Prediction of surface roughness in CNC end milling by machine vision system using artificial neural network based on 2D Fourier transform

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ORIGINAL ARTICLE

Prediction of surface roughness in CNC end milling by machine vision system using artificial neural network based on 2D Fourier transform

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Abstract This paper presents a system for automated, non-contact, and flexible prediction of surface roughness of end-milled parts through a machine vision system which is integrated with an artificial neural network (ANN). The images of milled surface grabbed by the machine vision system could be extracted using the algorithm developed in this work, in the spatial frequency domain using a two-dimensional Fourier transform to get the features of image texture (major peak frequency F_1, principal component magnitude squared value F_2, and the average gray level G_a). Since F1 is the distance between the major peak and the origin, it is a robust measure to overcome the effect of lighting of the environment. The periodically occurring features such as feed marks and tool marks present in the gray-level image can be easily observed from the principal component magnitude squared value $F_{2.}$ The experimental machining variables speed S, feedrate F, depth of cut D, and the response extracted image variables F_1, F_2, and G_a could be used as input data, and the response surface roughness R_a measured by Surfcorder SE-1100 (traditional stylus method) could be used as output data of an ANN ability to construct the relationships between input and output variables. The ANN was trained using the back-propagation algorithm developed in this work due to its superior strength in pattern recognition and reasonable speed. Using the trained ANN, the experimental result had shown that the surface roughness of milled parts predicted by machine vision system over a wide range of machining conditions could be got with a reasonable accuracy compared with those measured by traditional stylus method. Compared with the stylus method, the constructed machine vision system is a useful method for prediction of the surface roughness faster, with a lower price, and lower environment noise in manufacturing process. Experimental results have shown that the proposed machine vision system can be implemented for automated prediction of surface roughness with accuracy of 97.53%. The results are encouraging that machine vision system can be extended to many real-time industrial prediction applications.

Keywords CNC end milling · Surface roughness · Machine vision · Fourier transform · ANN

1 Introduction

The quality of components produced is of main concern to the manufacturing industry, which normally refers to dimensional accuracy, form, and surface finish. Surface roughness of work parts plays an important role on mechanical properties. The proper functioning of a machined part is, in many instances, largely dependent on the quality of its surface. Engineering properties such as fatigue, hardness, and heat transfer are affected by surface finish. The traditional stylus method is the most widely used technique in industry. A precision diamond stylus is drawn through the surface being detected and the perpendicular motion is amplified electronically [1–3]. The accuracy of stylus method depends on the radii of diamond tips. When the surface roughness falls below 2.5 μm, the stylus instruments are affected by large system error. The

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major disadvantage for such methods is that they require directed physical contact and line sampling which may not represent the real characteristics of the surface [4].

In this study, we investigate the assessment of surface roughness of end-mill parts using machine vision. Machine vision allows the assessment of surface roughness without touching or scratching the surface. It provides the advantages of a measurement process for 100% inspection and the flexibility for measuring the part under test without fixing it in the precise position. In contrast to the stylus-based methods that trace the surface roughness in one dimension, machine vision can generate many more readings of a 2D surface in a given time, and this makes the estimation method for roughness measurement more reliable. Extensive research has been performed on machine vision applications in manufacturing because it has the advantage of being non-contact and as well faster than the contact methods.

Using machine vision, it is possible to evaluate and analyze the area of the surface, which makes it a 2D evaluation [5].

