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선삭가공에서 시계열모델 및 주파수대역에너지법에 의한 공구마멸과 채터의 검출

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Tool Wear and Chatter Detection in Turning via Time-Series Modeling and Frequency Band Averaging

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ABSTRACT

기계가공프로세스에서 절삭공구의 마멸과 채터진동은 공작기계의 가동율과 생산성을 크게 저해하는 요인이 되고 있다. 본 연구에서는 공구마멸과 채터현상이 혼재하는 상황에서, 이들 두 현상을 동시에 검출하는데, AE 및 가속도센서에서 검출된 신호와 AR계수 및 주파수대역 평균에너지를 특징입력으로 하는 인공신경회로망을 이용하였다. 그 결과, 공구마멸과 채터현상에 대응하는 서로 다른 신호특징의 차이를 동시에 식별하는데 인공신경회로망의 유용성을 입증하였으며, 시계열모델의 AR계수(70~90%)보다는 주파수대역에너지법의 평균에너지(80~100%)를 신경회로망의 특징입력으로 하는 경우가 높은 성공률을 나타내었다.

Key Words : Tool Wear, Chatter, Detection, Acoustic Emission , Acceleration, Time-Series Modeling, Frequency Band Averaging, Artificial Neural Network, Turning

1. Introduction

The objective of this paper is to discuss a methodology for on-line detection of tool wear and chatter in machining. The approaches presented will be based on the integration of acoustic emission (AE) and tool acceleration signals. These signals are processed by either time series modeling or frequency band averaging for use in conjunction with an artificial neural network in developing the knowledge regarding the state of tool wear and chatter.

The extent of tool wear in a machining operation has a strong impact on the surface finish and dimensional tolerance of the work, as well as the vibration level of the machine tool. To monitor tool wear during machining, a wide variety of methods has been proposed to capture the change of rubbing contact of the work and tool flank interface due to the enlarging wearland in machining. These methods include the measurements of spindle power, acceleration, cutting force, and AE[1-3].

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In addition to tool wear, chatter vibration of the cutter presents yet another nuisance to metal cutting processes. Chatter in machining has adverse effects on surface finish, dimensional accuracy, tool life, and machine life[4] thereby making the monitoring of its behavior an important issue. There has been a considerable amount of research attention focused on the monitoring of machine tool chatter. Among the candidate solutions are the measurement and analysis of workpiece displacement, velocity, acceleration, and machined surface characteristics[3, 5, 6].

Although many studies have been documented in the area of tool wear or chatter monitoring, few reports have studied the simultaneous monitoring of both tool wear and chatter. Investigations on the dynamic characteristics of cutting force signals in relation to the level of tool wear showed that the dynamic variation of the force becomes important under worn tool conditions because of the vibrations produced due to flank friction between the tool and workpiece[7, 8]. These studies indicated a strong coupling between the wear and the chatter of cutting tools thereby suggesting that any monitoring system concentrating on only one of these phenomena may not be practical and cost effective for actual factory floor applications.

In this paper the detection of both chatter and tool wear is performed using an artificial neural network with AE and acceleration signals. These signals are pre-processed by either time series modeling or frequency band averaging. The use of time series models is motivated herein by the uncertainty and time-variation involved in the signal characteristics during actual machining. For instance, the possible shift of chatter vibration frequency in turning[4] renders any monitoring approach based on a slow-varying signal feature incapable, on the other hand, time series models can be made adaptive to reflect the instantaneous cutting condition as affected by tool wear and chatter. In the frequency band averaging method, the problem of signal analysis in the frequency domain is converted into the time domain, therefore the characteristics of cutting states in the frequency domain can be extracted conveniently without further spectral analysis[9], and the contradiction between data processing speed and accuracy can be overcome.

The following sections discuss the sensing and signal processing methodology involved, the turning set up, experimental procedure and the results.

2. Sensing System Design

2.1 Acoustic Emission and Acceleration in Machining

The wear of a cutting tool is expected to affect AE signals through the change in the tool geometry and the change in the chip form due to a lower strain hardening effect brought about by a higher temperature. Thus the dynamic variation of an AE signal often carries information regarding the state of tool wear. In the case of chatter vibration, AE signal characteristics change in response to the variation in the basic mechanics of the cutting process accompanying the tool-work vibration. This includes the change in strain rate due to the change of the tool tip velocity and of the volume of material being removed at any instant of time as a result of varying chip thickness. Therefore the analysis of AE can be a relevant tool for the monitoring of machining chatter[10] as well.

