

ESTIMATION OF SURFACE ROUGHNESS PARAMETER BASED ON MACHINED SURFACE IMAGE

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Abstract

The prediction of machined surface parameters is an important factor in machining centre development. There is a great need to elaborate a method for on-line surface roughness estimation [1–7]. Among various measurement techniques, optical methods are considered suitable for in-process measurement of machined surface roughness. These techniques are non-contact, fast, flexible and three-dimensional in nature.

The optical method suggested in this paper is based on the vision system created to acquire an image of the machined surface during the cutting process. The acquired image is analyzed to correlate its parameters with surface parameters. In the application of machined surface image analysis, the wavelet methods were introduced. A digital image of a machined surface was described using the one-dimensional Digital Wavelet Transform with the basic wavelet as Coiflet. The statistical description of wavelet components made it possible to develop the quality measure and correlate it with surface roughness [8–11].

For an estimation of surface roughness a neural network estimator was applied [12–16]. The estimator was built to work in a recurrent way. The current value of the Ra estimation and the measured change in surface image features were used for forecasting the surface roughness Ra parameter. The results of the analysis confirmed the usability of the application of the proposed method in systems for surface roughness monitoring.

Keywords: machining, surface roughness, wavelet analysis, neural networks.

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1. Introduction

Surface roughness is one of the indexes of product quality. Surface roughness is, however, difficult to measure on-line and usually evaluated after the process is finished. The problem with surface roughness on-line measurement and prediction lies in the nature of its formation. So far, surface roughness models have very rarely dealt with reconciling the connection between the physical nature of the process and strictly mathematical approximating of the relationships between inputs and outputs of the process. This paper develops the idea of linking the process knowledge with mathematical signal analysis.

Strictly theoretical models are very limited in accuracy because the machining process is still not fully understood [1]. We cannot establish a quantitative relationship between surface finish and the phenomena influencing it. In turning the tool, geometry and kinematics are at the origin of feed marks determining the whole surface texture. The other phenomenon is surface plastic deformation in the form of side flow. The material is turned out on the ridge of the unevenness left by the subsequent passing of the tool. The increase in surface parameters is significant with the increase of cutting temperature, but still difficult to predict. The third cause of the deterioration of surface finish is connected with the dynamics of the cutting process. Self-excited and machine tool vibrations change the process conditions during the cutting operation, limiting the part dimensional accuracy and surface finish.

The limitations of existing theoretical models leave us no choice but to develop empirical models. Empirical modeling methods use experimental data to tune the parameters of the model. In this way they compensate for the inability to completely and adequately describe the process mechanisms.

Connecting theoretical knowledge with experimental measurements can establish a good basis for adequate surface modeling [2]. In this paper, a theoretical model is tuned with the signals gathered during the cutting process. The machined surface image is used as the main source of on-line measurements. Although it has been shown that the surface roughness is strongly correlated with the surface image, measurements of surface roughness based on computer vision technology are complex. The main problem is how to accurately describe the surface images so that the surface roughness parameters are reliable.

To predict surface roughness during cutting, different approaches were applied for machine vision elaboration [3–5]. Nonetheless, the basic structure of such a system was defined in a similar way. The computer vision system for surface image acquisition was elaborated upon to comprise a digital camera connected to a PC and an appropriate light source. The images obtained constitute the basic source of information. In [4] the images were analyzed to calculate the arithmetical average of shades of grey. The cutting parameters and the single image feature were given, for four inputs, to the system and the roughness value was assessed. In [5, 6] the machined surface image was described with the use of more refined methods – image texture description methods and wavelet features. The features were analyzed and successfully applied in the monitoring of well-known processes. However, each change in the process conditions necessitated restarting the whole preparatory process.

