

Research Article

An On-Machine Measurement Method for Touch-Trigger Probe Based on RBFNN

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Abstract: The touch-trigger probe is a kind of sensor installed in a machining center to measure the dimension of the work piece. A method for On-Machine Measurement (OMM) and its error compensation by the probe based on Radial Basis Function Neural Network (RBFNN) is advanced in this study. The advantages and disadvantages for touch-trigger probe of OMM system are discussed. Major factors that influence the probe measurement precision are analyzed. The measurement error compensation based on RBFNN is presented. At last the experimental system with touch-trigger probe is put forward and the experiment indicated that, using the touch-trigger probe makes on-machine measurement more automatic and efficient and by using RBFNN for error compensation make on-machine measurement more precise.

Keywords: Error compensation, on-machine measurement, radial basis function neural network, touch-trigger probe

INTRODUCTION

In tradition, a work piece after manufactured will be inspected for form and position errors by the Coordinate Measuring Machines (CMM) which are stand-alone measurement instruments and generally located separately from a Machining Center (MC) (Caballero-Ruiz, 2007). This is called offline measurement. Nowadays, as the development of the sensor and the demand of efficiency, another measurement method for conventional manufacturing process called On-Machine Measurement (OMM) appears. The difference between them depends on whether the machining process and inspection process are done on the same equipment (Kwon and Yongjin, 2005).

The offline measurement method by CMM is the most popular now and many research works are done about CMM (Erkan *et al.*, 2011; Nafi *et al.*, 2011; Marek and Wozniak, 2005). However this increases the overall manufacturing cost and time to obtain the final product and the bottleneck phenomenon may be caused by the product stagnation due to the time lag between the machining and inspection process. In addition it is hard to measure the complex, large-sized parts (Kwon and Yongjin, 2005). Furthermore, it inevitably reduces the measurement precision due to the secondary fixture error when transfer the work piece from machine center to CMM (Choi *et al.*, 2004).

To overcome these problems, the methodology of OMM is accepted. As for OMM, it also has 2 types. One is in-process gauging and the other is in-cycle

gauging. In-process gauging means machining and gauging at the same time for which probe is hardly to use because the cutting tool and the probe can't work in concurrence. The in-cycle gauging means gauging is done only before or after the machining process, however the work piece will not be disassembled from fixture. In this study in-cycle gauging will be mainly discussed.

There are some advantages to use touch probe in an OMM system. First a touch probe is a, relatively inexpensive and easy-to-use. In a machine center, the motion of a probe treated as a cutting tool, is controlled by G code or macro program. After the machining process is finished, the touch probe replaced with a cutting tool starts the measurement in the normal direction to the machined surface. Second as an accessory of certain machine center the probe is easy to be integrated with Computer Numerical Control (CNC) system. OMM system with touch-trigger probe can reduce the production time and cost, can be widely used for automating and speeding part processing, eliminate errors caused by secondary fixture.

However for high-accuracy applications with touch-trigger probe, it measures parts along the machine tool axes (Chattopadhyay, 2008), the measured data inevitably include the probing errors originated from the structure of the probe and the positioning errors originated from the inaccurate axis motion of a machine tool. There are largely systematic errors influence the accuracy, such as pre-travel variation in different probing directions, stylus length, diameter, measure speed, trigger force, etc. These errors should

be eliminated from the measured data to obtain the true machining error. Caballero-Ruiz, only researched the geometrical error (Caballero-Ruiz, 2007), Reddy, Tippa S. focused on the tool wear (Reddy and Reddy, 2011), Valino, G. did some work for tool compensation (Valino *et al.*, 2009). In fact, all the factors influenced the accuracy should be taken into account together.

When the probe touches certain point of a work piece that is loaded in the machining center and get the position of this point that is measurement point. However, due to the existence of probe errors, the measurement point has deviation with the actual point. Although we don't know the exact position of actual point, we can use theory point to substitute the actual point. In order to get more precise result, we need eliminate the deviation between the measurement point and theory point. However, due to the many types of error existing in the measurement process, it's impossible to find a formalize way to express all the error. The Radial Basis Function Neural Network (RBFNN) is a good method to map the measurement point to actual point (Hongtao Zhang, 2011).