The behavior of flexural vibrations of a cutting tool during machining in relation to tool wear has been investigated by Del Taglia ***et al.*** [11]. His work, using a carbide tool in turning carbon steel workpieces, showed that the spectral magnitude of the tool acceleration signal, in the range up to 2.5 kHz, increased up to seven times while tool wear increased from a very small value to about 1.5mm. The same methodology was applied to the monitoring of chatter stability[12] and results showed that the modal damping ratio in combination with the distribution of modes to the total vibration power of the acceleration signal were good indicators for imminent or existing chatter conditions. These studies suggested that useful information regarding both tool wear and chatter is expected to be coded in the measurement of tool acceleration and vibration.

In this paper, AE and acceleration signals are measured and processed in parallel for the monitoring of machining conditions in terms of both tool wear and chatter vibration. Each signal is either decomposed in the orthogonal parameter space of an adaptive time series or represented by the energy level averaged over frequency bands. The non-stationary model parameters, or the average energy levels, were used as feature inputs to an artificial neural network for optimal weighting of signal sensitivity to the machining condition. The details of the signal processing schemes are provided in the following sections.

2.2 Autoregressive Time Series Model

Autoregressive n-th order time-series are used to model both the AE and acceleration signals in this study. The models specify current value of the measurement, $y(k)$, as a linear combination of n previous values,

$$y(k)=w(k)+\sum_{i=1}^{n}a_i y(k-i) \tag{1}$$

where k is a discrete time index, $w(k)$ a white noise, and a_i's are the time series model parameters. Defining the parameters vector $\theta^T(k)$ and the measurement vector $\phi(k)$ as :

$$\theta^T(k)=[a_1 a_2 ,\ldots, a_n] \tag{2}$$

$$\phi^T(k)=[-y(k-1),-y(k-2),\ldots,-y(k-n)] \tag{3}$$

a parameter adaptation algorithm based on the minimzation of least square estimation errors[13] is implemented to calculate the parameters recursively at each sampling cycle,

$$\overline{\theta}(k+1)=\overline{\theta}(k)+\frac{F(k)\phi(k)}{1+\phi^T(k)F(k)\phi(k)}(y(k+1)-\overline{\theta}^T(k)\phi(k)) \tag{4}$$

$$F(k+1)=\frac{1}{\lambda_1(k)}[F(k)-\frac{\lambda_2(k)F(k)\phi(k)\phi^T(k)F(k)}{\lambda_1(k)+\lambda_2(k)\phi^T(k)F(k)\phi(k)}] \tag{5}$$

where $\overline{\theta}^T(k)$ is the estimated parameter vector at time k, and F is an adaptation gain matrix and λ_1, λ_2 are the constant adaptation gain.

2.3 Banded Energy Method

In the analysis of banded energy only the average spectral density function over certain frequency band is considered, and it is not necessary to obtain the power spectrum distribution over the entire frequency range. Given the low and high cut-off frequencies of a band pass filter as f_1 and f_2, the band average energy can be expressed as :

$$E_{x,BPF}(t)=\lim_{T\to 0}\frac{1}{T}\int_t^{t+T}x^2(\tau)_{BPF}d\tau = \int_{f1}^{f2}G_x(f)df \tag{6}$$

where $G_x(f)$ is the one-sided power spectral density function of the signal $x(t)$, while $x_{BPR}(t)$ is the band-pass filtered version of $x(t)$. Based on this transformation, direct monitoring of the output signal of the filter in the time domain extracts frequency characteristics that are varying with time.

2.4 Artificial Neural Networks

Studies in the area of artificial neural nets started in the 1940's, however, the technology arrived at its current form with the contributions of many researchers from different fields[14]. Typical application development includes the works of Dornfeld ***et al***[15], Chryssolouris ***et al.***[16] and Okafor ***et al.***[17] for the monitoring of machining processes and machined products.

