A Module for Feature Extraction in Process Tool Wear Recognition

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Abstract: The paper presents a model of the developed fuzzy system for tool wear classification. The system comprises of three modules: module for data acquisition and processing, module for tool wear classification, and module for decision-making. In this work, Short Term Discrete Fourier Transform (STDFT) spectra obtained from the particular vibration sensors signal utterance, as the 2D textured image. The selected method for feature extraction is presented within the module for data classification and processing.

Key words: tool wear, feature extraction, signal processing

1. INTRODUCTION

With the development in information technologies and signal processing technologies, a wide specter of online sensors has been incorporated in order to receive information relevant for tool condition. Likewise, the obtained information is more and more significant for process control. The signals obtained from diverse sensors have to be transformed into data containing relevant information on the fundamental processes. A large amount of data acquired from multi-sensor systems enables the extraction of diverse features, creating in that manner enough diverse features that are to be used with the purpose of tool condition classification in tool monitoring systems.

The development of the monitoring systems that operate in a real time provides the basis for tool condition monitoring in the contemporary automated manufacturing. Qualitative information on the degree of tool wear in the real time presents a necessary requirement for tool durability identification. The acquisition and selection of significant information from a process, by applying the adequate sensors, significantly increases the quality and productivity of the machining process. Apart from a positive influence on the stability of the machining process and the quality of the processed workpiece, this method of processing provides a higher degree of productivity and the maximal tool usability in the sense of a working cycle.

The conventional methods in cutting tool wear monitoring are based on well-known physical principles, as well as the visual, auditory and intellectual abilities of the operator, which are utilized in order to recognize tool wearing. Contemporary intelligent systems for cutting tool wear monitoring are supposed to employ their characteristics to replace and upgrade human drawbacks and provide possibilities in the sense of a continual, fast and precise determination of tool wear condition, leading to the following:

- Increasing the degree of the process system stability, which is especially evident in the situations of the high degree of wearing and tool breakage;
- Optimization of the processing parameters related to the demanded tool durability, with the considerations of technological process limitations;
- Quality control of the processed surface and demanded dimensional accuracy of the workpiece; and
- Additional rationalization of the production costs.

More intensive research related to the development of “intelligent” systems for cutting tool monitoring began in the 1990s by applying the multi-sensor approach, i.e. wearing classifiers based on the artificial intelligence algorithms. The beginning of the research in the area assumed that the application of these methods should result in the industrially applicable solutions for cutting tool wear monitoring.

2. APPLICATION OF FUZZY SYSTEMS IN TOOL WEAR MONITORING

The combination of diverse signal analyses, several sensor technologies, and artificial intelligence algorithms, based on the fuzzy logic, leads towards the solution that will be able to answer the demands of high performances and provide an adequate solution for tool wear monitoring [1, 2]. Fuzzy decision-making is a process of making decisions from a set of insufficiently precise premises. In the last years, most researchers have used fuzzy decision-making systems for tool wear classifications. One of the attempts is presented by Sharma et al. [3] by applying the fuzzy system for tool wear estimation. The defined decision-making rules form a base used for making decisions. The process of fuzzy decision-making includes the membership functions, fuzzy logic operators and if-then rules. The membership function is a curve defining the manner each point in the input information field is positioned in relation to the membership value (or membership degree) between 0 and 1. If the given variable is more susceptible to noise, then its observation field is larger, as well as the membership function width.

3. SOLUTION FOR FEATURE EXTRACTION

On analyzing the diverse presented models, advantages and drawbacks of individual models have been observed, and therefore considered in developing a new model. Having in mind the observed models, the following demands have been set for the development of a new laboratory system:

- Application of the sensor for vibration acceleration measurement in order to detect the dynamic properties of the cutting process better, as well as their implementation into the monitoring system.
- Usage of new artificial intelligence algorithms in the
field of tool wear monitoring based on the application of the a priori knowledge on the tool wear condition.

- Finding the adequate methods for input characteristic vector extraction by applying transformations in the time-frequency domain.

