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ORIGINAL ARTICLE

Application of audible sound signals for tool wear monitoring using machine learning techniques in end milling

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Abstract

Due to the demands of Computer-Integrated Manufacturing (CIM), the Tool Condition Monitoring (TCM) system, as a major component of CIM, is essential to improve the production quality, optimize the labor and maintenance costs, and minimize the manufacturing loses with the increase in productivity. To look for a reliable, efficient, and cost-effective solution, various monitoring systems employing different types of sensing techniques have been developed to detect the tool conditions as well as to monitor the abnormal cutting states. This paper explores the use of audible sound signals as sensing approach to detect the cutting tool wear and failure during end milling operation by using the Support Vector Machine (SVM) learning model as a decision-making algorithm. In this study, sound signals collected during the machining process are analyzed through frequency domain to extract signal features that correlate actual cutting phenomenon. The SVM method seeks to provide a linguistic model for tool wear estimation from the knowledge embedded in this machine learning approach. The performance evaluation results of the proposed algorithm have shown accurate predictions in detecting tool wear under various cutting conditions with rapid response rate, which provides the good solution for in-process TCM. In addition, the proposed monitoring system trained with sufficient signals collected from different positions has been proved to be position independent to monitor the tool wear conditions.

Keywords Tool condition monitoring · Tool wear · Audible sound · Machine learning · Support vector machine

1 Introduction

The application of intelligent manufacturing systems in the machining industry has been significantly increased with the profound technology advancements in the manufacturing industry. In the present scenario, industry tool changing procedures are based on a conservative tool life estimation where the theoretical value of tool life is not considered [1], thereby resulting in avoidable changes in time and cost losses. The cutting tool life is a function of wear progression as the wear rate increases and reaches to failure thereby deciding the tool life period. Tool wear is defined as the gradual change in shape of the cutting edge during the machining process. The excessive tool wear may cause catastrophic tool breakage and failure, which can lead to the loss of productivity, the rejection of parts, and consequential economic loses. Thus, an effective TCM is a vital demand to increase productivity and hence competitiveness by maximizing tool life, minimizing downtime, reducing scrappage, and preventing damage.

Tool wear is a critical indicator describing the gradual failure of cutting tools, which is caused by a combination of various thermos-mechanical mechanisms. The excessive tool wear results in increased tool interface temperatures, inefficient chip formation and flow, unacceptable machining surface finish quality, and shorter tool life. Generally, tools experience three stages of wear: break-in, steady state, and failure. Break-in is a stage where the first few minutes of use as cutting shape is established, whereas in steady state the cut quality gradually deteriorates with use, and finally, the failure stage is a rapid deterioration that occurs as the tool reaches the end of its useful life. It has been realized that crater wear, flank wear, built-up edge, chipping, and breakage are the main modes of tool wear [2], which are identified by their locations and geometry. These types of wear affects the dimensional

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accuracy, surface quality of the finished component and even process stability will be deteriorated. Therefore, tool wear must be controlled and should be kept within the desired limits for any machining process. For any machining system, reliable wear data can be used not only for scheduling tool changes more efficiently but also for adaptive process control and optimization.

Tool wear monitoring is a difficult task because many machining processes are nonlinear time-variant systems, which makes them difficult to model and it is extremely hard to measure the tool wear directly during the cutting process. Tool condition monitoring has been extensively studied by many researchers since the late 1980s to implement different types of monitoring systems to detect the tool wear and failure in advance to the occurrence of the actual event [3–5] by adopting different sensor functions to collect information. However, these attempts involving various sensing methodologies have different degrees of success in practical applications, and it has also been reported that utilization of insufficient reliability sensing methods under varying cutting conditions limits the practical application of such systems. Therefore, developing an automated tool monitoring system is a process-orientated problem where the selections of the sensory system and modeling approach are closely related to different types of practical applications. Typically, the major functions of the tool wear monitoring system include signal acquisition, signal pre-processing and feature extraction, and decision-making [6].

Typically, various measuring techniques are categorized into direct and indirect approaches, based on the method of measurement technique and complexity of the machining process [7]. The direct approaches consist of visual inspection, radioactive isotopes, laser beams, and electrical resistance. These approaches involve measurement of the corresponding process variables through analysis by interrupting the process. Thus, these systems are confined to laboratory techniques and the processes are complex enough for usage in industrial applications. But, these approaches are considered to have a higher degree of accuracy and applied in research labs to study the fundamental measurable phenomena behind the cutting process.

The indirect approaches consist of systems that are flexible and dependent upon secondary process parameters of the machining process. These process parameters are found to be optimal for correlating the tool condition and especially in the application for in-process TCM systems [8]. Usually, these approaches include dynamometers, accelerometers, current sensors, and acoustic emission (AE) sensors and sound monitoring microphones. The dynamometer is based on the measurement of cutting forces during the machining process, and it was found to be the most reliable approach to monitor the tool condition [9]. This approach is focused on cutting forces, which are considered sensitive to the frictional force that changes with the increase of wear on the cutting tool thereby resulting in increased cutting force. However, this approach has its limitations in correlating the cutting tool conditions within a restricted frequency range [7, 10, 11]. Besides, the high setup cost also restricts the wide application of this sensor. Vibration monitoring is an approach based on the variation in vibration amplitude concerning the progressive flank wear during the machining process. This approach is mainly seen in monitoring the surface roughness [8, 11], which has shown a great potential in the tool condition monitoring field [10, 12, 13, and]. But, by comparing with other indirect sensors, this approach has found to be highly sensitive to the sensor position and the machine speed range [14]. Current measurement is another indirect approach commonly found in the development of monitoring systems in the machining field. This method is based on the principle proportionality between the torque of DC motor in machine tool and cutting forces developed during machining. Although many studies [15, 16] have been performed to apply TCM systems, this approach has its own significant limitation in collected information accuracy as the system is not suitable for accurate sensing due to its relatively low sensitivity. Acoustic emission is another prominent indirect approach based on measuring the characteristics of acoustic (elastic) waves developed in solids during the machining process. This method was found to be one of the most intense research focused area in the development of monitoring systems for the machining field due to the high sensitivity to cutting tool wear and failure coupled with signals' high response rate [17]. Studies conducted in the past pointed out acoustic emissions during the metal cutting process could be generated from various sources which exhibit different signal characteristics since the mechanisms by which AE is produced in these occasions are fundamentally different [18, 19]. Although some research works have recommended the use of AE sensors instead of dynamometers for tool wear diagnosis [20], other researchers argue that the use of AE sensors as an indicator of tool wear is inappropriate because they are more sensitive to noise and variations in cutting conditions than to the condition of the tool itself [21].

