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Transformations in machining. Part 1. enhancement of wavelet transformation neural network (WT-NN) combination with a preprocessor

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Abstract

Properly selected transformation methods obtain the most significant characteristics of metal cutting data efficiently and simplify the classification. Wavelet Transformation (WT) and Neural Networks (NN) combination was used to classify the experimental cutting force data of milling operations previously. Preprocessing (PreP) of the approximation coefficients of the WT is proposed just before the classification by using the Adaptive Resonance Theory (ART2) type NNs. Genetic Algorithm (GA) was used to estimate the weights of each coefficient of the PreP. The WT-PreP-NN (ART2) combination worked at lower vigilances by creating only a few meaningful categories without any errors. The WT-NN (ART2) combination could obtain the same error rate only if very high vigilances are used and many categories are allowed.

Keywords: Manufacturing applications; Process monitoring; End milling; Micro machining; Wavelet transformation; Neural network; ART2; Genetic algorithm; WT-NN

1. Introduction

Transformation methods have been used for a long time to calculate the parameters, which represent the most significantly changing characteristics of the data at the considered states. Depending on the number and complexity of these parameters, and the user's preference, the state of the data has been classified by using simple rules, Neural Network (NN), Fuzzy Logic (FL), and many other approaches. Multipurpose transformation hardware and software have been developed and used in many engineering applications at a fraction of the cost of customized solutions with serious limitations. Fast Fourier Transformation (FFT) is the best known and widely used multipurpose transformation method. Wavelet Transformation (WT) found their niche at the compression of the data and has been widely used, particularly at the computer graphic applications. In this paper, enhancement of the capabilities of the WT-NN combination is proposed by using the Genetic Algorithms (GA).

FFT [1] represents a signal with a series of harmonic waves and has excellent fixed resolutions. WT [2–5] use dilations and translations of a mother wave. WT could obtain a very compact representation of complex signals by using the customized, or a suitable generic mother wave. Depending on the application, the multi-resolution characteristics and time domain information of the WT could be very useful. It has been widely used for the detection of tool breakage and the estimation of wear in machining operations [6–21]. The compact representations of WT easily reduce the data size to 1/8th or less and carry the information about a large frequency range. However, the complex patterns of the estimated coefficients require a trainable or a self-learning computational tool such as NN.

Backpropagation (BP) [22] and Adaptive Resonance Theory 2 (ART2) [23] type neural networks have been used in many mapping and classification applications. WT-NN combinations have been introduced in 1993 [6] and have been successfully used in machining operations [24–31] to estimate wear and detect tool breakage by evaluating the WT coefficients. WT-NN (ART2) combination is a very convenient tool to start to monitor the machining operations

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with minimal or no previous training. WT-NN (ART2) combination will warn the operator when the tool wears out and the cutting characteristics of the observed force, spindle current, acceleration or sound change. The sensitivity of the ART2 depends on the selected vigilance. If the vigilance of the ART2 is selected low, it might miss the change of the cutting characteristics. On the other hand, a high vigilance will create extensive false alarms.

GAs [32–33] are very flexible optimization tools. They can be used from simple curve fitting to extremely complex rule making as long as the objective function is properly prepared. In this study, the use of a preprocessor (PreP) is proposed between WT and NN (ART2) to minimize the number of categories and errors. The GA is proposed to estimate the weights of the PreP during the training process. The GA will automatically identify and give the maximum weight to the most influential WT coefficients, which has the highest correlation with the desired outcome. On the other hand, the coefficients, which confuse the NN (ART2), will have small weights and less influence on the decisions of the ART2.

In the following section, the theory of the WT, ART2 and GA will be discussed very briefly. The proposed method, experimental setup, results and discussion, and conclusions will be presented in the rest of the paper.

2. Theoretical background

WT, NN (ART2) and GA have found many applications in recent years because of their flexibility, efficiency, and reliability. In the following sections, these methods will be introduced very briefly, since extensive information is available in the literature.

