Pergamon International Journal of Machine Tools & Manufacture 39 (1999) 1717–1731

INTERNATIONAL JOURNAL OF MACHINE TOOLS & MANUFACTURE DESIGN, RESEARCH AND APPLICATION

Indirect cutting force measurement in multi-axis simultaneous NC milling processes

Tae-Yong Kim[a], Joongwon Woo[b], Dongwon Shin[c], Jongwon Kim[d,*]

[a] *SENA Technologies, Inc., Seoul, South Korea*
[b] *Institute of Advanced Machinery and Design, Seoul National University, Seoul, South Korea*
[c] *School of Mechanical Engineering, Kum-Oh National University of Technology, Kumi, South Korea*
[d] *School of Mechanical and Aerospace Engineering, Seoul National University, Seoul, South Korea*

Abstract

There have been many research works for the indirect cutting force measurement in machining process, which deal with the case of one-axis cutting process. In multi-axis cutting process, the main difficulties to estimate the cutting forces occur when the feed direction is reversed. This paper presents the indirect cutting force measurement method in contour NC milling processes by using current signals of servo motors. A Kalman filter disturbance observer and an artificial neural network (ANN) system are suggested. A Kalman filter disturbance observer is implemented by using the dynamic model of the feed drive servo system, and each of the external load torques to the *x* and *y*-axis servo motors of a horizontal machining center is estimated. An ANN system is also implemented with a training set of experimental cutting data to measure cutting force indirectly. The input variables of the ANN system are the motor currents and the feedrates of *x* and *y*-axis servo motors, and output variable is the cutting force of each axis. A series of experimental works on the circular interpolated contour milling process with the path of a complete circle has been performed. It is concluded that by comparing the Kalman filter disturbance observer and the ANN system with a dynamometer measuring cutting force directly, the ANN system has a better performance.

Keywords: Milling; Cutting force; In-process measurement; Kalman filter; Artificial neural network

1. Introduction

In-process cutting force measurement system is one of the most important sensor systems for cutting condition monitoring and control in machining [1,2]. Among them, commercial dyna-

* Corresponding author. Tel.: + 82-2-880-7138; fax: + 82-2-883-1513; e-mail: mejwkim@asri.snu.ac.kr.

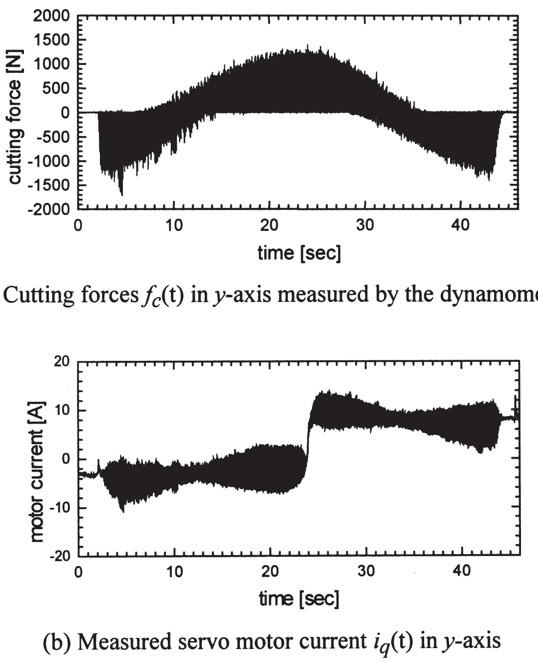
0890-6955/99/$ - see front matter
PII: S0890-6955(99)00027-9

mometers provide the most accurate measurement of cutting forces, though it has some disadvantages such as high cost, fragility to overload, inherent measurement stroke limit, intricate wiring harnesses within the machining space, etc.

To overcome the impracticability of a dynamometer, there have been many research works on the indirect cutting force measurement methods by using the current signals of the servo drive motors or the spindle motors [3–7]. All of these approaches, however, have some problems to be solved. The major one is that the observed current signal of the servo drive motor contains undesirable components which resulting from accelerating or decelerating the mass of table, and that overcoming the friction force in the guide way. This problem becomes more serious in the case of multi-axis simultaneous cutting process. For example, in circular interpolated contour milling, the continuous change in the magnitudes of the feedrate in x and y-axis resulting in the variation of the motor current components. Moreover, at the point where the feed direction is reversed, the motor current component due to friction force experiences a sudden sign change.

A typical example showing the discrepancy between the cutting force $f_c(t)$ and the motor current $i_q(t)$ in case of circular interpolated contour milling is in Fig. 1. As stated the difference is very large when the feed direction is reversed. Hence, $i_q(t)$ can not simply represents the cutting force without proper process. In the case of multi-axis simultaneous cutting, the previous works on the indirect cutting force measurement are no more valid, since only the static relation between cutting force and feed drive motor current has been considered.

To solve the aforementioned problem, two different methods are proposed in this paper. First,



(a) Cutting forces f_c(t) in y-axis measured by the dynamometer

(b) Measured servo motor current i_q(t) in y-axis

Fig. 1. An example showing the discrepancy between $f_c(t)$ and $i_q(t)$ in the y-axis under the identical *cutting condition A*: circular interpolated contour milling, half immersion, flat end mill (diameter 20 mm, 2 flutes), axial depth-of-cut 2 mm, feed rate 300 mm/min, steel workpiece, spindle speed 600 rpm, cutting path radius 35 mm.

a Kalman filter disturbance observer is implemented. The main idea is to estimate the disturbance load which is exerted to the feed drive system due to the cutting force. A dynamic model of the feed drive system of a commercial horizontal machining center is presented for model based Kalman filter observer. Then, the signals of the servo drive motor current, the position command, and the actual position of each feed drive axis are applied to the Kalman filter as an input set. Second, an artificial neural network (ANN) system is presented for cutting force estimation. The input variables to the ANN system are the signals of the servo motor currents and the feedrates of x and y-axis servo motors. The output variable is the signal of the cutting force of each axis. The ANN system is trained first so that the network can describe the nonlinear mapping relationship between the input and output variables. Then, in the next procedure, a set of the measured data of the servo motor currents and the feedrates of x and y-axis servo motors is applied to the trained ANN system to obtain the corresponding estimated cutting force value. It has been found through the series of experimental works that the ANN system reveals better estimation performance than the Kalman filter disturbance observer, especially, when the feed changes its direction during the multi-axis simultaneous cutting processes.