Audible sound monitoring is another indirect approach in developing TCM systems for the machining process by analyzing audio waves generated during the machining process. One of the earliest works conducted based on this measuring technique was performed by Weller [22] to correlate the features of audio signals with tool conditions from good to the failure state. In the following study conducted by Delio et al. [23], chatter in the drilling process has been studied using audio signals. In addition to the above correlation studies, there has been considerable research conducted based on audio signals with the application of advanced analyzing techniques for better correlation accuracy. Advance analyzing techniques like Singular Spectrum Analysis (SSA) and Singular Value Decomposition (SVD) analysis have been applied in several studies to extract the information regarding tool conditions [24, 25]. Sound monitoring approach has also been studied in a sensor fusion approach for a better correlation between the tool condition and acquired information. For example, a study conducted by Tangjitsitcharoen et al. [26] involves a combination of cutting force, vibration, and acoustic emission measurements coupled with sound measurement to investigate the correlation between acquired information and tool wear. Although these studies using audible sound signals have shown significant monitoring accuracy, there have been other studies [27, 28] that concluded that the application of this method in the industrial floor is impractical due to high ambient noises.

Besides the various approaches with a single sensor mentioned above, the sensory fusion approach which combines two or more types of sensors can predict the tool state more accurately by more obtained features. The success of sensor fusion depends on which types of signals are good candidates for a given machining outcome and which extracted features and in which way they must be complemented [29]. This type of systems involves a complex setup and requires huge investments in installing and maintenance.

In a literature review conducted above for various sensing approaches for TCM, the audible sound monitoring approach seems most practical to be applied to an in-process TCM system. The prime nature of this approach has been used by experienced machinists on the shop floor to determine the tool conditions. The principle benefits of this approach compared to others are the compactness of setup and the non-intrusive nature which are the primarily focused features for any in-process monitoring systems. Even though the limitations of this approach implicitly state that the accuracy of information collected is relatively low, with the application of advanced analyzing techniques and decision-making models, the accuracy of this method can be improved dramatically. Anderson [28] has patented a method for an in-process monitoring system that can be practical on the industrial floor, in which, he considered audible sound monitoring with a novel methodology to determine the tool conditions based on frequency bands.

Signal pre-processing and feature generation module is an important stage before analyzing the correlation of tool condition with the sensing method. This process involves extracting the features that correlate best with the actual tool conditions, and there have been various techniques and methods considered in the past for this process [6]. In this study, frequency domain analysis as a feature generation module was used to extract required features.

For the TCM system, the decision-making is a critical function that involves monitoring tool condition with the help of features developed from the signal processing scheme. Generally, the signals generated from the sensing methods are nonlinear in relation with the tool condition [18]. Thus, an effective model is required to correlate these types of nonlinearity relationships, which typically involves complex mathematical techniques. Commonly used decision-making models in TCM systems are fuzzy classifiers and neural networks [30]. However, these methods have limitations, which requires complex data for the better correlation between tool conditions and collected signals.

In the past decade, there have been many studies involving the development of TCM systems with the application of advanced techniques that have been evolved recently in the field of machine learning. This type of technique observes the nonlinear correlation based on the patterns in data, through which develops a mathematical model and iterates the process for better correlation until the model predicts correlation with high possible accuracy. Application of these techniques has shown promising results in process monitoring of machining systems through both direct and indirect sensing approaches.

A study which belonged to the above stated advanced techniques [31] presented a hybrid SVM-Bayesian Network (BN) for predicting the thermal error. This study is based on nonlinear deformation of the machine tool resulted from the flow of heat through the machine structure which is caused by varying temperatures in a machine environment. The proposed decision-making model provides a more generalized prediction model than the conventional method of directly mapping error and temperature irrespective of operating conditions. In other researches carried out as in [32, 33], tool wear has been classified using SVM based on manufacturing considerations and proposed a new performance evaluation function for TCM. With this approach, a tool is replaced or continued not only based on the tool condition alone but also the risk of the cost incurred due to the underutilized or overused tool.

Apparently, it is evident from past studies that the applications of machine learning techniques in TCM are less explored. In consideration of audible sound monitoring as a sensory approach for compact setup and best cost/benefit ratio, there have been very limited applications of machine learning techniques as a decision-making model for the TCM system. In general, noise as the major influential disadvantage of sound monitoring in machining applications has made this type of TCM system to be less studied in the past. However, this disadvantage can be overcome by using machine learning techniques, such as the SVM approach. Meantime, considering the better generalization ability of SVM than Artificial Neural Networks (ANN) and other methods with a limited number of samples [34] and the difficulties to obtain sufficient machining data, SVM has many advantages for feature recognition in tool condition monitoring. With this approach, a tool needs to be replaced or continued not only based on the tool condition alone but also the risk of the cost incurred due to the underutilized or overused tool [29]. The robustness and complexity of the SVM classification concept would likely be an advantage in training and developing the system to be able to work effectively in the presence of noise.

