A MODEL OF TOOL WEAR MONITORING SYSTEM FOR TURNING

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Acquiring high-quality and timely information on the tool wear condition in real time, presents a necessary prerequisite for identification of tool wear degree, which significantly improves the stability and quality of the machining process. Defined in this paper is a model of tool wear monitoring system with special emphasis on the module for acquisition and processing of vibration acceleration signal by applying discrete wavelet transformations (DWT) in signal decomposition. The paper presents a model of the developed fuzzy system for tool wear classification. The system comprises three modules: module for data acquisition and processing, module for tool wear classification, and module for decision-making. The selected method for feature extraction is presented within the module for data classification and processing. The selected model for the fuzzy classifier and classification in experimental laboratory conditions is shown within data classification and clustering. The proposed model has been tested in longitudinal and transversal machining operations.

Keywords: artificial intelligence, feature extraction, tool wear monitoring

Model sustava za klasifikaciju trošenja alata pri obradi tokarenjem

Prikupljanje kvalitetnih i pravovremenih informacija o stanju alata u realnom vremenu predstavlja nužan uvjet za identifikaciju stupnja istrošenosti alata čime se u značajnoj mjeri poboljšava postojanost i kvaliteta procesa obrade. Ovaj rad se bavi definiranjem modela sustava za klasifikaciju istrošenosti alata uz poseban osvrt na modul za prikupljanje i obradu signala ubrzanja vibracija primjenom diskretnih "wavelet" transformacija (DWT) pri dekomponiranju signala. U radu je prikazan model razvijenog fuzzy sustava za klasifikaciju trošenja alata. Sustav sačinjavaju tri podsustava: za prikupljanje i obradu podataka, za klasifikaciju istrošenosti alata i odlučivanje. U okviru podsustava za prikupljanje i obradu podataka prikazana je izabrana metoda izdvajanja značajki. U okviru klasifikacije i grupiranja podataka prikazan je izabrani model fuzzy klasifikatora i provjera klasifikacije u eksperimentalnim laboratorijskim uvjetima. Primijenjeni model testiran je za zahvate uzdužne i poprečne obrade.

Ključne riječi: izdvajanje značajki, praćenje trošenja alata, umjetna inteligencija

1 Introduction

Major directions in the research aimed towards advancement of productivity, cost-effectiveness, and cost reduction in large-batch automated manufacturing are focused on the vibrations, detection of tool break and monitoring of cutting tools wear [1, 2]. Most investigations in the area of tool monitoring systems' development focus on the particular type of machining rather than the types of signals, methods and techniques for signal processing and types and numbers of extracted features [3]. The development of tool wear monitoring systems which operate in real time and employ indirect methods, represents the mainstream in today's automated manufacturing. Intensive research in the area of cutting tool wear monitoring systems based on application of artificial intelligence (AI), has begun in the nineties of the twentieth century. The focus of research was placed on the application of multi-sensor systems and the development of AI-based tool wear classifiers able to operate with a large number of features. Although the initial results promised the design of an industrially applicable solution, such breakthrough did not happen. Numerous AI-based tool wear monitoring systems have been developed to optimize and predict tool wear condition, or control the machining processes. Most of these solutions have employed various methodologies, without revealing clear directions or focusing on key issues pertaining to development of monitoring systems. Development of a model and practical application of a multi-sensor tool-wear monitoring system was proposed by Dutta et al. [4] and Balazinski et al. [5]. Scheffer and Heyns [6], emphasize that majority of the developed systems uses the following input signals: force

components, acoustic emission and vibrations, or a combination of them. In addition, indirect tool wear monitoring methods based on acquisition and processing of sensor signals represent major topic in majority of current experimental investigations [7]. Since most indirect methods are still under development and improvement, none of them represent tool wear on the level required for industrial application [8, 9]. The methods used to determine parameters from acquired signals and their correlation with the tool wear process and tool breakage can be classified into three categories [10]:
– Methods based on heuristic tools with a-priori knowledge of process parameters.
– Methods which require formal knowledge of the process (analysis of time series and fast Fourier transform).
– Methods for extraction of features based on AI, machine learning and feature recognition (fuzzy logic, genetic algorithms and knowledge-based systems).

