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To The Study of Flushable Sensors for Classification of Tool Conditions

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Abstract

The machine learning techniques used for the purpose of classifying tool conditions. Using these techniques, we can choose the best classifier for time domain vibration and AE signature and evaluate the classification efficiency. The time domain signatures acquired at the first stage of the inquiry do not include the frequency data. These wavelet coefficients are used in machine learning techniques for tool condition classification. To determine the frequency content, the original AE and vibration signals are first converted from the time domain to the frequency domain using Fast Fourier Transform. The statistical data is derived from the frequency domain features of vibration and acoustic emission. improving the reliability of machine learning systems using sensor fusion technologies. Acoustic emission signals and vibrations are combined at the feature level to enhance the classification performance using Machine *Learning algorithms*.

Keywords: Sensors, Tool, Technologies, Classification and Conditions

Introduction

Health care, quality of life, economic development, and other metrics are all improved thanks to micro components, which are essential to the goods' operation. Numerous industries, including aircraft, biomedicine, electronics, the environment, communications, automobiles, and more, rely on micro components. Research has shown that tool-based micromachining is one processing approach for creating micro components. According to Masuzawa and Tonshoff (1997) [1], Dornfeld *et al*. (2006) [2], and Jain (2010) [3], tool-based micromachining is a mechanical cutting feature that allows for components of any size to have geometrically defined cutting edges that are smaller than 1 mm in size. Alting *et al*. (2003) [4] and Masuzawa (2000) [5] later adjusted the dimension range to 500 µm. Chae *et al*. (2005) [6], Rahman *et al*. (2006) [7], Asad *et al*. (2007) [8], and Liow (2009) [9] list micro milling, micro turning, micro drilling, and other tool-based micromachining operations. Machining various materials using tool-based micromachining provides many advantages, such as a greater material removal rate (MRR), better finish, reduced production cost, and so on. To guarantee dependability and reproducibility, researchers have lately shown a strong interest in producing micro components using tool-based mechanical micromachining procedures.

The researchers have extensively used AE, ACC, and cutting force dynamometers for TCM, and they primarily analyse the signals in the time domain and frequency domain to correlate them with the condition of tool wear. Additionally, researchers have tried to use the discrete wavelet transform (DWT) method to examine the collected signals. The data was first demodulated into its component frequencies using the DWT method. In order to determine the process of tool wear, the decomposed signal proves to be quite beneficial. This study aims to monitor the tool condition during micro end milling of various materials, including aluminum copper, and steel (SAE 1017) alloys. It employs multiple sensors, including an AE, an ACC, and a cutting force dynamometer. The signals are processed in the time domain, frequency domain, and DWT.

We need sensors that can identify process anomalies and start corrective action in order to deploy process monitoring and control. Depending on the signal, several sensing and processing methods may be necessary for process monitoring. There is a range of dependability levels that each of these signals may provide about the process. Gathering data from all the signals that may be captured throughout the operation is essential for achieving optimal control. The term "data fusion techniques combine data from multiple sensors and related information from associated databases to achieve improved accuracy and more specific inferences than could be achieved by the use of a single sensor alone." This definition was given by Hall and Llinas [1997] [10] and is widely recognized in the field.

The use of dynamometers, accelerometers, spindle power sensors, and acoustic emission sensors is common in tool condition monitoring. At the decision level, there is a fusion approach; at the feature level, there is another. Following the steps outlined in earlier chapters, a decision-level approach uses a tool condition monitoring system that makes use of one or more sensors to operate as an expert within its own feature space. Next, a meta-classification judgement is reached by pooling opinions using a majority vote method, which is better than fusing individual classifiers

Literature Review

Raja & Baskar (2020) [11] The ideal machining parameters for surface grinding, single-pass and multi-pass turning, and other operations were investigated by using three different evolutionary optimisation methods: SA, GA, and PSO. Several mathematical models were used to study the behavior of optimisation approaches. Particle swarm optimisation outperformed simulated annealing and genetic algorithm, according to the results. In addition, the global optimum solution is often found more quickly using the particle swarm optimisation approach. Using the algorithms on online systems for selecting optimal machining settings, all of the above methods may quickly find a global optimum solution on a desktop computer.