In recent years, many optical measuring methods have been applied to overcome the limitations of stylus method in measuring the surface roughness of work parts. Galante applied an image processing technique for the on-line control of the surface roughness in the finishing turning operation by means of tool image detection and processing. The authors also built a model to estimate the value of the effective roughness of the work pieces from one related to the deal profile. Yet, tests varying the cutting speed were not carried out in their study [6]. Choudhury, I.A. used a model for surface roughness prediction using the response surface method by combining its methodology with factorial design of experiments developed [7]. Dimla, E. adopted the application of perception-type neural networks for tool-state classification during metal-turning operation that has been studied [8]. They investigated both single-layer networks and multi-layer networks and found that the multi-layer networks had better performance than the single-layer tool-state classification. Al-Kindi assessed a system in the automation inspection of engineering surface. The parameters they got were based on spacing peaks and the number of peaks per unit length of a scanned line in the gray-level image. This one-dimensional (1D) image is sensitive to lighting and noise [9]. Luk and Huynh used the gray-level histogram of the surface image to characterize surface roughness. They found the “optical roughness parameter (R)=¼std. dev./rms” to be a non-linear, increasing function of average surface roughness. Since their method was based on the histogram, it is sensitive to the uniformity and degree of illumination presented [10]. K. Venkata Ramana examined the intensity histograms of the surface image that have been utilized to characterize surface roughness and quality. Statistical methods such as co-occurrence matrix approach, the amplitude varying rate statistical approach, and run length matrix approach have also been used to compare the texture features of machined surfaces [11]. Hoy and Yu applied the algorithm of Luk and Huyuh to characterize surface roughness. They found one exception where the value of the ratio may lead to incorrect measurement. So, they used the Fourier transform (FT) to characterize surface roughness in the frequency domain. Yet, no quantitative description of FT features for the measurement of surface roughness is described [12]. Risbood et al. studied the prediction of surface roughness and dimensional deviation by measuring the cutting force and vibrations in the turning process. In their work, surface finish could be predicted with a reasonable degree of accuracy by taking the acceleration of radial vibration of the tool holder as a feedback [13]. Lee et al. presented a system for measuring surface roughness of turned parts through a computer vision system, and the trained abductive network was used in this application [14]. Brezocnik et al. proposed a genetic programming approach to predict surface roughness in end milling process [15]. The genetic programming is an evolutionary computation method that was first introduced by Koza in the year 1992 [16]. It aimed at finding out computer programs (called as chromosomes) whose size and structure dynamically changes during the simulated evolution that best solved the problem. Cutting parameters, viz., spindle speed, feed, and depth of cut as well as vibration between tool and work piece, were used to predict the surface roughness, and the authors found that the model which involves all these variables accurately predict the surface roughness. Reddy and Rao developed an empirical surface roughness model for end milling of medium carbon steel, whose parameters were optimized using genetic algorithm (GA) [17]. Oktem et al. determined the optimum cutting conditions for minimum surface roughness in milling operation. The surface roughness was modeled by based on response surface method, and GA was used for optimizing the cutting conditions [18]. Reddy and Rao used genetic algorithm to optimize tool geometry, viz., radial rake angle and nose radius and cutting conditions, viz., cutting speed and feed rate to obtain desired surface quality in dry end milling process [19]. Prakasvudhisarn et al. proposed an approach to determine optimal cutting condition for desired surface roughness in end milling. The approach consists of two parts: machine learning technique called support vector machine to predict surface roughness and particle swarm optimization technique for parameters optimization. The authors found that PSO shows consistent near-optimal solution with little effort [20]. Chen and Savage used fuzzy net-based model to predict surface roughness under different tool and work piece combination for end milling process. Speed, feed and depth of cut, vibration, tool diameter, tool material, and work piece material are used as input variables for fuzzy system. The authors found that the predicted surface roughness is within an error of 10% [21]. Iqbal et al. developed a fuzzy expert system for parameter optimization that includes prediction of tool life and surface finish in hard-milling (high-speed milling of steel having 45 HRC hardness) process [22]. S.-S. Liu analysis and discrimination in additive noise processes tend to dramatically alter local spatial variation of intensity while having relatively uniform representation in spatial frequency [23].

Over the years, the non-contact optical methods have attracted researchers' attention for the prediction of surface roughness. Most of the methods are based on statistical measures of gray-level images in the spatial domain. In their experiments, they found one exception where the ratio of the spread and the mean of the gray-level distribution is not a strictly increasing function of surface roughness and, therefore, the value of the ratio may lead to incorrect measurement. Most of the investigations mentioned above studied the effect of cutting variables on surface roughness by considering one variable at a time. When previous studies are taken into consideration, it is seen that there are still some problems to be resolved. The models that have been developed for surface roughness must be used in all process types and must contain all the cutting parameters.

The present paper deals with the cutting variables cutting speed S, feedrate F, and depth of cut D with the corresponding response variables such as F_1, F_2, and G_a taken simultaneously and, in addition, the cutting variables corresponding to a desired surface roughness were obtained. The first and most important task in roughness assessment with machine vision is to extract the roughness features of surfaces. Frequency domain features should be less sensitive to noise than spatial domain features.

Therefore, the major effort that was taken by authors in this study was to construct a machine vision system for prediction of the surface roughness in end milling process automatically. We choose to extract features of surface roughness in the spatial frequency domain using the 2D FT. The FT is particularly useful for surfaces in noisy conditions owing to tool wear marks, dust, and dirt. The FT characterizes the surface images in terms of frequency components. The periodically occurring features such as feed marks and tool marks present in the gray-level image can be easily observed from the principal component magnitude squared value F_2. Major peak frequency F_1, which represents the frequency (or, inversely, the wave length) of the feed marks in the image, generally outperforms other roughness features for roughness assessment. Since F_1 is the distance between the major peak and the origin, it is a robust measure to overcome the effect of lighting of the environment.