The basic structure of an artificial neural network may be generalized by Fig. 1. The inputs are connected to the input layer of the network. Each connection between the layers has a weighing function and each node has a logistic activation function. The values of the weights can be selected using the back propagation method. This process, commonly referred to as the "training", has two phases. In the first phase the output value is calculated for each unit after the input is represented and propagated forward. Then the output values are compared with the expected outputs to formulate an error. In the second phase, the error value is passed through the network backward and weight changes are made. Once the weights reach stable values over repeated back propagation, the training can be considered complete and the weights can be utilized to determine the values of the outputs in actual service.

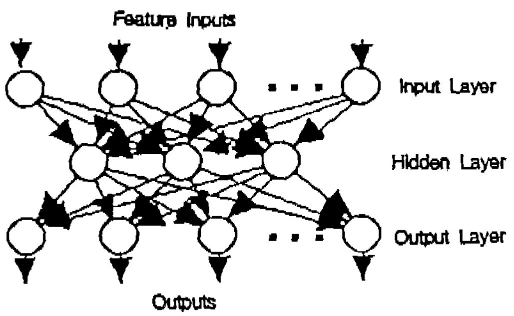

Fig. 1 The structure of a multi-layered artificial neural network.

3. Description of Experiments

Machining experiments were performed on a conventional lathe using carbide insert cutters to turn 1045 steel workpieces of 235mm length and 50mm diameter. A piezo-electric AE sensor (Physical Acoustics R15) was mounted to the tool shank. Signals from the AE sensor were first amplified by a 40 dB preamplifier (Physical Acoustics 1220A), and then postamplified with an Acoustic Leak Monitor (Physical Acoustics ALM-8). An energy measurement board contained in this monitor provided a voltage signal proportional to the root-mean-square of the input signal. Meanwhile, an accelerometer (Kistler 8638B) with 0.5-5kHz bandwidth was mounted to the back side of the tool shank. The accelerometer signal was amplified by a charge amplifier (Kistler 5004) prior to being digitized with an emulated digital oscilloscope. The digitization rate for both the AE and the accelerometer signal was 20kHz. To avoid aliasing, the signals were pre-filtered at 10kHz. The schematic diagram of the set up is shown in Fig. 2.

In the machining tests, the cutter traveled, parallel to the spindle axis, from a positon near the chuck to the other end of the work. Fig. 3

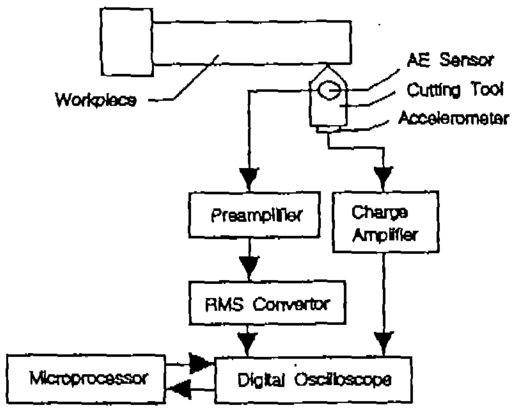

Fig. 2 Schematics of the experimental set up.

shows a typical recording of the AE and the acceleration signals for a cut conducted at 550rpm spindle speed, 0.066mm/rev feed, 0.762mm radial depth of cut, while a fresh tool was used. Also shown in the figure is the machined surface profile as measured off-line with a stylus profilorometer (Hommelwerke LV-50). Note that the AE and acceleration data are presented with respect to the cutting length in lieu of the cutting time, thereby allowing the data to be synchronized to the surface profile measurement. The onset of chatter can be recognized at around 10mm of cutting length in view of the increased AE and acceleration signal intensities. The transition from stable cutting conditions to chatter vibration was indicated by the marks left on the workpiece.