The idea of vision system application in surface roughness estimation was developed in this paper. The novelties concern the general look at the process as a whole. An important feature of the method is that the application of neural networks is continual – once prepared it works automatically. Training the neural network can be performed whenever it is needed. The neural estimator is initially prepared for estimation of surface roughness parameters. Then, the inflow of data from the vision system enables the initial estimation of surface roughness parameters. When the estimation is in agreement with the measurement, then in this case the estimator is ready to work. In other circumstances it must be tuned. The accuracy of estimation is checked periodically and, again, it can be tuned whenever needed.

2. Experimental procedure

An experiment was proposed in order to explore and evaluate the usability of the idea of utilizing machined surface imaging in estimating the surface roughness parameter R_a . Turning tests were performed using CNC NEF 400. The attempts of continuous cutting were realized for feed = 0.15 mm/rev, cutting speed = 500m/min, depth of cut = 0.5 mm. Steel C45 (PN-EN 10250-2:2001) of 137 HB hardness was cut. Sandvik Coromant coated sintered carbide TNMG 160408 PF 4015 tool insert was applied.

During the experiment the changes in tool geometry were observed both on tool flank and rake faces. For the tool wear description the criteria defined in the ISO 3685 standard were applied. The applied tool life criterion was flank wear. A tool is considered to have reached its life if the maximum width of the flank wear land is of a certain value. In finishing operations where the depth of cut is small, the flank wear land width in the nose area represented by VBC (in zone C) is a more meaningful parameter for assessing tool life, particularly when surface finish quality is the main criterion. Flank wear in zone C is visible from the top of the nose area of the cutting tool. The nose radius wear VBr appears as tool nose radius wear and is caused by material lost from the nose area.

The wear of the tool was observed with the use of an optical technique. Sequences of tool flank images were obtained and joined together to achieve one combined photograph of the tool flank (Fig. 1). The wear traces are equally stretched along the cutting edge, and their width is rather small. On both minor and major flank, the development of wear width for all the wedges considered during the experiment was observed to be small and all of the wear indexes were below the tool life criterion for finish turning.

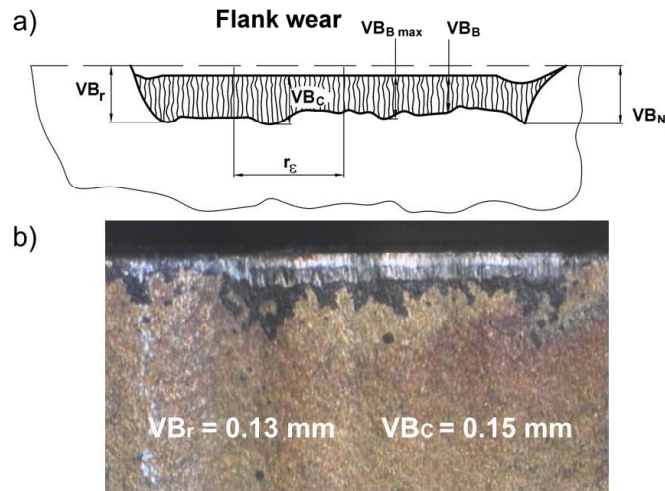


Fig. 1. Flank wear of the tool a) definition of parameters: VB_r – width of minor flank wear, VB_c – width of nose wear; b) combined photograph of minor and major flank.

As a result of the cutting process, the obtained machined surface is of certain quality. For a sharp tool, in the initial stage of cutting, the machined surface is created by a rounded cutting edge. The wedge is sharp and the machined surface is of good quality. The most important factor in this case is the tool geometry itself as well as the cutting parameters.

With cutting time, the cutting edge radius increases and the wedge becomes blunter. It influences the whole cutting process. Despite the changes observed on the surface, the roughness parameters remain almost on the same level. It may be inferred that changes in surface finish are of a local character and global parameters are not appropriate to describe their nature.

