TWO DIMENSIONAL FEEDRATE CONTROL FOR HIGH PERFORMANCE CNC MACHINE TOOLS

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Abstract: This paper proposes a new feedrate control technique of CNC that can achieve high machining accuracy and high productivity. The proposed adaptive neuro-controller adjusts both components of the feedrate and makes an improved command of contour geometry. This control architecture consists of a neural network identifier (NNI) and an iterative learning algorithm with inversion of the NNI. The NNI is an identifier for the non-linear characteristics of CNC and composed of two outputs that are identified with individual axis dynamics of the contour error. The iterative learning algorithm is exploited to derive an optimal feedrate control law by minimizing a performance index that is a measurement of the contour error and the machining time.

Keywords: CNC, neural network, learning algorithm, performance index, geometry.

1. INTRODUCTION

In the position control of a computerized numeric control(CNC) machining center, one of the most important issue is the elimination of the contour error, which requires the 2-dimensional accuracy of machining process. The reduction of the contour error helps to increase accuracy and improve quality of final products. Recently, many researches are focused on this issue. However, not only contouring accuracy but contouring speed is important for high productivity. But the increase of the feedrate for good productivity may cause poor contouring accuracy. Therefore, many researchers are investigating feedrate control methods to improve contouring speed and contouring accuracy simultaneously.

Imamura and Kaufman (1989) presented a non-linear programming method that divides the elliptic contour into several linear contours. But this method is only applicable to the case of the elliptic contour. Linear relationship between the feedrate and the contour error proposed by Chuang and Liu (1996) is not acceptable for real-world application because real relationship is highly non-linear. And Tsai, *et al*. (1995) proposed a fuzzy adaptive feedrate control. Yoon and Jeon (2000) used a network inversion algorithm to search the fastest feedrate within a tolerable error bound. But, in all of these papers, they change only the magnitude of the feedrate and the contour geometry remains the same. Yang (1993) proposed an analytic method to set an additional reference contour for precision and productivity. However, the model was assumed simplified linear equations and the control strategy was adopted to merely corner motion.

In this paper, we propose a new feedrate control method that adjusts both components of the feedrate. This method destroys the original contour and makes a new desired trajectory. This is based on a network inversion algorithm (Kindermann and Linden, 1990). Since the relationship between the contour error and the feedrate is highly non-linear, we use the neural network identifier (NNI) that is identified with individual axis dynamics of the contour error. With this identified relationship, the network inversion algorithm searches the optimal feedrate component of each axis that minimizes the performance index. The proposed feedrate control method takes advantage of the recent contour error model (Lee and Jeon, 1999) and the effectiveness of the proposed method is shown by computer simulations.

2. THE CNC SYSTEM

In this section, we show the typical configuration of the CNC machine system and the recently developed contour error model used in this paper.

2.1 The CNC machine system.

A typical CNC machine system shown in Fig. 1 consists of an input/output unit, arithmetic processing unit, a PLC (programmable logic controller), a servo spindle control unit, and graphic control unit. The input/output unit undertakes the input of NC program, information conversion and distribution, operator interface and processing of external input/output signal. The arithmetic processing unit downloads NC program from the input/output unit, determines feedrate, position, and interpolation, and consists of microprocessor and memory for data and program. The PLC performs ON/OFF control such as substitution of machine tools, supplement of oil, and lamp lighting. The servo spindle control unit controls servo motor for actual machining. Graphic control unit displays the computed two or three-dimensional image.

2.2 The contour error model.

In machining process, there are many factors to cause the contour error that determines the quality of final products. Among them, the contour error due to each axial dynamic characteristic is the main origin of error in high-speed machining. In general, the contour error is defined as the shortest distance between the desired and the actual trajectory. Consider an arbitrary contour as shown in Fig. 2. Let $P^*(t)$ be a position on the desired contour, $P(t)$ be a current tool position, and $P_c^*(t)$ be a closest desired position to $P(t)$. The vector E (dashed line)

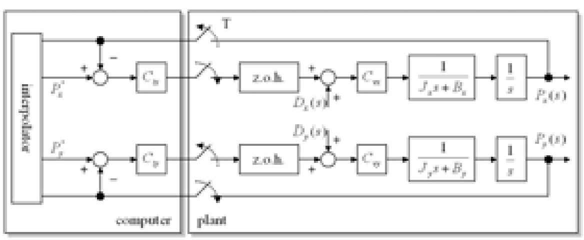

Fig. 1. The composition of a CNC system.