The remainder of this paper is organized as follows: In the next section, the implemented Kalman filter disturbance observer is presented with the experimental results. Then, the ANN system is described and the results of the ANN system application are given in the subsequent section. Finally, in the last section, the paper concludes with a short summary.

2. Kalman filter disturbance observer

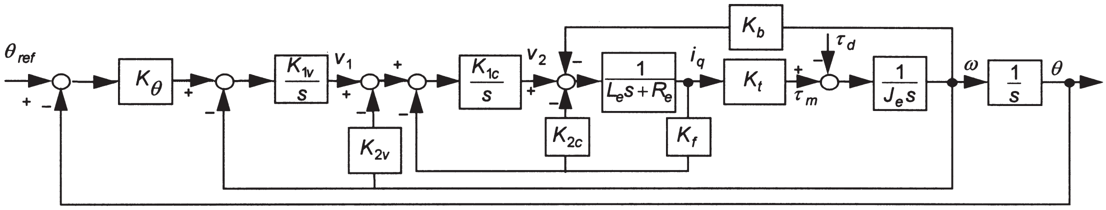
A Kalman filter is implemented as a model based disturbance observer for indirect measurement of cutting forces in milling process. The inputs to the Kalman filter are the signals of the measured servo motor current, the position command, and the actual position value. Then, the Kalman filter estimates, based upon the given CNC dynamic system model, the values of the state variables, which include the external load torque to the servo motor. The purpose of using the Kalman filter is to filtering out the undesired current component due to the acceleration or deceleration from the measured servo motor current signal.

The total external load torque to the servo motor consists of the torque induced from the cutting force and that from the friction force in the guide way. The friction force fluctuates strongly according to both the lubrication state and the magnitude and direction of the traversing feedrate [8].

The approach used in this paper is following. First, as a setup procedure, the load torque induced by the friction force is estimated under the air cutting condition (i.e. no chip producing cutting condition with z-axis motion locked or in the "dry-run" mode) by using a Kalman filter and storing it in the memory. Second, during the actual cutting process, the total load torque is estimated online by using the same Kalman filter, and simultaneously, the stored friction torque profile is subtracted, thus resulting in only the load torque induced by the cutting force.

2.1. Modeling of the feed drive system

For the purpose of applying the Kalman filter to estimate the external load torque to the servo motor, the feed drive system model used in the experiment should be identified. A horizontal



J_e	0.17 $kgf\,cm\,s^2$	L_e	1.2 mH	K_{1v}	676.9 $V\cdot sec/rad$	K_{1c}	421.6	K_b	0.36 $V\cdot sec/rad$		
K_t	5.52 $kgf\,cm/A$	R_e	0.15 Ω	K_{2v}	7.6 $V\cdot sec/rad$	K_{2c}	1.0	K_f	0.05 V/A	K_θ	25 sec^{-1}

Fig. 2. Block diagram of the feed drive system of the machining center used in the experiment.

machining center, with a 32-bit micro-processor CNC system, is the main machine in this study. The three feed axes (x, y, and z) of the machine have ball screw drives and are directly driven by permanent magnet synchronous (i.e. PMSM type) AC servo motors. The identical servo motors are used in all axes. The block diagram of the feed drive system can be derived as in Fig. 2 based upon the technical data provided from the manufacturer of the CNC system [9].

The linear transfer function between the external load torque τ_d and that of the measured servo motor current signal i_q for y-axis feed drive system is identified as

$$G(s) = \frac{i_q(s)}{\tau_d(s)} = \frac{1761(s^2 + 89.52s + 2244)(s + 8831)}{(s + 41.13)(s + 91.48)(s^2 + 266.1s + 86930)(s + 589.7)}. \tag{1}$$

Fig. 3 shows the experimental and simulation frequency responses of y-axis feed drive system. The simulation response is in good agreement on the experimental result, which shows the validity

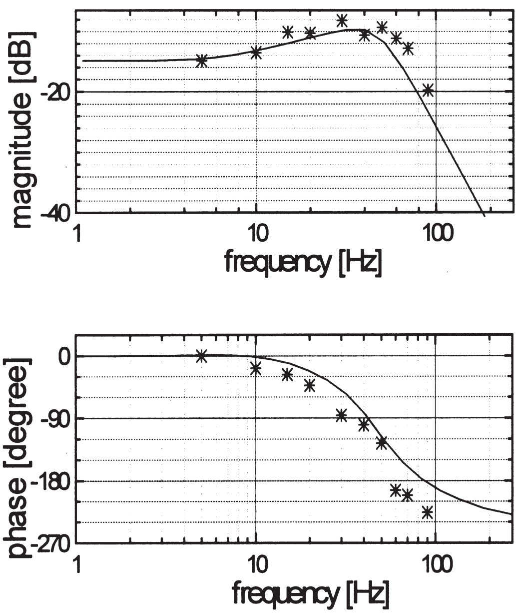


Fig. 3. Frequency response of the y-axis feed drive system $i_q(s)/\tau_d(s)$.

of the modeling. The bandwidth of the dynamic system shown in Eq. (1) is 70 Hz. Hence, the cutting forces can be tracked based on the servo motor current signals when the tool passing frequencies are below this bandwidth.