To study the effect of a worn tool, prolonged periods of cutting were implemented to naturally develop the wearland on the insert. Fig. 4 shows the recording of the AE and the acceleration signals with the same cutting parameters as Fig. 3 except for the use of a worn tool with an average wearland of 0.3mm and a maximum wearland of 1.1mm. Similarly, the onset of chatter can be concluded from the increased signal intensities at around 8.5mm. This point can be further confirmed by the surface profile as shown in the figure. Comparing Fig. 4 to Fig. 3, however, the coupling between chatter and tool wear(7) is qualitatively evidenced by the fact that the chatter occurred at a shorter overhang distance from the chuck while a worn tool was used. However, it is seen that the stable cut with a worn tool can have a signal intensity comparable to that seen in chatter with a fresh tool. This suggests that the individual contribution from the tool wear and chatter to the AE or the acceleration signal cannot be readily distinguished as far as signal intensity is concerned. The ability to effectively monitor and differentiate tool wear and chatter requires a more sophisticated signal processing scheme other than simple observation of the signal intensity.

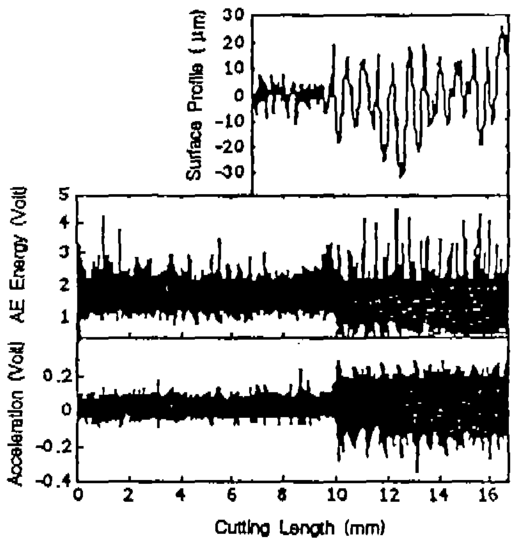

Fig. 3 AE, acceleration, and surface roughness at the onset of chatter in a fresh tool cut.

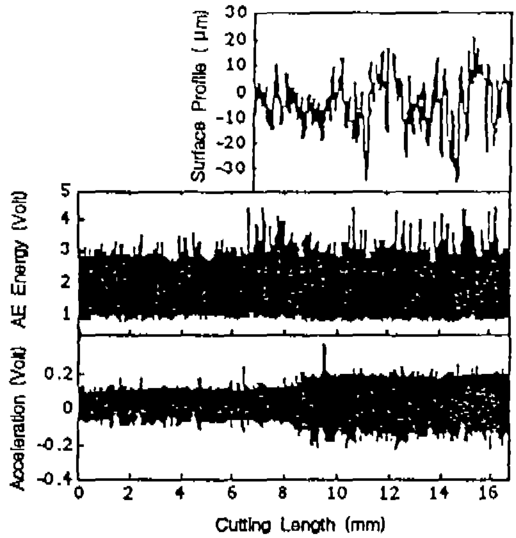

Fig. 4 AE, acceleration, and surface roughness at the onset of chatter in a worn tool cut.

Average energy level for the frequency band of 80-500 Hz was calculated for both the AE and acceleration signals. This band was closely related to tool wear and chatter vibration as the first order resonance frequency of the chuck-work system was identified to be around 200-250 Hz by impact tests. Fig. 5 and 6 shows the AE and acceleration power spectral densities in different tool wear and chatter instability conditions. Again, conclusive remarks can not be made regarding the state of tool wear and chatter based on the observation of these frequency contents, especially in light of the 230Hz AE signals that took place even while the cutting was stable with no chatter marks left on the work.

As a step further, the AE and the acceleration signals were modeled individually via two autoregressive time series, each of 4-th order. Then the two sets of model parameters and average energy levels over 80-500 Hz, 80-5,000 Hz, and 80-10,000 Hz bands were processed by a sigmoid function based artificial neural network with 3 layers. Fig. 7 shows the overall

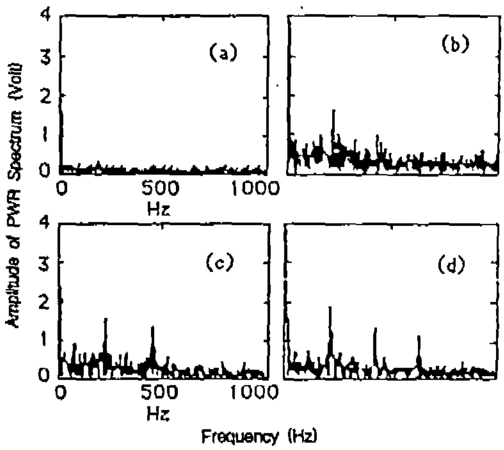

Fig. 5 Acoustic emission power spectrum in turning with (a) fresh tool in stable condition, (b) worn tool in stable condition, (c) fresh tool in chatter, and (d) worn tool in chatter.