This study mainly focuses on the development of an intelligent TCM system through audible sound monitoring approach in end milling using machine learning techniques, which is known to perform effectively in detecting tool wear and failure. To realize this objective, tool wear of end mill tools is classified into different classes in terms of flank wear thickness. A series of experiments are conducted using the six wear class tools under a wide range of cutting conditions (feed rate and cutting speed) for the end milling process. The emitted sound signals during each cut are collected and further analyzed by a developed TCM model using machine learning methods. The performance of the proposed algorithm is analyzed by evaluating the confusion matrix and another performance metrics.

One of the major challenges in the application of this type of sensory system is to position the sensor in a precise location for effective and reliable signal acquisition. In addition, the sensor would be susceptible to faults due to environmental conditions, such as coolant and chips, when the position is too close to the source of signals. In this study, the developed system is trained to be able to perform the wear monitoring irrespective of locations of the sensors. Furthermore, the variation of prediction accuracy with respect to a number of sensors is also investigated in this study.

2 Tool wear classification

Tool wear is a gradual process under severe shear and frictional forces during the cutting process. Per the standard ISO 8688 parts 1 and 2(ISO 1989), the flank wear observed on the clearance face of the end milling tool is the major tool wear pattern considered in this study. The measurements of flank wear are classified into three different types: uniform flank wear (VB1), non-uniform flank wear (VB2), and localized flank wear (VB3), as shown in Fig. 1. In this research work, the uniform flank wear has been found to be predominant in most of the observations.

In this study, the cutting tools used for experiments are uncoated high-speed steel end mill tools with two flutes and 3/8 in. in diameter. To characterize the tool wear, the cutting tool conditions were classified into six different classes with respect to various thickness ranges of flank wear lands on cutting edge of tools. Per the standard ISO 8688, the flank wear thickness was calculated by averaging different measurements within the cutting zone from the cutting edge tool corner to the distance of axial depth of cut on the cutting edge as shown in Fig. 2. For each test, the cutting tool was cleaned to remove dirt and chips before measuring the flank wear thickness. Table 1 summarizes the specification of each tool condition class according to the average flank wear thickness. The tool wear was observed using an optical microscope, and through which images of the wear regions were captured and displayed in Fig. 3.

3 Design of experiments

The experiments were conducted on a numerically controlled TRACK K3 EMX conventional milling machine under dry, end milling conditions. All the experimental runs were performed as side milling operations with up-milling (conventional milling) configuration. Workpiece used in this study is a 6061 aluminum bar with dimensions (6″ × 2″ × 1.25″) in

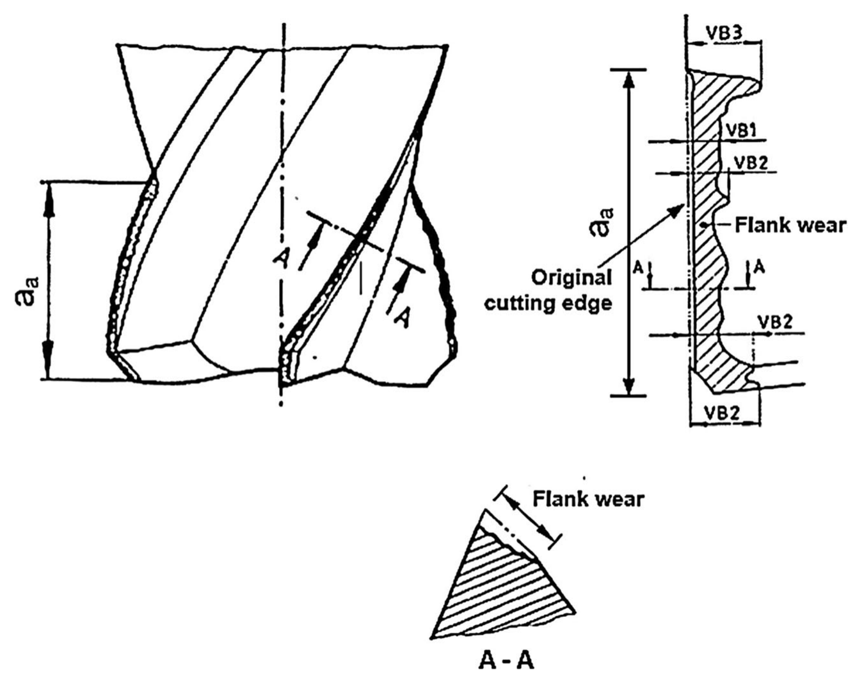

Fig. 1 Types of flank wear: *VB 1* uniform flank wear, *VB 2* non-uniform flank wear, *VB 3* localized flank wear (ISO 8688)

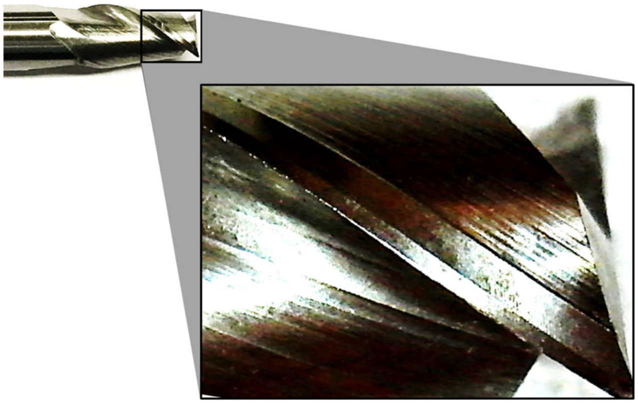

Fig. 2 Observed wear range on cutting edge

inches for all the experiments. For the sound signal collection, three professional EO-200 condenser microphones were positioned at 8, 12, and 15 in. away from the cutting zone in different angles as shown in Fig. 4. Microphones were connected through a multi-channel audio interface device (Steinberg UR44) which was further connected to a computer for sound signal acquisition. The whole experimental system is illustrated in Fig. 5.

