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Machined surface quality estimation based on wavelet packets parameters of the surface image

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Abstract

Machined surface image, destined for monitoring, was represented by the diagnostic feature vector, correlated with maladjustment of the process. Maladjustment is manifested by the increase of the signal random component in relation to deterministic one. Such a behavior of the system was the basis for diagnostic measure elaboration. From the definition of entropy, it increases with the increase of the random component. So, the entropy of normalized energy vector for optimal decomposition tree coefficients was selected as the diagnostic measure. The correlation between the entropy of energy vector of decomposition tree coefficients and machined surface parameters and tool wear was demonstrated.

Keywords: machined surface, wavelet packet decomposition, surface image, entropy.

Estymacja jakości powierzchni obrobionej na bazie parametrów rozkładu pakietów falkowych obrazu tej powierzchni

Streszczenie

Środowisko zautomatyzowanego wytwarzania wymaga szybkich pomiarów chropowatości, jeszcze przed ostatecznym ukształtowaniem wyrobu. Do tej pory nie udało się opracować takiego układu, który spełniałby wymagania systemów sterowania produkcją, ze względu na wiele niekontrolowanych czynników wpływających na ostateczną jakość powierzchni. Jednym z możliwych do zastosowań przemysłowych układów inspekcji powierzchni jest system bazujący na obrazie tej powierzchni, szerzej omówiony w [1-4]. Obraz powierzchni po obróbce toczeniem, podobnie jak powierzchnia, jest strukturą kierunkową, w której dane zebrane w kierunku prostopadłym do śladów obróbki, w kolejnych chwilach czasu, reprezentują przebieg procesu skrawania. W artykule dane jasności obrazu powierzchni, zebrane w kierunku prostopadłym do kierunkowości, modelowano przy zastosowaniu pakietów falkowych. Problem analizy czasowo-częstotliwościowej obrazów powierzchni po toczeniu sprowadził się do przeprowadzenia odpowiedniego schematu dekompozycji przestrzeni czasowo-częstotliwościowej i wyznaczenia wektorów składowych [5-7]. Dobór drzewa dekompozycji pozwolił na ograniczenie liczby analizowanych wektorów składowych do ośmiu: $w_{2,2}$, $w_{2,3}$, $w_{3,2}$, $w_{3,3}$, $w_{4,0}$, $w_{4,1}$, $w_{4,2}$, $w_{4,3}$. Zaproponowano miarę nieuporządkowania energii (entropia znormalizowanej energii) dla opisu poszczególnych składowych drzewa dekompozycji [8], które skutecznie charakteryzują nieregularność profilu obrazu powierzchni i rozregulowanie procesu. Potwierdzono zależność statystyczną między wartościami miar nieuporządkowania energii poszczególnych składowych a parametrami powierzchni i zużycia ostrza.

Słowa kluczowe: powierzchnia obrobiona, dekompozycja pakietów falkowych, obraz powierzchni, entropia.

1. Introduction

What is required in the environment of automated production is fast roughness measurement, realized even before the final formation of the product. Quality of the machined surface was inspected with machined surface monitoring system, based on the surface image, widely discussed in [1, 2]. Digital image of the machined surface is represented with a matrix of numbers, which describe the condition of the light being reflected from the surface. Value of the pixel brightness depends on the illumination conditions and vision layout, its location and other factors. What is more important from the point of view of information content is the inner changeability of the intensity image. Due to orientation of structure of the image after turning and to its uniformity along machining traces, profile observed on one plane can represent the whole image [3, 4].

In case of surface monitoring with its image, the problem consisted in working out the features able to detect any maladjustment in the machined surface image. Each non-ideal mapping of the tool on the surface is visible in the surface image in the form of derangement of the basic shape.

The idea of application of wavelet decomposition for surface analysis has its origins in contemplations over the basic shape of a single microroughness, angles and dimensions describing it. The observed change of the image during cutting and distortions resulting from increase in process' randomness led to the conclusion that the machined surface image signal should be analyzed in relation to both time and frequency.

The aim of the research was to decompose the image profile of the machined surface into a group of time-frequency signals and to determine the properties describing the signal's randomness on every decomposition level. The article describes the choice of surface image decomposition method, including the basic wavelet and wavelet packet decomposition tree. Image profile decomposition was performed for the chosen tree structure. Next, signal energy dispersion indexes were determined for approximation and detail vectors on particular decomposition levels. Comparison of the values of the determined image indexes in real parameters function allowed for determination of relationship between the image and the machined surface.