Modern tool wear monitoring systems based on artificial intelligence should replace and augment conventional systems, providing continuous, fast and accurate determination of tool wear. Application of such systems in industry allows:
– Increase of reliability of the machining system, which is especially important in situations when cutting is performed with tools nearing life end,
– Optimization of cutting parameters with tool life as goal function, considering technological limitations,
– Provision of required workpiece dimensional

accuracy and surface quality,
– Additional rationalization of manufacturing costs.

2 Tool wear monitoring

Tool wear monitoring employs strategy which, based on the sensor signals placed on the machining system, allows quick reaction to all emerging process disruptions.

Tool wear condition is defined as the change of tool cutting geometry. Indirect tool wear monitoring methods allow monitoring of the degree of correlation between sensor signals and the monitored phenomenon. Due to its practical applicability, the approach based on indirect method has advantage over direct methods [11]. In addition, considering the placement of sensors on machine tools, there are various approaches, involving a multi-position tool carrier, spindle and other locations. Through monitoring the machining dynamics, as well as the influence of the type of chip cross-section generated during machining, it is possible to gain insight into the tool wear condition [12]. Moreover, numerous researchers have employed finite elements analysis to define the influence of machining process parameters on the tool wear, using special types of finite elements [13]. Tamizharasan and Senthil Kumar [14] evaluated the effect of tool geometries on performance measures of flank wear, surface roughness and cutting forces. They applied finite element analysis to minimize flank wear of uncoated carbide inserts during machining.

Within the analysed studies, Abellan-Nebot and Subirón [15] review application of various sensor systems and techniques for signal processing in building laboratory systems for tool wear monitoring. They analyse various design solutions in terms of the number and types of sensors. The selection of sensor system, and type and characteristics of sensors are directly related to specific features of the machining process, as reported by [16, 17]. In turning and milling, force monitoring sensors are one of the most often used sensors in laboratory investigations and practical application [18]. The variation of cutting forces is directly reflected on machine accuracy and machining quality. Through force control, it is possible to directly improve machining quality and prolong tool life. Also, the changes in machining process can be identified through monitoring of variations in the structure of vibrations, which allows the correlation to the quality of machined surface and tool life to be established [19, 20].

2.1 Tool monitoring systems

Majority of investigations which deal with the development of tool wear monitoring systems focus on the type of machining and the machining process to which they are applicable, rather than the types and kinds of input signals, methods and techniques of signal processing and feature extraction. Thus, they artificially limit the application range of their investigation in the domain of tool monitoring systems, especially when focusing on specific machining technologies [3, 21].

Suitable for defining a multi-sensor system model are neural networks, fuzzy logic and a combination thereof, also known as the hybrid systems [22, 23]. Due to their

feature recognition ability, these algorithms can be applied in machining to allow adequate recognition of process features. Development of tool monitoring system based on pattern recognition approach can be conducted in three characteristic steps. The first step is acquisition and processing of sensor signals, $x(t)$, which requires noise removal by filtering. The acquired data are then grouped as the input function, used in the subsequent process. Information relevant to samples classification is extracted from the pre-processed input signal, $x'(t)$, and a vector function, $y(t)$, is formed. The main goal of feature extraction is to enhance the features of various tool wear parameters which have been suppressed by the filtering. Finally, tool wear condition is defined and final classification performed. The input data vector, $y(t)$, is defined as one of the k-states of tool wear, C1, C2, ... , Ck, while the classification code is based on the applied type of classification criteria [24, 25].

2.2 Methods and techniques of feature extraction

Input sensor signals and other input data depend on the type of machining and the time-frequency decomposition of signal. S*hort time Fourier Transformation* (STFT) in combination with wavelet transformations yields very good results compared with other time-frequency methods [3, 22]. Application of wavelet transformations in processing and analysis of the data acquired from the machine tool, allows efficient analysis of various dynamic and stationary signals from mechanical systems which proves its efficiency in feature extraction. It has been shown that time-frequency methods are very good for the extraction of features which would otherwise, through application of other methods, remain undetected. The area which requires further investigation is the integration of machine tool dynamics and the correlation between the cutting process and tool wear monitoring system. Little has been done to use that information within systems for tool wear monitoring. There are a number of methods which can be used to generate dynamic models of machine tools in order to allow integration of tool wear monitoring systems. Use of mathematical models has a potential to widen applicability of tool wear monitoring systems taking into consideration dynamic characteristics of machine tools.

