Prediction of Surface Roughness in CNC Turning Process using Adaptive Neural Fuzzy Inference System

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ABSTRACT

This paper presents the methodology of surface roughness inspection in the CNC Turning process. Adaptive Neural Fuzzy Inference System classifier can predict the high accuracy roughness value by insisting on surface roughness image. The vision system captures the image and determines the mean value by using the ANFIS algorithm. Training sets variables speed, depth of cut, feed rate, and mean value are feed as the input, and manual stylus probe surface roughness value is feed as the output. After the simulation process, the testing input was performed, and finally getting the vision measurement value. This higher accuracy (above 95%) and low error rate (below 4%) can be achieved by using the ANFIS classifier, which is predominantly helpful for the industry to measure surface roughness. Assign the quality of the product by evaluating the manual stylus probe and vision measurement value.

Keywords : CNC Turning; Al6063; Adaptive Neural Fuzzy Inference System classifier; Stylus Instrument; Vision Measurement.

Introduction

Surface roughness widely controls the quality of the product. Especially the friction contact assembly, the surface roughness decides the overall work status. So, we could move the CNC Turning process, which is produced the high accuracy of surface roughness. In the current scenario, even most of the industries used the manual stylus probe instrument for measuring surface roughness values. Some of the small-scale industries were not ready to move towards the computer vision inspection methodology because they used work sampling techniques for mass and batch production with stylus probes. Ho, Shinn-Ying, et al(2002) studied ANFIS Model was getting high accuracy compared with the existing polynomial network. This work was carried with 57 training samples and 16 testing samples and achieved the mean error rate was 0.38% only. Radhakrishnan,B, et al (2018) choosed Al6063 as the workpiece material, and a single workpiece was carried to the overall process. The material was machined in CNC Lathe and image extracted to predict the grayscale value. 10 training sets and 10 testing samples havebeen done and attain 95 % above the accuracy level.

Adaptive Neural Fuzzy Inference System

Adaptive Neural Fuzzy Inference System was constructed by Artificial Neural Network and Fuzzy Inference System. Speed (S), Depth of Cut (D), Feed Rate (F), and Grey Scale value (Ga) as input parameters and surface roughness value (Ra) set as the output parameter.

$$Ga = \frac{1}{n}\sum_{i=1}^{n} [g_i] \qquad \text{Ga = Gray Scale value} \tag{1}$$

$$Ra = \frac{1}{n}\sum_{i=1}^{n} [y_i] \qquad \text{Ra = Surface roughness value} \tag{2}$$

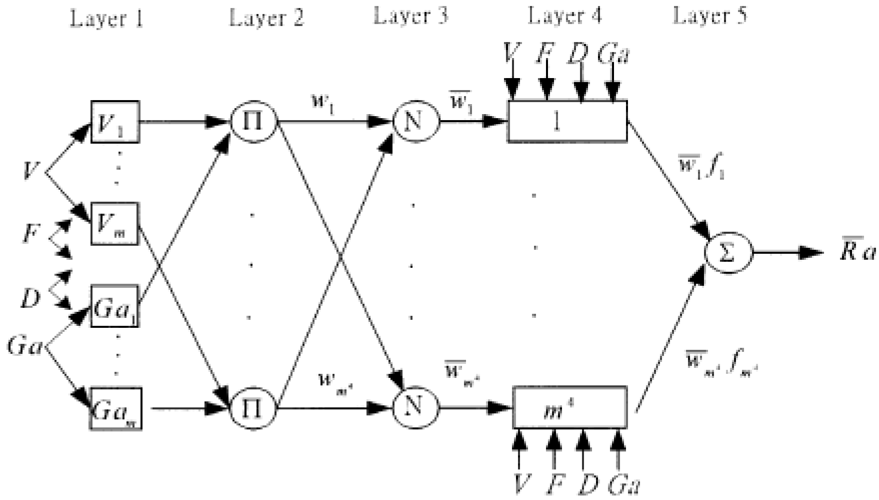

Figure-1. Structural diagram of ANFIS

Here I denoted the output node, and l denoted the layer formation.

Layer1: Adaptive node is defined in every node.