To ensure the developed monitoring system can successfully detect the tool conditions irrespective of cutting conditions, in this study, cutting conditions were selected over a wide range of cutting speed and chip load within the capability of the milling machine. More specifically, for each tool condition class, five spindle speeds were chosen, and for each spindle, three different feed rates were selected to perform the experiments. Overall, 15 cutting cycles were performed for each tool condition class that totaled up to 90 cutting cycles for the whole experiment. Both the radial depth of cut (0.1875 in.) and the axial depth of cut (0.2 in.) were kept constant throughout all the experiments. The cutting tool was prepared for each wear class corresponding to the wear width assigned to the respective class. After each cut, the cutting tool was measured again to ensure the progression of wear within the specified wear thickness range. According to this method, advancement of wear width of the tool is avoided within the wear class.

Table 1 Tool wear classification

Serial no.	Tool condition class	Thickness range (μm)
1	Good	0–20
2	Light wear	20–40
3	Average	40–70
4	Advanced wear 1	70–100
5	Advanced wear 2	100–150
6	Failure	> 150

4 Diagnosis approach for TCM using SVM

The capability of the developed TCM system mainly depends upon three basic elements. Firstly, with the experimental methodology proposed in the previous sections, the dataset of audio signals, corresponding to six wear levels, was developed. Then, it was followed by a pre-processing step where collected audio signals were converted into samples and the samples were transformed into frequency domain using the Fast-Fourier Transformation (FFT) method, through which the features essential for the decision-making system were extracted. Finally, SVM was used as a decision-making model to correlate the characteristics of signals with the features of tool wear.

4.1 Audio signal collection

Audio signals for each cutting cycle have been collected through three microphones. The length of the signal was considered from the start of the actual material removing until the point where the cutting tool edge left the workpiece. The sound signals were collected with a sampling frequency of 44.1 kHz. As shown in Table 2, the sound signals collected for all the cutting cycles were labeled with corresponding wear classes and tabulated with different timestamps, different cutting conditions, and different positions. This table served as an input data recognition file for the algorithm. From this file, algorithm categorized every sound signal features into the corresponding wear class and other related conditions. In this study, a total of 270 samples of sound signals with corresponding experimental data have been collected and utilized for the development of the proposed tool wear prediction model.

4.2 Pre-processing of sound signal

The collected sound signals are transformed into a digital format which is non-stationary and often overlaps with other various sound sources, whose waveforms and arrival times are unknown. In general, TCM systems for machining applies signal processing as a pre-processing procedure to extract the physical parameters of interest that best correlate with the exact tool wear. Many signal processing methods have been proposed to extract the features from sound signals for monitoring systems [35]. In this study, the collected sound signals in time domain were cut into window length of 1 s as each sample to analyze the data in samples. In order to generate features through the frequency domain analysis technique, samples were processed through FFT algorithm based on Discrete-Time Fourier Transformation (DTFT). For this study, an only absolute value of Fourier transformation was extracted as features, and these features serve as inputs to the proposed decision-making model. In order to overcome the preset

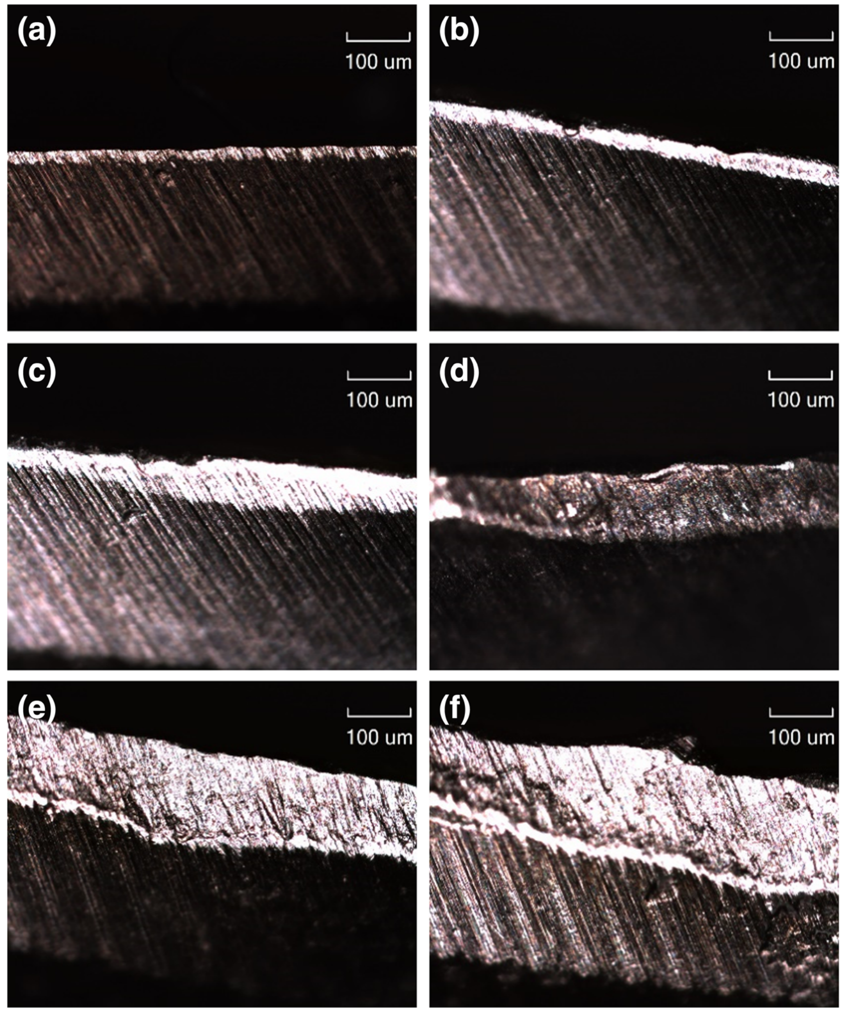

Fig. 3 Exemplary tool wear classes: **a** good, **b** light wear, **c** average wear, **d** advanced wear 1, **e** advanced wear 2, and **f** failure