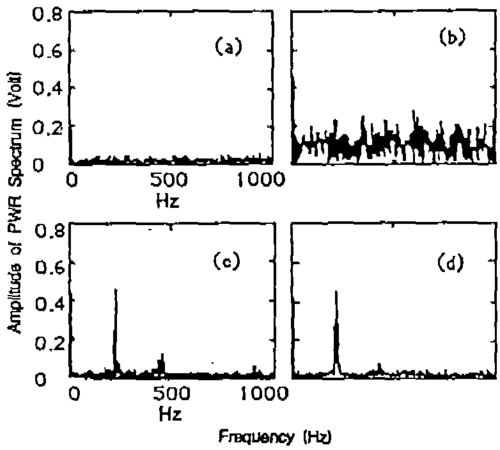

Fig. 6 Acceleration power spectrum in turning with (a) fresh tool in stable condition, (b) worn tool in stable condition, (c) fresh tool in chatter, and (d) worn tool in chatter.

schematics of the signal processing scheme utilized in this study. The hidden layer contained 10 nodes, and the output layer delivered 2 outputs. The first output refers to the condition of tool wear with "-1" being assigned to the state of fresh tool and "1" for a worn tool;the second output refers to the condition of chatter vibration where "-1" represents a stable cut with no chatter and "1" represents the case of chatter. The inter-layer weights were developed through the back propagation method using

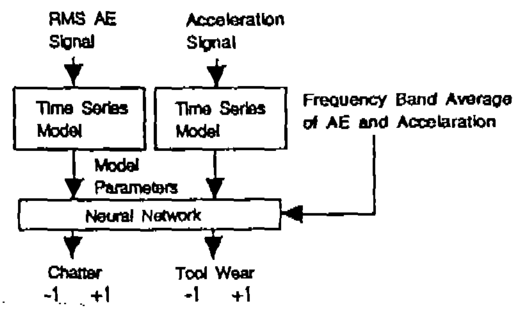

Fig. 7 Artificial neural network with multiple time-series models and band-filter energy.

either 22 sets of AE and acceleration time series data, or 14 sets of AE and acceleration average energy levels from known tool wear and chatter conditions. The cutting process parameters ranged from 340 to 900 rpm of spindle speed, 0.041 to 0.084mm/rev of feed, and 0.76 to 1.02mm of depth of cut.

4. Result and Discussion

4.1 Model Parameter and Average Energy Level

Fig. 8 shows a plot of the first parameter in the acceleration time series, $C_{AC,1}$, with respect to the first parameter in the AE time series, $C_{AC,1}$, over the range of cutting condition tested. The "X's" represent the parameter values associated with the case of a worn tool, while "O's" are for the case of a fresh tool. Note that with this designation the chatter condition is not specified. From the clusters in the plot it is seen that the wear of the cutter caused the first parameter of the AE model to assume a greater value. However, the liner in-separability of the two clusters on the plot suggests that the possible existence of chatter tends to confuse the detection of tool wear based on the two parameters alone.

The same two parameters are plotted again in Fig. 9 to show their sensitivity to chatter. The "X's" represent the parameter values associated with the case of chatter vibration, while "O's" are for the case of a stable cut. The first parameter of the acceleration model took on a greater value as chatter occurred. In this plot the cluster for chatter was separable from that for stable cuts. Compared to Fig. 8, the condition of chatter appeared to be more detectable than tool wear based on the two parameters presented.

On the other hand, Fig. 10 and 11 show the results of the average energy within 80~500 Hz in the acceleration signal with respect to that of the AE. It can be seen that chatter vibration was again more detectable than the tool wear condition.