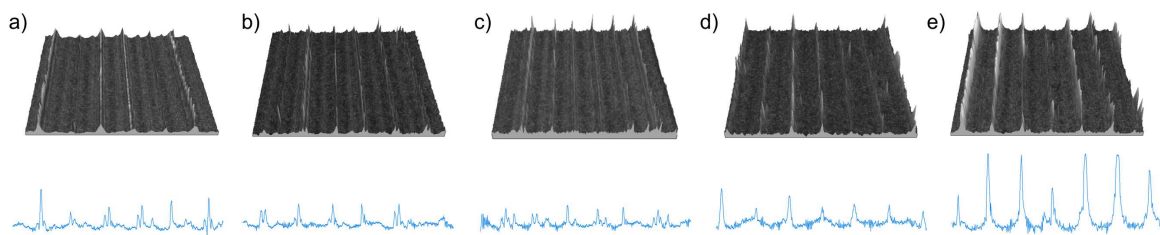


Fig. 2. Machined surface image in 3D projection and its profile for a cutting time of a) 5min; b) 8min; c) 11min; d) 14min; e) 17min.

Exemplary machined surface images and their profiles were compared considering their variable origin back to the cutting process. After a stable turning process, the machined surface is expected to possess repeatable and homogenous features, like steady and identical ridges. However, the machined surface with time becomes more diversified and alternated. The texture of the surface image is still uniform, but the ridges are more exposed and ragged (Fig. 2).

Along the cut the values of surface roughness parameter Ra were measured with a Talysurf CCI 6000 profilometer. The mean roughness was between 1.5 to 2.5 μm . The relative difference between the given value and its preceding one was indicated as quite small. It was smaller than 10%.

3. Measurement system

The vision system was developed for the purpose of obtaining an image of the machined surface. The system was composed of several elements. The most important of these are a computer with a frame-grabber card, digital camera, lenses, and a stand for the camera with movable worktable and lighting system (Fig. 3) [7].

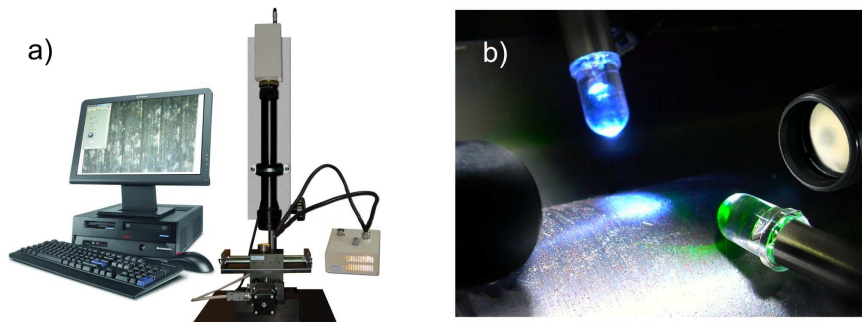


Fig. 3. a) Vision system for machined surface image acquisition; b) lighting system configuration.

The two-sided lighting system, based on a halogen white light, was applied in illuminating the machined surface. The halogen illumination system was located to reveal the main shape of irregularities. The surface lay and the extent of randomness in the main shape of the surface profile were thus exposed. The digital image of the machined surface presented next to the measured surface confirms the surface complexity (Fig. 4). It reflects the whole character of surface texture. Periodic mappings of the cutting tool modulated by tool feed disturbances are even more underlined in the image. Each strip of digital image at a perpendicular angle to the lay direction in the image is similar in character to the profile obtained from the machined surface.

Nonetheless, the additional lighting was positioned to illuminate the machined surface along the traces. This part of the illumination system exposed the complexity of the machined surface texture. In this way the image was littered with weak, small, pale dots as footprints of the material side flow.

Surface image data, like surface data, are characterized by different stochastic measures. Appropriate selection of image data for analysis is crucial for its description. Improper selection of the measurement point can, in turn, undermine the statistical parameters. Equally, randomly selecting the measurement point and size of the analyzed data can reduce the usability of the image. Nonetheless, an image profile must be chosen; the problem is how to do it, how to overcome the difficulties of the signal nonstationarity.