A method to implement the OMM with the touch-trigger probe and error compensation based on RBFNN was advanced in this study. The basic technique of probe measurement error modeling was researched. The basic technique of probe measurement error modeling was discussed. At last the method was validated in the experimental system composed of DIXI 50 machining center, Fancu 16i control system, Blum CNC P82.046 probe and PC. The experiment indicated that, using the touch-trigger probe makes on-machine measurement more automatic and efficient. In addition, once the model has been trained and tested, it can be implemented either on-line or off-line to compensate for probe errors.

THE MAJOR ERRORS FOR THE PROBE PRECISION

A generalized probe error model is discussed in Caballero-Ruiz *et al.* (2007), in which the influencing factors of probe are group into the following four categories: impact force, probe rigidity, stylus rigidity and operating environment. Besides these factors we also find there some other factors, such as the probe movement, the structure of probe, the work mode of probe. So the probe error model can be rearranged as Fig. 1.

In Fig. 1, there are five categories that consist of several factors, respectively. Operating environment includes the environment temperature and machining temperature. Probe structure includes probe rigidity, stylus rigidity, stylus ball's radius, stylus length and

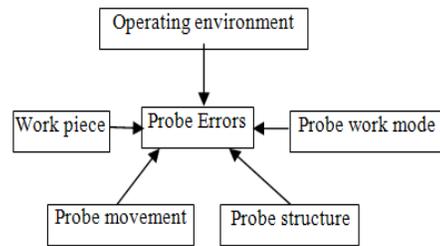


Fig. 1: The probe error model

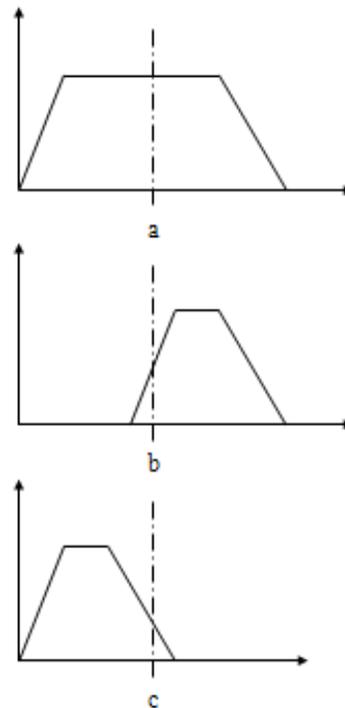


Fig. 2: The error factor of probe's federate

single emitting angle. Probe movement includes federate, direction of probe to approach work piece and impact force. Work piece to be measured includes the shape, material of work piece. Probe work mode includes measurement path and the number of point to measurement.

Each factor could impact the measurement precision more or less. For example, we know that high probe approach speed results in bigger forces transmitted through the probe system and so a bigger distortion of the stylus. As far as federate of probe concerned, as show in Fig. 2, at the measuring time, the measuring axis should move with constant federate Fig. 2a. Measuring when the machine is acceleration Fig. 2b or deceleration Fig. 2c can decline the repeatability or result in measurement error. And so calibration and tool measurement should be done with the same federate.

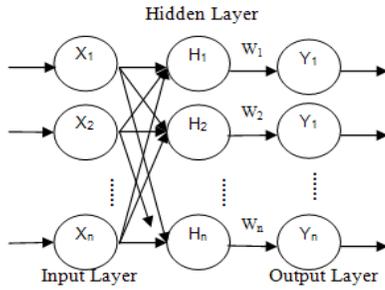


Fig. 3: RBFNN architecture

THE RBFNN

RBFNN is a famous feed-forward network that is used for approximation, classification, regulation and pattern recognition (Hongtao Zhang, 2011). RBFNN just has a hidden layer whose activation functions are calculated based on distance of the inputs and center of the activation functions. The general scheme of the RBFNN is shown in Fig. 3. RBFNN includes three layers, namely input layer, hidden layer and output layer. W_i is the weighted value vector between the hidden layer and output layer.