Feature extraction is based, according to the authors' knowledge, on a completely new approach comprising the application of the short-time discrete Fourier transform (STFT) over the specter of a determined vibration signal, which is observed as a 2D "image" texture. Time scale is identified as the first dimension, while frequency scale is the second dimension. The intention is to utilize the influence of differences in the structure of the set segment textures onto the class discrimination of tool wear conditions. Possible changes can occur in the texture shape and properties on certain image segments, yet at the same time with a significantly small number of parameters, in order to obtain the description robustness of the observed processes. The hypothesis, which is experimentally confirmed, is that the dominant physical process of the tool wear condition change is closely related to the structure of the obtained 2D texture after the signal processing by applying the developed method. Based on the above, the application of certain filter banks is proposed, which is widely used in texture recognition problems in order to efficiently extract information in the form of robust features.

The proposed feature selection is based on using the Least Absolute Shrinkage and Selection Operator (LASSO) regression method, proposed by Tibshirani [4], which is widely used in the feature selection tasks [5]. This method finds the optimal features related to the observed data set in order to obtain compromises between the representation error (e.g. square error) and the numbers that are not zero coefficients yet match the most significant functions, which in our case are mostly discriminative. Feature set becomes more robust, even in the case of a limited training data set, based on the conducted experiments.

A majority of features obtained using the 2D method, out of the total number of features selected by the Lasso regression, prove the significance and the robustness of the extracted 2D features in the developed tool wear monitoring systems.

Let $F(x,y)$ be the image texture matching the identified spectrogram STDFT of the observed sensor signal $s$, where the STDFT is the spectrogram $S(k,\omega)$ defined as:

$$S(k,\omega) = \sum_{n=-K/2}^{K/2} s(n)w(k-n)e^{-j\omega n}$$

where $k$ is a discrete time frame, $\omega$ is a discrete time frequency, i.e., discrete frequency of the covered zones, while $w$ is a window sequence used (Hamming function is utilized), with the length $K$. The discrete time window $k$, for $k = 0, \ldots, K_{\max}$ is identified as the $x$ axis of the image texture, so that $x_{\max} = k_{\max}$. Likewise, $\omega$, for $\omega = 0, \ldots, \omega_{\max}$ is identified as the $y$ axis, hence $y_{\max} = \omega_{\max}$.

Now, the following stands:

$$F(x,y) = |S(k,\omega)|^2$$

for $x = 0, \ldots, x_{\max}$, $y = 0, \ldots, y_{\max}$, $k = 0, \ldots, k_{\max}$, $\omega = 0, \ldots, \omega_{\max}$.

All further analyses are conducted over the image texture $F(x,y)$, and are obtained from the above stated procedure; for the reason of simplicity, without the loss of generalization, the continual variables $x \in [0, x_{\max}]$ and $y \in [0, y_{\max}]$ are observed. Then,

$$G(\sigma_1, \sigma_2, \omega, x, y) = \frac{1}{2\pi\sigma_1\sigma_2} |2\pi\omega^2|^{|\sigma_1^2 + \sigma_2^2|} e^{-\frac{1}{2\pi\sigma_1^2 + \sigma_2^2} (\omega^2 - \pi^2)}$$

(3)

is directed towards the anisotropic Gauss core. The fixed values $\sigma_1 > 0$ and $\sigma_2 > 0$ determine the scale $x \in [0, x_{\max}]$, $y \in [0, y_{\max}]$ and the direction respectively, while $\theta$ and $A(\theta) = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix}$ for $\theta \in [0, 2\pi]$ determine the kernel orientation (3) and its 2D rotational matrix, respectively. A filter bank is obtained and applied over the certain image textures with the signal $F(x,y)$ defined in (2), using the Laplician kernel (3), i.e., bar detector, in several diverse scales $S_k = \{(\sigma_1, \sigma_2)\}_2 = 1, \ldots, R$. Only the changes of the vertical orientation of image texture are being considered, since those alterations bear the information content related to the discrimination in the classification task of interest. Namely, only $\theta = \pi/2$ is used, thus considering only the vertically oriented anisotropic core components (3), $[0, y_{\max}]$ is divided into 4 subintervals $\{(y_{i-1}, y_i)\}_2 = 1, \ldots, R$ in the fixed time frame $k$, and $\{(y_{i-1}, y_i)\}$, which correspond at appropriate frequencies $|S(k,\omega)|^2$. I-th band of the filter bank is equivalent to the interval $[y_{i-1}, y_i]$ and comprises $R$ vertical components and LM MR8 filter banks [LM], applied to three priori defined scales. An individual vector for a fixed time frame $k$ is obtained by applying the proposed filter banks on the k-th texton $F_k(x,y)$, $x \in [k, k+1]$ acquired from the image texture $F(x,y), x \in [0, x_{\max}]$ over the time frame $k$. Actually, for every $k$, new R components are added, each for a different scale, onto the previously processed vector. The components are calculated as follows:

$$v_{kli} = G(\sigma_1, \sigma_2, \pi/2, x, y) * F_k(x,y) \mid_{x=k,y=y_i}$$

(4)

for $i = 1, \ldots, R$.