2. Research procedure

The research was performed on CNC NEF520 machine tool. Sandvik Coromant turning inserts, type TNGA 160408 TO 6090 were used and the machined item was a steel roller C45 (PN-EN 10250-2:2001) 137 HB. The research included machining with parameters in accordance with the experiment plan (f=0.06÷0,2 mm/rev, $v_c = 100 \div 250$ m/min, $t = 1 \div 11$ min, a_p=0.5 mm).

The flank wear traces for finishing turning depend on the geometry of the active part of the cutting tool and cutting conditions. The cutting edge of an insert is subjected to a combination of high temperatures and stresses, which cause chemical reactions.

Flank wear occurs primarily by rubbing of the flank face against the workpiece surface, as can be seen in Fig.1. When the wear increases, the characteristic point appears in which cutting edge crosses the strained layer. The position of this point designates the cutting depth. The concentrated wear traces appear around this point (notch wear - VB_N). The rubout along the cutting edge is in a shape of the rectangular band and is called flank wear - VB_B. The width of this band increases with cutting time. But for finishing processes the outline of tool wear being the result of shortening of the tool is in a form of ellipse - VBr. It is visible particularly in Fig.1c when the cutting time is longer. Tool wear parameters are very important because they affect the cutting process by changing the tool and workpiece contact conditions.

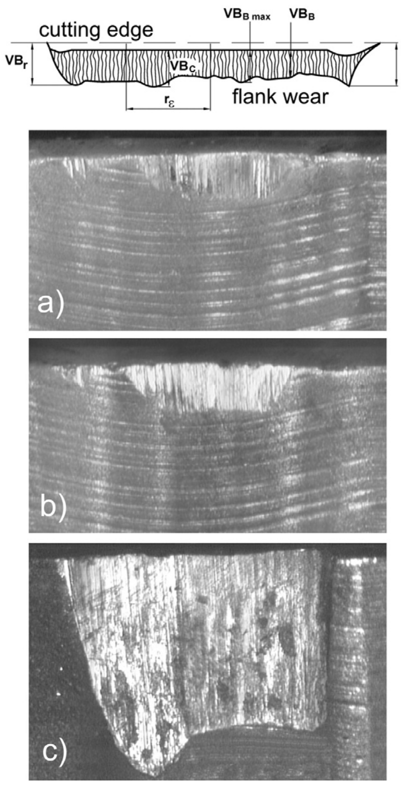

Fig. 1. Tool wear of TNGA 160408 TO 6090 for f = 0,09 mm/rev., v_c = 100 m/min; a) t = 3 min, b) t = 6 min, c) t = 9 min
Rys. 1. Zużycie narzędzia TNGA 160408 TO 6090 dla f = 0,09 mm/obr., v_c = 100 m/min; a) t = 3 min, b) t = 6 min, c) t = 9 min

The machined surface was measured with the use of stylus profilometer. 2D parameters were determined with the elementary length of 0.8 mm. The images of machined surface were collected using an optimized vision system working in LabView environment. 196 images of the machined surface in various machining periods were gathered in this way. The machined surface was illuminated bilaterally with white LED directional light.

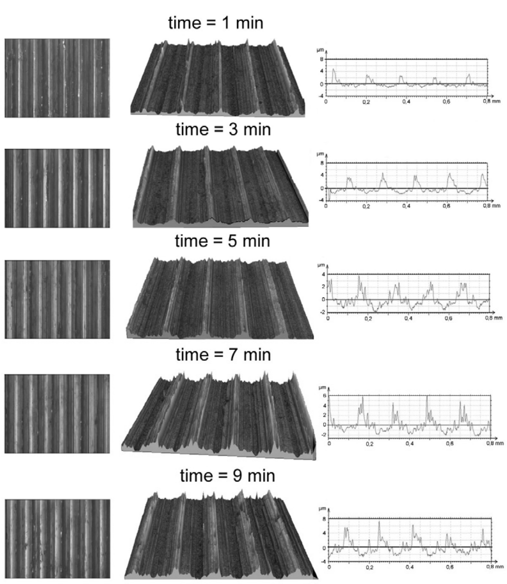

Fig. 2. Machined surface image in a function of time - representation 2D, 3D and image profile
Rys. 2. Obraz powierzchni obrobionej w funkcji czasu skrawania – reprezentacja 2D, 3D oraz profil obrazu

Features of machined surface image are the reflection of cutting tool geometry. When the cutting time is grater, the diversification of machined surfaces is more noticeable. In Fig. 2 for the small cutting time the machined surface image is characterized by a lot of light regions. Because of the two-sided lighting the slopes in a thread-like surface are perfectly distinguished. Only the bottom of the valleys is slightly darker because gradients of ridges make the penetration of the light in this region difficult.