Wavelet transformation is the most popular and most important method for signal analysis in the time-frequency domain. It allows analysis of signals on a local level, which is especially important when processing non stationary signals. Transformation is based on the comparison between the wavelet function of a certain width (frequency) defined by the scanning parameter (s) and the parts of signal of equal width within a defined time interval ($t - k\tau$). The scale is inverse to signal frequency, as shown in (1):

$$\gamma(\tau, s) \frac{1}{\sqrt{|s|}} \int_{-\infty}^{\infty} x(t)\varphi^*\left(\frac{t - \tau}{s}\right)dt, \qquad (1)$$

where τ is translation parameter, s is scale parameter, $x(t)$ is the signal being transformed, γ is the frequency content

of the signal $x(t)$ within a time interval $k\tau$ and considering the scale s, while φ^* is the scaled and translated projection of the original wavelet $\varphi(t)$. When the analysis of the complete signal is performed using the original function of the defined scale, the procedure is reiterated for another scale value, i.e., time interval. If the signal contains the spectral component which corresponds to current scale value, the product between the wavelet function and the signal is relatively large at the spot where the component is located.

Parallel to the development of the model of tool wear monitoring, analyses have been performed of characteristics of various forms of wear identification parameters, to assess the quality of wear identification they allow. According to these analyses, the low-frequency signals (forces, motor currents) are most often present when extracting parameters in time domain, followed by the parameters from the frequency domain, and statistical parameters. In high-frequency signals, such as the acoustic emission or vibrations, the most frequent parameters are the parameters from the frequency domain, followed by statistical parameters and the parameters from the time domain. The least frequent parameters are from the time-frequency domain. Review of available contributions in this field reveals that, in most of the cases, the optimal number of parameters is a priority over the selection of the set of parameters which is most favourable from the aspect of tool wear identification. The analysis of the selection of tool wear parameters has been approached in several ways in the literature. Most often, exact explanation for their selection is omitted. Analysis of papers which report on extraction of sets of parameters based on their relatedness to the tool wear process reveals that the most frequently the methods have been: SFS (Sequential Forward Search); SBS (Sequential Backward Search), PCA (Principal Component Analysis) and their combined application. Some of the methods use the so called sequential selection of parameters, which requires their independence in the assessment of tool wear, while other methods utilize combination of parameters for that assessment. In general, unlike the combined approach, the individual selection of parameters and their number tends to require less complex models and smaller number of analyses. On the other hand, there are situations in which interrelation of parameters can yield higher correlation to the wear dynamics than is the case with the individual approach.

3 Development of a laboratory system for tool wear monitoring

Current experience with the development of various AI-based models of tool wear monitoring was used in the development of the new model proposed in this paper. Analysis of the existing models yielded advantages and disadvantages of particular approaches which was valuable in the development process of the novel model. Bearing in mind the previous discussion, the following requirements were imposed on the novel model:
– Use of sensors for measurement of vibration acceleration in order to efficiently detect dynamic characteristics of the cutting process and implement them into the proposed tool wear monitoring system.

– Use of novel AI techniques in the area of tool wear monitoring which are based on a-priori knowledge of tool wear condition.
– Definition of a satisfactory way to extract the input features vector through transformations in the time-frequency domain.

Based on the stated requirements, a novel model of the system for tool wear monitoring was designed (Fig. 1).

Essentially, the model consists of three modules combined into a unique system. The developed modules of the proposed laboratory system for tool wear monitoring are:
– module for data pre-processing,
– fuzzy classification module,
– decision module.

The sensor part of the data pre-processing module consists of accelerometer for the measurement of vibration acceleration which is positioned at the tool handle. Also belonging to the pre-processing module is the A/D card, NI USB 6281 18 bit, 625 kS/s, which receives analogue data from the sensor, converts them into digital format, and sends them to the measurement database on a PC. MATLAB was also used to control the card operation. The system allows selection of the sampling speed, as well as the other data acquisition parameters.

3.1 Modules for data pre-processing and fuzzy classification

The structure of the module for pre-processing of data allows realization of three basic tasks, as shown in Fig. 2. During data acquisition task, data are collected from the sensors and filtering band is selected. The proposed system uses the flat frequency response Butterworth filter to filter various types of noises present in the measurement signal.