$O_{1,i} = \mu_{vi}(\mathrm{v})$ for i=1,…., m, (3)

$O_{1,i+m} = \mu_{Fi}(\mathrm{F})$ for i =1,…., m, (4)

$O_{1,i+2m} = \mu_{Di}(\mathrm{D})$ for i =1,…., m, (5)

$O_{1,i+3m} = \mu_{Gai}(\mathrm{Ga})$ for i =1,…., m, (6)

Here V,F, D, Ga as the input node, and V_i, F_i, D_i, $Ga_i$are derived as the fuzzy set associated membership of this node. M denoted the fuzzy set for the input parameter.

Layer 2: In this layer, every node is a fixed node. It is labelled at π, used to multiply the receiving signal, and outputs the product.

$O_{2,k}=w_k=\mu_{vg}(V)\times\mu_{F_h}(F)\times\mu_{Di}(D)\times\mu_{Gaj}(Ga), forg,h,i,j=1,...,m,k=1,..., m^4.$ (7)

Layer 3: Every node i, in this layer [2], is a fixed node. It was labeled N.

$O3,i=\overline{w_i} = \frac{w_i}{w_1 + w_2 + \ldots + w_{m^4}}$, $i=1,2,\ldots, m^4$.(8)

Layer 4: in this layer, every node is an adaptive node.

$$O_{4,i} = \overline{w_i} fi = \overline{w_i}(p_iV + q_iF + r_iD + s_iGa + t_i),\ i = 1,2,\ldots,m^4. \quad (9)$$

Layer 5: constructed by the single node and also it fixed node, labeled at ∑. It was the overall output of all incoming signal.

$$O_{5,1} = \sum_{i=1}^{m^4} w_i f_i \quad (10)$$

Experimental setup

The computer vision system consisted of the DSLR canon ED1300 Camera. Al6063 was selected as the workpiece for its specific application, shaft fitting, shaft and bearing assembly, door, and furniture fittings.

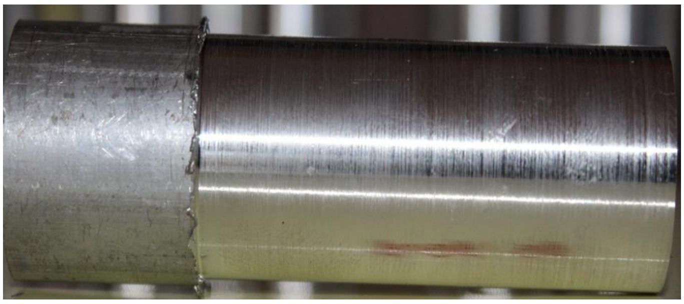

Figure-2. Al 6063 Machined workpiece

The Al6063 was machined in CNC lathe with cutting speed (1000-1800 rpm), depth of cut (0.1-1 mm/rev), and feed rate (0.5-1.5 mm).

Table 1. Experimental training parameter

S.No	Speed (rpm)	Depth of Cut (mm)	Feed Rate (mm/ rev)	Gray Level (Ga)	Stylus Instrument Ra (um)
1	1000	0.5	0.5	32.65	0.421
2	1000	0.6	0.5	38.45	0.455
3	1000	0.7	0.5	39.46	0.772
4	1000	0.8	0.6	40.56	0.821
5	1000	1	0.6	41.16	0.921
6	1000	1.2	0.7	38.45	1.115
7	1000	1.3	0.7	37.49	1.215
8	1100	1.4	0.5	33.29	1.321
9	1100	1.5	0.5	35.08	1.301
10	1100	0.6	0.5	36.89	0.487
11	1100	0.7	0.6	41.89	0.562
12	1100	0.8	0.6	40.89	0.82
13	1200	0.9	0.7	40.89	0.921
14	1200	0.6	0.5	36.48	0.487
15	1200	0.5	0.5	34.89	0.41
16	1200	0.7	0.5	32.78	0.621
17	1200	0.8	0.6	36.48	0.803
18	1300	1	0.6	35.98	0.962
19	1300	1.2	0.7	40.48	1.222
20	1300	1.3	0.5	33.25	1.301
21	1300	1.4	0.5	34.89	1.398
22	1400	0.5	0.5	39.75	0.421

23	1400	0.6	0.6	37.29	0.489
24	1400	0.7	0.6	32.56	0.569
25	1400	0.8	0.7	35.69	0.875
26	1400	1.5	0.5	36.59	1.418
27	1500	0.6	0.5	42.56	0.489
28	1500	0.7	0.5	34.98	0.759
29	1500	0.8	0.6	37.59	0.789
30	1500	0.9	0.6	31.59	0.875

Stylus probe instrument used to measure the roughness value, which is considered as the actual roughness value for reference to the machine vision roughness value. Then the machined surface images capture and converted into the grayscale value.