2.1. Wavelet transformation

WT [2–5] represent a signal by using a family of functions derived from a single function. The following equation represents the wavelet transform of a $f(t)$ function:

$$f(t) = \sum_{n=-\infty}^{\infty} c(n)\Phi_n(t) + \sum_{i=0}^{\infty}\sum_{j=-\infty}^{\infty} d(i,j)\Psi_{i,j}(t) \tag{1}$$

where

$$c(n) = \int f(t)\Phi_n(t)\mathrm{d}t \quad d(i,j) = \int f(t)\Psi_{i,j}(t)\mathrm{d}t.$$

The coefficients of the wavelet transform are $c(n)$ and $d(i,j)$. $\Phi(t)$ and $\Psi(t)$ are the scaling function and primary wave, respectively. Digital filters are used to obtain the WT coefficients efficiently [5]. In this study, Daubechies 3 [34, 35] type scaling functions have been used.

2.2. Adaptive resonance theory (ART2)

The ART2-type neural networks were developed by Carpenter and Grossberg [23]. They are designed to achieve a self-organized stable pattern recognition capability in real time by using the adaptive resonance theory. If the input and the feedback expectancies match, the adaptive resonance occurs. The ART2 compares the input patterns with previously encountered patterns. If the input pattern is found similar to any of the previous ones, it will be placed in the same category with them. Otherwise, a new category will be assigned to it. The responsiveness or sensitivity of the ART2 is adjusted with the vigilance. Highly sensitive ART2 will make fewer mistakes; however, it will create many categories and may cause many false alarms. Low vigilance values create fewer categories but also increase the errors. For successful use of ART2 the optimal vigilance value should be selected.

2.3. Genetic algorithm (GA)

Genetic algorithms [32–33] use the biological evolution principles including natural selection, and the survival of the fittest. The parameters, rules, and switches of the considered problem are represented by a binary combination called chromosome. The goal is to obtain the optimal 0 and 1 combination for the chromosome to minimize or maximize the objective function by using the following five-step process: (1) selection of the mating parents; (2) selection of the hereditary chromosome from parents; (3) gene crossover; (4) gene mutation, and (5) creation of the next generation. Penalty functions are used to change the value of the objective function if any of the considered parameters are out of the boundaries. The user selects the population size, the number of children for each set of parents, and the probability of mutation according to the problem to complete the optimization process quickly and accurately.

3. Proposed WT-PreP-NN (ART2) classifier for micro-end-milling operations

The WT-NN approach for tool breakage detection was introduced in 1993 [6]. Afterwards, the neural network based periodic tool inspector (N^2PTI) concept was developed to monitor tool wear (usage) during the micro machining of soft materials in 2000 [7]. In this section, the WT-PreP-NN approach will be introduced after (N^2PTI) with WT-NN combination is briefly reminded.

3.1. Neural network based periodic tool inspector (N^2PTI) With WT-NN (BP) combination

The N^2PTI was developed to estimate the tool condition with a highly reliable low cost system even if the cutting path is complex and the material is soft [7]. The operation of the N^2PTI is outlined in Fig. 1. The N^2PTI estimates the tool wear (usage) periodically when a slot is cut on an aluminum test piece at the identical cutting condition. The workpiece is attached to the table of the milling machine. The material of the actual workpiece, tool path, and cutting conditions do