2.2. Kalman filter configuration

The Kalman filter is a linear, unbiased, and minimum error variance recursive algorithm to optimally estimate the unknown state of a dynamic system from a noisy environment. The external load torque $\tau_d(t)$ is introduced as an augmented state variable. It is assumed that the load torque remains constant and that its derivative is zero during a few sampling periods since the sampling frequency of the signal processor is much higher than that of the external load torque variation. Thus,

$$\frac{\mathrm{d}\tau_d}{\mathrm{d}t} = 0 \tag{2}$$

From Eqs. (1) and (2), the state equation is given by

$$\dot{x} = Ax + Bu,$$
$$y = Cx \tag{3}$$

where,

$$A = \begin{bmatrix} 0 & 0 & 0 & -K_{1v} & -K_{1v}K_\theta & 0 \\ K_{1c} & 0 & -K_{1c} & -K_{1c}K_{2v} & 0 & 0 \\ 0 & 1/L_e & -(R_e + K_{2c})/L_e & -K_b/L_e & 0 & 0 \\ 0 & 0 & K_t/J_e & 0 & 0 & -1/J_e \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix},$$

$$B = K_{1v}K_\theta\ \ 0\ \ 0\ \ 0\ \ 0\ \ 0]^T,\ C = \begin{bmatrix} 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix},$$

$$x = [v_1\ \ v_2\ \ i_q\ \ \omega\ \ \theta\ \ \tau_d]^T,\ u = \theta_{\mathrm{ref}}.$$

The input variable u is the position command θ_{ref}; state variables x are the internal variable in the velocity loop v_1, the internal variable in the current loop v_2, the motor current signal i_q, the mechanical angular velocity ϖ, the mechanical angular position θ, and the disturbance load torque τ_d ; the output variables y are the mechanical angular position θ and the mechanical angular velocity ϖ. Including the system noise ξ_k with system noise matrix Γ and the measurement noise η_k in the system modeling, the discrete form of Eq. (3) is rewritten as

$$x_{k+1} = A_k x_k + B_k u_k + \Gamma_k \xi_k,$$
$$y_k = C_k x_k + \eta_k \tag{4}$$

where A_k, B_k, C_k, Γ_k are the discrete forms of system matrices A, B, C and Γ. Both ξ_k and η_k are assumed to be zero-mean white Gaussian noise inputs and Q_k and R_k are their covariance matrices, respectively. Γ, ξ and η are written as

$$\Gamma = \begin{bmatrix} K_\theta K_{1v} & 0 & 0 & 0 & 0 & 0 \\ 0 & & 0 & 0 & 0 & 0 & 1 \end{bmatrix}^T \quad \xi = [u_{\text{noise}} \ \ \tau_{\text{noise}}]^T, \ \eta = [i_{q,\text{noise}} \ \ \theta_{\text{noise}}] \tag{5}$$

where u_{noise} = the system noise in control input; τ_{noise} = the system noise in disturbance load torque; $i_{q,\text{ noise}}$ = the measurement noise in motor current; and θ_{noise} = the measurement noise in rotor position.

Then, the recursive Kalman filter process for this system is given by [10]:

$$\begin{aligned} P_{0,0} &= Var(x_0) \\ P_{k,k-1} &= A_{k-1}P_{k-1,k-1}A^T_{k-1} + \Gamma_{k-1}Q_{k-1}\Gamma^T_{k-1} \\ G_k &= P_{k,k-1}C^T_K(C_kP_{k,k-1}C^T_K + R_k)^{-1} \\ P_{k,k} &= (I - G_kC_k)P_{k,k-1} \\ \hat{x}_{0|0} &= E(x_0),\ \hat{x}_{k|k-1} = A_{k-1}\hat{x}_{k-1|k-1} + B_{k-1}u_{k-1} \\ \hat{x}_{k|k} &= \hat{x}_{k|k-1} + G_{k-1}(y_k - C_k\hat{x}_{k|k-1}) \end{aligned} \tag{6}$$

where $P_{k,l}$ = the estimated variance matrix; $Var(x)$ = the variance of random variable x; $E(x)$ = the expectation of random variable x; G_k = the Kalman gain matrix; Q_k = the variance matrix of random vector ξ_k; and R_k = the variance matrix of random vector η_k.

2.3. Experimental results of the Kalman filter application

The configuration of the experimental setup is shown in Fig. 4. The machine tool used in the experiment is the commercial horizontal machining center with its pallet size 500 × 500 mm and equipped with a FANUC CNC 15M. A specific signal pre-processing unit has been developed for measuring and pre-processing the servo motor current signals from the CNC. The functions of this signal pre-processing unit are hall sensor signal amplification, noise filtering, encoder signal branching, and calculation of *d–q* transformed currents i_q and i_d [4,7]. The current signals i_q from *x*, *y* and *z*-axis are fedback into the A/D board of the signal processing main computer. The sampling time is 1.0 ms including the recursive Kalman filtering algorithm. By using the signal pre-processing unit, the whole scheme presented in this paper can be interfaced practically with the commercial CNC without any major change.

Fig. 5 presents the estimated friction forces $f_{fr}(t)$ in *x* and *y*-axis by the Kalman filter based on the measured motor current under the air cutting condition and the dynamic system model Eq. (3). Here, the air cutting condition means the same one as *cutting condition A* shown in Fig. 1 except that the *z*-axis motion is locked or in “dry-run” mode, hence no chip is produced.

