their output is combined in the second level to produce a single, better solution (Fig. 1).

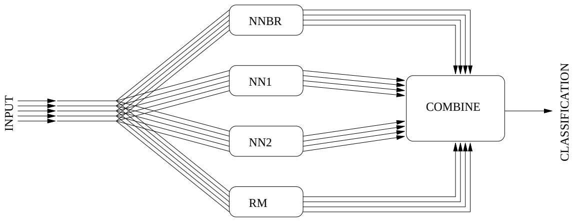


Fig. 1: The system architecture

To address some of the problems outlined above, we propose the fusion of diagnostic estimates via fuzzy validation curves called Fuzzy Diagnostic Validation and Fusion (FUDVAF). This technique is related to the FUSVAF (Fuzzy Sensor Validation and Fusion) algorithm developed for sensor fusion [10, 11, 12]. The fusion algorithm uses confidence values obtained for each diagnostic output from validation curves and performs a weighted average fusion. With increasing distance from the predicted value, readings are discounted through a non-linear validation function. The predicted value in the FUDVAF algorithm is obtained through application of an exponential weighted moving average time series predictor

The confidence value which is assigned to a particular diagnostic output depends on the specific tool characteristics, the predicted value, and the physical limitations of the diagnostic value. The assignment takes place in a validation region which assigns a maximum value to readings which coincide with the predicted value. The curve is dependent on the sensor behavior. Generally, this is a non-symmetric curve which is wider around the maximum value if the diagnostic tool is more reliable and narrower if it is less reliable.

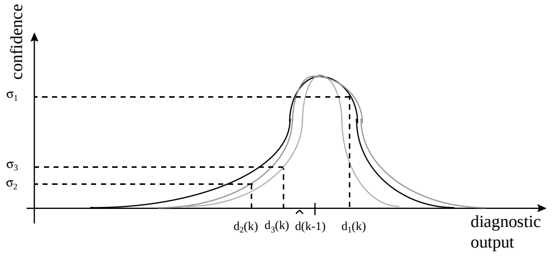
A choice for validation curves σ(z) could be a bell curve of the form

$$\sigma(d_t) = 1 - e^{-\left(\frac{\left(d_t - \hat{d}\right)^m}{a_t}\right)^2}$$

where

m is a scaling parameter
a_i is the tool accuracy
d_i is the diagnosis of tool i
$\hat{d}$ is the estimated diagnosis

A validation gate is shown in Fig. 2.



d_t	diagnostic output
σ_i	confidence values
$\hat{d}(k-1)$	fused value

Fig. 2: Validation gate for the assignment of confidence values

The fusion is performed through a weighted average of confidence values and diagnostic output. The sum of the confidence values times the measurements rewards measurements closest to the old fused value the most, depending on the validation curve which expresses a trust in the operation of each diagnostic tool through the design of its shape. Measurements further away are discounted. The operative equation in the FUDVAF algorithm is

$$d_f = \frac{\sum_{t=1}^{n} d_t \sigma(d_t)}{\sum_{t=1}^{n} \sigma(d_t)}$$

where

d_f: fused value
d_t: diagnostic output of tool t
σ: confidence values

Note that if all diagnostic outputs lie on one side of the predicted value, the fused value will also be pulled to the same side. This ensures that evidence from the diagnostic tools is closely followed yet discounted the further it gets away from the predicted value.

We used a time series filter to further improve the result of the system using the standard EWMA predictor of the form

$$\hat{d}(k) = \hat{d}(k-1)\alpha + \frac{\sum_t \sigma_t d_t}{\sum_t \sigma_t}(1-\alpha)$$

where

α is the smoothing parameter; α=0.1

Experimental Setup

A milling machine under various operating conditions was selected as the manufacturing environment. In particular, tool wear was investigated in a regular cut as well as entry cut and exit cut. Data sampled by three different types of sensors (acoustic emission sensor, vibration sensor, motor current sensor) were used to determine the state of wear of the tool. As the wear measure, flank wear VB (the distance from the cutting edge to the end of the abrasive wear on the flank face of the tool) was chosen. The flank wear was observed during the experiments by taking the insert out of the tool and physically measuring the wear. The setup of the experiment is as depicted in Fig. 3. The basic setup encompasses the spindle and the table of the Matsuura machining center MC-510V. An acoustic emission sensor and a vibration sensor are each mounted to the table and the spindle of the machining center. The signals from all sensors are amplified and filtered, then fed through two RMS before they enter the computer for data acquisition. The signal from a spindle motor current sensor is fed into the computer without further processing. Data are categorized into four classes and are approximated by fuzzy membership functions (no wear, little wear, medium wear, high wear) shown in Fig. 6.

