

Modelling and prediction of surface roughness in Ti-6Al-4V turned surfaces: use of DTCWT image fusion and GLCM

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Abstract. In manufacturing process the quality of the surface roughness is one of the most important requirements. Nowadays, evaluations of surface roughness using machine vision methods are widely used. In this work, an attempt has been made to develop a feature extraction method which includes Dual Tree Complex Wavelet Transform (DTCWT) based image fusion and Gray-Level Co-Occurrence Matrix (GLCM) for surface roughness modeling of turned Ti-6Al-4V surfaces. Coated carbide tool inserts have been used for turning Ti-6Al-4V bars. A simple computer vision system has been developed to capture the different turned surface images. The captured images are subjected to image pre processing. Pre processed turned images have been subjected to DTCWT based image fusion. These fused image coefficients are converted into GLCM and the second order textural features like Energy, Entropy, Contrast and Homogeneity have been extracted. These second order statistical features along with cutting conditions namely, speed, feed rate and depth of cut and flank wear are given as inputs to a Radial basis function neural network (RBFNN) for modeling and prediction of surface roughness parameter R_a from the turned surface images. Finally, a comparison has been made with regard to prediction accuracy of surface roughness obtained using DTCWT based image fusion features and feature extracted using DTCWT without image fusion.

1. Introduction

Roughness of turned surfaces is evaluated by the variations in the direction of the normal vector of an actual surface from its ideal pattern. When these variations are high, rough surface is obtained, and smooth surface is attained with small variations. In an industry of manufacturing finishing quality of surface of workpiece plays an important role [1]. Contact and non contact methods are used to measure the surface roughness of the turned surfaces. Direct contact method uses stylus instrument which require physical contact with the surface to be measured, whereas indirect contact method uses computer vision system, which is an online method to capture the surface images. Stylus instrument has limitations over certain geometrical parts like it is time consuming, can damage the surface of the components and it depends mainly on diameter of the tip of the probe for surface roughness measurement. Machine vision method of surface roughness prediction are widely used because of their inherent advantages like, non-contact measurement, availability of more information and capability of quick surface roughness measurement [2]. Many research work have focused on use of several modelling techniques for predicting the surface roughness of a workpiece using computer vision technology. B.Y Lee and Tarng [3] developed a polynomial neural network model for predicting surface roughness of turned images by mapping actual surface roughness of turned workpiece along with extracted features from turned images and various machining conditions. S.H. Yang et al. [4] used a differential evolution algorithm (DEA) based artificial neural network model (ANN) for the prediction of surface roughness of turned surface images using computer vision system. The most generally used titanium alloy is Ti-6Al-4V. Due to various mechanical properties such as low thermal conductivity and modulus of elasticity the titanium alloys are considered as one of the difficult to cut material [5]. Titanium alloy has exceptional combination of large strength to weight ratio, high fracture resistance, and special resistance to corrosion, because of these characteristics, the titanium



alloys are widely used in aerospace related applications [6]. Titanium alloys have a wide range of applications other than aerospace, such as biomedical, chemical and other corrosion-resistant environments. It is a high-strength, thermal resistant titanium based alloy [7].