It is important for manufacturer that the surface roughness can be determined according to the machining parameters like cutting speed (S), feedrate (F), and depth of cut (D) prior to the operation. When previous studies are taken into consideration, it is seen that there are still some problems to be resolved. The models that have been developed for surface roughness must be used in all process types and must contain all the cutting parameters. Artificial neural network (ANN) is popular, and there are many industrial situations where they can be usefully applied. It is suitable for modeling various manufacturing functions due to this ability to learn complex non-linear and multivariable relationships between process parameters. In this study, authors used an ANN model as an alternative way to predict surface roughness in end milling operation.

In order to predict surface roughness in real time, a neural network back-propagation algorithm is used to construct the relationships between the input variables machining parameters (cutting speed S, feedrate F, depth of cut D), features of extracted image texture (major peak frequency F_1, principal component magnitude squared value F_2, average gray level G_a) and output variable cutting performance (surface roughness R_a).

Applying ANN can recognize surface roughness without stopping the machining operation and with reasonable accuracy. Finally, the computer vision system for measuring surface roughness prediction system has been established for the end milling process.

This paper is organized as follows: in section 2, the extraction of milled surface roughness image features in the spatial frequency domain is discussed. Section 3 explains the modeling of surface roughness based on ANN. In section 4, the experimental setup and training database is presented. Section 5 deals with the experimental verification and discussion and section 6 concluded this paper.

2 Extraction of milled surface roughness image features

The quantitative measures of surface roughness are extracted in the spatial frequency domain using the 2D FT. The FT approach has the desirable properties of noise-immunity, orientation dependency, and enhancement of periodic features.

The term image refers to a two-dimensional light-intensity function, denoted by $g(m,n)$. Where the value at spatial coordinate's m, n gives the intensity (brightness) of the image at that coordinate [24]. As light is a form of energy, $g(m,n)$ must be non-zero and finite, that is,

$$0 < g(m,n) < \infty \tag{2.1}$$

The basic nature of $g(m,n)$ may be characterized by two components: (1) the amount of light incident on the object being viewed and (2) the amount of light reflected by the object. Respectively, they are called the illumination and reflectance components and are denoted by$i(m,n)$; and $d(m,n)$.The function $i(m,n)$ and $d(m,n)$ combine as a product to form $g(m,n)$:

$$g(m,n) = i(m,n)d(m,n) \tag{2.2}$$

The nature of $i(m,n)$ is determined by light source, and $d(m,n)$ is determined by the characteristics of the object.

We call the intensity of a monochrome image 'g' at coordinates (m,n), the gray level 'l' of the image at that point. It is evident that 'l' lies in the range

$$L_{\min} \le l \le L_{\max} \tag{2.3}$$

To be suitable for computer processing, an image function $g(m,n)$ must be digitized both spatially and in amplitude. Digitization of the spatial coordinates (m,n) is called as image sampling, and amplitude digitization is called as gray-level quantization.

Let $f(m,n)$ be the gray level of a pixel at (m,n) in the original image of size $N\times N$ pixels centered on the origin. The discrete 2D FT of $f(m,n)$ is given by:

$$F(u,v) = \frac{1}{N}\sum_{m=\frac{-N}{2}}^{\frac{N}{2}-1}\sum_{n=\frac{-N}{2}}^{\frac{N}{2}-1} f(m,n)e^{-j2\prod\left(ux+\frac{vy}{N}\right)} \tag{2.4}$$

For $u,\ v=-N/2,\ -N/2+1,\ 0,\ 1\ldots,\ N/2-1$

The FT is generally complex; that is

$$F(u,v) = R(u,v) + jI(u,v) \tag{2.5}$$

Where $R(u,v)$ and $I(u,v)$ are the real and imaginary components of $F(u,v)$, respectively.

The power spectrum $P(u,v)$ of $f(m,n)$ is defined by:

$$P(u,v) = |F(u,v)|^{.2} = R^2(u,v) + I^2(u,v) \tag{2.6}$$

The quantitative definitions of these features are given below. Let

$$P(u,v) = \frac{P(u,v)}{\sum_{(u,v)\neq(0,0)} P(u,v)} \tag{2.7}$$

be the normalized power spectrum, which has the characteristics of a probability distribution.