resolution problem of the DTFT, the Wavelet Transform (WT) will be used in the future studies.

Figure 6 shows frequency spectrums of the sound signals that belong to same cutting conditions for six tool wear levels. The frequency scale of the spectrum was plotted in logarithmic scale to focus on the low-frequency range where the signals retain more tool wear information. From the figures, it is evident that the amplitudes of multiple frequencies constitute correlate to the tool wear condition, which requires an advanced decision-making model to represent these intricate correlations.

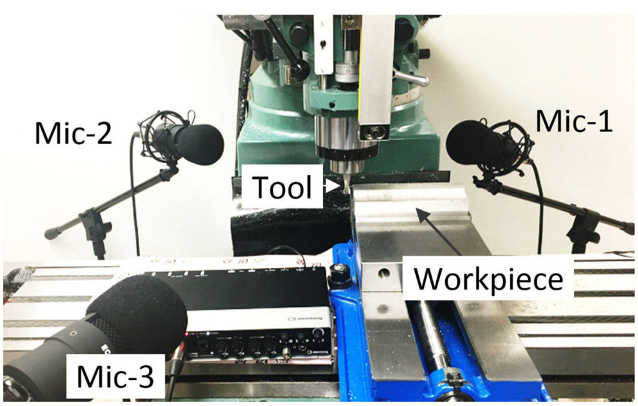

Fig. 4 Experimental setup of the proposed system

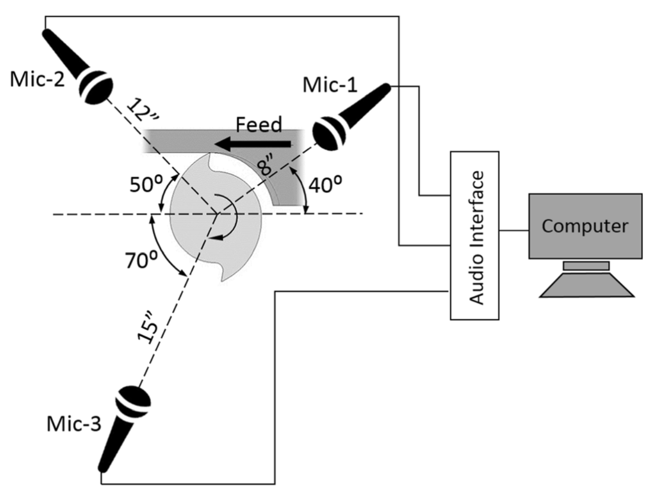

Fig. 5 Schematic diagram of the experimental layout

Table 2 Input data sheet of experimental data

Tool condition	Cutting speed (sfpm)	Feed rate (ipm)	Microphone no.
Good	176.8	9.0	1
Good	176.8	9.0	2
Good	176.8	9.0	3
Light wear	167.0	8.0	1
Light wear	167.0	8.0	2
Light wear	167.0	8.0	3
Average	147.4	7.0	1
Average	147.4	7.0	2
Average	147.4	7.0	3
Advanced wear1	137.5	12.0	1
Advanced wear1	137.5	12.0	2
Advanced wear1	137.5	12.0	3
Advanced wear2	127.7	9.0	1
Advanced wear2	127.7	9.0	2
Advanced wear2	127.7	9.0	3
Failure	196.5	24.0	1
Failure	196.5	24.0	2
Failure	196.5	24.0	3

Table 2 is an overview of actual datasheet with only a few data points per each class are displayed