3. Signal processing

3.1. Wavelet decomposition

Decomposition of the signal using digital wavelet transform (DWT) is based on digital filtration algorithm. The analyzed signal is let through a system of filters complementing one another: low- and highpass. As a result of operation of DWT, details coefficient vector and approximation coefficient vector are obtained, which carry information on the primary signal on various minuteness levels. The approximation coefficient vector is a low-frequency rough approximation of the signal, while the details coefficient vector is responsible for high frequencies occurring in the analyzed signal.

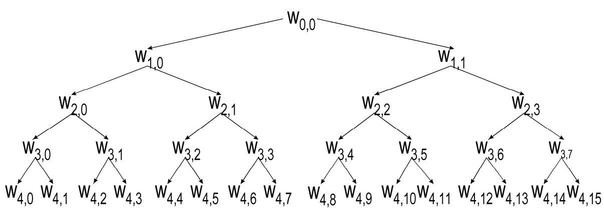

Fig. 3. Specification of wavelet packet vectors
Rys. 3. Drzewo dekompozycji pakietów falkowych

In the digital wavelet transform, the algorithm divides the signal into two parts. After the division, an 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 division of the approximation vector into approximation and detail vectors. The detail vector is not divided any further. Next, the approximation vector is further divided and in this way a digital wavelet transform decomposition tree is obtained. In wavelet packet transform each details coefficient vector is divided like approximation coefficient vector. A complete binary wavelet packet analysis tree is created. The Fig. 3 presents wavelet packet decomposition tree up to the fourth level.

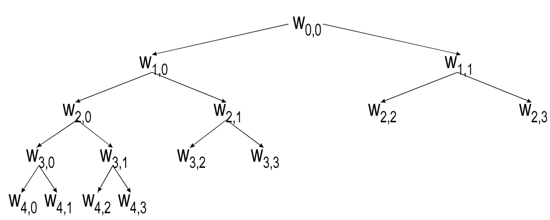

Fig. 4. Optimal decomposition tree for machined surface profile description
Rys. 4. Optymalne drzewo dekompozycji pakietów falkowych do opisu profilu powierzchni obrobionej

The method of decomposition depends upon the type of signal and its analysis. It is advisable for the time-frequency structure to be adjusted to properties of the signal. The criterion of its choice should be minimization of non zero signal decomposition coefficients, i.e. adjustment of the basic wavelet shape to the signal shape and the moment of their occurrence. Basic Coiflet wavelet was chosen, which is characterized by high regularity; it is almost symmetric. It resembles the basic microroughness of surface. Choice of the right basic wavelet is widely described in [5, 6].

Due to fact that the wavelet packet decomposition tree can adapt various forms and the number of different extensions of the tree is considerable, finding an optimal decomposition becomes a crucial issue. Analysis of division of surface profiles performed in [7] revealed that the tree of the discreet wavelet transform was the tree optimal for analysis in 69% of cases. However, it was noted that additional decomposition of detail vectors $w_{1,1}$, $w_{2,1}$ and $w_{3,1}$ allows the tree to be complemented in such a way that 97% of the optimal subtrees will be located in the chosen wavelet analysis tree. The tree was composed in such a way was treated as statistically optimal (Fig. 4).

3.2. Parameters of wavelet packet decomposition components

Properties of wavelet packet energy decomposition are applied in various fields of diagnostics. They are applied mainly in search for variables for temporary signal distortions. The normalized energy signal vector is often chosen as a vector of features describing the signal [8]. Each of deregulations in process manifests itself in increase of random component in relation to the determined component. It was assumed that energy value is of random nature. Here you can examine value dispersion in the energy vector, indicating decomposition of the process. Decomposition of the process is characterized by greater entropy. Energy entropy vectors should therefore have higher value as the process' randomness increases. Energy entropy vectors can be examined as a property detecting the process' condition and its decomposition. The following operations were performed for the image profile:

- Determination of the signal component vectors.