The second task is feature extraction. The basic goal of feature extraction is to significantly reduce the dimensions of raw data collected from the sensors in the time and frequency domain, while at the same time preserving the data relevant for tool wear condition. Spectrogram matrix S, of the signal $s(n)$, is composed of the columns which represent the square of the modules of discrete Fourier transformation (DFT) of the sampled signal $s(n)$. Major spectrogram parameters are shape and length, as well as the degree of superposition between two neighbouring window functions $w(n)$. Averaging of all column values from the spectrogram matrix S, yields the assessment of the signal spectral power. Since, based on conducted analyses, it was established that the signal spectral power alone is insufficient to allow discrimination of features, the spectrogram was normalized by subtracting the approximation of the signal spectral power from each column of matrix S. Once normalization is performed, the following steps are executed:
– extraction of certain spectrogram ranges (~10 kHz to ~45 kHz),

- spectrogram is treated as a two-dimensional signal,
- selected filters from the LM bank of filters are applied,
- statistical parameters are calculated based on the data extracted by filtering,
- features are formed and subsequently used for classification in the next step.
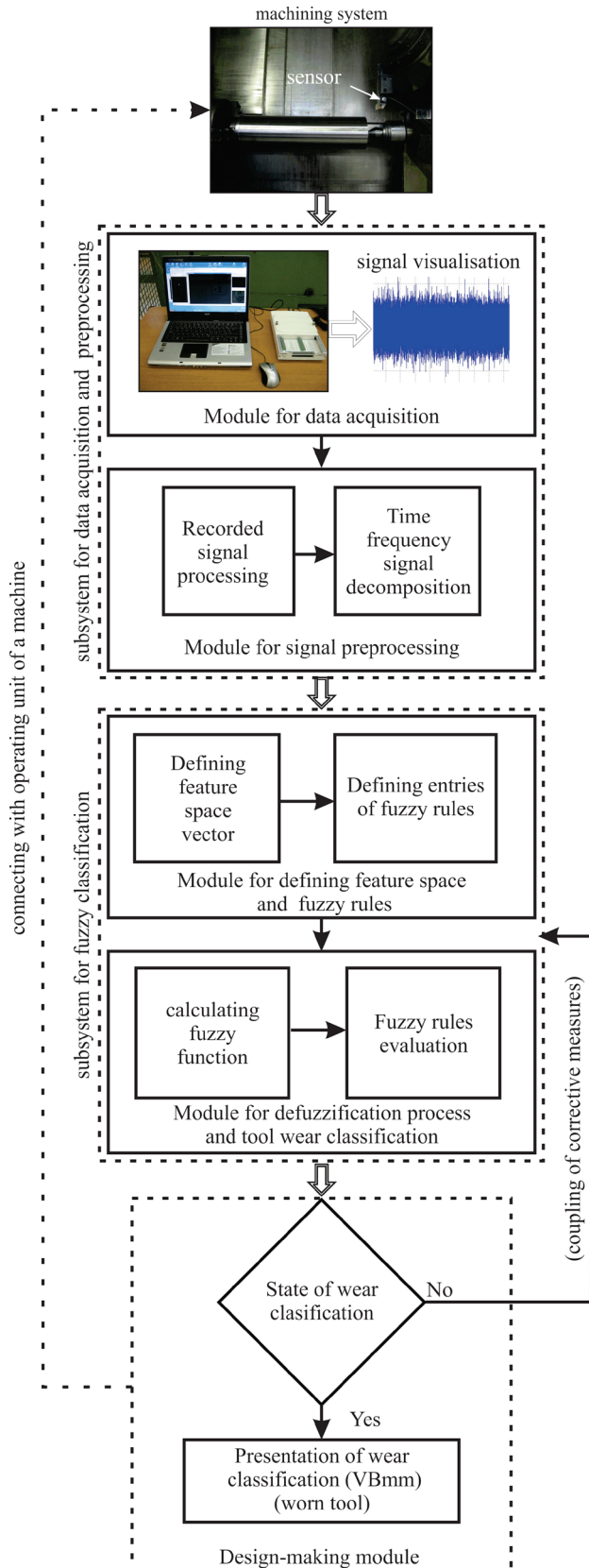
machining system