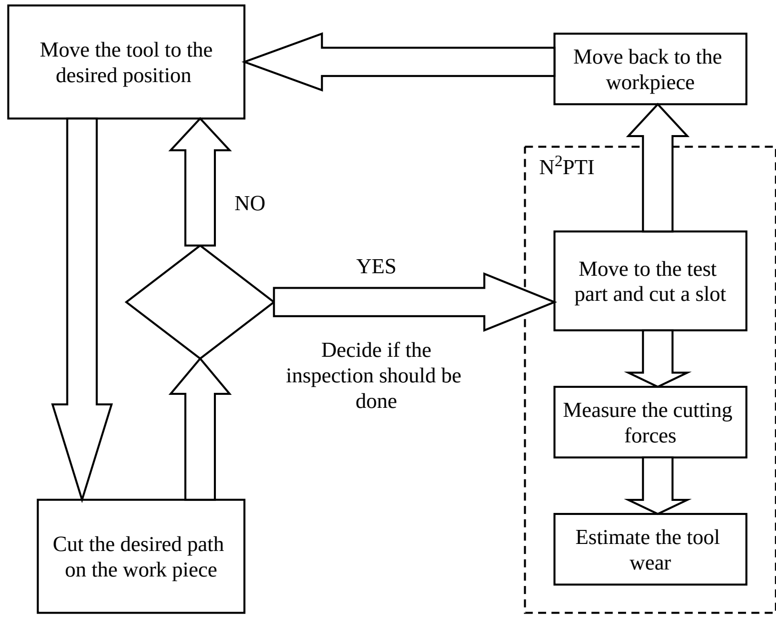

Fig. 1. Operation of the N^{2}PTI.

not affect the performance of the monitoring system since the data is not taken during the machining of the part. Preferably an aluminum test piece is installed on a dynamometer, which is attached to the table next to the workpiece. The user prepares the part program to cut the workpiece and periodically moves the tool to the test piece to cut a slot on it. The feed and thrust direction cutting forces were measured while the test piece was cut. Only one load cell could have been used to lower the cost of the system.

To estimate the tool usage (wear), the raw data was processed in two stages when the method was introduced: encoding and classification (Fig. 2). In the first step, the WT of each cutting force was performed five times to reduce the data to eight approximation coefficients. In the second stage, BP type NN was used to estimate the wear level of the micro-tool from these 16 approximation coefficients (8 for each force). The BP type NN was trained on the experimental data with known usage.

3.2. Neural network based periodic tool inspector with (N^{2}PTI) and WT-PreP-NN (ART2) combination

The proposed approach collects the experimental data periodically based on N^{2}PTI concept and uses ART2 type NN instead of previously used BP type NN. In addition, a preprocessor (PreP) multiplies each approximation coefficient of the WT with a weight just before passing them to the ART2. The new approach is presented in Fig. 3.

WT-PreP-NN (ART2) collects experimental data for training and to obtain the coefficients of the PreP. The coefficients of the PreP are determined by using the GA. This process is presented in Fig. 4. The vigilance is selected between 0.94–0.96 to keep the number of assigned categories low. The objective function is the minimization of the (Categories of ART2-Desired number of categories) while no wrong classification is allowed. At the beginning, the operator selects the desired number of categories = 2 (good and worn tool) and the GA finds the weights of the PreP. Generally, the second category develops at an earlier stage, before the tool wears out. He sets the desired number of categories = 3 and obtains the PreP coefficients from the GA. He continues to increase the desired number of categories until a new category is created at the desired tool usage (wear) level. If there is no wrong classification or they are below the acceptable level, the PreP uses the optimized weights of the GA to preprocess the WT approximation coefficients before giving them to the ART2.

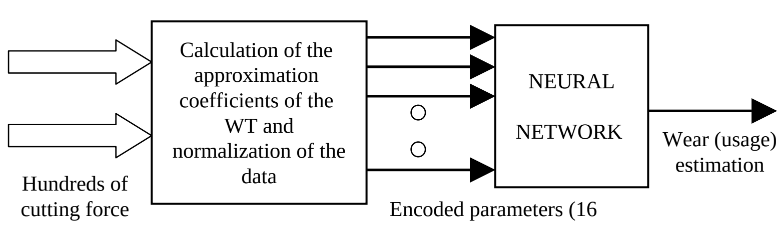

Fig. 2. Tool wear estimation from the cutting force variations.

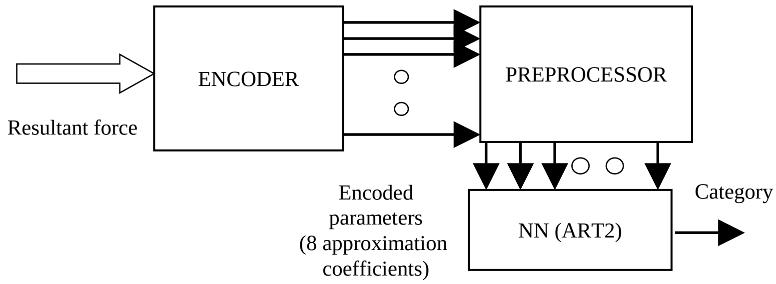

Fig. 3. The operation of the proposed WT-PreP-NN (ART2) combination.