(a) Major peak frequency (F_1)

$$F_1 = \left({u_1}^2 + {v_1}^2\right)^{1/2} \tag{2.8}$$

Where $(u_1,\ v_1)$ are the frequency coordinates of the maximum peak of the power spectrum, i.e.,

$$P(u_1,v_1) = max\{p(u,v), \forall(u,v) \neq (0,0)\} \tag{2.9}$$

Feature F_1 is the distance of the major peak $(u_1,\ v_1)$ from origin (0, 0) in the frequency plane.

(b) Principal component magnitude squared (F_2)

$$F_2 = \lambda_1 \tag{2.10}$$

Where λ_1 is the maximum Eigen value of the covariance matrix of $p\ (u,\ v)$; the covariance matrix M is given by:

$$M = \begin{bmatrix} Var(u^2)\,Var(uv) \\ Var(uv)\,Var(v^2) \end{bmatrix} \tag{2.11}$$

For which

$$Var(u^2) = \sum_{(u,v)\neq(0,0)} \left[u^2.p(u,v)\right] \tag{2.12}$$

$$Var(v^2) = \sum_{(u,v)\neq(0,0)} \left[v^2.p(u,v)\right] \tag{2.13}$$

$$Var(u,v) = Var(v,u) = \sum_{(u,v)\neq(0,0)} [uv.p(u,v)] \tag{2.14}$$

Features F_2 indicate the variance of components along the principal axis in the frequency plane.

(c) Average gray level (G_a)

G_a is the arithmetic average of gray-level intensity values. The arithmetic average of the gray level G_a can be expressed as:

$$G_a = \frac{1}{n}\sum_{i=1}^{n} |G_i| \tag{2.15}$$

Where G_i is the average gray level of surface image deviated from the mean gray value and n is the number of sampling data.

3 Modeling of surface roughness based on ANN

An ANN is a parallel, distributed information processing structure that mimics the human brain to learn from examples or mistakes [25]. Neural networks, based on their biological counterparts, attempt to model the parallel, distributed nature of processing in the human brain. Since this concept was introduced in 1950s, ANN technology has been adapted in many applications that are complex and non-linear in nature, with an unknown and hard-to-identify algorithm [26]. The mathematical model of an artificial neuron's behavior is the simplification of the biological brain neuron as shown in Fig. 1:

Various inputs $x(n)$ to the network multiplied by weights $w(n)$ are sent to a neuron. Performing accumulation and threshold, the neuron sums the weighted inputs, passes the

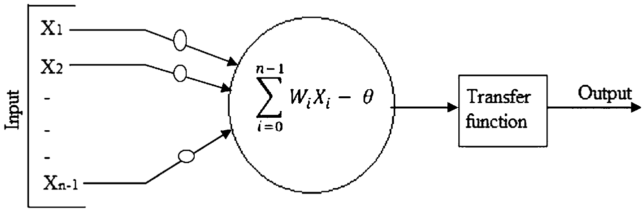

Fig. 1 The behavior of an artificial neuron

result through a non-linear transfer function, and provides an output Yi:

$$Y_i = f\left(\sum\nolimits_{i=0}^{n-1} w_i x_{i-}\theta\right) \tag{3.1}$$

where the inputs of x_i in this study corresponds to feed rate, spindle speed, depth of cut, and vibration signals; θ is the internal threshold or offset of a neuron; and f is the non-linear transfer function. The most commonly used f is defined by the sigmoid logistic function as:

$$f(x) = \frac{1}{1+e^{-x}} \tag{3.2}$$

A neural network provides a networking structure in which artificial neurons are interconnected as shown in Fig. 2. Each neuron in a layer receives weighted inputs from the neurons in the previous layer. The output of the neuron in the previous layer is, in turn, connected as the input to several other neurons in the following layer, which forms a complete network. Beyond the input and output layers, several other layers of neurons in the middle, called hidden layers, might be needed to build an effective neural network that is capable of solving problems. The principle underlying neural networks is pattern recognition. Among the variety of neural network algorithms, back-propagation (BP) is the most commonly used due to BPs superior strength in pattern recognition and reasonable speed. The training procedure for a back-propagation network is usually iterative and involves a trial-and-error approach that consists of the following steps:

Step 1: Initialize weights and offsets, starting from a small random value.
Step 2: Present inputs and desired outputs to the neural network model.
Step 3: Calculate actual outputs, y_m.
Step 4: Calculate the error between the output from the neural network and the desired output by E

$$E = \frac{1}{nm}\sum\nolimits_{m\cdot}\sum\nolimits_{n\cdot}(ym, n - dm, n).^2 \tag{3.3}$$

Where m is the number of neurons in the output layer (in this study m=1), and n is the number of training data set. If E is smaller than the required accuracy, then no other learning procedures are needed.