The activation function of i^{th} hidden neuron is defined by:

$$Z_i(x) = \exp\left(\frac{-\|x - u_i\|^2}{2\sigma_i^2}\right) \tag{1}$$

where,

- x = (x_1, x_2, \dots, x_n) is the input set
- u_i = The center of i^{th} activation function
- σ_i = A parameter to control the smoothness of the activation function
- $\|x - u_i\|$ = The Euclidean distance between the inputs and the function center

Mapping function of the common RBFN with Gaussian activation function and weighted linear summation in output neurons is given by:

$$y = \sum_{i=1}^m w_i Z_i(x) \tag{2}$$

where,

- $Z_i(x)$: The activation function of i^{th} node
- w_i : The weight of i^{th} node

In order to provide greater performance, The RBFN with local linear model in the hidden layer is used. In this way the connection weights between the hidden layer units and output units of the RBFN are replaced by a local linear model:

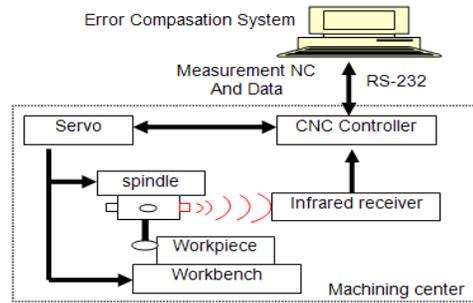


Fig. 4: An OMM system structure

$$w_i = w_{i1}x_1 + w_{i2}x_2 + \dots + w_{in}x_n \tag{3}$$

where, w_{ij} is the j^{th} weight of i^{th} node and $j = 1, \dots, n$.

For optimization a cost function $f(x)$, in initialization some particles are scattered in an n -dimension space randomly. Position of every particle is displayed by x_i and velocity of them by w_i . In every iteration, $f(x)$ is calculated so individual best position p_i and global best position p_g are indicated. The position and velocity vectors are updated by:

$$w_i(t+1) = \chi(\alpha w_i(t) + c_1 \phi(p_i(t) - x_i(t)) + c_2 \phi(p_g(t) - x_i(t))) \tag{4}$$

$$x_i(t+1) = x_i(t) + w_i(t+1) \tag{5}$$

where,

- χ & α : Real number, the parameter χ controls the magnitude of w_i
- a : Magnitude of the old velocity
- c_1 & c_2 : Positive constant
- ϕ : Distributed random number in $[0, 1]$

CASE STUDY

The On-Machine Measurement (OMM) experiment system structure is shown in Fig. 4. The probe is composed of Optical Module Probe (OMP) and Optical Machine Interface (OMI). OMP, located between the probe head and the shank, receives CNC control signals via servo and transmits probe signals. Communication between the probe and the OMI is done via the optical transmission system. RS-232 serial communication is used to transmit the measurement NC program to the CNC controller and receive the measured data for further analysis using a personal computer.

The experiment system hardware is composed of DIXI 50 machining center, FANUC 16i control system, Blum CNC P82.046 probe, micrometer, standardized ring gauge and PC. The probe styli are made of steel

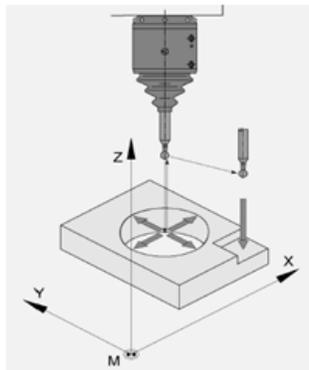


Fig. 5: Measurement system for standardized ring gauge

Table 1: The parameters used for RBFNN

Parameter	Value
Population size	40
χ	0.8
α	1
c_1	2
c_2	5

and carbon with $\phi 5$ mm, length 50 mm. The diameter of standardized ring gauge is $\phi 10 \pm 0.0012$ mm.

In this case, by using high precise micrometer, the standardized ring gauge is put on the machining center, whose center is consistent with the center of spindle, as shown in Fig. 5. Then make this center point as origin of work piece coordinate system, so each point in the standardized ring gauge in the direction of +X, -X, +Y, -Y can be pinpointed by calculating, called theory points. These points can be treated as points in output layer of RBFNN. And the points measured by probe are points in input layer of RBFNN, called measurement points. By this way, the margin between measurement points and theory points expresses the error of the whole on-machine measurement system. In addition, the points in the direction of +X, -X, +Y, -Y are symmetry, so the points in the direction of +X are inspected. The choice of samples is arbitrary and is better to cover the whole work piece.