As a next step, the external load torque $\tau_d(t)$ under the *cutting condition A* shown in Fig. 1 is estimated by using the same Kalman filter. Since the estimated total external torque $\tau_d(t)$ includes the torque component $t_{fr}(t)$ induced by the friction force $f_{fr}(t)$ shown in Fig. 5, the stored profile of $t_{fr}(t)$ is subtracted on-line from $\tau_d(t)$. Thus, finally, the estimated cutting force $f_c(t)$ can be obtained as in Fig. 6(a) after the conversion of the torque unit into the force unit.

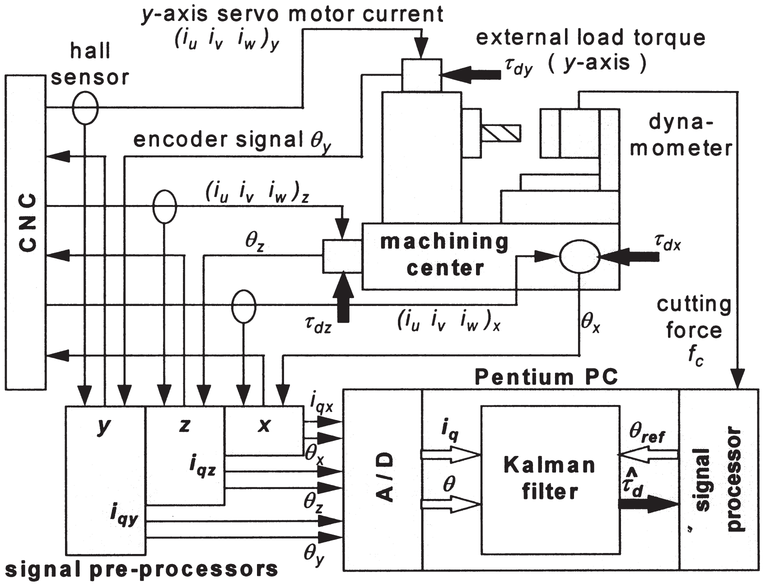


Fig. 4. Schematic diagram of the experimental setup.

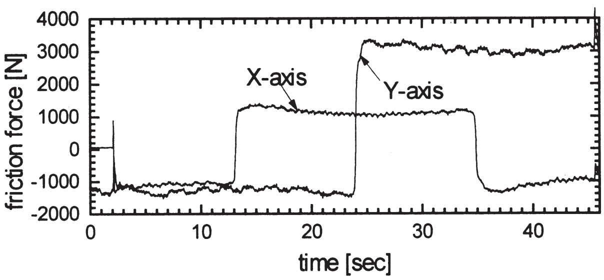
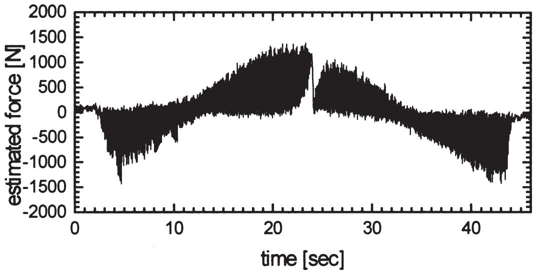


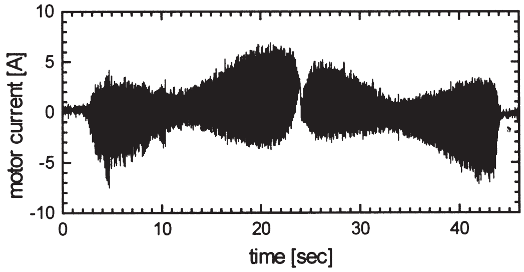
Fig. 5. Estimated friction forces $f_{fr}(t)$ in x and y-axis by the Kalman filter (under air cutting condition).

It is clear that the estimated cutting forces by the Kalman filter disturbance observer shown in Fig. 6(a) and Fig. 7(a) have a better tracking capability of the cutting force measured by the dynamometer [see Fig. 1(a) and Fig. 7(b)] than the simply calibrated motor current signal shown in Fig. 6(b). Fig. 7(a) presents the estimated cutting force in x-axis, which is the counterpart of the y-axis cutting force in Fig. 6(a) in case of circular interpolated contour milling.

However, there still exist some problems. One of them arises when the feed direction is reversed as shown in the middle spans of Fig. 6(a) and Fig. 7(a). Since the backlash compensation is executed by the CNC system and the friction force experiences a sudden sign change in these spans, the linear dynamic system model Eq. (3) is not effective within these spans. Since the Kalman filter is a model based disturbance observer, the estimation performance is affected by the accuracy of the feed drive system modeling. The signals of the feed drive motor current and the mechanical angular position of the feed motor are also required to estimate the cutting force. As shown in Fig. 1(b), the magnitude of the feed motor current i_q is decreased in the range where

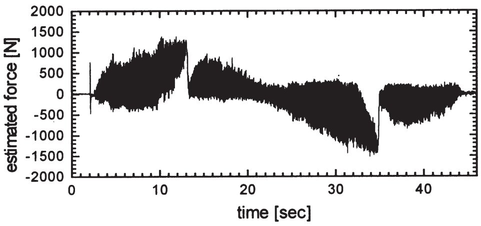


(a) Estimated y-axis cutting force (based on the Kalman filter method)

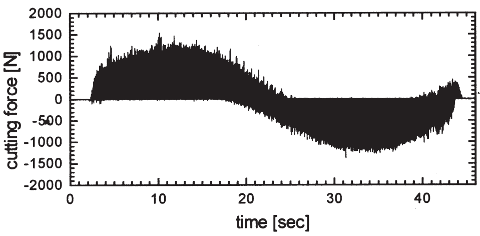


(b) Motor current signal (y-axis) after the subtraction of the friction induced current

Fig. 6. Estimated y-axis cutting force based on the Kalman filter method (*cutting condition A* in Fig. 1).