Step 5: If E is larger than the required accuracy, adjust the weights of the networks. The weights are adjusted by:

$$w_{ij}(t+1) = w_{ij}(t) + \eta\delta_j x_i' \tag{3.4}$$

Where x_i' is either the output of neuron i or an input, η is a gain term, and δ_j is an error term for neuron j.

Step 6: Repeat steps 3–6 until the error of the entire set is less than the required accuracy.

4 Experimental setup and training database

Building an ANN for a machine vision system that can predict the surface roughness under a variation of cutting conditions, a training database needs to be established with regard to different cutting parameters and surface roughness. A number of end milling experiments were carried out on a CNC milling machine as shown in Fig. 2 (variable speed 0.370 kw PMDC, 0–4000 rpm) using a high-speed steel end-mill cutter (6 mm) for machining aluminum alloy work pieces.

A digital camera (Olympus C1400L) captures the image of the surface with 1,280–1,024 resolution, 1/30 s grabbing speed, and eight-bit digit output as shown in Fig. 3. The equipment used for measuring surface roughness was a surface roughness tester, Surfcorder SE-1100. A schematic diagram of the computer vision system for measuring surface roughness is shown in Fig. 4:

The feasible spaces of the cutting parameters were selected by varying the cutting speed in the range 28–47 m/min, the feed rate in the range 0.002–0.0466 mm per revolution, the depth of cut in the range 0.6–1.0 mm. The average surface roughness R_a, which is the most widely

Fig. 2 Machining status in CNC milling

Fig. 3 Rapid 1 computer vision system for acquiring the images

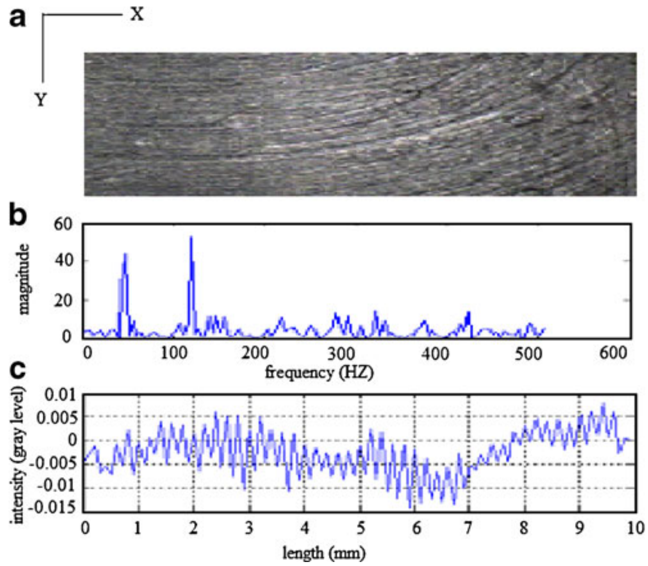

Fig. 5 Experimental results for texture analysis: **a** milled work piece surface image (cutting condition: cutting speed 28 m/min, feed 0.002 mm/rev, depth of cut 0.6 mm), **b** major peak frequency, and **c** gray level

used surface finish parameter in industry, is selected in this study. It is the arithmetic average of the absolute value of the heights of roughness irregularities from the mean value measured within the sampling length of 8 mm and measurement speed of 0.5 mm/s.

The features of surface image texture were shown in Fig. 5. The image of work piece surface captured by the digital camera was shown in Fig. 5a. The major peak frequency extracted from surface texture was shown in Fig. 5b. Extracting the digital data on the central line of Fig. 5a, the distribution of gray level of image could be obtained and was shown in Fig. 5c. The major peak frequency (F_1) and the principal component magnitude squared (F_2) could be calculated from the image texture by FT. The average gray level (G_a) in spatial domain also could be got by the statistic method. Those were the parameters for training the ANN.