In computer vision system and processing of images the word feature extraction is considered as one of the main concern. Several researchers have developed image analysis techniques to facilitate the measurement and inspection of machined surfaces. Wavelet transform is one of the most important and powerful tool for image decomposition. Ivan W. Selesnick et al. [8] explained that a relatively new enhancement to the discrete wavelet transform (DWT) is the Dual-Tree Complex Wavelet Transform (DTCWT), with more additional properties like, nearly shift invariant and directionally selective in two and higher dimensions. Nick G. Kingsbury recommended that DTCWT is used to avoid the disadvantages of conventional wavelet transform. V Naga Prudhvi Raj et al. [9] proposed a denoising scheme which utilizes DTCWT to decompose the image to remove the noise. The obtained results show that the denoising with DTCWT has improved balance between smoothness and accuracy than Discrete Wavelet Transform (DWT). Adriaan Barri et al. [10] explored the shift error of the modulated DTCWT that can be significantly reduced by performing phase compensation on the coefficients and suggested that DTCWT have higher degree of shift invariance and a great directional selectivity. The second order statistical features were extracted using Gray Level Co-occurrence matrix (GLCM) method. It is a statistical way of comparing the texture which uses the spatial relationship of pixels. GLCM also represents the tabulation of how often different combinations of pixel brightness values occur in an image [11]. Nagaraj N. Bhat et al. [12] presented multi-classification of tool wear states using a kernel-based support vector machine (SVM) technique applied for the machined surface image features extracted from the GLCM. S Dutta et al. [13] Extracted the statistical features from the turned surface images using GLCM and discrete wavelet transform based approach for suggesting the progressive tool flank wear. E.S. Gadelmawla et al. [14] suggested an approach for surface roughness characterization of captured images using gray level co-occurrence matrix (GLCM) based image processing techniques.

Most of the researchers measured the surface roughness of turned parts using neural network modeling. Multilayer perceptron (MLP) neural network is commonly used neural network for modeling and prediction of surface roughness of turned surfaces, which works on back propagation algorithm for predicting the surface roughness. Radial basis function (RBF) neural network is faster and accurate when compared with MLP neural network. Many researchers have used Radial Basis Function Neural Network (RBFNN) as a predictive neural network model for machining related applications [16-18].

This paper presents, a modeling technique for the prediction of surface roughness in Ti-6Al-4V turned surface images using DTCWT image fusion and GLCM. A unique contribution of this paper is the use of DTCWT with and without image fusion, along with GLCM for surface roughness modeling in Ti-6Al-4V surfaces. These fused DTCWT coefficients are converted into GLCM to extract the required second order statistical features for the prediction of surface roughness of the turned surface images. The current paper is divided into following sections, in section 2; the details of the experiments are mentioned. In section 3, DTCWT image fusion and GLCM are explained. 4, RBFNN modeling of surface roughness is presented. Section 5 gives results and discussion, 6 gives the comparison of models with fusion and without fusion, and conclusions are given in section 7.

2. Experimental details

For the present work, the experimental details and procedure carried out are summarized as follows: CNC turning centre is used to conduct the turning experiments on Ti-6Al-4V bar under different machining conditions namely speed rate, feed rate and depth of cut. Design of experiments (DOE) methodology has been used for planning the machining tests using MINITAB, for conducting the turning experiments. A 3^3 factorial design is the most suitable DOE configuration and have been used for designing the experiments. The total number of turning experiments is 27. Each experiment consists of several number of passes based on tool flank wear reached and its limiting value is 0.4 mm.

From these experiments a total 461 data were generated out of which 75% (346) data is considered as training data, 20% (92) as test data, and remaining 5% (23) for validation. The values of cutting speed are 150, 175 and 200 m/min, feed rates are 0.15, 0.2 and 0.25 mm/rev and depth of cut 0.8, 1, and 1.2 mm. Coated carbide tool inserts 883 with MR4 chip breaker (SECO make) and PCLNL 2020 K12 (SECO make) tool holder are used for turning experiments. A 200 mm length round Ti-6Al-4V bar is used for turning experiments and it is divided into three segments to achieve a turning pass of 48 mm.

Using Mitutoyo Tool Maker's Microscope (TM 505/510) the tool flank wear is recorded at the end of each pass. It has a provision for measurement, using micrometers in X and Y direction with a least count of 0.005 mm which has a magnification of 15X. After each machining pass, using a stylus type instrument, Taylor Hobson Taly Surf 50, the average arithmetic surface roughness parameter (R_a) is measured using a sampling length of 2.5 mm. Surface roughness was measured at three different locations 120° apart on the surface of the workpiece and the average surface roughness value has been considered.