When the turned surface is considered, its parameters are often described by taking into analysis only one profile of the surface at a perpendicular angle to the lay direction. For a filtered profile, the sampling length is equal to the cut-off length. On a raw profile, the sampling length is equal to the assessment length. Parameters are calculated on each sampling length and expressed then as the average of all the sampling lengths used. It is recommended to use 5 sampling lengths.

When the surface image is considered, its parameters should be described similarly to the surface in a range of measurement point selection and size of the analyzed data – take one

cross-section from a machined surface image of the sampling length. The sampling length selected in this case was 0.8 mm.

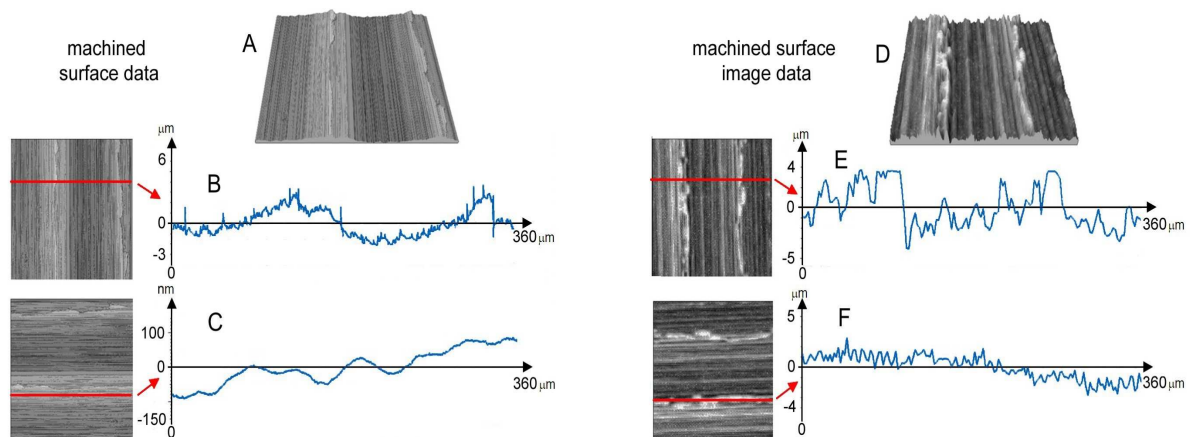


Fig. 4. The machined surface measured with Talysurf CCI 6000 and acquired with a vision system A – 3D view of surface data, B, C – cross-section of surface data in two orthogonal directions, D – 3D view of scaled image data, E, F – cross-section of scaled image data in two orthogonal directions.

4. Parameters of surface image

Mathematically, a grey scale image is defined by one matrix describing the variability of identified shades of grey. Image data are of high correlation and describe the surface in a strongly redundant way. There is a high probability that if one pixel is of certain luminosity, its neighbor would be of the same or similar one. In this way, the image matrix is not the best representation for the analysis. Image data, in their original form, can be used for visualization but they should be processed before applying them in a monitoring system.

Taking into account the character of the machined surface image and its basic pattern, the representation which is more suitable for the goal of image analysis is wavelet decomposition.

4.1. Wavelet decomposition of surface image

Wavelet analysis breaks the signal up into shifted and scaled versions of the original wavelet. In this way, it enables the examination of the data both in space and frequency. Selection of a basic wavelet from a rich family of wavelets also makes it possible to match it more accurately to the data. Additionally, decomposition can be performed on a different level of detail, characterized by the decomposition tree and level.

To choose the main wavelet, the surface profiles were decomposed with the use of various wavelet functions. The first level of decomposition broke up data into approximation and detail coefficient vectors. Then the approximation was applied as a model of a raw signal. The residuals of the model – details were determined to be white noise. The better the wavelet is matched, the better the approximation can be used to identify the signal, and the residuals as white noise. The best results for turned surface modeling were achieved for Coiflets – the main family of wavelets [8, 9].