Fig. 4 Schematic diagram of the machine vision system for measuring surface roughness in end milling

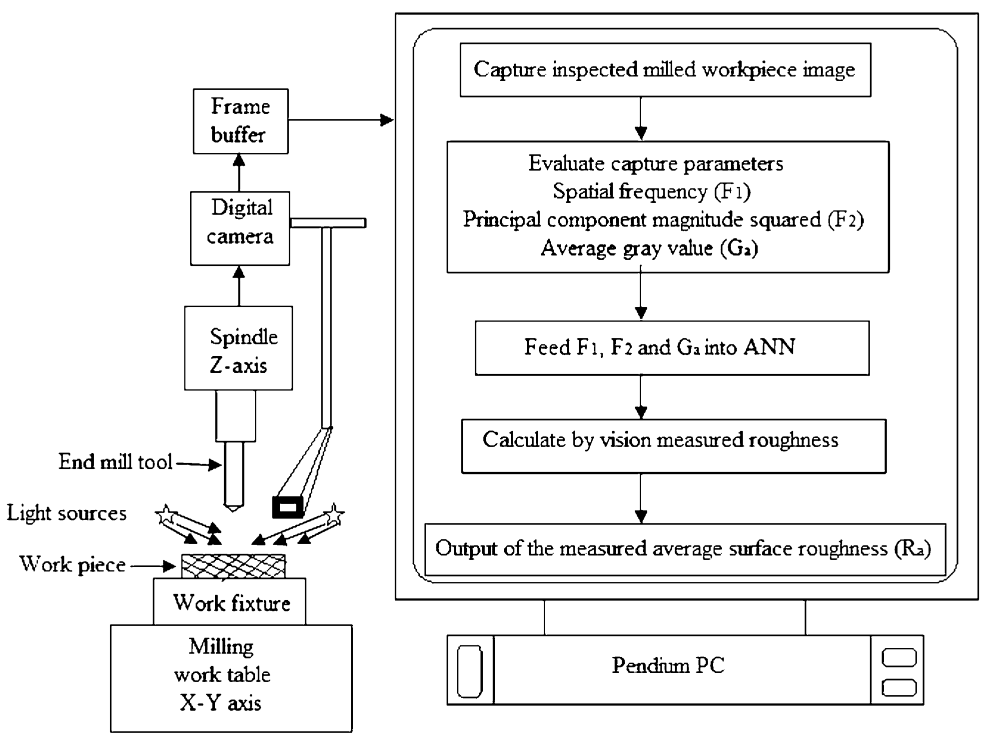

Table 1 Experimental features of image texture of work piece and surface roughness for training database

Sl. no.	Cutting speed (V), m/min	Feed rate (F), mm/rev	Depth of cut (D), mm	Frequency		Gray level (G_a)	Stylus instrument measured roughness (R_a), µm
				F_1	F_2		
1	28	0.0020	0.6	121.35	33.42	109.563	0.6371
2	28	0.0020	0.8	88.45	38.84	140.910	0.5705
3	28	0.0020	1.0	102.38	42.76	124.460	0.5039
4	28	0.0333	0.6	60.58	39.24	139.622	0.777
5	28	0.0333	0.8	95.36	41.26	109.787	0.670
6	28	0.0333	1.0	92.86	40.72	110.750	0.644
7	28	0.0466	0.6	51.26	36.52	165.813	0.9183
8	28	0.0466	0.8	73.68	35.72	153.845	0.8517
9	28	0.0466	1.0	107.82	36.21	123.449	0.687
10	38	0.0020	0.6	56.75	39.81	143.451	0.370
11	38	0.0020	0.8	118.93	34.82	117.280	0.3025
12	38	0.0020	1.0	65.38	40.87	138.275	0.2359
13	38	0.0333	0.6	97.62	37.82	125.892	0.5097
14	38	0.0333	0.8	62.65	37.02	150.378	0.4431
15	38	0.0333	1.0	59.86	38.84	145.970	0.3765
16	38	0.0466	0.6	97.59	39.64	111.837	0.6503
17	38	0.0466	0.8	58.88	37.33	144.170	0.5837
18	38	0.0466	1.0	59.24	38.17	144.985	0.587
19	47	0.0020	0.6	72.86	42.26	134.268	0.178
20	47	0.0020	0.8	62.92	40.52	26.100	0.0345
21	47	0.0020	1.0	71.82	41.82	24.210	0.0321
22	47	0.0333	0.6	83.28	40.32	141.670	0.2417
23	47	0.0333	0.8	64.11	39.86	138.334	0.236
24	47	0.0333	1.0	96.34	36.72	81.840	0.1085
25	47	0.0466	0.6	65.68	38.34	148.220	0.3823
26	47	0.0466	0.8	112.38	37.74	122.400	0.3157
27	47	0.0466	1.0	92.60	41.28	128.623	0.286