(a) Estimated x-axis cutting force (based on the Kalman filter disturbance observer)



(b) Cutting force f_c(t) in x-axis measured by the dynamometer

Fig. 7. Estimated x-axis cutting force by Kalman filter disturbance observer (*cutting condition A* in Fig. 1).

the feedrate changes the direction. The cutting force estimation error during the interval when the feed direction is reversed arises not only from the non-linearity of the frictional behavior but also from the decreased current signals.

3. Artificial neural network (ANN) system

Since the Kalman filter disturbance observer is unable to accommodate the inherent non-linearity of the feed drive system when the feed direction is reversed, as a next approach, an ANN system has been applied for indirect cutting force measurement. For the Kalman filter application presented in the previous section, the feed drive system model is required to estimate the external disturbance to the feed drive system. The ANN system does not need any modeling of the feed drive system.

3.1. Neural network configuration

The configuration of the ANN system used in the experimental works is shown in Fig. 8. The input data set is composed of total eight sampled signal values: the motor current signals of x and y-axis servo motors, $i_{qx}(t)$ and $i_{qy}(t)$, its corresponding one-step behind values, $i_{qx}(t-1)$ and $i_{qy}(t-1)$, the sampled feedrate signals of x and y-axis servo motors, $v_x(t)$ and $v_y(t)$, and its corresponding one-step behind values, $v_x(t-1)$ and $v_y(t-1)$. The output of the network is one node, which can be chosen among the cutting force signals in x or y-axis or the resultant force $f_c(t)$. In this paper, two separate networks of same configuration are used for estimating the cutting forces in x and y-axis, respectively.

It has been found from the experimental works that even for the estimation of the cutting force in either one of x or y-axis, the training input data set should be composed of both axis signals of the servo motor current and the feedrate since there exists the coupling effect between the x and y-axis cutting force. In two-axis simultaneous milling processes, the friction force in x-axis feed drive system is influenced by the y-axis cutting force, and vice versa. So, the servo motor current in one-axis is effected by the other axis directional cutting force.

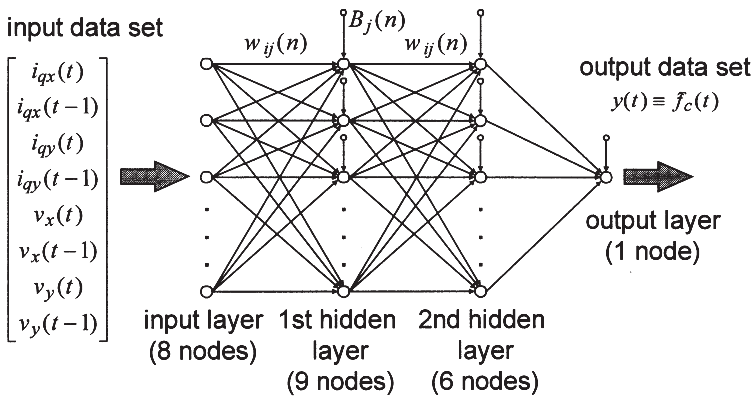


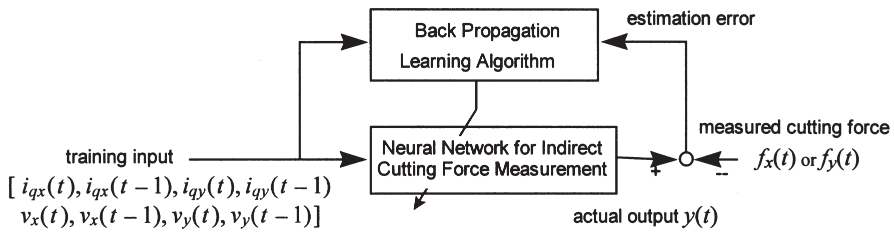
Fig. 8. Neural network configuration for the indirect cutting force measurement in multi-axis milling processes.

It has been also observed from the experimental works that the one-step behind signals of the feedrate and the servo motor current are very important. By adding the one-step behind signals into the input data set, the effects of the variation rates of the feedrate and the servo motor currents can be considered simultaneously when finding the nonlinear mapping relationships in the training stage of the ANN system at hand.

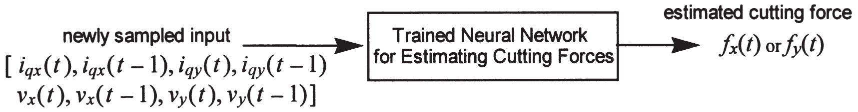
In the training stage of the ANN system, the network parameters such as the synaptic weight and the threshold are updated so that the training error reaches minimum value [11,12]. The training of the network is performed in the supervised manner with the highly popular algorithm known as the error back propagation algorithm. It is based on the error-correction learning rule. It consists of two procedures through the entire layers of the network: a forward procedure and a backward procedure. In the forward procedure, a set of network input is applied to the nodes in the input layer, and its effect propagates through the network, layer by layer. It is activated by the intra-nodal transmission and by the inter-nodal transmission. Finally, the actual response of the network is produced as a set of nodal output in the output layer. During this procedure, the network parameters are all fixed, and the actual output of the network is simply produced. Then, in the backward procedure, the network parameters are all adjusted in accordance with the error-correction rule. An error signal is produced simply by the subtraction of the actual network output from the desired network output. The error signal is propagated backward to the input layer through the network, and the network parameters are adjusted so as to the make the actual response of the network move closer to the desired response. For the detail procedures, please refer to [11,12].