To choose the best decomposition tree, the surface profile data were decomposed with the use of wavelet packets. In 69% of cases, the preferred decomposition tree was the tree of digital wavelet transform. In the digital wavelet transform, the algorithm divides the signal into two parts. After the division, approximation and detail vectors are obtained. Both vectors are in a rough scale. The information lost between the signal and approximation vectors is collected in the detail vector. The next stage is the division of the approximation vector into

approximation and detail vectors. After this, the detail vector is not divided any further. The approximation vector is further divided, however, and in this way a digital wavelet transform decomposition tree is obtained [10]

To choose the best decomposition level, the universal image quality index was used to discern how much information was contained in a particular level of decomposition. A universal image quality index, defined in [11], models the loss of correlation, luminance and contrast distortions between two images. In this paper, the index was used to measure objective image quality loss when the data were filtered to obtain approximations for a particular level. The amount of information lost in each level of decomposition was examined. It was discovered that:

- The details of the first and second levels of decomposition contain mainly noise.
- The details of the third, fourth and fifth levels of decomposition constitute the valuable signal.
- The sixth level is the highest level of decomposition because it still indicates some similarity to the original signal, but not higher levels.

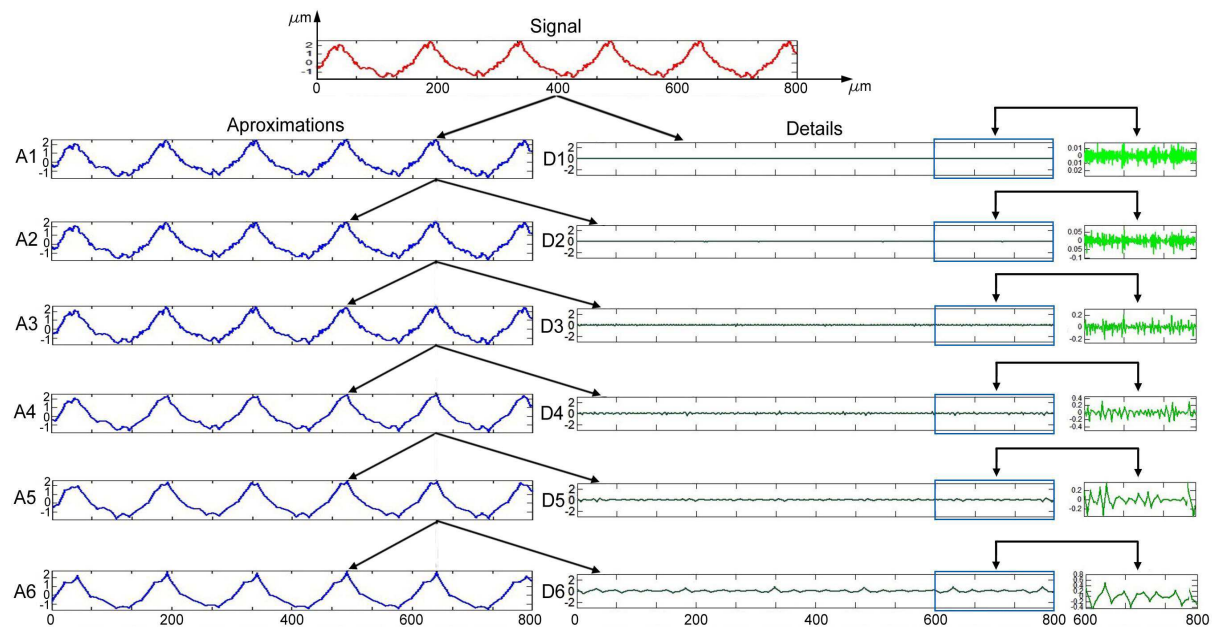


Fig. 5. Six-level wavelet decomposition of machined surface image profile.