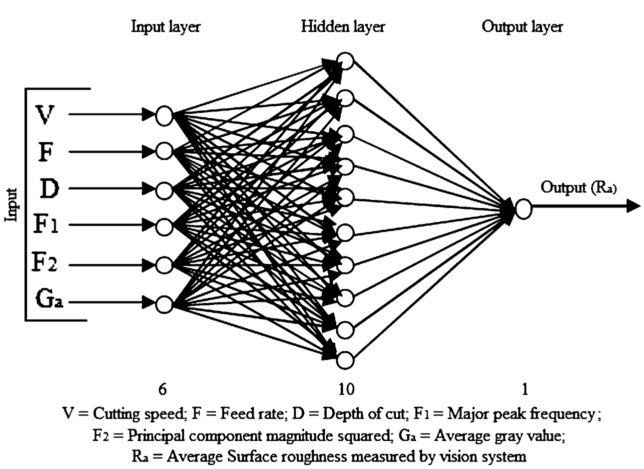

Fig. 6 Structure of the ANN for predicting the surface roughness by vision system

In the experiments, 27 milled specimens were operated based on the range of cutting conditions. The experimental results are listed in Table 1 for the training database.

The neural networks model for the surface roughness prediction was trained in the following training procedure. In the training process, the "trial-and-error" method is employed to determine the number of hidden layers, the neurons in each hidden layer, the learning rate, and the momentum factor in the neural networks model. A few neural network structures with varied numbers of hidden neurons are compared and the structure of 6-10-1 that creates the least prediction errors is selected as the system model.

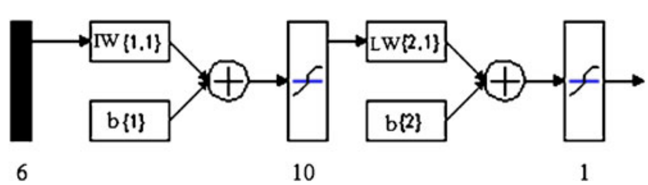

Fig. 7 Network architecture 6-10-1

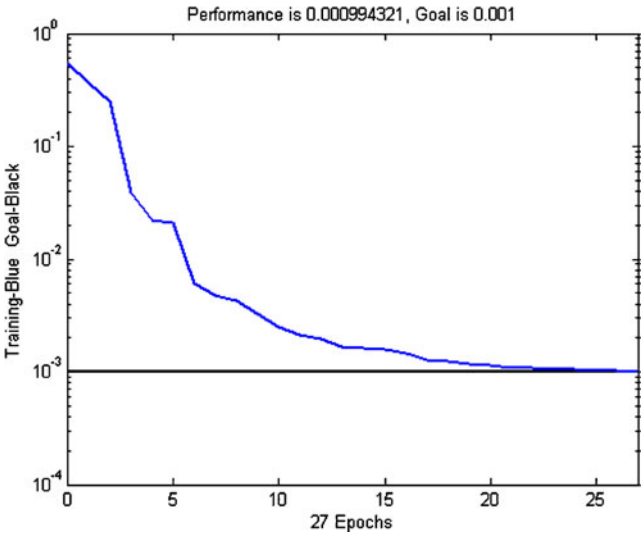

Fig. 8 Performance of neural network (6-10-1)

By following the same procedure, the learning rate is set as 1 and the momentum factor is set as 0.5. As a result, the architecture of the ANN model is specified as 6-10-1, as shown in Figs. 6 and 7.

After the training procedure, the weights between each neuron and the bias of each neuron were obtained. Performance of neural network (6-10-1) is shown in Fig. 8.

This neural network model can be used for predicting surface roughness in real time.

5 Experimental verification and discussion

Verifying the developed networks to predict the surface roughness of end milling, ten more milled specimens using different cutting parameters were performed. As the cutting speed, feedrate, depth of cut, major peak frequency, principal component magnitude squared value, and the average gray level is fed into the ANN, the surface roughness measured by the vision system can be calculated directly. A comparison of R_a' (measured by vision system) and R_a (measured by stylus method) has been presented in Table 2.