3.2. Experimental results of the ANN system application

The schematics of the ANN system used in the experiment is shown in Fig. 9. The same data set used in the Kalman filter application is applied to the ANN system for the purpose of the



(a) Off-line training procedure



(b) On-line estimation procedure for indirect cutting force measurement

Fig. 9. Schematics of the ANN system for the on-line indirect cutting force measurement.

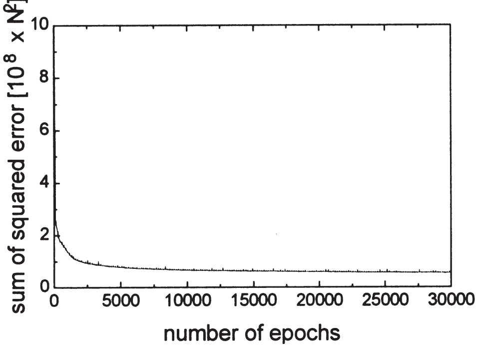
exact performance comparison. By trial and error, the number of hidden layer of the ANN system is selected to be two, and the numbers of the nodes in the first and second hidden layers are determined to be 9 and 6, respectively, as shown in Fig. 8.

A set of the network parameters such as the weight $w_{ij}(n)$ and the threshold $B_j(n)$ are updated until the training error $e_j(n)$ converges to a desired value. As shown in Fig. 10, the sum of squared error of the cutting force estimation in each of x and y-axis reduces rapidly within 2000 epochs.

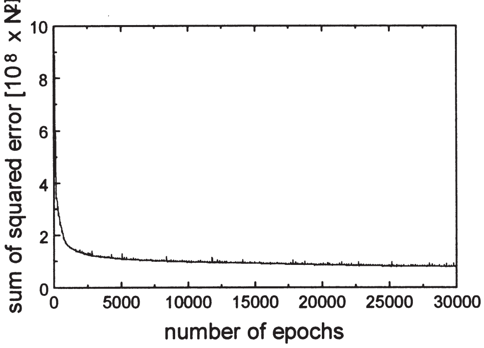
Figs. 11 and 12 show the comparison of the performance of the Kalman filter disturbance observer with that of the ANN system. The actual cutting force in x-axis measured by the dynamometer and the corresponding x-axis servo motor current (with the friction component subtracted) are presented in Fig. 11(a) and (b), respectively. Since the cutting process is a full circular half-immersion end milling process (refer to the *cutting condition A* in Fig. 1), there exists the feed direction change in the middle span in x-axis. The estimated cutting force by the Kalman filter disturbance observer and the ANN system are shown in Fig. 11(c) and (d), respectively. The Kalman filter is effective to subtract the current component due to the acceleration or deceleration from the measured servo motor current signal, however, unable to estimate the cutting forces when the feed direction is reversed. On the other hand, the ANN system successfully estimates the cutting force in full ranges of circular cutting path. The performance comparison in y-axis cutting can be found in Fig. 12. In this case, there exist two points where the feed direction is reversed. The estimated cutting force by the ANN system shows a better agreement with the actual value obtained by the dynamometer than that by the Kalman filter.

Now the trained ANN system under the *cutting condition A* is applied to other cutting condition with the network parameters maintaining the same values. It is to test the interpolation capability of the trained ANN system. The axial depth of cut is reduced to 1 mm from 2 mm and the feedrate is increased to 600 mm/min from 300 mm/min. It is the full circular contour milling with the diameter of 35 mm as in the previous *cutting condition A*.

The experimental results are presented in Fig. 13. Fig. 13(a) is the actual x-axis cutting force measured by the dynamometer, and the estimated cutting force in x-axis from the trained ANN system is shown in Fig. 13(b). A good agreement can be found. In case of y-axis cutting force estimation, Fig. 13(c) and (d) can be compared with each other. The amplitude of the estimated



(a) Cutting force estimation error in x-axis



(b) Cutting force estimation error in y-axis

Fig. 10. Evolution of the sum of squared error during the off-line training procedure.