The digital wavelet transform was performed for five cross-sections of the image, 0.8 mm in length. Coiflet filters were used to decompose the original cross-section of the image into seven components – one that was treated as an approximation (A6) of the signal and six detail components (D1–D6) (Fig. 5). The image profile data were cut into different frequency components, and then each component was studied in a resolution matched to its scale. Low frequencies correspond to global information of an image profile, whereas high frequencies correspond to detailed information of image hidden pattern.

4.2. Wavelet features

For each of the six levels of wavelet decomposition of image profile, eighteen statistical parameters were computed. The computation was repeated for five cut-off lengths and then averaged. The number of coefficients is 126 for each single image. However, the evaluated image coefficients are of varying value for the purpose of surface roughness estimation. Some of them are useless, others are redundant. So, the correlations between each image feature and

several surface roughness parameters were examined. In Fig. 6 the averaged absolute value of the correlation coefficient is presented. It was considered as the strength of correlation.

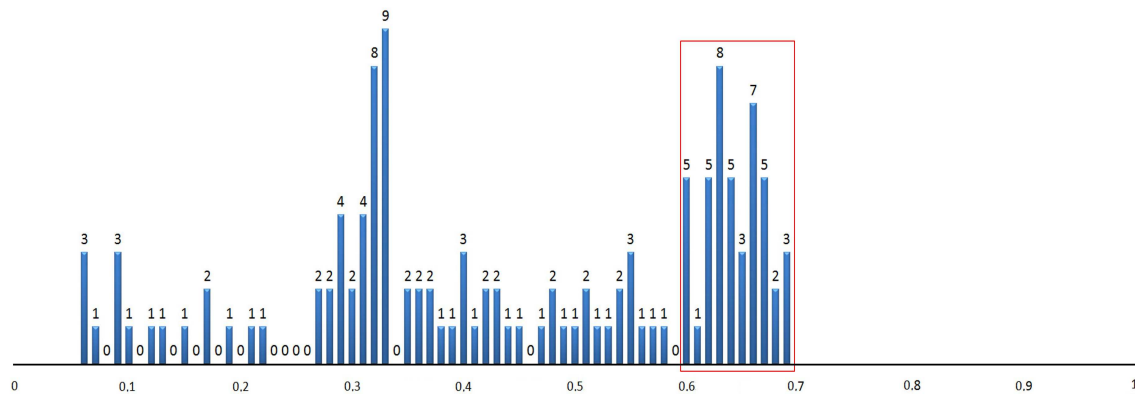


Fig. 6. Distribution of correlation coefficient describing the relationship between surface and image parameters.

Detailed analysis of correlations was performed. Each correlation coefficient was computed for almost 200 images and 10 surface parameters. From the range of 126 features only forty four were chosen for further analysis. They displayed a high correlation with the surface roughness parameters. The largest number of features was chosen by approximation (A6), as well as from D2, D3 and D5 details. The performed reduction of features limited their number, but still, definition and distribution of features might be redundant. Further reduction of the feature set was performed with the use of pruning of the neural network.

4.3. Selection of features using neural network pruning

The neural network is often used when the equation describing the relation is difficult to formulate. The main source in establishing the correlation is a set of examples. For the neural network, finding the relation means identifying the network parameters, or weights. The idea in using the neural network in feature selection is to analyze the usability of particular features in establishing the relation.

For the purpose of feature selection, the neural network was elaborated to be a multilayer perceptron. The number of neurons in an input layer was equal to the number of image features. A single hidden layer with biases and an output layer were applied. The neurons in the hidden layer have a hyperbolic tangent activation function; the single neuron in the output layer has a linear activation function. The data were divided into training and testing sets.

The neural network was analyzed using the Lavenberg–Marquard method. In the algorithm, the parameter settlement is based on an error minimization between reference surface roughness parameters and the output values from the neural estimator. The optimal feature subset was determined by means of pruning experiment. Firstly, a vector with thirty features was created, and then reduced to those features which produced substantial changes of the output error. The Optimal Brain Surgeon Method was applied in optimizing the input features. The problem of feature selection in the case of applying the neural network became reduced to the problem of optimization of the input layer *i.e.* selection of such inputs which changed and produced the biggest output error (change of the cost function) during training and elimination of that input, which further produced small changes in the output error [12, 13].