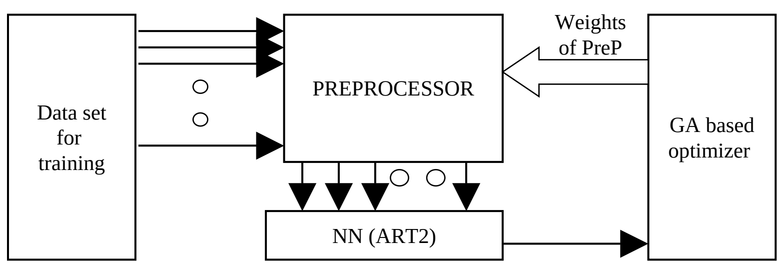

Fig. 4. Calculation of the weights of the PreP by using the GA.

4. Experimental data collection

The experimental set-up is presented in Fig. 5 [7]. A POCO-EDM-C3 electrode and an aluminum test piece were attached to a 9257B three-component Kistler dynamometer. The feed and thrust direction cutting forces were recorded while the aluminum test piece was cut. A 1/16″ carbide tool was used to collect the experimental data. The spindle speed was 15,000 rpm. The POCO EDM-C3 electrode material was machined with a 20 inch/min feed rate and 0.030 inch depth of cut. Experimental data was collected by cutting the aluminum test piece at 15,000 rpm with a 5 inch/min feed rate and a 0.015 inch depth of cut. Experimental cutting conditions are presented in Fig. 5.

5. Results and discussion

Previously, WT was repeated 5 times and 8 approximation coefficients were estimated for each cutting force. BP type NN used a total of 16 approximation coefficients (two cutting forces). After the training, BP estimated the usage with less than 10% error (relative to the range) in 32 training and 24 test cases. The average usage estimation error was less than 4% in training and less than 8% in the test cases; the neural network never saw it before. As long as ample training data is available, this approach is expected to perform well.

Self-learning NN may start to monitor the sensory signals with no training. When the characteristics of the signal

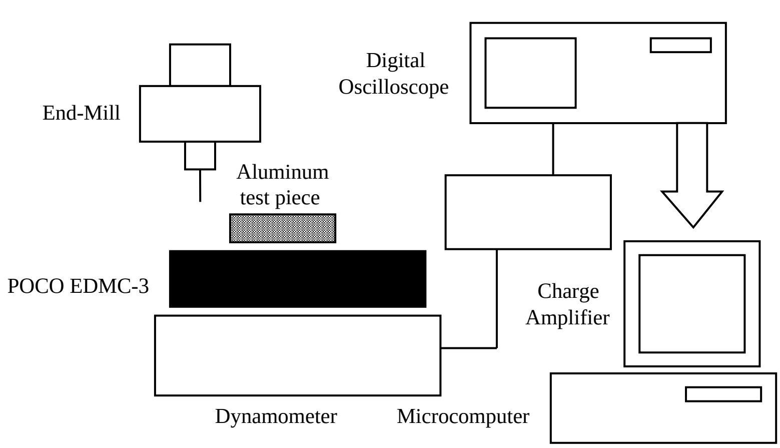

Fig. 5. The diagram of the experimental set-up for tool wears on POCO EDMC-3.

change, they create a new category. Their sensitivity is adjusted by selecting the vigilance coefficient of the ART2. The objective of this study was to use PreP to create a minimum number of categories and to have preferably no misclassifications.

In this study, the resultant cutting force was calculated from the feed and thrust direction cutting forces and used to estimate the tool wear (usage). WT was performed 3 times by using Daubechies 3 type wavelets [34–35] and 9 approximation coefficients were obtained, 8 of them were used for classification.