The main thing in any machine vision system is the capturing of the images. For capturing the different turned surface images, a simple computer vision system have been developed, which consists of a digital camera (Sony DSC H300), lighting arrangement, work table, and PC for image processing which is as shown in Figure 1. A Total of 1383 images (3 images for each one pass) are captured from turning experiments conducted at different cutting conditions.

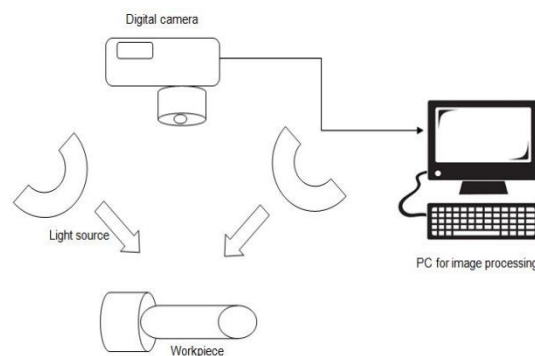


Figure1. A simple computer vision system for surface roughness measurement

3. DTCWT Image Fusion and GLCM

3.1 DTCWT Image Fusion

DWT has proven less effective in the field of image processing, because of high translation sensitivity and small shifts in the input signal may entirely change the wavelet coefficient pattern.

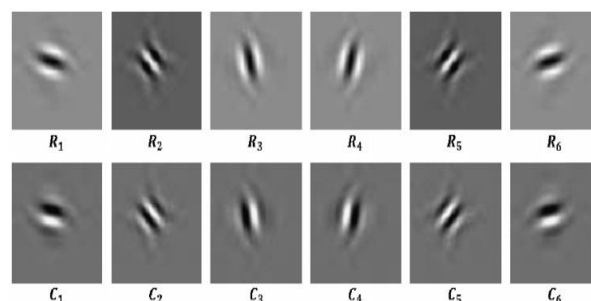


Figure2. DTCWT 2D decompositions of image into each of 6 real coefficients (R) and imaginary coefficients (C)

Dual-Tree Complex Wavelet Transform (DTCWT) determines the complex transform of an image by considering DWT decompositions in two separate trees (tree A and tree B). The used filters in one tree

are different from filters used in another tree. The real coefficients are produced in tree A of DWT and the imaginary coefficients are produced in tree B of DWT. DWT decomposes images in only 3 directions, where as DTCWT decomposes the images into 12 directional wavelets, each of 6 as real coefficients and imaginary coefficients located at angles of $\pm 15^\circ$, $\pm 45^\circ$, $\pm 75^\circ$ in 2 dimension, as shown in Figure 2 [15].

Image fusion is a process of combining two or more images to obtain a new image with more required information, compared with single image. The coefficients of high frequency have more detailed information compared with coefficients of low frequency. Therefore, for image fusion a high frequency fusion rule is used [19]. Image A and image B shows two different original images. Figure 3 shows the block diagram of image fusion scheme.

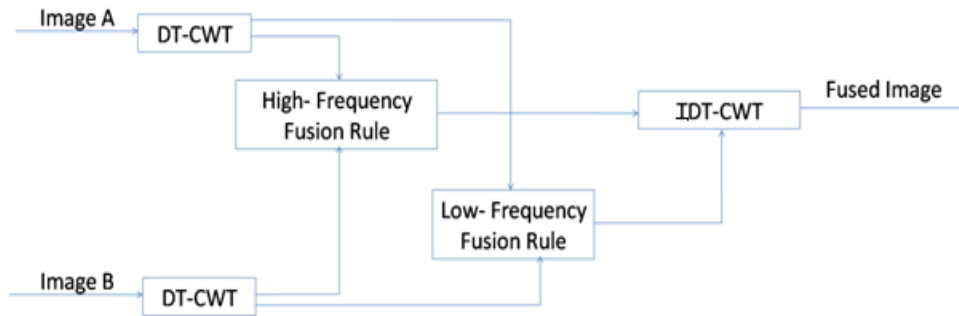


Figure3. DTCWT based image fusion scheme

3.2 High frequency coefficients fusion rule:

A high frequency coefficient fusion rule is explained as follows;

$$I(x, y) = \sum_{i=0}^{y-1} \sum_{j=0}^{x-1} |c(x+i, y+j)|^2 \quad (1)$$

where c is matrix of the high frequency coefficient

The high frequency sub band matrix coefficients $I_{j,k}^A$, and $I_{j,k}^B$ are calculated using eqn. (1) and the selection rule based on the following equation.