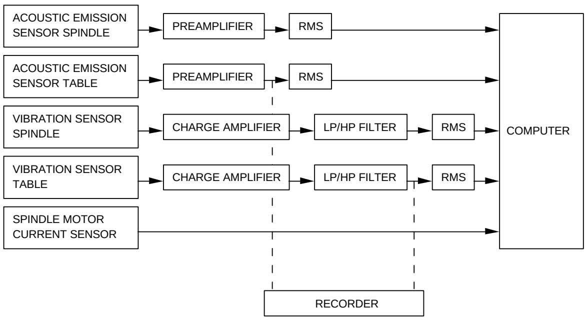


Fig. 3: Experimental setup

Input data transformations

Before being used, the following transformations were applied to the data:
1.) The data was smoothed by averaging using a window of 50 points, and then the sample size was reduced by sampling the resulting data set at 50 point intervals. 2.) Each input and the output data was normalized to lie between 0 and 1. 3.) Since the output variable was sampled at much larger intervals than the input variables, and since it represents tool wear, the output data was further smoothed by fitting a 3rd order polynomial.
Fig. 4 and Fig. 5 show the normalized and smoothed input and output data. The output data was categorized into four classes using fuzzy membership functions.

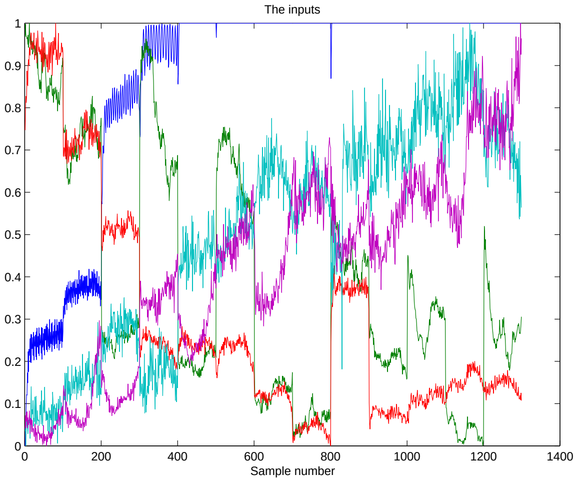


Fig. 4: Input data

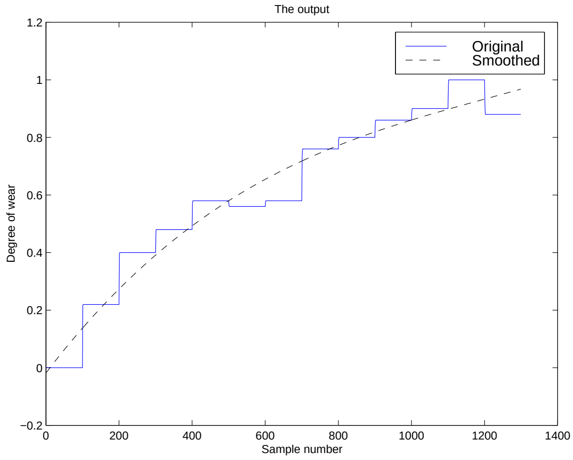


Fig. 5: Ouput data

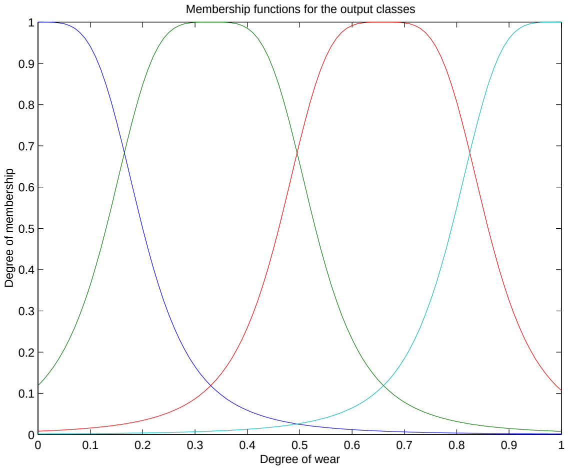


Fig. 6: Membership functions

Diagnostic tools employed

***Nearest neighbor classifier (NNBR)**:* The first subsystem uses a nearest neighbor scheme for classifying the data. The case base consists of a set of sensor readings and the associated unclassified wear value. Given an input, the k nearest data points are determined and the associated wear values are averaged. This average is then used to compute the membership degree for each of the four classes.
Neural network (NN1): The second subsystem is a neural network that was trained on binary classes. That is, the target values were 0 and 1 vectors determined by the maximum membership value over the four classes.
Neural network (NN2): The third subsystem is also a neural network, but this was trained to learn the membership values themselves, as opposed to the classes.
Fuzzy inference system (RM): The fourth subsystem is a fuzzy inference system implemented using a relation matrix.