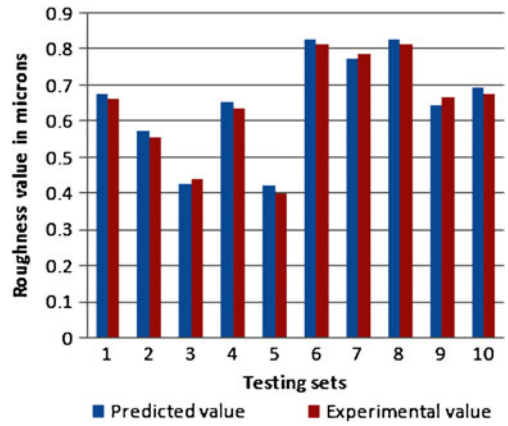

Fig. 9 Validation of predicted and experimental values in end milling process

As the cutting speed, feedrate, depth of cut, major peak frequency, principal component magnitude squared value, and the average gray level is fed into the ANN, the surface roughness measured by the vision system can be calculated directly. The percent of error between the predicted value and experimental value is calculated by the given formula.

$$\%\,\text{of Error} = \frac{\text{Predicted value} - \text{Experimental}}{\text{Experimental value}}$$

The predicted roughness values through machine vision result validated by the ten sets of testing data from the experimental value of the surface roughness in end milling is shown in Fig. 9:

The result shows the average error of the prediction of surface roughness in milling using ANN is 2.47%, i.e., the accuracy is 97.53%.

Table 2 Experimental end milling parameters and surface roughness for verification tests

Sl. no.	Cutting speed (V), m/min	Feed rate (F), mm/rev	Depth of cut (D), mm	Frequency		Gray level (G_a)	Vision measured roughness (R_a'), µm	Stylus measured roughness (R_a), µm	Error (%)
				F_1	F_2				
1	32	0.0120	0.7	50.5200	58.9230	171.8620	0.6753	0.6633	1.5
2	30	0.0220	0.9	41.7300	57.8090	186.2800	0.5718	0.5543	3.15
3	34	0.0320	0.95	41.0780	60.4100	187.8700	0.4266	0.4391	−2.83
4	36	0.0400	0.97	66.4000	61.5680	142.3800	0.6523	0.6358	2.59
5	37	0.0380	0.8	71.2650	62.0100	26.4400	0.4191	0.3971	5.5
6	40	0.0420	0.98	83.4700	63.9200	140.4800	0.8274	0.8164	1.34
7	42	0.0360	0.85	92.0460	65.0910	129.8600	0.7751	0.7866	−1.07
8	44	0.0280	0.75	100.6100	66.2600	128.6800	0.8298	0.8153	1.77
9	45	0.0180	0.65	104.9900	66.8200	116.9200	0.6443	0.6633	−2.86
10	46	0.0450	0.90	108.6760	67.2980	121.7900	0.6919	0.6774	2.14

6 Conclusions

In this paper, we have proposed a non-contact machine vision system for the determination of surface roughness in end milling. It proves a reliable assessment of surface roughness over a given 2D area rather than single 1D trace. Since end-milled surfaces are directional patterns with the appearance of periodic, parallel feed marks, the roughness features are extracted in the spatial frequency domain based on the 2D Fourier transform.

The FT approach characterizes the surface image in terms of frequency components. The magnitude of frequency components enhances the periodically occurring features present in the surface image, and the directionality of frequency components preserves the lay direction of a surface. Major peak frequency $F_{1,}$ which represents the frequency (or, inversely, the wave length) of the feed marks in the image generally outperforms other roughness features for roughness assessment. Since F_1 is the distance between the major peak and the origin, it is a robust measure to overcome the effect of lighting of the environment.

The computational time of the Fourier transform with size 256×256 is approximately 2 s on a Pentium 100 MHZ personal computer. It compares favorably with the traditional stylus-based methods. We believe the computational time can further be reduced with the higher-performance personal computer or workstations, or with hardware implementation of the Fourier transform for on-line, real-time assessment of surface roughness.

A self-organized ANN to model vision measuring system on surface roughness inspecting has been established. Several verification tests have shown that the maximum absolute error between the surface roughness measured by vision system and that measured by the stylus instrument is less than 5.5%, the average error of the prediction is 2.47%, i.e., the accuracy is 97.53%. As the fluctuation is the nature property of surface roughness, the error is considered to be acceptable. In other words, the developed measuring system using machine vision can be used effectively to predict the surface roughness over a wide range of cutting conditions in end milling. The direct imaging approach is effective and easy to apply in the shop-floor level.

The proposed methodology can be applied to the machined surface in a manufacturing environment where the on-line surface inspection can be implemented. Therefore, the machine vision system and ANN approaches could very well be used for the on-line prediction of roughness.

The cutting parameters in the testing stage were randomly set but different from the original experimental design, and the desired surface roughness was set following industrial norms. The success of being able to perform the successful prediction of surface roughness indicated that the proposed system was flexible enough to meet cutting conditions in industry settings.

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