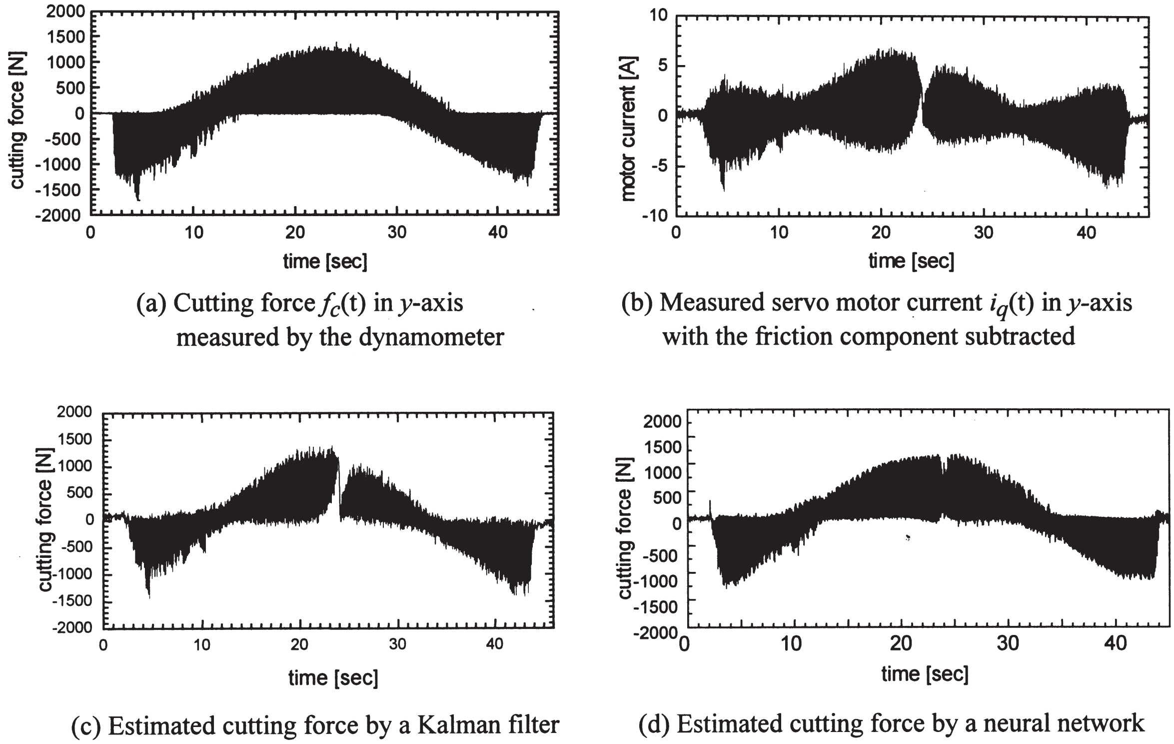


Fig. 11. Performance comparison of the Kalman filter with the ANN system for on-line estimation of the cutting force in y-axis (same *cutting condition A* in Fig. 1).

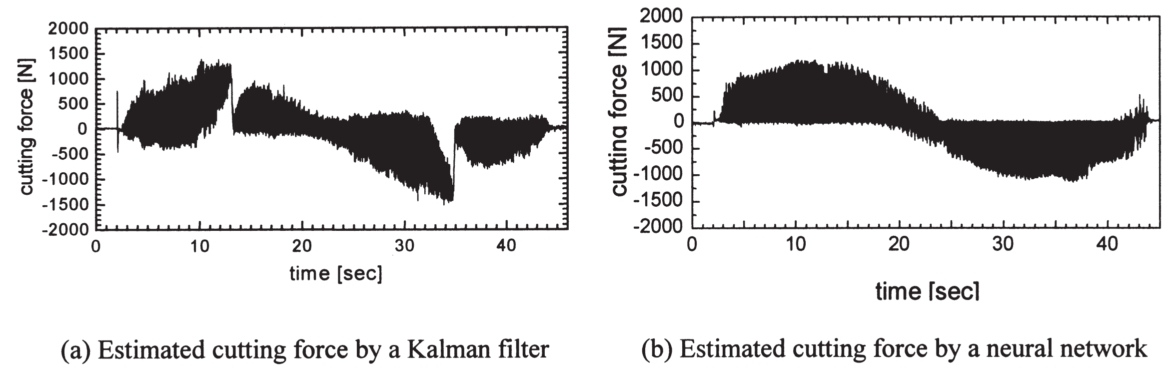
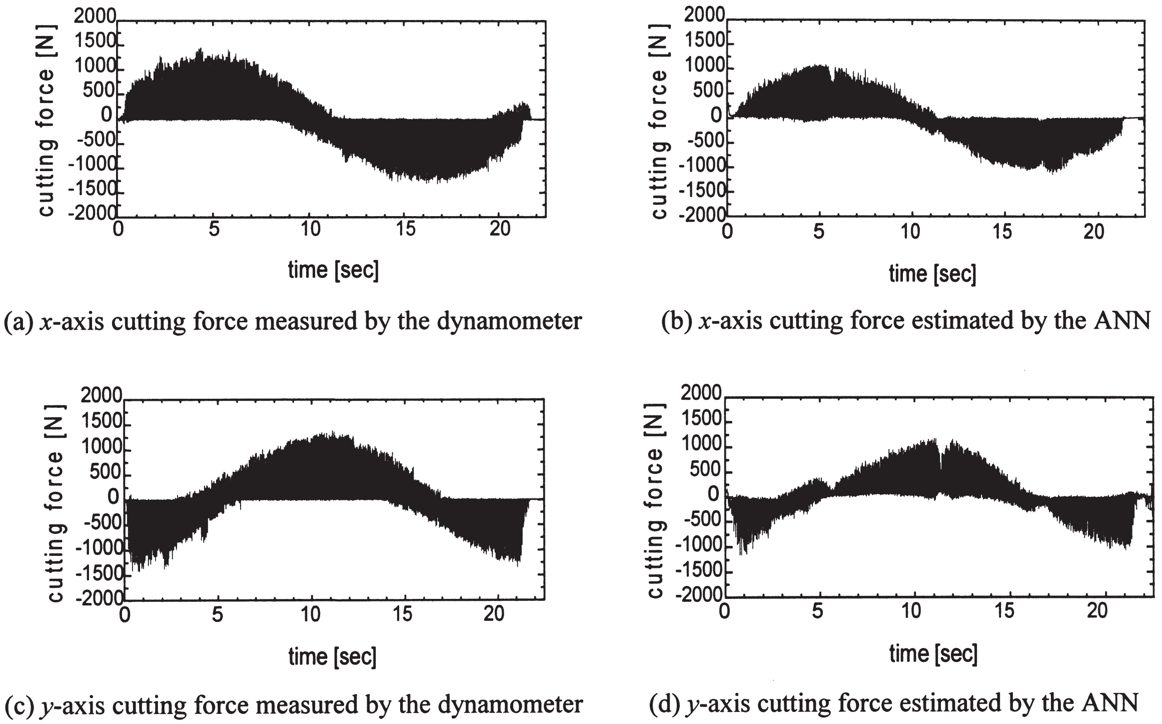