Yang *et al*. (2019) [12] The optimal process parameters for the EDM process may be determined using a restricted multi-objective optimisation framework, as suggested by. Using experimental data, a counter-propagation neural network was used to develop the system model. The model was used to optimize the rate of material removal and minimise surface roughness via the use of a simulated annealing strategy all at once.

Zain *et al* (2020a) [13] used the SA method to determine the best cutting circumstances for achieving a low surface roughness value. Radial rake angle, cutting speed, and feed are the primary cutting conditions. Following this, it was discovered that the minimum surface roughness could be reduced by 27%, 26%, and 50% utilizing the experimental sample data, regression modelling, and response surface methodology methodologies, respectively, when simulated annealing was used.

Kuruvila and Ravindra (2021) [14] used the taguchi method and a genetic algorithm to find the best wire-EDM process parameters. Dimensional error, surface roughness, and material removal rate are the dependent variables in the multi-objective problem. The independent variables are pulse-on duration, current, pulse-off length, bed-speed, and flushing rate. The optimal process parameters were achieved by using the equal and distinct weighting systems.

Palanisamy *et al*. (2017) [15], Minimizing machining time while considering restrictions such as surface roughness, cutting force, tool life, and amplitude of vibration in end milling operations was shown by. The convergent results were acquired by using the genetic algorithm to address such a complicated optimisation challenge. Genetic algorithms were shown to be accurate and effective in measuring the process performance of cutting forces, according to the findings.

Research Methodology

Fusion methodology

Titanium alloy high-speed machining collects vibration and acoustic emission signals. The acoustic emission sensor is attached to the work (Ti-6Al-4V), while the vibration sensor is put on the spindle head. A single data set is created by combining the retrieved statistical characteristics. Figure 1. displays the methods that was used for this fusion investigation.

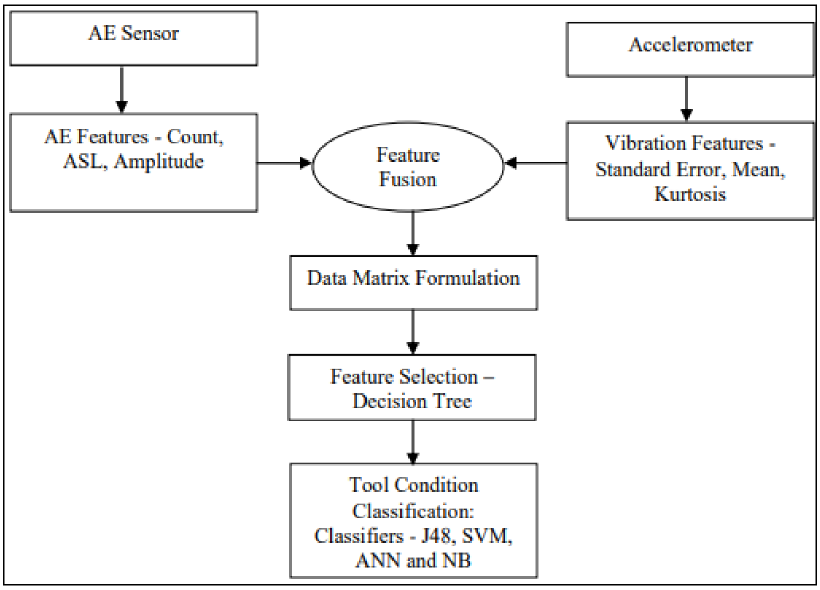

Fig 1: Data fusion methodology

The prominent characteristics were identified from this pooled data using a decision tree technique. To classify the data, these traits were considered prominent. Various methods such as Decision Tree, Naïve Bayes, Support Vector Machines (SVM), and Artificial Neural Networks are used for classification analysis. The time, frequency, and wavelet domains are all used in this data fusion study.

Feature level fusion in time domain

The extracted features from acoustic emission (count, ASL, and amplitude) and vibration signals (standard error, mean, and kurtosis) were fused in to a single data matrix.