Architecture

As shown in Fig. 1, the input to the first level of the system are the measured features. The output consists of four values indicating the degree of membership for each of the four output classes. We chose this approach over an approach where the first level subsystem generates a crisp class (from 1 to 4) because this approach gives more flexibility and information to the second level system. This is in response to the need recognized after development of the neural-fuzzy diagnostic tool [9] which attempted to segment the data into five crisp classes. In the approach chosen here, the membership approach allows a softer classification. The second level system then combines the results of the first level systems and classifies the input into a single class. We will be focusing in this paper on the fusion task and evaluate performance based on the fused membership values.

One basic problem in averaging techniques or majority voting techniques is the danger of ending up with a system which performed worth than the best individual tool because the poor estimates drag down the better estimate. One potential solution is to weigh the tools according to their performance which must be known beforehand. The FUDVAF tries to perform this task. Stand alone tests were performed to establish the accuracy of the individual diagnostic tools which are shown in Table 1.

Table 1: Classification rates

System Rate	(%)
Nearest neighbor (NNBR)	96.8
Neural network 1 (NN1)	80.6
Neural network 2 (NN2)	86.7
Relational matrix (RM)	81.0

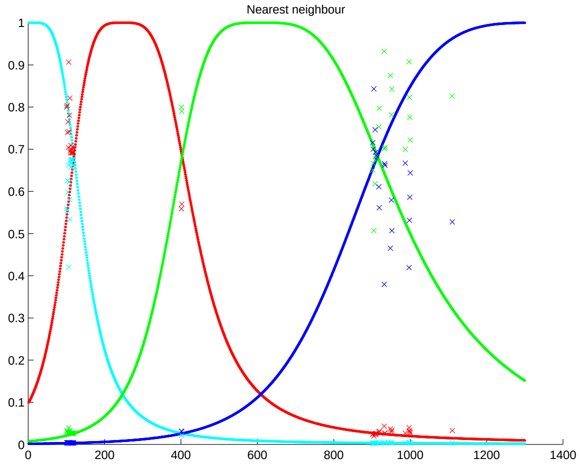


Fig. 7: Output NNBR

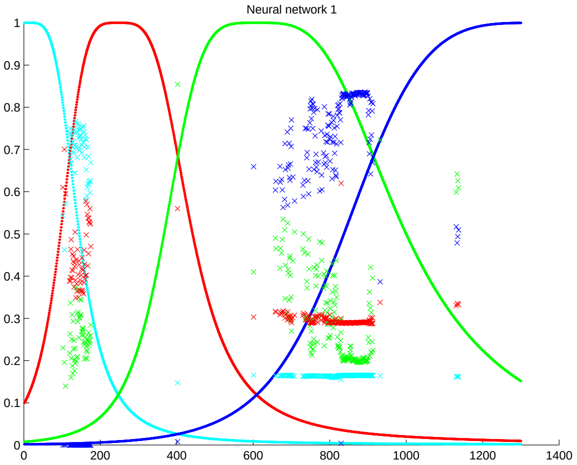


Fig. 8: Output NN1

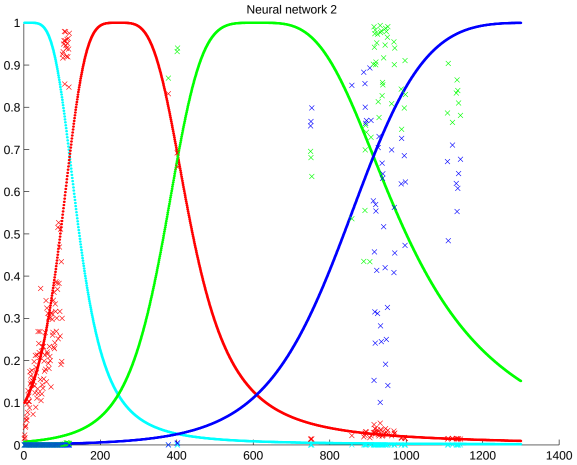


Fig. 9: Output NN2

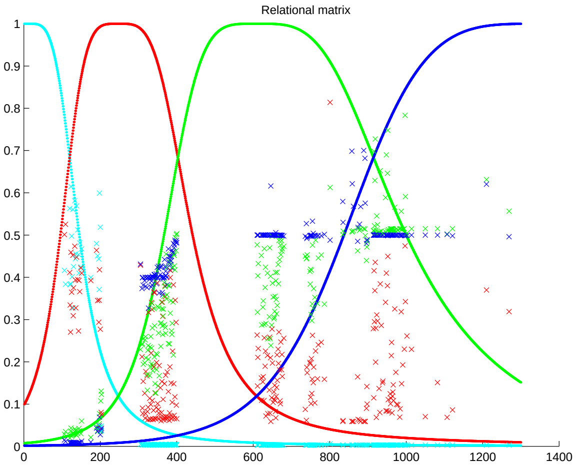


Fig. 10: Output RBS

Fig. 7 to Fig. 10 depict the performance of the individual systems. The solid lines show the true membership values for the data. The crosses indicate the membership values generated by the system when the system disagrees on the classification. Thus, the crosses are an indication of the area(s) in which the system has difficulty in deciding on a class. Fig. 7 shows that NNBR has classification errors only near the cross-over points of the membership functions. These are areas where classification errors are expected, because a small change in the membership value results in an incorrect classification. Even at these points, however, NNBR membership values are very close to the true membership values. The success of this system is due to the continuous nature of the wear measure, and the averaging technique used in the nearest neighbor classification. The other systems are not as successful, and the membership values output do not approximate the true values to the degree that NNBR does.