$$C_{j,k}(x, y) = \begin{cases} C_{j,k}^A(x, y) & \text{if } I_{j,k}^A \geq I_{j,k}^B(x, y) \\ C_{j,k}^B(x, y) & \text{if } I_{j,k}^A < I_{j,k}^B(x, y) \end{cases} \quad (2)$$

3.3 Gray Level Co-occurrence Matrix (GLCM)

GLCM are used to extract the second order statistical features attain from co-occurrence of two pixels at specified directions. GLCM has been introduced by Haralick [11], which transforms an image into a matrix according to the relationship of pixels in the original image. Energy, Entropy, Contrast and Homogeneity are calculated using following equations.

$$\text{Energy} = \sum_{r=0}^{K-1} \sum_{q=0}^{K-1} \{P(q, r)\}^2 \quad (3)$$

$$\text{Entropy} = - \sum_{r=0}^{K-1} \sum_{q=0}^{K-1} P(q, r) \log(P(q, r)) \quad (4)$$

$$\text{Contrast} = \sum_{r=0}^{K-1} n^2 \left\{ \sum_{p=1}^K \sum_{r=1}^K P(q, r) \right\}, \text{ where } |q - r| = n \quad (5)$$

$$\text{Homogeneity} = \sum_{q=0}^{K-1} \sum_{r=0}^{K-1} \frac{P(q, r)}{1 + |q - r|} \quad (6)$$

where K is the value of gray levels used in $P(q, r)$ and $P(q, r)$ denotes the element of GLCM.

4. Radial basis function neural network (RBFNN)

Figure 4 represents the architecture of a RBF neural network for prediction of surface roughness, which consists of three layers; a layer of inputs, secondly a non-linear processing neurons layer, and a layer of output. Hidden layer of RBF network has two specifications, a center x_i and a width σ_i . The Gaussian transfer function in the neurons in the hidden layer is given in eqn. (7) [16].

$$\phi_i(x) = e^{-\frac{\|x_i - \phi_i\|^2}{2\sigma_i^2}} \quad (7)$$

where $i=1, 2, \dots, j$, j is the number of centers. These centers are used to calculate the network input vector to obtain a radially symmetrical feedback.

Extracted second order statistical features along with cutting speed, feed rate, depth of cut and tool flank wear are given as inputs to RBF neural network to predict surface roughness parameter R_a .

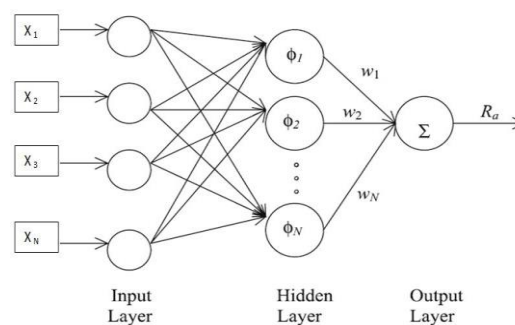


Figure 4 A general construction of RBF neural network

5. Results and Discussion

The captured Ti-6Al-4V bar images are cropped to 256x256 resolution using Picasa software and subjected to pre-treatment of the images to enhance the quality of the image, which includes image cropping and gray level conversion. Based on the maximum peak signal to noise ratio (PSNR) value and minimum mean square error, bior 3.7 is taken as mother wavelet. In present work, first level decomposition has been performed using DTCWT on the images.