Figure 1 Structure of the developed system for tool wear classification

Basically, maximum number of features should be used to train the classifier. However, this is not always the best approach, since some features with less discriminative power can impact the performance of the training set. In order to improve accuracy and efficiency of classification and diminish hardware requirements, the final number of significant features is carefully considered and defined within the third segment of the pre-processing module.
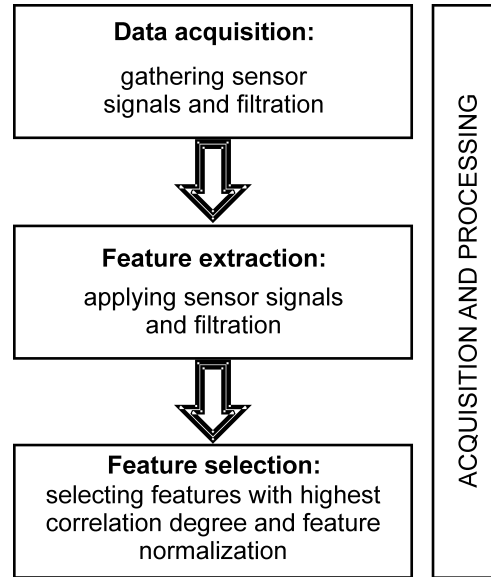

Figure 2 The pre-processing module

Within the investigation aimed at filtering and calculation of vibration signal spectrum, "Leung-Malik" (LM) set of filters was used as a multi-scalar and multi-oriented bank with 48 filters. Complete LM set consists of the first and second derivatives of the Gauss function, in 6 orientations and 3 scales with a total of 36 filters, 8 filters derived using Laplace operator on a two-dimensional Gauss function, and 4 shape filters in the form of Gauss function. Images of the applied vertically oriented filters, sorted scale-wise, are shown in Fig. 3.
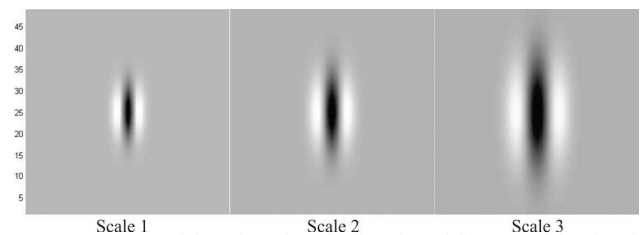

Figure 3 Images of the selected vertically oriented filters used for signal processing during feature extraction
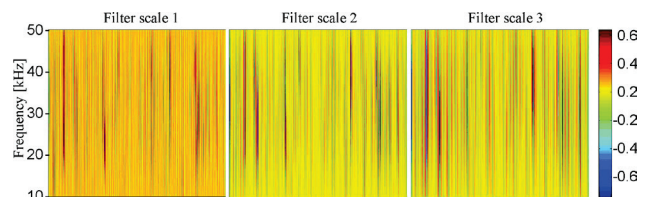

Figure 4 Spectrum segments separated by scales and filtered by LM filter (window 256 and 3/4 overlap)

The selected filters with vertical orientation at particular scales, were applied to the high-frequency part of spectrum of the recorded vibration signal. The resulting

filtered spectrograms are shown in Fig. 4. This figure shows the variation of signal spectrogram at particular scales, after the application of LM filters for feature extraction.

3.2 Defining the input feature vector

Based on the analyzed feature extraction methods reviewed in literature, following statistical parameters were selected for input feature vector: mean, variance, skewness and kurtosis, also known as the measures of central tendency. In probability theory and statistics, the kth moment of mean (or the kth central moment) of the real random variable X is $\mu(X)_k = E(X - E(X))^k$, where E is the expectancy operator. For a continuous, univariate probability distribution with the probability density function of $f(x)$, the mean moment μ, is given by (2):

$$\mu(X)_k = E\left\{\left[X - E(X)\right]^k\right\} = \int_{-\infty}^{+\infty} (x - \mu)^k f(x)\,\mathrm{d}x. \qquad (2)$$

Since the distribution function is not known, the expected value is derived as estimation of (3) and (4), where:

$$\hat{E}(x) = \frac{1}{N} \sum_{i=1}^{N} x_i = \mu, \qquad (3)$$

$$\hat{\mu}(X)_k = \hat{E}\left(X - \hat{E}(X)\right)^k = \frac{1}{N} \sum_{i=1}^{N} \left(x_i - \frac{1}{N} \sum_{i=1}^{N} x_i \right)^k. \qquad (4)$$

The moment of the generated function of random variable X can be written as (5):

$$M(t) = M_X(t) = E\left(e^{tX}\right) \qquad (5)$$

where t is a real number, and $M_X(t) = 1 + tX + t^2 X^2/2! + t^3 X^3/3! + \ldots$ if $\mu n = E(Xn)$ n-th moment of X, then the expected value is (6):

$$M(t) = 1 + E(X)t + \frac{E(X^2)t^2}{2!} + \ldots + \frac{E(X^n)t^n}{n!} + \ldots +. \qquad (6)$$

Since the coefficient tn in the Taylor order $Mn(0)/n!$, where Mn is the n-th derivative of M, then $\mu n = Mn(0)$. The characteristic function is approximated using the moments, which are represented by input feature vectors for the fuzzy classifier. The distribution is derived based on the first four moments at different scales of the frequency spectrum, applying the DFT.