Cutting speed, feed rate, speed, and grayscale value feed as input to the ANFIS Network model and the surface roughness value feed as the output.

For the testing process, 30 workpieces are selected with different parameters on various levels, the training datas are listed in table 1.

Results and Conclusion

After the testing process, which is done with 10 work samples, the readings are listed in the table2. ANFIS module the output roughness value consider as Vision measurement roughness value, which is compared with the actual surface roughness value for predicting the error percentage, shown in table 3. The time duration for each module generation is 0.2 sec per workpiece.

Table 2. Experimental Turning parameters and vision measurement roughness values

S.No	Speed (rpm)	Depth of Cut (mm)	Feed Rate (mm/ rev)	Gray Level (Ga)	Vision Measurement Ra (um)	Stylus Instrument Ra (um)
1	1000	1.4	0.5	34.88	1.398	1.36
2	1100	0.5	0.7	31.99	0.584	0.564
3	1200	1.2	0.7	33.45	1.212	1.198
4	1300	0.5	0.6	38.46	0.421	0.409
5	1400	1.2	0.5	41.33	1.012	1.002
6	1500	0.5	0.7	40.88	0.521	0.492
7	1400	1	0.5	42.69	0.954	0.947
8	1200	1.4	0.5	32.59	1.398	1.29
9	1100	0.6	0.6	33.45	0.598	0.489
10	1000	1.5	0.7	36.38	1.541	1.502

Error percentage of the vision measurement value is 3.86 %, which is an acceptable range in the inspection process at industries in Figure 3.

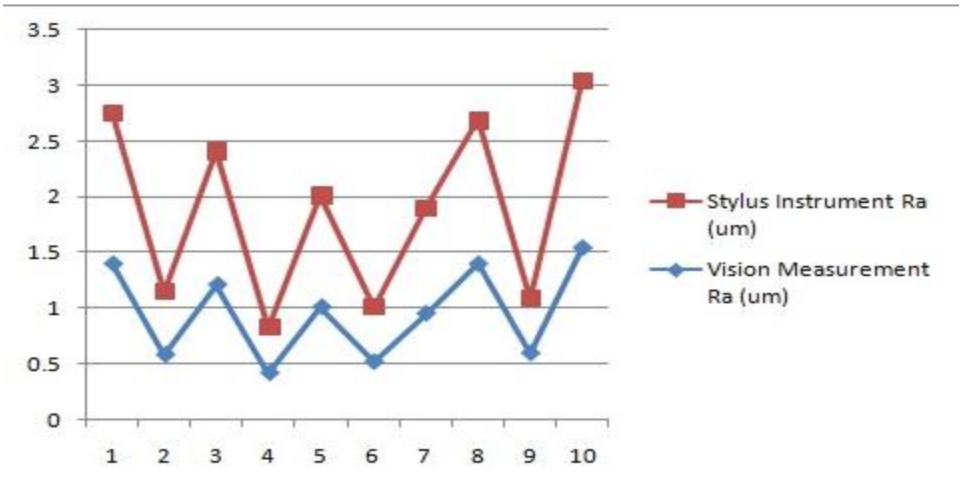

Figure-3. Comparison of Actual and vision measurement value

Based on the results,we can inspect all the products in mass production with a specific time interval. The accuracy of the process, 96.14%, has proved to possibilities can replace the stylus probe method with computer vision for rapid inspection, especially in mass production and batch production.

Conclusion

The results show the vision measurement results achieved the above 95 %, producing a good quality of the product in the machining process. Shaft and other machine components, especially the circular components,are difficult in the stylus probe method. But our machine vision concept can makeit very simple for the circular job in the inspection. Future can modify the algorithm for surface roughness measurement like Random Forest Classification, Convolution Neural Network.

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