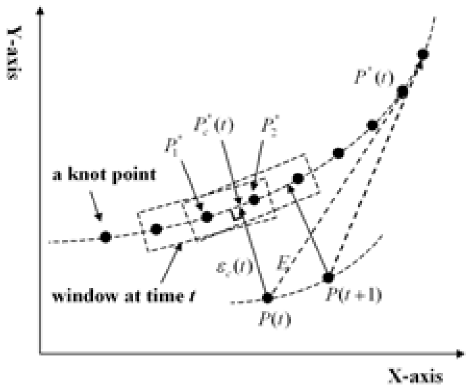

Fig. 2. The contour error model using variable windows.

represents the tracking error and $\varepsilon_c(t)$ (solid line) means the contour error. But, we don't know the exact point such as $P_c^*(t)$. Only the desired position vectors of $P^*(t)$ including P_1^* and P_2^* are known. Therefore, the error for curved contours cannot be directly computed in real-time motion and an approximation of contour error suitable for real-time computation is required.

In this paper, we use the recent algorithm (Lee and Jeon, 1999) to calculate the contour error by use of current slide position $P(t)$, and the two points (P_1^* and P_2^*) closest to $P(t)$ and found among the previously stored *N* reference position data in a shift register. The interpolator of CNC system generates reference knot point every sampling time as shown in Fig. 2. The interval between two reference points can be linearized as a straight line. Let the contour error $\varepsilon_c(t)$ is defined as the shortest distance between $P(t)$ and the straight line connecting P_1^* and P_2^*. A variable size window is used to find P_1^* and P_2^* and reduces the calculation time. In every interpolation period, $\varepsilon_c(t)$ can be determined from the geometrical relationship as follows.

$$\varepsilon_c(t) = \begin{cases} e'_y \cos\theta - e'_x \sin\theta \quad , \quad if \quad x_2 \geq x_1 \\ e'_x \sin\theta - e'_y \cos\theta \quad , \quad if \quad x_2 \prec x_1 \end{cases} \tag{1}$$

$$\theta = \tan^{-1}\frac{y_2 - y_1}{x_2 - x_1} \tag{2}$$

P_1^* is (x_1, y_1) and P_2^* is (x_2, y_2). The θ is an angle that is made by the straight line connecting P_1^* and P_2^*. e'_x means the X axis error and e'_y means the Y axis error between $P(t)$ and P_2^*. With this contour error computation method, it is possible to calculate the contour error for an arbitrary curved trajectory.

3. THE PROPOSED FEEDRATE CONTROL

3.1 The schema of the proposed controller.

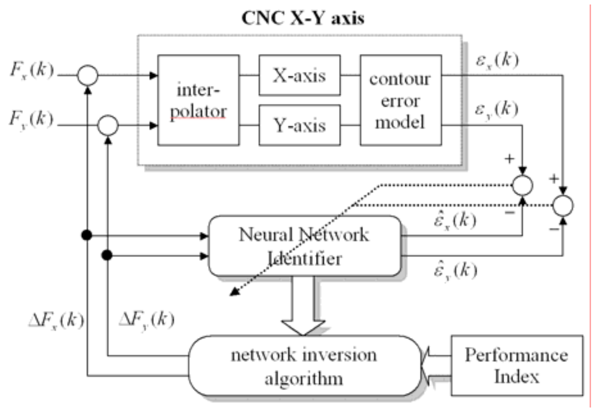

Fig. 3. The schema of the feedrate controller

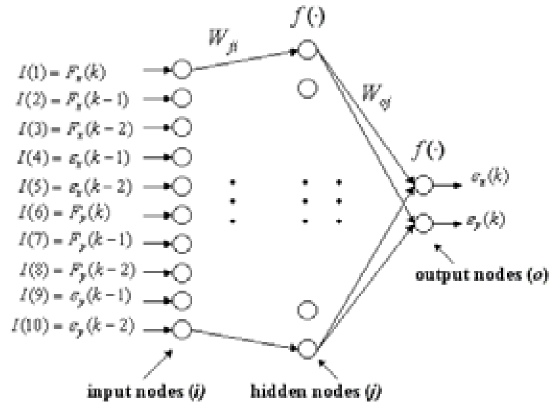

Fig. 4. The neural network identifier.