The Optimal Brain Surgeon optimization procedure conducts estimation based on variation of the cost function after changing the value of network weight to zero (the branch with this weight is cut off) and then the variation of the network error is estimated. The neural network

weights, which produce small variations in the cost function, are less important for the final cost function value (output error) and therefore they could be pruned *i.e.* their values are changed to zero.

During the optimization procedure, the neural network was trained several times and then the input layer was pruned. Each time the pruned weights were counted again. At the end of the optimization procedure the rank of each input neuron was determined. Neurons from the input layer, whose weights were frequently pruned, were rejected. At the beginning, the network was composed of forty four neurons in an input layer, four neurons in the hidden layer and one neuron in the output layer (44-4-1). Fifty pruning experiments were carried out. During each experiment the network was trained and then the weights were pruned.

A set of six features was selected with the use of Optimal Brain Surgeon Method, namely:

- standard deviation of A6 – SD(A6);
- maximal difference of A6 – MD(A6);
- Minkowski norm of D5 – LP3(D5);
- normalized absolute error of D3 – NAE(D3);
- Minkowski norm of D3 – LP3(D3);
- normalized absolute error of D2 – NAE(D2).

5. Surface roughness estimator

The estimation of surface roughness for turning operation was performed with the use of a neural network. The estimation is based on applying the time variable statistical parameters of one-dimensional wavelet transform of the machined surface image.

Because of the difficulties arising from the changes in description of the machined surface parameters during cutting, the process was assumed to be a “black box”. The relation between variables was developed with the use of mathematical model identification methods. The machined surface image features were combined together with surface roughness parameters to obtain a model of their relation. The estimated surface roughness Ra parameter (Ra_e) was described with the use of a non-linear function:

$$Ra_e(n+1) = f(Ra_e(n), F1(n) - F1(n-1), F2(n) - F2(n-1), F3(n) - F3(n-1), \dots, F4(n) - F4(n-1), F5(n) - F5(n-1), F6(n) - F6(n-1)) + w(n)$$

where:

- $Ra_e(n+1)$ – estimated value of surface roughness Ra parameter in $n + 1$ step;
- $Ra_e(n)$ – estimated value of surface roughness Ra parameter in n step;
- $F1(n) - F1(n-1) .. F6(n) - F6(n-1)$ – difference of $F1..F6$ for the n and $n + 1$ steps;
- $w(n)$ – noise.

The neural network was used for approximation of $Ra_e(n+1)$ function. It was decided that seven neurons should be applied in the input layer, three neurons in the hidden layer (with the activation function in form of hyperbolic tangent) and one neuron in the output layer (with the linear activation function). The Extended Kalman Filter was applied as an algorithm for training the neural network [14–16]. This algorithm allows the optimal estimation of state variables when white noise is present. The advantage of this algorithm is that it works in a recurrent way.

The random vector of weights was generated, then modified according to reference values with use of the recurrent algorithm. After several presentations of the following values of the training set, the vector was adjusted so that the results of both estimated and reference values overlapped. The process of training was then interrupted. The network for the earlier fixed weights started to estimate the value of surface roughness parameter Ra for the determined

points of turning. It was in a testing/estimating mode. The predicted Ra value was computed on the basis of a current Ra value and the difference in surface image features.