Table 1 Segment of calculated central moments at particular scales, for cutting inserts at various stages of wear

Central moments	Fresh cutting insert	Flank wear width 0,25 mm	Flank wear width 0,55 mm	Completely degraded tool
Scale I				
1. c.m. mean	−0,137948	−0,124728	−0,114365	−0,125417
2. c.m. variance	4,330044	1,615277	0,594966	1,001746
3. c.m. skewness	−1,477805	−0,968251	−0,414221	−1,216634
4. c.m. kurtosis	0,113820	0,0648663	0,045874	0,125414
Scale II				
1. c.m. mean	−0,223837	−0,187959	−0,163723	−0,186785
2. c.m. variance	3,065497	1,239542	0,369396	0,633905
3. c.m. skewness	−1,172901	−0,773771	−0,482947	−1,060141
4. c.m. kurtosis	0,082590	0,052103	0,045751	0,086592
Scale III				
1. c.m. mean	−0,303524	−0,239589	−0,208368	−0,243573
2. c.m. variance	1,568939	0,754010	0,179956	0,337788
3. c.m. skewnes	−1,070404	−0,636266	−0,575057	−1,133315
4. c.m. kurtosis	0,067576	0,046091	0,045890	0,078246

From the results shown in Tab. 1 there follows that the central moments are directed. The directedness of the central moments at particular scales was considered from the aspect of the frequency with which the chip lamellae were generated during machining with cutting inserts of various wear degree [12]. The exception is the deviation of directedness in the case of tool insert with the highest degradation of cutting geometry. This can be explained by the fact that this insert was fully degraded which resulted in the complete change of the type of chip segmentation, leading to the change of the vibration signal spectrum.

3.3 Module for tool wear classification

Feature recognition using analytical functions consists of two well defined stages: the stage of transduction and stage of classification. Let Ω be a set of physical objects, i.e., objects and processes. These objects can be characterized using a finite set of parameters, relevant for the classification task. Each of the parameters, or a pair of them, represents the specific features of the object $q \in \Omega$. Each object parameter can be measured using some measuring procedure. It is also possible to measure certain features, after applying arbitrarily complex measuring procedures, m, which is related to those features. In this way, object q can be related to mathematical object $x = M(q) = m_1(q), \ldots, m_i(q) \in X$, where $m_i(q)$ denotes the value of ith feature. Both the feature of object q and the corresponding set X are connected into the mathematical form of all objects. Such mathematically generated objects x, are called samples.

The second stage of feature recognition is the classification of sample vectors. Classification means that a given mathematical object x can be assigned to a class of similar or partially similar objects. Thus, within a rigid system of feature recognition, the value of membership

equals zero or one, $\mu(x)$, while the fuzzy feature recognition assigns membership values between zero and one to each sample within the membership function $\mu F(x)$. Accordingly, in fuzzy feature recognition, the classes of similar objects are represented by a fuzzy set $\widetilde{F}$ ($\widetilde{F}$ is class designation). Assessment of class membership for object x is the degree of its similarity to the class representative object. The best-know standard algorithm to apply to this problem is *Fuzzy c-mean* (FCM) algorithm, which is why it was also used in the case of tool wear identification. The algorithm was applied using MATLAB numerical computing environment, using the following optimization model (7):

$$\min_{\{U,V\}}\left\{ J_m(U,V,w) = \sum_{i=1}^{c}\sum_{k=1}^{n} u_{ik}^m D_{ik}^2 + \sum_{i=1}^{c} w_i \sum_{k=1}^{n}\left(1-u_{ik}\right)^m \right\} \qquad (7)$$

where:

$V = \left\{ v_1, v_2 ... v_c \right\} \subset R^{cp}$ is prototype vector, $v_i \in R^p$ - point of ith prototype.