Based on the above, a set of pre-processed features of the sub-vector $V_k = [v_{k1}, \ldots, v_{kR}]$ is obtained. From every extracted feature $u_k$, $u_k$ is selected, and the pre-processed vector $V_k = k = 1, \ldots, q_u$ is formed. Vector $V$ is in this case a random variable, hence $V^u$ are its realiztions for every time frame $k$. Further on, the compactification and robustification of features is conducted, by utilizing the representation via statistic moments, which presents a method to simultaneously conduct the reduction of the model dimensionality. A motive is a fact that a satisfactory number of moments (averaging per time) can be used to present the distribution $V$. Actually, it can be observed (considering the continual time $t$ instead of the discrete time frame $k$), that there is a unique correspondence between the distributions of probabilities $p_{u\theta}$ and $k_{u\theta}$, with the characteristic function being as follows:

$$k_{u\theta}(t) = E[e^{it\theta u}] = \sum_{\theta=0}^{\theta-1} \frac{(it)^{j}}{j!} E((V^u)^j)$$

(5)
4. VERIFICATION OF THE DEVELOPED MODEL

The verification of the proposed model was performed on experimental data divided into two groups – a training set containing approximately three quarters of experimental data, and a test set containing the remaining one quarter of data. All data were gathered during a series of experimental research. Data sets were carefully organized so that each contains data from all combinations of processing parameters and tool wear degrees.

The presented classification method utilized for the classification of the extracted features forms clusters on the basis of the classification matrix. After the feature extraction is performed using the presented method, the next step is to cluster the input data into apriori clusters. The classification, i.e. feature gathering, is performed simultaneously in three dimensions defined via three vectors, i.e. three central moments: variance, skewness and kurtosis. The analyses have shown that, for the selected feature extraction method, the combinations of their correlations provide the best results. The classification model is evaluated using the training function which is set by defining six cluster centers, one cluster centre for every wearing group in three diverse scales shown of figures 1, 2 and 3.

In order to estimate the successfulness of the classification, i.e. the number of successfully classified features in individual scales, a statistic validation of the representation of well classified features per scale has been conducted. Figure 4, 5 and 6 presents the percentage of the representation of successfully classified features per individual scales by applying the algorithm, in relation to the apriori classification for individual cutting tool wearing conditions.

From the Figures, it can be observed a somewhat lower percentage of the accurately classified features for the tool from the second group in the first scale. On Figures is shows, spindle speed, feed rate and cutting depth combination. However, for other scales, it can be noted that the percentage of the representations of successfully classified features is significantly increased; hence the average percentage value can be considered to be satisfactory.
Fig. 4. Presents the percentage of the representation of successfully classified features, \( v=180 \text{m/min}, \ f=0.2 \text{mm/rev}, \ a=1.5 \text{mm} \)

Fig. 5. Presents the percentage of the representation of successfully classified features, \( v=200 \text{m/min}, \ f=0.2 \text{mm/rev}, \ a=1.5 \text{mm} \)

Fig. 6. Presents the percentage of the representation of successfully classified features, \( v=220 \text{m/min}, \ f=0.25 \text{mm/rev}, \ a=2 \text{mm} \)

5. CONCLUSION

This approach uses the robust method to classify the tool wear condition. The experiment results demonstrate that this approach surpasses the standard methods in tool condition monitoring. Furthermore, the proposed procedure can also be utilized in condition estimation of other machining processes, such as drilling and milling. As a drawback in using the method, one could state a demand for high performances of a computer system in the training stage. In the future, certain improvements are to be conducted in increasing the feature extraction performances and model flexibility. The experiments conducted on the real TCM system, show that the proposed descriptors, together with the fuzzy classifiers provide very high recognition accuracy in the tool wear state recognition task, making it suitable for application in efficient TCM systems. Likewise, the procedure of feature extraction from wavelet and time domains can contribute to a better overview of the dynamics of the tool cutting geometry degradation, i.e. the tool wear process and the increase in resolutions.

REFERENCES


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