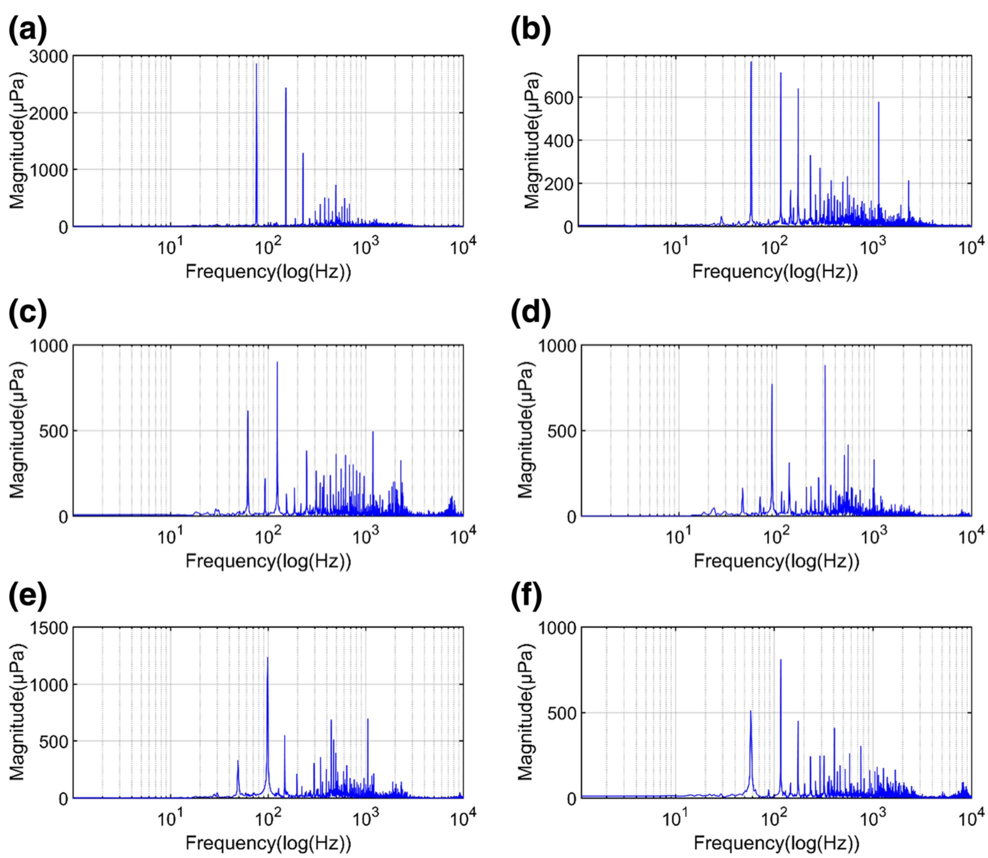

Fig. 6 Frequency spectrums of pre-processed data samples **a** good, **b** light wear, **c** average wear, **d** advanced wear 1, **e** advanced wear 2, and **f** failure

4.3 Support vector machines

SVM classification is a supervised binary classifier method. Given a training set, the algorithm constructs a hyperplane which maximizes the margin between two input classes.

The representation of SVM in mathematical terms can be explained by considering a binary classification problem with labels $y \in \{-1, 1\}$ and features x. In addition to that, parameterizing the linear classifier with weights w and bias b, from which the linear classifier can be written as:

$$\boldsymbol{y} = \begin{cases} +\mathbf{1}; (\boldsymbol{w}^{\mathrm{T}}\boldsymbol{x}_{\mathrm{i}} + \boldsymbol{b}) \geq \mathbf{0} \\ -\mathbf{1}; (\boldsymbol{w}^{\mathrm{T}}\boldsymbol{x}_{\mathrm{i}} + \boldsymbol{b}) < 0 \end{cases} \tag{1}$$

Equation (1) can be generalized for all training samples as shown in Eq. (2), and it also can be defined as a linear discriminant function *g(x)* as shown in Eq. (3):

$$\boldsymbol{y}_{\mathrm{i}}(\boldsymbol{w}^{\mathrm{T}}\boldsymbol{x}_{\mathrm{i}} + \boldsymbol{b}) \tag{2}$$

$$\boldsymbol{g}(\boldsymbol{x}) = (\boldsymbol{w}^{\mathrm{T}}\boldsymbol{x}_{\mathrm{i}} + \boldsymbol{b}) = \mathbf{0} \tag{3}$$

The goal of this method is to find a hyperplane which maximizes the margin or the distance from the nearest data point to the hyperplane, which requires finding w, b while maximizing $M = 1\ /\ ||w||$. To find a solution while minimizing $||w||$ subject to constraints in Eq. (2), a quadratic optimization problem which can be solved using a Lagrange duality:

$$\min_{w,b}\tfrac{1}{2}\,||w^2\|\mathrm{s.t.y_i}\left(w^{\mathrm{T}}x_{\mathrm{i}} + b\right)b\,y, 2, 3, \ldots n \tag{4}$$

To form the Lagrange, constraints are written as:

$$\mathbf{v}(\mathbf{w}) = -\mathbf{y_i}(\mathbf{w^T x_i} + \mathbf{b}) + \mathbf{1} \leq \mathbf{0} \tag{5}$$

The Lagrangian for optimization is written as:

$$L(w, b, \alpha) = \tfrac{1}{2}||w^2\|-\sum_{i=1}^{\mathrm{n}} \alpha_{\mathrm{i}}\left[y_{\mathrm{i}}\left(w^{\mathrm{T}}x_{\mathrm{i}} + b\right) - 1\right] \tag{6}$$

where α, is the Lagrange multiplier and $\alpha_i \geq 0$. To find the dual form, the first step is to minimize $L(w, b, \alpha)$ with respect to w, b (fixing α) which can be found by setting derivative of L with respect to w to zero which is given in Eq. (7) and with respect to b which is given in Eq. (8):

$$\nabla_{\mathrm{w}} L(w, b, \alpha) = w - \sum_{i=1}^{\mathrm{n}} \alpha_{\mathrm{i}} y_{\mathrm{i}}(x_{\mathrm{i}}) = 0 \tag{7}$$

$$\nabla_{\mathrm{b}} L(w, b, \alpha) = \sum_{i=1}^{\mathrm{n}} \alpha_{\mathrm{i}} y_{\mathrm{i}} = 0 \tag{8}$$

The remaining support vectors we have are $\alpha_i \neq 0$,; hence, the solution becomes:

$$w = \sum_{i=1}^{\mathrm{n}} \alpha_{\mathrm{i}} y_{\mathrm{i}}(x_{\mathrm{i}}) = \sum_{i \in \mathrm{SV}} \alpha_{\mathrm{i}} y_{\mathrm{i}}(x_{\mathrm{i}}) \tag{9}$$

Also, b can be found by substituting w in $y_i(w^T x_i + b) - 1 = 0$ where $i \in SV$.

In the above discussion, it has been assumed that data must be linearly separable, which is not the case in most situations. Using kernels, nonlinear data can be mapped into higher dimensional space to make them linearly separable. In this study, Gaussian radial basis function is used as the kernel.