4   Verification of model

To verify the proposed model, experimental data were divided into two sets, the training set containing about 3/4 of experimental data, and a test set containing the remaining 1/4 of data. All data were collected during the same series of experimental investigations. Data sets were carefully organized so that each contained the data from all combinations of cutting parameters.
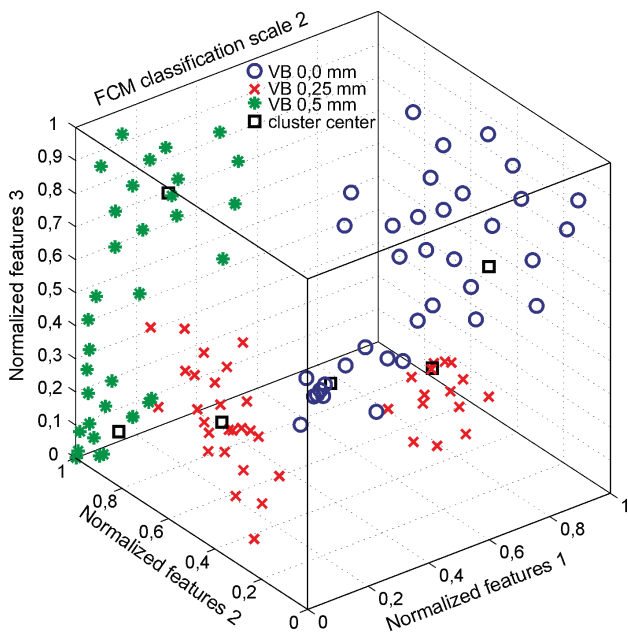

Figure 5 Classification of the training set for features variance, skewness and kurtosis, classified using FCM algorithm at the second scale

The selected FCM classification method was used to classify the extracted features into clusters, based on their classification matrix. Upon feature extraction, the next step is to group input data into a-priori groups. This classification, i.e., definition of feature groups, is simultaneously performed in three dimensions, defined by the three vectors, i.e., three central moments: variance,

skewness and kurtosis. The analyses showed that, for the selected method of feature extraction, their combined correlation yields best features. Classification model was verified using a training feature set by defining six cluster centroids, one for each wear group at three different scales.

Shown in Fig. 5 are the results of classification using FCM algorithm at the second scale with the mutual relationship for the three features. Defined for each scale are the mutual relationships between the features, which are defined by input feature vectors.
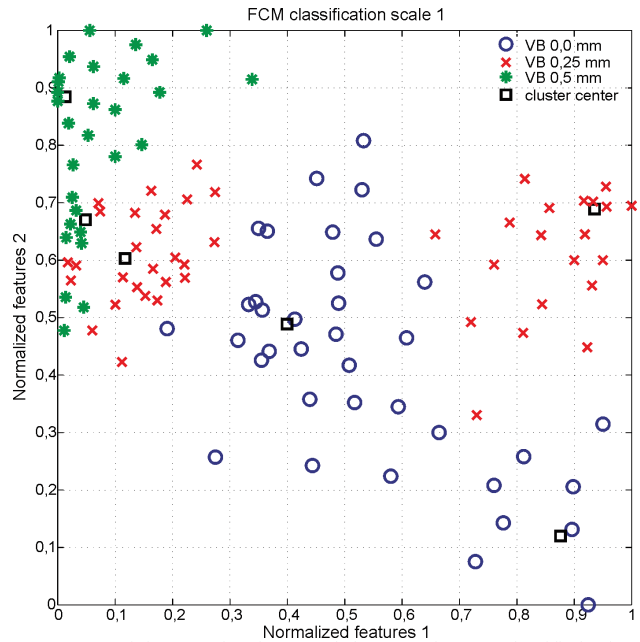

Figure 6 Training set of variance and skewness features classified using FCM algorithm at the first scale and longitudinal machining
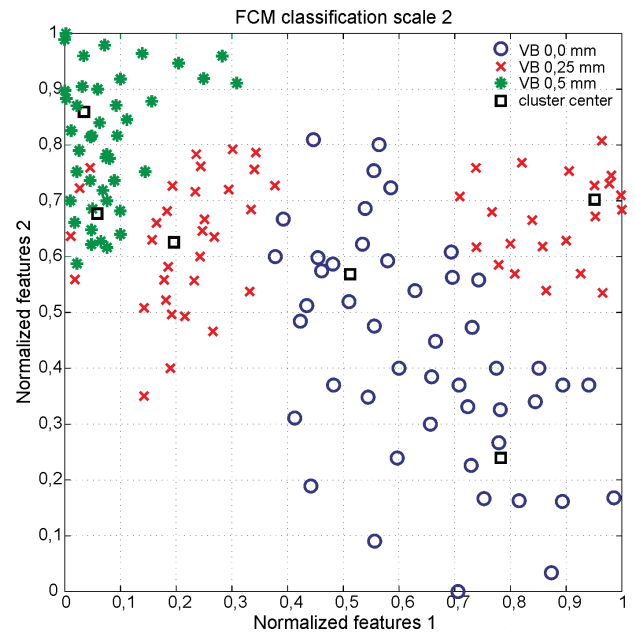