  What was realized for surface image profile was wavelet packet decomposition for statically optimal tree, using Coiflet basic wavelet. The following component vectors were obtained $w_{2,2}$, $w_{2,3}$, $w_{3,2}$, $w_{3,3}$, $w_{4,0}$, $w_{4,1}$, $w_{4,2}$, $w_{4,3}$. Selected wavelet decomposition components were described with parameters.
- Determination of the energy value for chosen decomposition components.

  For the component vector $w_{n,j} = \{w_{j,k}, k = 1,2,..,l\}$ (n - decomposition level, j - component index, l - length of the component vector) the following energy signal was determined

$$E_{n,j} = \sum_{k=1}^{l} \left| w_{j,k} \right|^2 . \qquad (1)$$

Total energy of the signal is estimated to be:

$$E_c = \sqrt{\sum \left| E_{n,j} \right|^2} . \qquad (2)$$

- Performance of energy value normalization.

  Signal energy value $E_{n,j}$ is additionally normalized for each vector (n, j) by following equation:

$$EN_{n,j} = \frac{E_{n,j}}{E_c} , \qquad (3)$$

- Entropy value was determined for the normalized energy.

  Energy entropy of each vector (n, j) can be defined as follows:

$$Entropy = -\sum EN_{n,j} \log EN_{n,j} . \qquad (4)$$

4. Results and discussion

4.1. Correlation analysis

Before the decomposition was performed of the image profiles set, dispersion of brightness levels in the image was analyzed. The surface image was leveled and filtered. The normalization procedure consisted of three operations performed on components of the discreet two-dimensional wavelet transform. Components of the first two levels had their values identified by the estimator as noise, thresholded. Values higher than the threshold were brought down to zero. Such elimination of components is called soft thresholding. It was noted that after hard thresholding, components of level three required reinforcement. Finally, approximation matrix of level six was filtered in such a way that the components standing for the low frequencies, especially the main trend resulting from heterogeneity of the surface's illumination, were removed. A group of representative profiles were chosen for the leveled image. The stability of determination of profile division in location function in image was analyzed. An exemplary image (Fig. 5) of the post-normalization surface and image profile are presented in the below pictures. A set of single image profiles underwent the decomposition process.

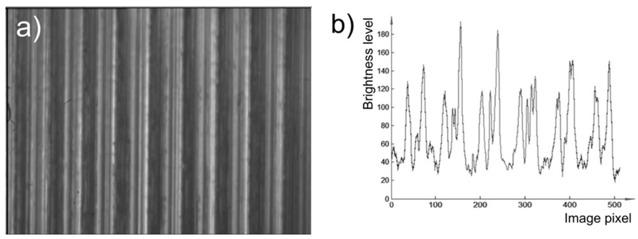

Fig. 5. a) Machined surface image, b) machined surface image profile
Rys. 5. a) Obraz powierzchni obrobionej, b) profil obrazu powierzchni obrobionej

Wavelet packet decomposition for statistically optimal tree was performed for the normalized profile in order to obtain the following components $w_{2,2}$, $w_{2,3}$, $w_{3,2}$, $w_{3,3}$, $w_{4,0}$, $w_{4,1}$, $w_{4,2}$, $w_{4,3}$. Normalized energy entropy was determined for each coefficient vector. Figure 6 presents two examples of entropy value of the normalized energy vector in logarithmic scale for particular component vectors. Making the comparisons of energy entropy vector of surface image profiles, it can be noted that it is lower for a new tool. Image data were of better arrangement. Only for $w_{2,2}$ component, the value is higher for a used tool wedge. It is the approximation of the detail vector of the first level and it suggests that the signal details of the machined surface shaped with the used wedge is better determined.

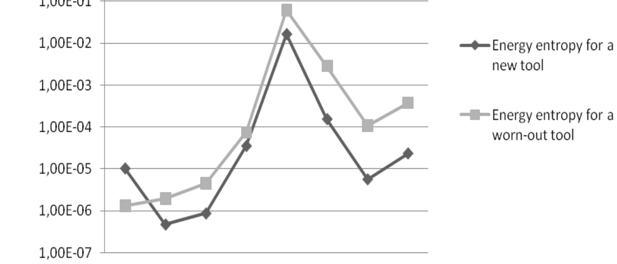

Fig. 6. Entropy of energy vector of machined surface image for a new and worn-out cutting wedges
Rys. 6. Entropia wektora energii dla obrazu powierzchni dla ostrza nowego oraz zużytego

The relationship between wavelet packet coefficients described in the above chapter and cutting parameters, surface roughness and tool flank wear parameters was examined. Values of correlation coefficient of particular decomposition components were then compared. The highest correlation coefficient value in relation to surface parameters was observed for $w_{4,0}$ and $w_{4,1}$ components. These are the daughter components of the approximation vector of the third level $w_{3,0}$. Value of the correlation index for approximation vectors $w_{4,0}$ and $w_{4,1}$ in relation to the examined roughness parameters was from 0.7 to 0.8 and therefore it could be described as considerable. Correlation of these vectors to the tool flank wear index was 0.59 and it was higher than the relationship with the machine cutting time, which was 0.4. Vectors of components showed considerable relationship with volume of the cut material (0.65).