Feature selection

We feed the statistical properties of the vibration data and acoustic emission signals into the J48 decision tree method. Figure 2. displays the resultant tree. At the very bottom of the decision tree are the vibration signal standard error and the acoustic emission signal ASL. These characteristics stand out from the rest of the vibration and acoustic emission signal data because of the wealth of information they provide.

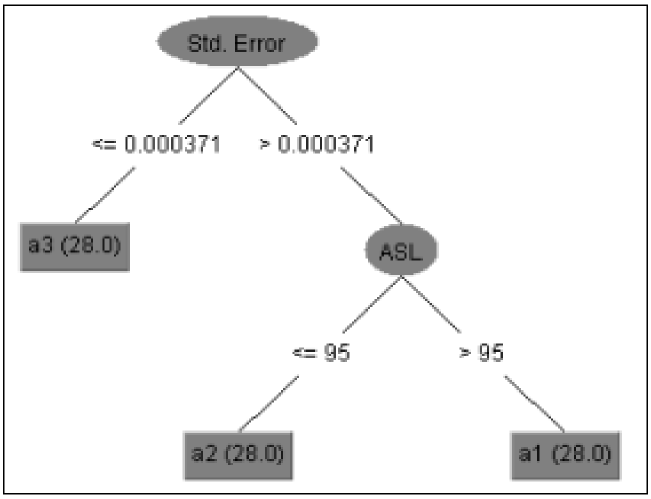

Fig 2: Decision tree of fused data in time domain

Tool condition classification

The selected features using decision tree are standard error from vibration and ASL from acoustic emission signals. These features are used as input in the decision tree algorithm, naive bayes, support vector machines and artificial neural network to identify the tool condition.

Decision Tree

For tool condition classification, the features that were chosen-standard error from vibration and ASL from acoustic emission signals-are again fed into the decision tree. Table 1 displays the decision tree's categorization performance. Good, medium, and worn-out are the three tool condition states represented by a, b, and c, respectively, in Table 1.

Table 1: Confusion matrix of decision tree algorithm using fused data in time domain

a	b	c	Tool condition	Classification efficiency, %
27	1	0	a	97.62
1	27	0	b	
0	0	28	c	

There are two misclassifications out of 84 data points presented to the decision tree. 1 data point belongs to class ‘a’ was misclassified as ‘b’. Similarly, 1 data point belongs to class ‘b’ was misclassified as ‘a’. The classification efficiency is 97.62%.

Naïve Bayes

Next, the features that were chosen (standard error from vibration and ASL from acoustic emission signals) are put to the test for tool condition classification using naïve bayes. The accuracy rate of the categorization is 100% and every data point was appropriately labelled. For testing purposes, the naïve bayes classifier employs a 10-fold cross validation model.

Data Analysis

To identify tool conditions, the feature level fusion approach combines features from many sensors into a single set before feeding it to classifiers. Because each classifier will have its own bigger input data area, classification accuracy can suffer. Redundancy and complementarity are two benefits that feature level fusion offers. During the high-speed machining of titanium alloy, the researchers in this work recorded vibration and acoustic emission data. Use of these two sensors allowed for the monitoring of tool wear in a carbide end mill cutter with four flute coatings. The feature-level merging of AE and vibration sensor data improved categorization efficiency. Classifiers are fed a combined matrix of statistical data from vibration and acoustic emission signal features in order to determine the tool's status.

Feature level fusion in frequency domain

Fourier transformations are used to translate signals from the time domain into the frequency domain. Statistical characteristics were retrieved from frequency-domain AE and vibration data. They include the following metrics derived from vibration and acoustic emission signals: total, mean, median, minimum, maximum, standard deviation, variance, kurtosis, and skewness.

Feature Selection

The statistical features of both the signals in frequency domain were given as an input to Decision Tree to identify the best features for classification.