4.2 Detection of Tool Wear and Chatter

All four parameters in the acceleration time series and the four in the AE time series used jointly as inputs to the artifical neural network yielded the results shown in Fig. 12. Also shown in the figure are the results based on AE or based on acceleration only. These results were based on 22 testing data. The tolerance in the plot refers to the acceptable output deviation from the designated output value for a certain

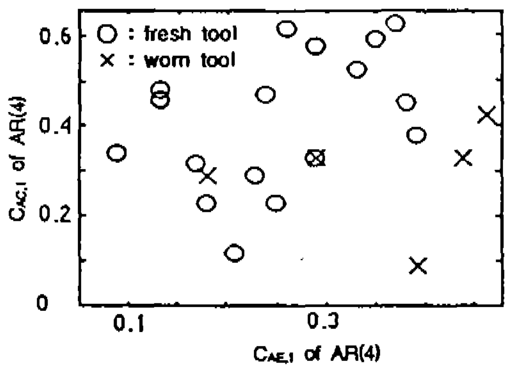

Fig. 8 An AE-acceleration parameter plane for different tool conditions.

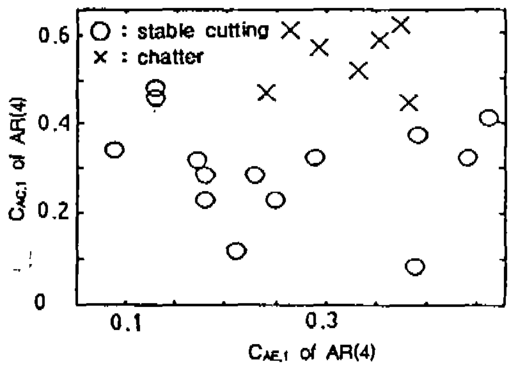

Fig. 9 An AE-acceleration parameter plane for different chatter conditions.

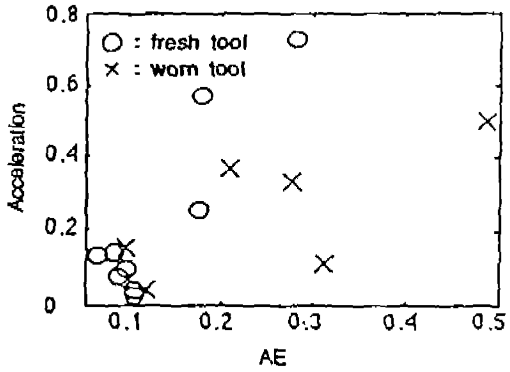

Fig. 10 An AE-acceleration average energy plane for different tool conditions.

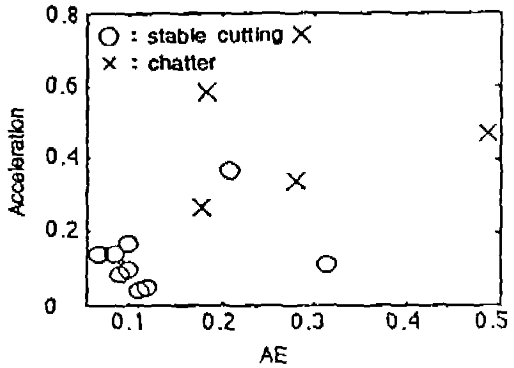

Fig. 11 An AE-acceleration average energy plane for different chatter conditions.

class of condition. For instance, with a tolerance of δ, the first output value that falls within 1 and 1-δ voices a worn tool. If it falls between 1-δ and -1 a fresh tool condition is indicated.

It is seen in Fig. 12 that the acceleration signal always performed better than acoustic emission in terms of tool wear monitoring. Additionally, the integration of both acceleration and acoustic emission measurements provided success rates comparable to the use of acceleration signal alone. In this figure the succes rate increased with tolerance as most of the marginal data, with neural net output values close to zero, yielded accurate diagnostic of tool wear.

The results of chatter detection are given in Fig. 13. The acceleration measurement consistently provided a noticeably better performanec than AE. The trend for the success rate to follow the tolerance is observed in neither acceleration nor AE measurement. It is indicated that the marginal data provided incorrect information therefore the inclusion of those data in decision making did not guarantee a better performance.

Fig. 14 shows the succes rate for combined detection of tool wear and chatter. Again the acceleration measurement outperformed AE with a widening difference in the success rate for larger tolerance. A tolerance of 60% appeared to be the optimal value for both the AE and acceleration in terms of the success rate. Generally speaking, the detection system based on AE alone showed success rates ranging from 55% to 70%, which can be considered rather low for practical applications. However, as acceleration signal was usad in conjunction with AE the success rate improved to between 70% and 90% depending on the cutting parameters, tool condition, chatter condition, and the tolerance selection.