Fig. 3. shows the organization of the controller and the CNC system. In 2-dimensional plane (x and y axis), the feedrate and contour error have each component for individual axis. Therefore, we assume the CNC block as a system that has two inputs and two outputs. The contour error at the arbitrary second is composed of x-axis element $\varepsilon_x(k)$ and y-axis element $\varepsilon_y(k)$. In addition, the feedrate has two components, $F_x(k)$ and $F_y(k)$, in the 2-dimensional plane. The proposed controller is based on a network inversion algorithm. To achieve the optimal feedrate, we must know about the system dynamics. In general, the dynamic characteristic between the feedrate and the contour error is highly non-linear. Moreover, the individual axis dynamics of the contour error is more severely non-linear. The NNI is used to identify the dynamics of the contour error. We can get the system dynamic characteristics from NNI indirectly. The network inversion algorithm makes the optimal individual axis component of feedrate minimize the performance index. The optimised feedrate generates a new improved trajectory.

3.2 The multi-layer neural network identifier.

The neural network shown in Fig. 4. has 10-12-2 multi-layer structure and is trained so as to identify the dynamic characteristics between feedrate and contour error. The output of the neural network is given by

$$\hat{\boldsymbol{\varepsilon}}(k) = \begin{bmatrix} \hat{\varepsilon}_x(k) \\ \hat{\varepsilon}_y(k) \end{bmatrix} = \begin{bmatrix} f(net_1) \\ f(net_2) \end{bmatrix} \quad (3)$$

$$net_o = \sum_{j=1}^{12} \{ W_{oj} f(net_j) \} \quad (4)$$

$$net_j = \sum_{i=1}^{10} \{ W_{ji} I(i) \} \quad (5)$$

net_o and net_j are inputs of output and hidden layer. W_{ji} is the connection weight between input and hidden layer and W_{oj} is the connection weight between hidden and output weight. $f(\cdot)$ is a hyperbolic tangent activation function. The weights of the neural network are updated in the direction to minimize the cost function defined as

$$E_n(k) = \frac{1}{2} \left\{ (\varepsilon_x(k) - \hat{\varepsilon}_x(k))^2 + (\varepsilon_y(k) - \hat{\varepsilon}_y(k))^2 \right\} \quad (6)$$

3.3 The network inversion algorithm.

Using the network inversion algorithm, the optimal feedrate of individual axis can be evaluated. The performance index that is used at the arbitrary second is defined as follows.

$$E(k) = \frac{1}{2} \|\boldsymbol{\varepsilon}(k)\|^2 + \frac{\rho}{\|\mathbf{F}(k)\|^2} \quad (7)$$

The first term of (7) means the magnitude of the contour error at an arbitrary second. To minimize this term is to improve the quality of the final products. However, if only the first term is minimized to improve the quality, the processing time may increase. Since the first term alone may cause the poor productivity, an inverse feedrate term is added to the performance index. The second term of (7) is the inverse of the magnitude of the feedrate vector. The feedrate vector, $\mathbf{F}(k)$, is composed of individual axis component $F_x(k)$ and $F_y(k)$. This term has the same meaning as the processing time. Therefore, to increase the feedrate at the arbitrary second is to minimize the performance index. Because these two

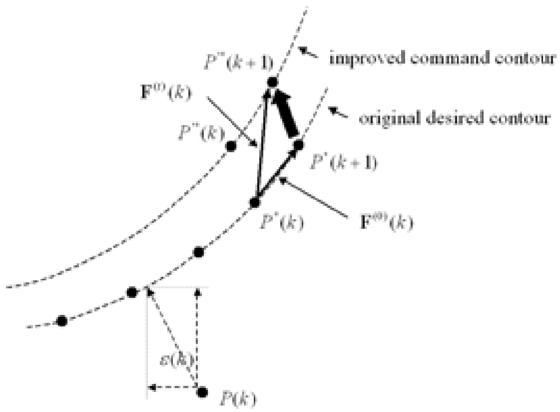

Fig. 5. The new trajectory improved by network inversion algorithm.

terms have trade-off relationship, the proper ρ must be selected appropriately to achieve high accuracy and shorten the processing time.

The inversion algorithm to evaluate the optimized feedrate is given by

$$\mathbf{F}^{(t+1)}(k) = \begin{bmatrix} F_x^{(t+1)}(k) \\ F_y^{(t+1)}(k) \end{bmatrix} = \begin{bmatrix} F_x^{(t)}(k) - \eta \dfrac{\partial E}{\partial F_x^{(t)}(k)} \\ F_y^{(t)}(k) - \eta \dfrac{\partial E}{\partial F_y^{(t)}(k)} \end{bmatrix} \quad (8)$$