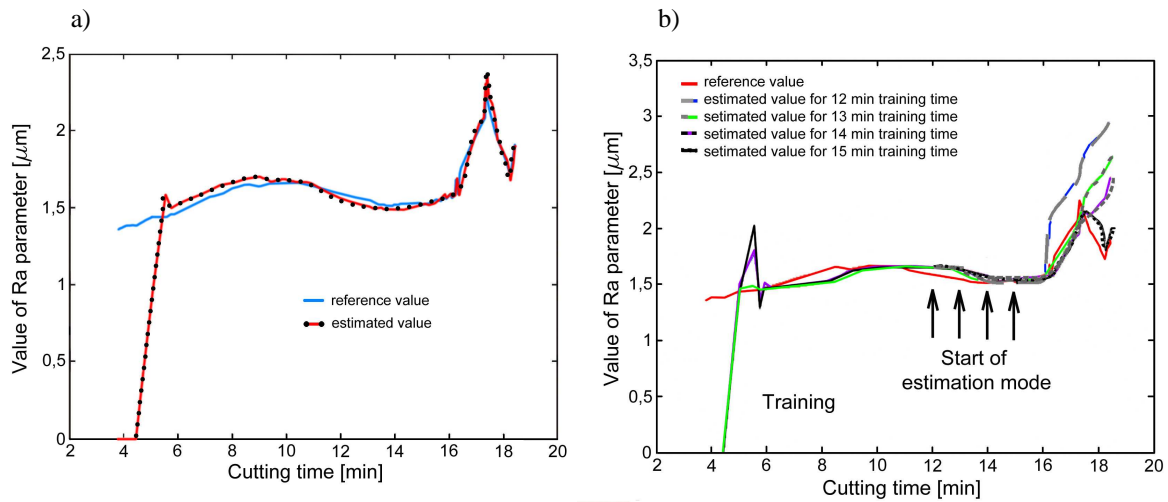


Fig. 7. a) Example of surface roughness Ra parameter estimation by means of recurrent neural network.
 b) Effect of training time on the estimation of Ra parameter.

The example of surface roughness estimation with the use of neural network is presented in Fig. 7. When enough examples for training were applied, the estimated and reference values got very close. Such a result can be seen in Fig. 7a. In Fig. 7b, the influence of training time on the accuracy of surface roughness estimation is demonstrated. For all the training times the neural network made an estimation of the surface roughness Ra parameter in the range of linear changes in reference Ra value possible. The network also allowed for identification of the point of accelerated deterioration of the surface roughness (when parameter Ra increased drastically). More detailed analysis of the training/testing process of neural network made the formulation of some general conclusions possible, namely:

- In the range of short time of neural network training (up to 12 minutes) the accuracy of estimation remained on the same level. The neural network, when trained on several examples, behaved almost the same as when trained for a longer time. All of the analyzed examples were allowed for assessment of the surface roughness Ra parameter for a stable process, for a normal work of a tool. The occurrence of a more significant increase in surface roughness (both in surface roughness parameters and in surface image features) caused an immediate increase in the predicted Ra value. In further steps this predicted Ra value kept growing in spite of the decrease of reference Ra value and of values of image wavelet features.
- In the range of a longer training time (from 12 minutes up), the increment of estimation accuracy depends on the time taken. In case of 12 minutes the neural network only notes changes, but cannot be tuned to reference values. The increase in the training time made it possible for the predicted value to follow the reference value. The estimated value unfortunately could not follow a significant decrease in the reference value. The internal structure of the neural network started to follow the entire conduct of surface roughness more precisely for a training time larger than 15 minutes.

6. Conclusions

An estimation of the surface roughness parameter Ra was performed with use of a neural network. The increment of machined surface image parameters was applied as input for the neural network estimator. Five cross-sections of the image were loaded, from which six

statistical parameters of the six levels of wavelet decomposition were computed. These six parameters were chosen via the Optimal Brain Surgeon Method. Applying the increments of these parameters and of the estimated value in a given time made it possible to establish the Ra estimator for the points in time when the surface roughness parameters were unknown.

The performance of the estimator of surface roughness parameter Ra indicated a great usability of the presented method for monitoring the quality of surface roughness in turning. The error for the testing set was definitely smaller than 20% and slightly above 5%. The recurrent neural network allowed for accurate estimation of the given value of Ra on a basis composed only of data from the machined surface image.

Acknowledgments

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