On the other hand, Fig. 12, 13 and 14 also display the success rate of the band averaging method. With this analysis, the performance of the artificial neural network for the integration of AE and acceleration signals, both with 14 testing data sets, were compared. The average energy level is seen to have a successful rate ranging from 85% to 100%, which outperformed the time series modeling in the detection or either tool wear, chatter, of both. A tolerance of 80% appears to be the best value for the energy analysis in yielding the highest success rate for all the cases tested in this study.

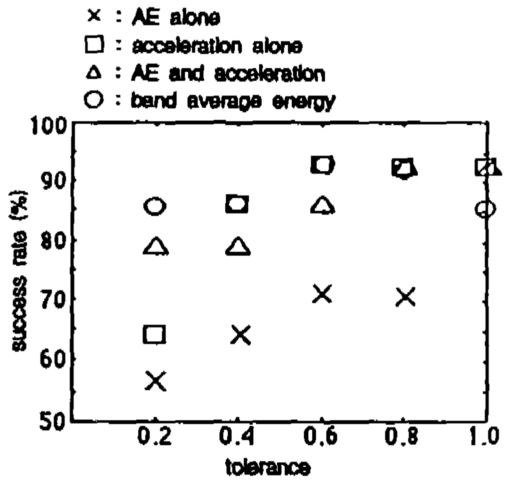

Fig. 12 Success rate as function of tolerance and sensor used for the detection of tool wear

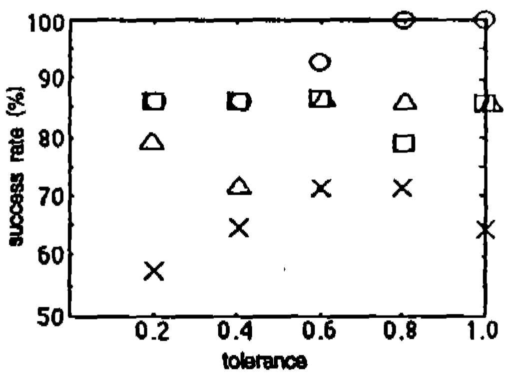

Fig. 13 Success rate as function of tolerance and sensor used for the detection of chatter. Legend is the same as Fig. 12

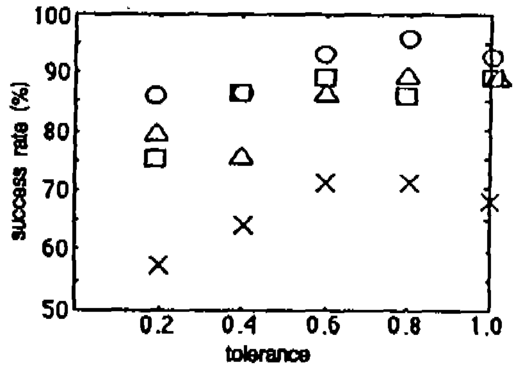

Fig. 14 Success rate as function of tolerance and sensor used for the detection of both tool wear and chatter. Legend is the same as Fig. 12

5. Summary

A technique to detect cutting tool wear and chatter using a neural network with features of either time series model parameters of frequency band energy levels, of acoustic emission and acceleration signals are discussed and comparatively evaluated in this paper. The study showed that acoustic emission and acceleration signals are sensitive to the fundamental changes of machining mechanics in the presence of tool wear and chatter.

Time series model parameters and frequency band average energy levels can be advantageously used to reflect the effect of tool wear and chatter on acoustic emission and acceleration measurements. Experimental results from a series of machining tests further revealed the effectiveness of artificial neura networks in decoding the subtle signal feature differences responding to tool wear and chatter. In general the condition of chatter appeared to be more detectable than the tool wear, and the detection methodology based on the energy levels was more effective than using time series modeling. Success rates ranging form 70% to 90% using time series parameters, and 80% to 100% using frequency band energy levels, depending upon the cutting parameters and tolerance specifications have been concluded experimentally.

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