The high success rate of one tool means that if it were used as part of the majority fusion, the performance degrades somewhat. This is to be expected, because the votes of the poor performers will sometimes out vote the correct one. The problem is greater with increasing number of classification regions, as there will be cases when each system will generate a different class, and the majority voting system will then pick one randomly.

Results

The fusion using assignment of confidence values provides a means to integrate a priori information about individual tool performance. This is accomplished by designing the validation curves of a better tool wider than the curves of the tools with worse performance. The fused performance improves the already very good performance of the NNBR tool from 96.8% to 99.1% correct classification with α=0.1 and m=0.1. Fig. 11 shows the result of the fused system where the membership functions no wear, little wear, medium wear, and high wear were estimated.

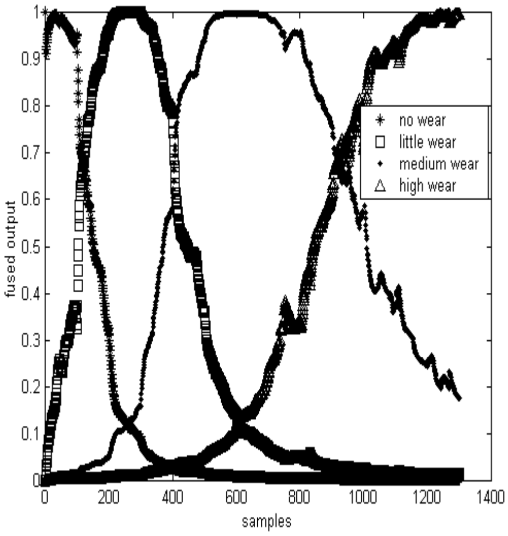


Fig. 11: Fused system output

Summary and Final Remarks

The use of the FUDVAF algorithm provides a means to improve performance of individual diagnostic tools. In experiments with data from a milling machine, we show how the FUDVAF can be used for extant systems. Much of performance improvement appears to be due to the smoothing and an increase of performance might also be expected when the smoothing is applied to the best tool alone.

Future research should address how to improve fine tuning of the validation curve parameters, depending on operating conditions and sensor history. This can be accomplished through machine learning techniques similar to the approach used for the FUSVAF algorithm [11]. Also helpful might be knowledge about locally changing diagnostic tool performance. Such local characteristics could be utilized in designing the validation curves in a dynamic manner by changing the width accordingly. Generally, it is desirable to maintain maximum independence of the diagnostic tools in the sense that tools which exhibit poor performance in certain operating conditions are matched with tools exhibiting better conditions there. This may, of course, not always be possible due to the limitations of observable conditions and shortcomings of the diagnostic tools because often times (and in this approach here), all sensor values are made available to all diagnostic tools.

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