Seventy two sets of data were collected at nine usage (wear) levels. There were eight sets at each wear level. Half of them were used for training; the other half was used for testing. ART2 inspected the approximation coefficients of the WT and classified them in categories starting from 1 during the training. It assigned a new category when the characteristics of the signal changed. The system was expected to create a new category at the 8th usage level. That category and the higher ones were referring to the worn tool while the previously assigned ones were good tool categories. It was not acceptable to assign any of the previously assigned categories to the data at the 8th and 9th usage level. After the training, ART2 was tested with the 36 test cases it had not seen before. It was expected to assign the previously assigned good tool categories to the data in the 1st to 7th usage (wear) levels. At the 8th and 9th usage (wear) levels, it was expected to assign the worn tool categories.

The performance of the ART2 on the training data is presented in Fig. 6. It created two categories for the vigilance of 0.92 and classified most of the cases wrong. The error was reduced to 0 with the vigilance of 0.998. However, ART2 created 35 categories. The performance of the ART2 on the test cases is presented in Fig. 7. The test cases had very similar trends in respect to the training cases. Optimal vigilance was 0.96. ART2 assigned nine categories to the data, and classified 1 training and 1 test case wrong.

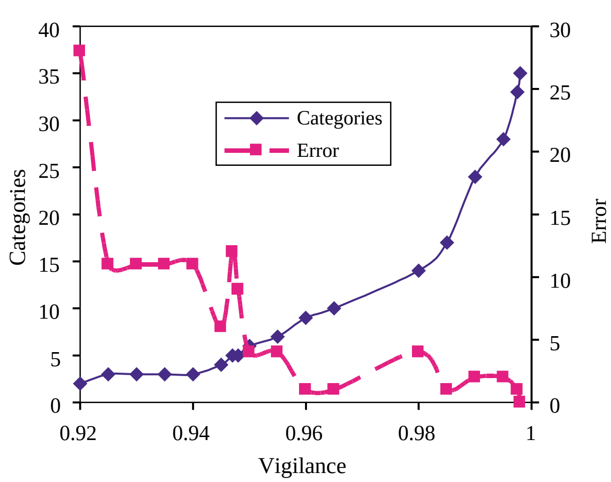

Fig. 6. Performance of the ART2 on the training cases when it classifies the approximation coefficients of the WT.

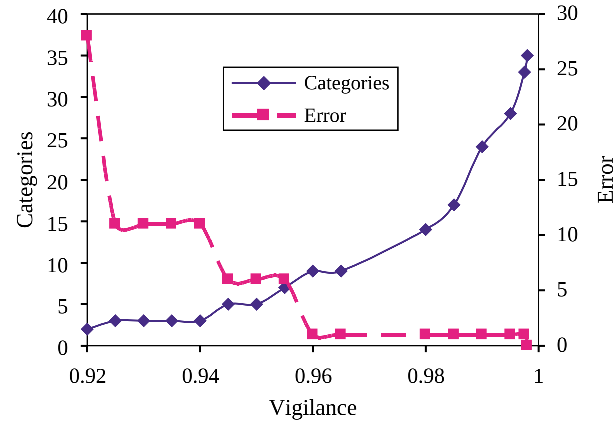

Fig. 7. Performance of the ART2 on the test cases when it classifies the approximation coefficients of the WT.

ART2 created fewer categories when it classified the approximation coefficients after they were processed by the PreP. The PreP multiplied each approximation coefficient of the WT with a constant. These constants were obtained by using the GA after the optimal values were found by following the procedure in Fig. 4. The performance of the WT-PreP-NN combination on the training and test cases are presented in Figs. 8 and 9, respectively. Optimal vigilance was 0.94. ART2 created four different categories without any misclassifications. In fact, this classification is very meaningful. Sharp tools create very small cutting forces. Forces significantly increase within the early stages of the tool life. ART2 used the first category for the new and the second category for the slightly worn tools. When the tool reaches to the 8th usage level, it is assigned to the third category. The fourth category was assigned for some of the data collected with worn tools at the 8th and 9th usage levels.