Using RBFNN to train the sample data and the net learns from training. The change rule of the weight and threshold are defined as Eq. (4) and (5). The activation Eq. (1) is used. The objective function is the Mean Square Error (MSE) between targets and the model outputs:

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (6)$$

where,

y_i : The points measured by the probe

\hat{y}_i : The RBFNN model output and n is the number of data

Table 2: The training data set in +X

Measurement points		Theory points	
+X	Y	+X	Y
0.0000	10.0012	0.0000	10.000
1.5650	9.8792	1.5636	9.8770
3.0899	9.5133	3.0887	9.5111
4.5302	8.9140	4.5278	8.9111
5.8723	8.0961	5.8753	8.0920
7.0712	7.0698	7.0683	7.0739
8.0839	5.8788	8.0874	5.8817
8.9035	4.5416	8.9075	4.5449
9.5101	3.0927	9.5086	3.0962
9.8719	1.5695	9.8758	1.5714
10.0009	0.0000	10.000	0.0000
9.8754	-1.5588	9.8782	-1.5557
9.5104	-3.0789	9.5135	-3.0811
8.9118	-4.5287	8.9148	-4.5307
8.0939	-5.8667	8.0967	-5.8688
7.0768	-7.0653	7.0795	-7.0626
5.8847	-8.0859	5.8881	-8.0827
4.5501	-8.9060	4.5519	-8.9039
3.1065	-9.5033	3.1038	-9.5061
1.5815	-9.8721	1.5793	-9.8745

Table 3: The error compensation data in +X

Measurement points		Theory points		Compensated points	
+X	Y	+X	Y	+X	Y
2.0744	9.7853	2.0780	9.7817	2.0753	9.7848
4.0681	9.1404	4.0654	9.1363	4.0670	9.1399
7.4312	6.6987	7.4285	6.6946	7.4301	6.6978
8.6608	5.0103	8.6575	5.0047	8.6589	5.0091
9.9407	1.0562	9.9444	1.0529	9.9428	1.0560
9.9499	-1.0321	9.9461	-1.0366	9.9477	-1.0331
8.6623	-4.9951	8.6657	-4.9905	8.6632	-4.9939
7.4431	-6.6865	7.4395	-6.6823	7.4411	-6.6852
4.0838	-9.1244	4.0804	-9.1297	4.0819	-9.1261
2.0976	-9.7740	2.0941	-9.7782	2.0957	-9.7753

The parameters are shown in Table 1. The maximal training time is 10000 and MSE is 0.001. The key problem lies in the exact quantity of hidden layer's neurons. We first use 1 neuron in hidden layer to train the net. In the training process, when in the set time and the MSE is less than 0.001, we think the training process finished and save the weight, threshold and quantity of hidden layer's neurons in a text file. And this process is so called error compensation. Afterward, measure another data to test the net that has been trained. If the result can't be accepted, then the RBFNN will be trained again, otherwise it's a good training. Table 2 lists some of data for training.

In this case, we all get 120 sample points in 4 directions, including 80 data for training and 40 data for test. Table 3 lists some of the data for test the training. All these 120 sample points are sent to the PC from machine center by RS232 and could be stored in the database for later net training and testing. The transfer macro in FANUC control system is POPEN and PCLOS which are originally used to send data to a

series printer. And we write a program to watch the series port and get data once the data is sent from machine center.

The method mentioned above can also be used to handle the direction of -X, +Y, -Y and is similar with +X. Due to the structure of the probe and the characteristic of machine center, the error in direction Z that is the spindle, can be ignored compared the error in other directions. So in this case we didn't consider the error of direction Z. The data listed in Table 2 show that the method for error compensation of touch-trigger probes is effective.

CONCLUSION

Radial Basis Function Neural Network (RBFNN) is a good kind of machine learning methods. In this study, an OMM system structure with touch-trigger probe is put forward and then the advantages and disadvantages for touch-trigger probe are discussed. Major factors that influence the probe measurement precision are analyzed. A method for On-Machine Measurement (OMM) and its error compensation by the probe based on RBFNN is researched. The experiment indicated that, using the touch-trigger probe makes on-machine measurement more automatic and efficient and by using RBFNN for error compensation make on-machine measurement more precise. In addition, the method can be used off-line, only if there is a file in which all the data has correct format that could be read by the measurement system in this study, an effective hand tracking method is proposed based on hand occlusion information. This method is simple to operate by moving the user's hand freely for interactive operations. Some experiments have been conducted to validate that the proposed method can correctly predict the position of the occluded parts and have better tracking accuracy. The future research will address to get the information of each finger and hand gesture spotting for sign recognition via single camera system.

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