Figure 7 Training set of variance and skewness features classified using FCM algorithm at the second scale and a longitudinal machining

In order to better assess the mutual influence of certain features and the disposition of the elements of the training set, Figs. 6 to 8 show the mutual influence of normalized feature 1 (variance) and normalized feature 2 (skewness). Shown in Fig. 6 is the disposition of the

training set elements at the first scale, within the normalized space variance - skewness. Figs. 7 and 8 show the same normalized space at scales two and three.
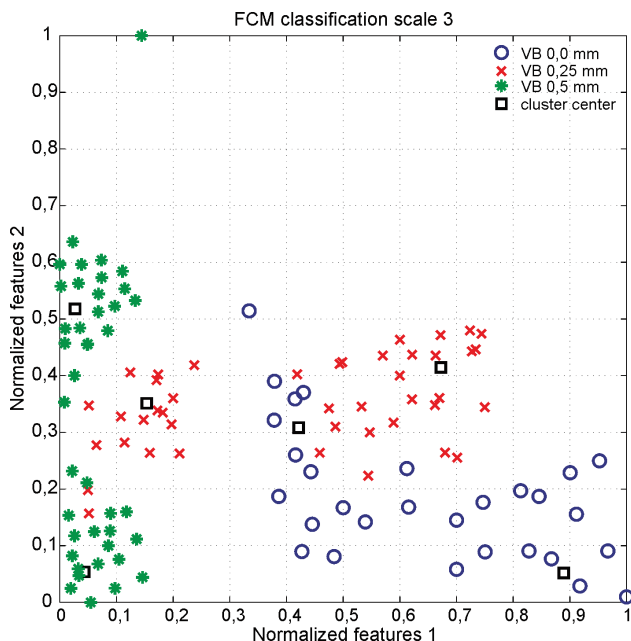

Figure 8 Training set of variance and skewness features classified using FCM algorithm at the third scale and a longitudinal machining
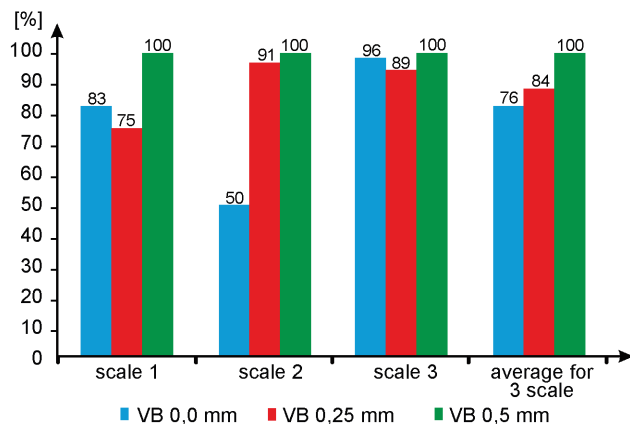

Figure 9 Statistical results of feature classification obtained for the test set using the proposed laboratory feature recognition system in longitudinal machining

Shown in Fig. 9 are statistical results of classification, obtained with the test set. Judging by the presented results, it is possible to conclude that the third scale yields the best classification results. This can be explained by the fact that the third scale pertains to the widest frequency range of the recorded signal, since it is least burdened with signal noise. At lower frequencies, the signal suffers from external noises, such as the vibrations of the machining system, etc. The results shown in Fig. 9 indicate that the application of the proposed model of classifier allows satisfactory accuracy of tool wear assessment.

5   Conclusion

The results presented in this paper confirm the assumption that the proposed model of feature classifier can obtain the required accuracy during wear monitoring of the longitudinal cutting tool. Moreover, the results

reveal that the proposed method of classification requires a training set which consists of a larger number of quality input vectors. Also, an important prerequisite for accurate classification is to apply a larger number of combinations between cutting parameters during initialization, i.e., during training of the feature recognition system.

6   References

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