$$\frac{\partial E(k)}{\partial F_x^{(t)}(k)} = -\frac{1}{4}\varepsilon_x(k)\cdot\left(1-\varepsilon_x(k)^2\right) \cdot \sum_j \left\{W_{1j}\left(1-f^2(net_j)\right)W_{j1}\right\} + \frac{\rho\cdot F_x(k)}{\left(F_x(k)^2+F_y(k)^2\right)^2} \quad (9)$$

$$\frac{\partial E(k)}{\partial F_y^{(t)}(k)} = -\frac{1}{4}\varepsilon_y(k)\cdot\left(1-\varepsilon_y(k)^2\right) \cdot \sum_j \left\{W_{2j}\left(1-f^2(net_j)\right)W_{j6}\right\} + \frac{\rho\cdot F_y(k)}{\left(F_x(k)^2+F_y(k)^2\right)^2} \quad (10)$$

In the above equation, (9) and (10) is the x-axis and y-axis dynamic characteristics of the CNC system. It can be calculated using the chain rule of (3), (4), and (5) and it is accomplished with the assumption that the neural network identifier is trained well.

Fig. 5. shows the results and the mechanism of the proposed controller. $P^*(k)$ is the original desired position at k-th time step, $P'^*(k)$ is the new knot point that is evaluated with the proposed controller, and $P(k)$ is the current tool position. The network inversion algorithm starts from step 0 and the feedrate vector is $\mathbf{F}^{(0)}(k)$. Owing to the performance index, the final feedrate vector $\mathbf{F}^{(t)}(k)$ is calculated in a several steps and the new knot point at (k+1)-th time step $P'^*(k+1)$ can be determined with $F_x^{(t)}(k)$, $F_y^{(t)}(k)$, and sampling time.

4. COMPUTER SIMULATION RESULTS

In this section, the effectiveness of the proposed method is presented by computer simulations based on a model of TNV-40 vertical machining center. The parameters of X-Y servo axes used in the simulations are shown in Table 1. The simulation model contains a tracking controller to reduce the contour error. The PD and P controllers are used for

Table 1 The parameters of each axis

	Inertia J_i (kgm^2)	Viscous Friction B_i (Nms)	Coulomb Friction F_i (Nm)	Disturbance D_i
X-axis	0.0103	0.0336	0.2	0.1
Y-axis	0.012	0.0308	0.3	0.1

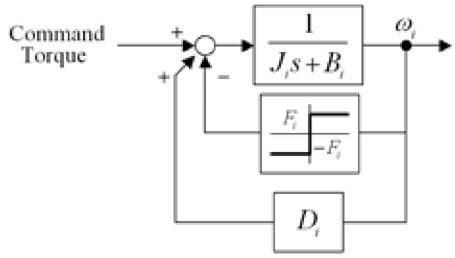

Fig. 6. The diagram of Disturbance for each axis.

position control and speed control of each axis, respectively. This model also contains non-linear terms such as a saturator and disturbance. The total disturbance includes not only the cutting force on workpiece, but also non-linear friction. Fig. 6. shows the disturbance for one axis. The neural network identifier uses the present feedrate, two delayed terms of feedrate, and two delayed terms of the contour error of x and y-axis as inputs and has 12 hidden nodes and 2 output nodes. The hyperbolic tangent function is used as an activation function of the neural network identifier. The connection weights of NNI are trained with BP algorithm. The maximum iteration number for the inverse mapping method is set to 5 and the magnitude of reference feedrate is 50 mm/sec. The acceleration and deceleration time to maximum reference feedrate is 0.5 second. The relative weight value ρ is set to 0.01 by trial and error. We compare the performance of the proposed method with that of the previous feedrate control method that can change only the magnitude of the feedrate. In this simulation, the results for the circle contour as a general non-linear contour is presented. The reference circle contour is described as

$$r_x(t) = R\cdot(1-\cos wt)$$
$$r_y(t) = R\cdot\sin wt \quad (11)$$

where the radius of the circle R is 10 mm and $r_x(t)$ and $r_y(t)$ represents X and Y reference position, respectively. Fig. 7. shows that the performance is

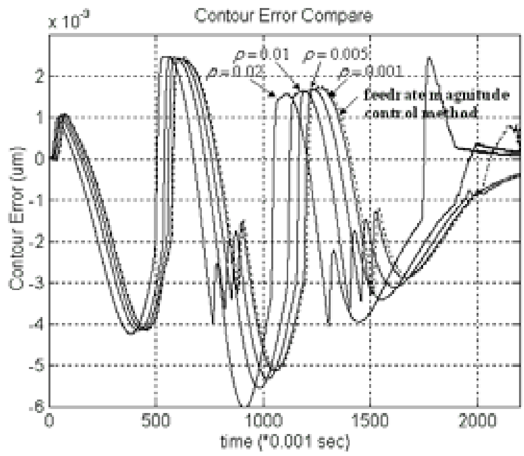

Fig. 7. The comparison of performance for the various relative weight values.