5.1 Features extraction using DTCWT Image Fusion and GLCM

For the fused image, the GLCM based second order statistical features namely Energy, Entropy, Contrast, and Homogeneity have been calculated, which describe the textural information of the turned surface images. The GLCM with distance $d=1$, and $\theta=0^\circ$ have been considered to extract the second order statistical features. Table 1 shows the extracted statistical second order features using DTCWT image fusion and GLCM.

Table 1: Sample values of DTCWT based image fusion and GLCM features extracted for cutting conditions of speed 150 m/min, feed 0.15 mm/rev and depth of cut 0.8 mm

Energy	Entropy	Contrast	Homogeneity
0.544306	0.960522	0.181892	0.921899
0.500283	1.001546	0.147945	0.934689
0.431067	1.1446	0.251169	0.881773
0.443075	1.109587	0.195692	0.911086
0.419543	1.167342	0.24919	0.886269
0.369017	1.238029	0.246032	0.887505
0.411639	1.178702	0.255106	0.884017
0.499031	1.033951	0.202561	0.91101
0.380106	1.20788	0.214987	0.900897

5.2 Features extraction using DTCWT and GLCM

For all the captured turned surface images, DTCWT and GLCM based second order statistical features have been extracted. Table 2 shows the sample of second order statistical features extracted for cutting conditions: speed 150 m/min, feed 0.15 mm/rev and depth of cut 0.8 mm.

Table 2: Sample values of DTCWT and GLCM based feature extraction for cutting conditions of speed 150 m/min, feed 0.15 mm/rev and depth of cut 0.8 mm

Energy	Entropy	Contrast	Homogeneity
0.255975	2.299788	6.481974	0.682144
0.253429	2.337036	6.756082	0.672878
0.240226	2.450482	6.688051	0.657344
0.237548	2.415882	7.690848	0.656251
0.242074	2.420971	6.910432	0.661489
0.238224	2.447803	6.959887	0.657679
0.24405	2.432242	6.73302	0.662233
0.244462	2.395754	6.702956	0.667059
0.243044	2.398036	7.280668	0.662617

5.3 RBFNN modeling for DTCWT based image fusion and GLCM

RBFNN model have been developed to predict the surface roughness using the extracted features from the turned surface images. All the extracted second order statistical features using image fusion along with cutting conditions which includes, speed, feed rate, depth of cut and tool flank wear were given as inputs to RBFNN to predict surface roughness. The training data set contained 346 data and test data set contained 92 data. Simulation parameters; $\eta=0.85$ and $\alpha = 0.05$; have been kept constant during RBF network training. The number of epochs is set to 1000. The network training goal is mean squared error (square of the difference between actual and predicted output) is fixed as 0.001. By trial and error method the width of the RBF units has been chosen based on prediction accuracy. The training of RBFNN is done using cFCM algorithm (Conditional Fuzzy C-means) for different widths of 0.1, 0.12, 0.14, 0.16, and 0.18. The maximum prediction accuracy obtained is 99.13% for training data and for test data 95.62% for 45 RBF units with a width of 0.12, as shown in Table 3.

Table 3: Results of RBFNN model considering DTCWT image fusion and GLCM data

width	0.10	0.12	0.14	0.16	0.18
Training data accuracy (%)	99.13	99.13	97.39	96.24	79.47
Testing data accuracy (%)	94.56	95.65	92.39	94.56	76.08
MSE	0.012	0.010	0.019	0.042	0.071

5.4 RBFNN modeling for DTCWT and GLCM (without image fusion)

The features extracted from DTCWT and GLCM (without image fusion) along with the machining parameters is used as inputs to this network. The maximum prediction accuracy obtained for training data is 95.66% and for test data is 95.65% for 50 RBF units with a width of 0.10, as shown in table 4.