The advantages of the WT-PreP-NN (ART2) over WT-NN (ART2) are clearly demonstrated in Table 1. When the WT-PreP-NN (ART2) combination is used, the monitoring could be started without any training. The second category

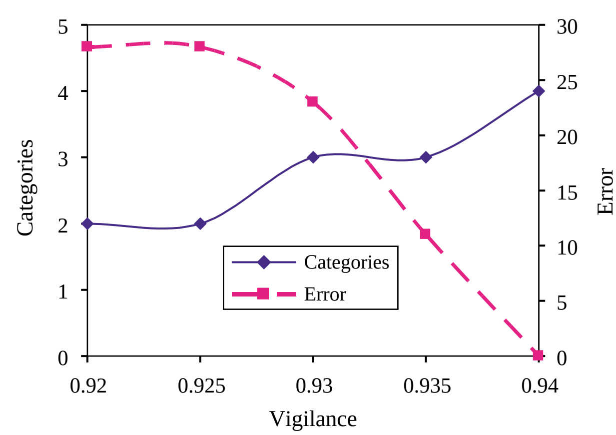

Fig. 8. Performance of the ART2 on the training cases when it classifies the processed approximation coefficients of the WT by using the PreP.

Table 1
Comparison of the performance of the WT-NN (ART2) and WT-PreP-NN (ART2) combos

Data	Classification	Vigilances					
		0.92		0.94		0.998	
		Categories	Error	Categories	Error	Categories	Error
Training	WT-ART2	2	28	3	11	35	0
	WT-PreP-ART2	2	28	4	0	N/N	N/N
Test cases	WT-ART2	2	28	3	11	35	0
	WT-PreP-ART2	2	28	4	0	N/N	N/N

will indicate the tool is slightly worn. Micro-end-mill should be changed when the WT-PreP-NN (ART2) assigns the third category.

6. Conclusions

Self-learning NNs such as ART2 are excellent classification tools and could be used even without training. The researcher should carefully select the vigilance, which adjusts the sensitivity of the ART2 to keep the number of assigned categories and the error to a minimum. Unfortunately, small vigilances assign a few categories as desired with a lot of misclassifications. Increasing the vigilance could control the errors; however, the number of assigned categories and possible false alarms will increase.

The proposed WT-PreP-NN (ART2) combination automatically adjusts the influence of the approximation coefficients one by one by using GA. This approach created meaningful number of categories and eliminated the misclassifications at the studied cases. If the characteristics of the signal gradually change, it is very unlikely that this approach will be able to create only two categories, which correspond to ‘good’ and ‘bad’. However, the number of the assigned categories, misclassifications and false alarms could be controlled. Depending on the desired precision, several categories would be allowed at the ‘good tool’ category to indicate the degradation of the cutting edges.

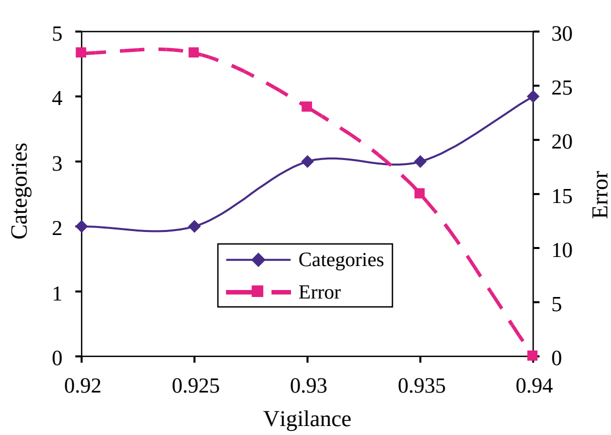

Fig. 9. Performance of the ART2 on the test cases when it classifies the processed approximation coefficients of the WT by using the PreP.

The proposed procedure involving the determination of the coefficients of the PreP by using the GA in a training session fine-tunes the sensitivity of the WT-PreP-NN (ART2) combination. Once the coefficients of the PreP are estimated, the WT-PreP-NN (ART2) combination may start to monitor the desired operation without any training just like a self-learning NN.

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