The discussion above deals with binary classification where the class labels take only two values. In our current problem, however, six wear classes were involved, for which, requires an application of multi-classification strategy. The following section describes the methodology followed by application of the SVM technique in condition monitoring for the proposed tool wear classification.

4.4 SVM in tool condition monitoring

In machine condition monitoring and fault diagnosis, SVM is employed for recognizing special patterns of the features generated from acquired sensory signals, and then the patterns are classified with respect to the type of complications in the machine. Based on the input data vectors that consist of representations of tool wear types observed during cutting, SVM is adapted to recognize these patterns. Usually, each tool wear type produces special features of acquired signals, which are considered as patterns. SVM is motivated to represent these patterns in a high dimension with an appropriate nonlinear mapping using a kernel function to separate data from two or more categories by a hyperplane.

In this study, the modeling process started by reading the data into an array, after which the signals were labeled with corresponding tool wear levels, cutting conditions and time stamps based on input data recognition file. The labeled signals with the period from the beginning to the end of the cut were trimmed into 1-s window length as samples of data. Further, each sample was converted from time domain to frequency domain using the FFT technique and considered as input features to the decision-making model. A random pattern shuffling module was developed to randomize the data features order in the array, and the dataset was divided into a 70% training set and a 30% testing set, which are standard training and testing percentage values in machine learning techniques for an optimal performance of the classifier [36]. Based on the training data, the decision-making model can develop a model knowledge function known as a classifier over the patterns of data features with respect to labels using SVM. The generated classifier model was validated by the testing data samples to evaluate the performance of the classifier in predicting the tool condition of the test samples.

5 Results and discussion

5.1 Evaluation of prediction accuracy

Based on the proposed TCM system, tool wear predictions of each class can be analyzed by the evaluation of the confusion matrix. A confusion matrix, also known as error matrix, is a particular kind of contingency table that is derived to evaluate the performance of a machine learning algorithm [37]. This type of matrix is displayed in a specific table layout in which a total number of samples is arranged in two dimensions, true (actual) and predicted, with an identical set of classes in both dimensions, shown in Fig. 7. The performance analysis of the confusion matrix of the proposed algorithm involves mainly evaluating misclassification (error) percentage and precision percentage of each wear class as tabulated in Table 3.

In Table 3, the precision percentage is obtained by dividing the predicted number of samples over the actual number of samples for the corresponding wear class. Error percentage, also called as misclassification percentage, can be calculated by dividing the total false predictions by the sample size in each specified class, and the sample size is the number of predictions of each class from the confusion matrix. From Table 3, wear classes average and advanced wear 1 were

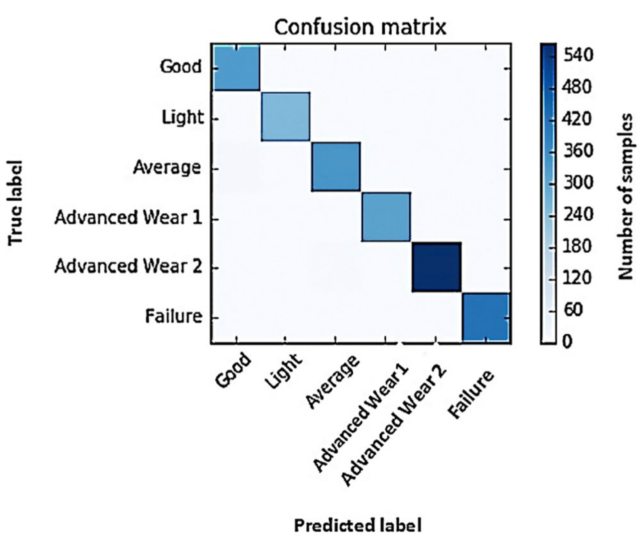

Fig. 7 Comparison of tool wear class prediction with actual wear class using confusion matrix

Table 3 Performance analysis of algorithm for each class

Wear class	Precision (%)	Error (%)
Good	99.4	0.6
Light	97.5	2.5
Average	90.7	9.2
Advanced wear 1	92.4	7.6
Advanced wear 2	98.5	1.5
Failure	97.0	3.0

found to be most affected by false predictions compared to other classes. It has also been found that most of the misclassifications in the average wear class were predicted as good, and most of the misclassifications in the wear class of advanced wear 1 were predicted as light wear. The main reason for those errors is associated with the fact that the pre-processing methods applied are not sufficient to filter the noise, and those were classified into the respective signal characteristic wear range, thereby the chosen pre-processing methods must be improved or in need of effective methods for better accuracy in signal conditioning.

5.2 Performance evaluation of prediction in the time domain

For the furthermore performance evaluation of the proposed algorithm, a concatenation of randomly selected sound signals under different cutting conditions from all six wear classes that belong to the test data set was run through the algorithm

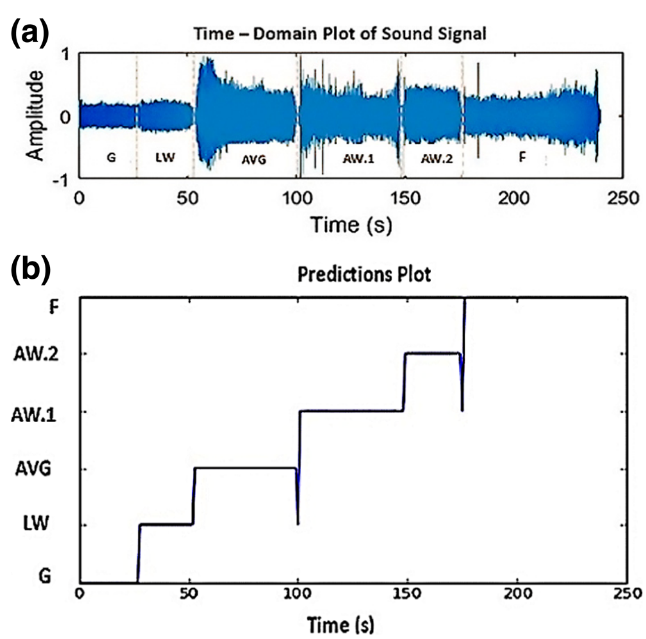

Fig. 8 Tool state prediction **a** time domain signal composed of the sound signals collected from good to failure cutting tools under random cutting conditions, **b** prediction results from the proposed machine learning approach

to observe the accuracy in multi-wear classification in the time domain. The results of the above-specified process have been plotted as shown in Fig. 8.