Table 4: Results of RBFNN model 2, considering DTCWT and GLCM (without fusion) data

width	0.10	0.12	0.14	0.16	0.18
Training data accuracy (%)	95.66	93.35	92.19	86.12	82.65
Testing data accuracy (%)	95.65	89.13	90.21	83.69	80.43
MSE	0.029	0.039	0.031	0.050	0.057

6. Comparison between with fusion and without fusion

Figure 5 (a) shows the comparison of experimentally measured and predicted values of R_a for test data with fusion. Similarly Figure 5 (b) shows the comparison of R_a for the test data without image fusion. It can be observed that, the predicted values of R_a for the RBFNN model using DTCWT image fusion and GLCM features show more prediction accuracy, when compared to without image fusion. Also the MSE is lesser. Further the model using features from image fusion has used lesser hidden neurons, resulting in a more compact network, with slightly higher width values.

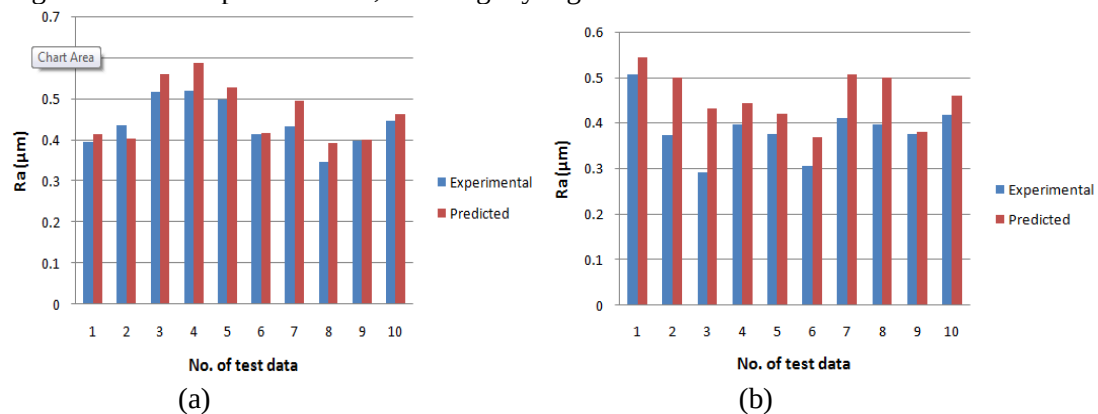


Figure 5 Variation of experimental and predicted R_a values (test data) using DTCWT based image fusion (a) and without image fusion (b)

The performance of the RBFNN model was evaluated using eqn. (8), which gives the absolute percentage error.

$$e_a = \left| \left(\frac{v_m - v_p}{v_m} \right) \right| \times 100 \% \quad (8)$$

where e_a gives absolute percentage error, v_m is the measured value and v_p gives the predicted value [17].

Table 5. Shows the error obtained for the sample values of experimentally measured and predicted R_a values with fusion for validation data and table 6 gives the error for without image fusion. It is observed that, the absolute percentage errors for DTCWT based image fusion and GLCM is less when compared with error obtained considering features extracted without image fusion.

Table 5: shows the sample values of experimentally measured and predicted R_a for validation data using image fusion features

Sl. no	Experimental R_a	Predicted R_a	error %
01	0.3958	0.4137	1.79
02	0.4013	0.4353	3.39
03	0.4144	0.4170	0.25

Table 6: shows the sample values of experimentally measured and predicted R_a for validation data using without image fusion features

Sl. no	Experimental R_a	Predicted R_a	error %
01	0.5076	0.5443	3.66
02	0.5173	0.5867	6.94
03	0.3958	0.4990	10.31

7. Conclusion

This paper presents a DTCWT based image fusion and GLCM technique for predicting the surface roughness of Ti-6Al-4V turned images using RBFNN modeling. Also a comparison has been made with results obtained using features from DTCWT without image fusion. The following conclusions have been made from the obtained results:

1. The DTCWT based image fusion and GLCM based statistical features like Energy, Entropy, Contrast, and Homogeneity are effective in modeling and predicting surface roughness in Ti-6Al-4V turned surfaces.
2. RBFNN model developed using features from DTCWT image fusion and GLCM give better prediction accuracy for training data (99.13%) with lesser mean square error and similar prediction accuracy for test data (95.65%), compared with without image fusion features.

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