Fig. 12. Performance comparison of the Kalman filter with the ANN system for on-line estimation of the cutting force in x-axis (same *cutting condition A* in Fig. 1).

y-axis cutting force is slightly less than that of the actual cutting force at the point where feed direction is reversed. Since the machine tool used in the experiment is the horizontal machining center, the y-axis is the axis of spindle movement in the vertical direction. Therefore, when the direction of feed changes, the dynamic balancing for spindle box weight by the counter-balance cylinder can cause the larger amplitude variation comparing to the x-axis movement as shown



(a) x-axis cutting force measured by the dynamometer

(b) x-axis cutting force estimated by the ANN

(c) y-axis cutting force measured by the dynamometer

(d) y-axis cutting force estimated by the ANN

Fig. 13. Performance of the ANN system under the different *cutting condition B* after it has been trained under the *cutting condition A* in Fig. 1 (*cutting condition B*: circular interpolated contour milling, axial depth of cut 1mm, feed rate 600 mm/min. Others are same with the *cutting condition A*).

in Fig. 5. This can be one of the causes for the slight amplitude shrinkage in y-axis cutting force estimation.

4. Conclusion

1. A signal pre-processor has been developed for measuring both the signals of the servo motor currents and the feedrates in x, y and z-axis. Since the pre-processor enables the interfacing with the commercial CNC without major modification of the system, the schemes presented in this paper can be readily implemented into most of commercial machining centers.
2. The transfer function between the external load and the measured servo motor current signal has been identified. The cutting force can be measured indirectly by using the servo motor current signal when the tool passing frequencies are below the bandwidth of 70 Hz.
3. This paper presents the on-line indirect measurement of the cutting force in multi-axis simultaneous milling processes. When the feed direction is reversed, the servo motor current signal changes accordingly in a step-wise pattern from the negative to positive values or vice versa due to the friction forces in the guide way. Therefore, simply measured servo motor current can not represent the cutting force.

4. In this paper two different methods are suggested. First, a real-time Kalman filter disturbance observer, which estimates the external load torque to the servo drive motors of the machining center, is proposed. Second, a method based on an ANN system is suggested. This method does not require any modeling of the feed drive system, while former one requires. The neural network has been trained by the experimental data set which consists of the signals of the feed drive motor currents and the feedrates of the feed drive axes.
5. The experimental works have been executed on the circular interpolated contour milling process. The cutting forces estimated by the Kalman filter show better tracking capability than the simply calibrated motor current signals. However, there still exists the difference of measured and estimated cutting force at every point in the contouring cutting path where the feed direction is reversed.
6. The ANN system shows better cutting force estimation performance than the Kalman filter disturbance observer, since it can be used effectively where the feed drive system and the cutting process show non-linearity and coupling effect exist between the feed drive axes during multi-axis cutting. The estimated cutting force shows a good agreement with the directly measured actual cutting force in the whole range of machining. The suggested schemes can be applied in the field of monitoring and control of the machining process.
7. To apply the ANN system in industry, the generalization of the neural network is the most important prerequisite. It means that a neural network trained under a specific cutting condition has to have a applicability in the various cutting condition of different tools and workpiece materials. The generalization of the neural network for cutting force estimation can be achieved by the further experimental works under various cutting condition.

Acknowledgements

This research work has been partially supported by the Engineering Research Center for Advanced Control and Instrumentation (ERC-ACI) at Seoul National University, Korea. The authors gratefully acknowledge the support.

References

[1] G. Byrne, D. Dornfeld, I. Inasaki, G. Ketteler, W. König, R. Teti. Tool condition monitoring (TCM)—the status of research and industrial application, CIRP Annals 44 (2) (1995).
[2] J. Tlusty. Automatic Supervision in Milling, Automatic Supervision in Manufacturing, in: M. Szafarczyk (Ed.), Springer, London, 1994.
[3] Y. Altintas, Prediction of cutting forces and tool breakage in milling from feed drive current measurement, ASME Journal of Engineering for Industry 114 (1992) 386–392.
[4] J.M. Lee, D.K. Choi, J. Kim, C.N. Chu, Real-time tool breakage monitoring for NC milling process, CIRP Annals 44 (1) (1995) 59–62.
[5] M.A. Mannan, S. Broms, Monitoring and adaptive control of cutting processes by means of motor power and current measurement, CIRP Annals 38 (1) (1989) 347–350.
[6] J.L. Stein, D. Colvin, G. Clever, C.H. Wang, Evaluation of DC servo machine tool feed drives as force sensors, ASME Journal of Dynamic Systems Measurement and Control 108 (1986) 279–288.

[7] T.Y. Kim, J. Kim, Adaptive cutting force control for a machining center by using indirect cutting force measurement, Int. J. Mach. Tools Manufact. 36 (8) (1996) 925–937.
[8] M. Weck. Handbook of Machine Tools, vol. 2, Wiley, New York, 1984.
[9] FANUC Ltd. FANUC AC Servo Amplifier Maintenance Manual, B-65005E, FANUC Ltd, 1992.
[10] C.K. Chui, G. Chen. Kalman Filtering with Real-time Applications, Springer, London, 1987.
[11] S. Haykin. Neural Networks—A Comprehensive Foundation, Macmillan, New York, 1994.
[12] S.S. Rangwala, D.A. Dornfeld. Learning and optimization of machining operations using computing abilities of neural networks. IEEE Transactions on System, Man, and Cybernatics 19(2) (1989).