The components obtained from decomposition of the component vector $w_{3,1}$ – components $w_{4,2}$ and $w_{4,3}$were characterized by a lower correlation index in relation to surface parameters and the tool flank wear. It was respectively of 0.43-0.52 for the surface parameters and 0.35 for the tool flank wear. The remaining components $w_{2,2}$ & $w_{2,3}$ and $w_{3,2}$ & $w_{3,3}$ had even lower correlation index, namely from 0.33 - to 0.43 for surface roughness parameters and from 0.2 to 0.26 for the tool flank wear.

4.2. Surface roughness Ra parameter estimation with neural networks

Feature set for the neural network estimator is presented in figure 7. Model value of *Ra* parameter, volume of cut material and energy entropy of wavelet packet components were applied for surface roughness *Ra* estimation.

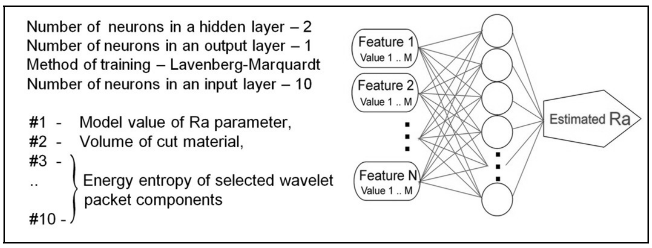

Fig. 7. Structure of the neural network estimator
Rys. 7. Struktura estymatora neuronowego

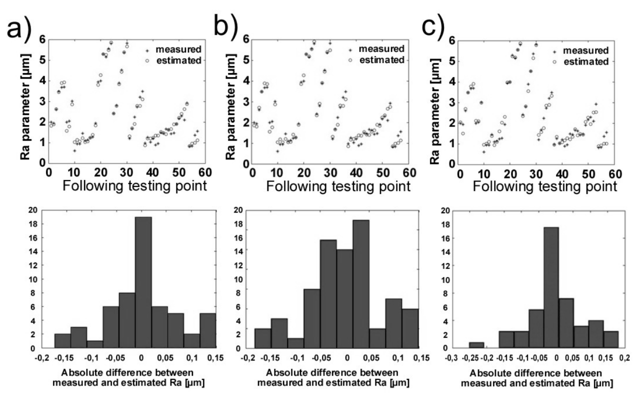

Fig. 8. Results of surface roughness *Ra* parameter estimation and error distribution
Rys. 8. Wyniki estymacji parametru *Ra* chropowatości powierzchni obrobionej oraz rozkład błędu estymacji

Neural network estimator was of a structure of 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 were characterized by hyperbolic tangent activation function; the single neuron in the output layer had a linear activation function. The data were divided into training and testing sets. The number of examples in a training set was two times bigger than in a testing set. The sets came from independent experiments.

The results of estimation of surface roughness Ra parameter are presented in figure 8. Measured and estimated values for tested set in three different cases of estimation are plotted together. The points in most cases cover each other or they are located in near neighborhood. Distribution of errors indicates normal distribution with the average value of zero.

5. Conclusions

The article analyzes the problem of surface image profile decomposition using wavelet packet transform. The issue of time-frequency analysis of images of the surface after machine turning, boiled down to realization of the right scheme of time-frequency decomposition and to determination of component vectors.

Selection of the decomposition tree allowed for limitation of the number of analyzed component vectors to eight: $w_{2,2}$, $w_{2,3}$, $w_{3,2}$, $w_{3,3}$, $w_{4,0}$, $w_{4,1}$ $w_{4,2}$, $w_{4,3}$. What was also suggested were measures of the lack of energy order (normalized energy entropy) able to describe the surface image profile irregularity and process maladjustment. The statistic relationship between measures of the lack of energy order values and surface and tool flank wear parameters were confirmed.

6. References

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