In the above figure, a time domain signal of the input concatenation signal consisting of six wear classes from good to failure classes consecutively is shown first, followed by the identification results of all six wear classes. From Fig. 8b, results show that the proposed algorithm has provided accurate prediction in the progression of wear class from one to another most of the time, besides some slight misclassifications in the transitions between adjacent wear classes. In addition, as shown in Fig. 8a, although there is no clear relationship between the amplitude of the signals and the tool wear classes in the time domain due to the influences of different cutting conditions, the program still can predict the tool wear accurately. It can be seen that, after being trained with enough signals, the developed program can realize the function to detect the tool wear classes irrespective of cutting conditions.

5.3 Study of microphone positioning

For the effective TCM system, one of the major concerns is the influence of the sensor position on the prediction accuracy. The specific requirements for the sensor position will significantly restrict the wide application of the monitoring system. In order to address this issue, this study used three microphones with different distances and angles, as shown in Fig. 2, with respect to the cutting zone to collect audible sound signals. Different datasets were labeled into Mic-1 to Mic-3 with sound signals collected by the corresponding microphones. By varying the position and the number of microphones for training and testing the program, the prediction accuracies for three combinations of datasets have been set as shown in Table 4.

Firstly, within every set, the prediction accuracy varies with different combinations between the training dataset and the testing dataset. Among Set-3 with the same training dataset, the testing dataset Mic-3 collected from the farthest place from the cutting zone displayed a higher accuracy due to reasons that the noise will be minimized by the longer distance between the microphone and the machine and there is no workpiece material between the microphone and the cutting zone to block the signals. The same trend has been followed in Set-2. Therefore, it is shown that the position of the microphone really influences the prediction accuracy to a certain extent. However, this positional error can be minimized by having more training data from different locations as described below.

Generally, from Set-1 to Set-3, the prediction accuracies of the developed program can be improved by increasing the number of datasets for training, which can be explained by the fact that training the program with more datasets collected from different positions can help separate the target signal features from the disturbances caused by the sensing position. However, this improvement of the prediction accuracy becomes insignificant as increasing the number of datasets. Besides the average value, the variation of the prediction accuracy also decreases from Set-1 to Set-3 as shown in Table 4. It is seen that the influence of the position for collecting the signals on the prediction accuracy can be reduced by using more training datasets collected from different positions. Expectedly, with adequate training, the system has proved that the developed monitoring system is not affected by positional variation within a specific range and independent of a number of sensors.

6 Conclusion

Tool wear monitoring remains to be a critical research field in developing intelligent monitoring systems to prevent cutting

Table 4 Position invariant prediction results

Combination sets	Training dataset[a]	Testing dataset	Prediction accuracy (%)
Set-1	Mic-1	Mic-2	90.6
	Mic-2	Mic-1	90.6
	Mic-3	Mic-1	92.0
	Mic-1	Mic-3	92.0
	Mic-2	Mic-3	89.1
	Mic-3	Mic-2	89.1
Set-2	Mic-1, Mic-2	Mic-3	96.1
	Mic-2, Mic-3	Mic-1	95.0
	Mic-1, Mic-3	Mic-2	93.8
Set-3	Mic-1, Mic-2, Mic-3	Mic-1	96.0
	Mic-1, Mic-2, Mic-3	Mic-2	95.1
	Mic-1, Mic-2, Mic-3	Mic-3	97.0

[a] Mic-1/2/3 represents the dataset of sound signals collected by the corresponding microphone

tool failures and cutting process anomalies beforehand to minimize production losses. This study focused on proposing a tool wear monitoring system with the application of machine learning techniques in an end milling process using audible sound signals. The results of the proposed work have shown a promising prediction accuracy, especially in tool wear progression. Essentially, the key concept in the proposed tool wear monitoring model is to identify the possibility to correlate the audible sound signals to the tool wear conditions using machine learning techniques for decision-making. This study highlights two important aspects: the development of a systematic methodology to set up the cutting experiments, notably allowing the proposed sensing approach for a better comparison of generated features in sound signal to correlate with the tool wear and application of SVM approach as a classifier for the prediction of tool wear. Additionally, this study explicitly proposes a new methodology for analyzing the sound signals irrespective of the type of noises associated with the signal to monitor and predict the condition of the tool.

The main shortage of this study was found to be the insufficient pre-processing which involves signal conditioning. The signal conditioning methods used in this study are of basic methods in digital signal processing which have shown less capability in noise separation that has led to misclassification in some cases. Thus, a sophisticated pre-processing method is required in predicting the tool wear with maximum accuracy. The future study in this approach involves two aspects. Firstly, other sophisticated machine learning techniques such as Convolution Neural Networks (CNN) and Recurrent Neural Networks (RNN) that can perform signal separation to isolate the actual signal from the machine and other environmental noises will be implemented. Secondly, the proposed model and experimental methodology will be applied in further complex applications, non-uniform material hardness material machining, and application of coated cutting tool monitoring.

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