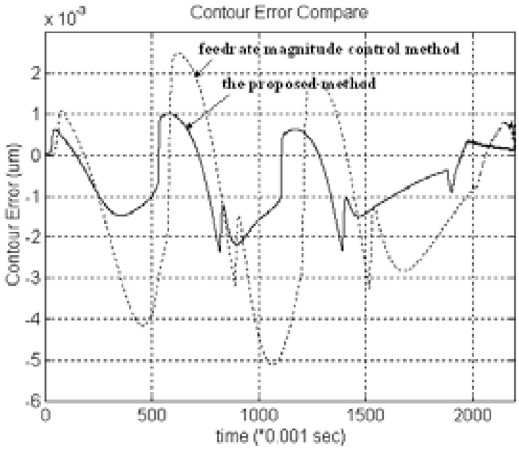

Fig. 8. The comparison of contour errors between the proposed method and the feedrate magnitude control method.

depending on the relative weight values. In this simulation, because the first term of (7) is set to zero, we can make an analysis of the effect of second term. The dashed line represents the contour error that is achieved with feedrate magnitude control method and the sold lines show the contour errors with various relative weight values. As expected the processing time increases as ρ increases. But the maximum of contour error increases on the contrary. So we set the ρ to 0.01. Fig. 8. shows the contour error that is achieved when all of two terms of performance index (7) are used. The dashed line is the contour error of the previous feedrate control method that can change only the magnitude of the feedrate and the solid line is that of the propose method. The scalar value of the feedrate with each control method is shown in Fig. 9. In fact, the magnitudes of the feedrates are not quit different. But the important thing is the feedrate of the individual axis. Because they are changed very much, the geometrical trajectory stays away from the original path. Fig. 10. shows the improved desired trajectory. The contouring result is shown in 500 times enlarged scale for better comparison. As a result, the performance of contouring is improved by

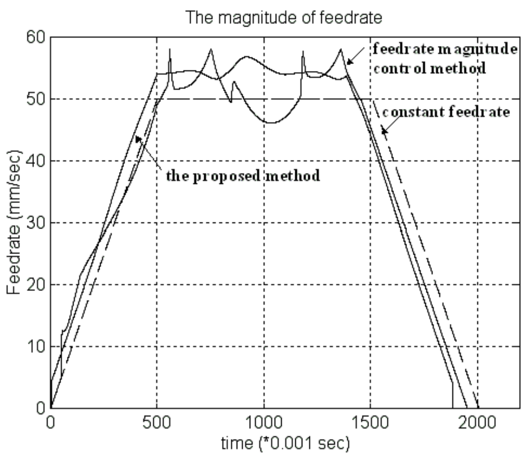

Fig. 9. The comparison of the magnitude of the feedrate.

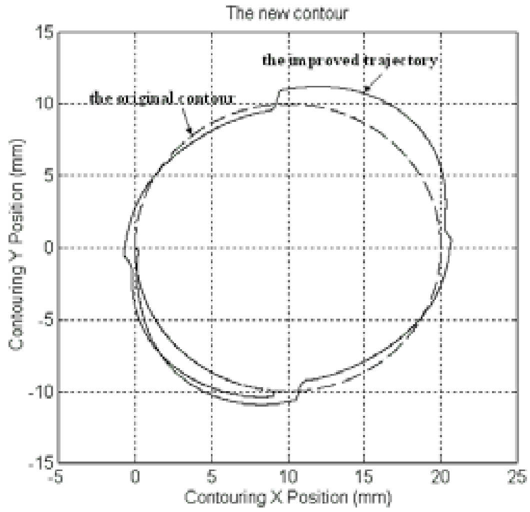

Fig. 10. The desired trajectories on x-y plane.

not only changing the x and y components of the feedrate but making a new trajectory.

5. CONCLUSIONS

Using the inverse mapping algorithm, new feedrate control of the CNC machine that improves the desired trajectory is proposed. It is possible to make the new desired contour achieve high accuracy by inserting the contour error term and high speed by the feedrate term in the performance index. And the total processing time can be managed by varying the relative weight factor. Using the inversed network information, the optimal feedrate is searched at an arbitrary second. It is shown by the simulations that the proposed method achieves higher productivity and precision than the magnitude control of the feedrate does.

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