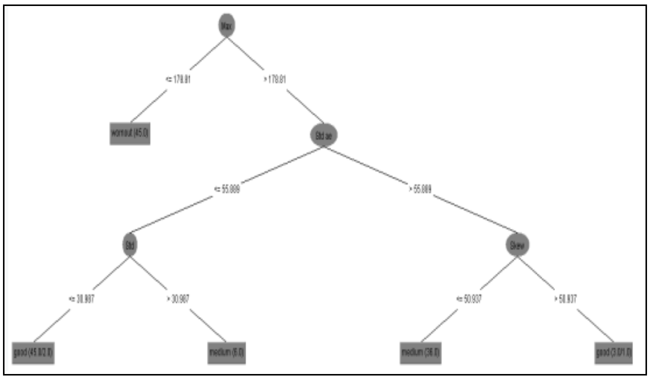

Fig 3: Decision tree of fused data in frequency domain

From the decision tree shown in Figure 3., it was found that maximum, skewness, standard deviation from vibration signal and the standard deviation from AE signals are the best statistical features in frequency domain to classify the tool condition.

Tool condition classification

The selected features from the decision tree were used for the classification of tool conditions using decision tree, Naïve Bayes, support vector machines and artificial neural network.

Decision tree

For the purpose of tool condition categorization, the characteristics that were chosen are fed into a decision tree. Table 2. displays the decision tree's categorization performance. Out of the 135 data points that were fed into the decision tree, eleven of them were incorrectly classified. Table 2.'s confusion matrix shows the following: Five data points that should have been in class 'a' were instead labelled as 'class 'a' and one as 'data class point 'a'. A classification efficiency of 91.8 is achieved.

Table 2: Confusion matrix of decision tree algorithm using the fused data in frequency domain

a	b	c	Tool condition	Classification efficiency, %
40	5	0	a	91.85
5	40	0	b	
1	0	44	c	

Naïve Bayes

The chosen characteristics are then put through their paces for tool condition classification using naïve bayes. In order to test the data, a ten-fold cross validation model is used. Table 3. displays the Naïve Bayes classification performance. The confusion matrix revealed that the Naïve Bayes classification effectiveness for the fused data in the frequency domain was 96.29%, with 1 data point belonging to class 'b' and 4 data points belonging to class c.

Table 3: Confusion matrix of Naïve Bayes using fused data in frequency domain

a	b	c	Tool condition	Classification efficiency, %
44	1	0	a	96.29
4	41	0	b	
0	0	45	c	

Support vector machine

Standard deviations from vibration signals and AE signals, as well as maximum and skewness, are provided as predictors in support vector machines. We want to determine the tool wear state. This research makes use of a c-SVC support vector machine trained with an RBF kernel function. When evaluating the data, a V-fold cross validation is used. According to Table 4, the SVM's performance with the combined data is shown as a confusion matrix. Out of the 135 data points that were fed into the support vector machine, 3 were incorrectly categorized as belonging to class 'a' while in fact they were mislabeled. For the combined data in the frequency domain, the machine achieved a precision of 96.29%.

Table 4: Confusion matrix of support vector machine using fused data in frequency domain

a	b	c	Tool condition	Classification efficiency, %
42	3	0	a	96.29
2	43	0	b	
0	0	45	c	

Artificial neural network

A three-layer feed forward back propagation network is used in this artificial neural network. The construction of the artificial neural network is shown in Figure 4. Number of hidden neurons used in this study is 10. The outputs from this network are tool conditions.

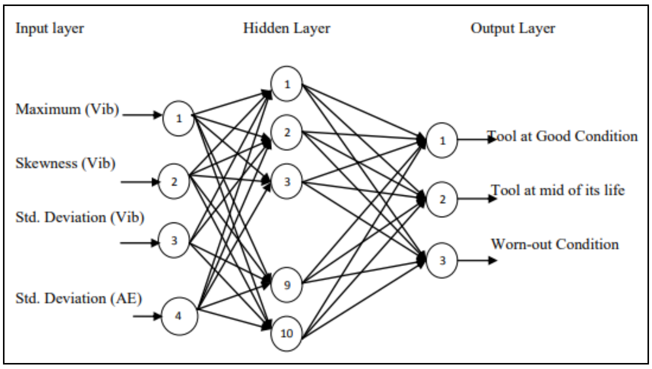

Fig 4: Artificial neural network architecture for fused data in frequency domain

The dominant features selected using the decision tree, are given as input to this network. The simulation of this artificial neural network yields 94.80% classification accuracy and the corresponding confusion matrix is presented in the Table 5. There are 5 data points which belongs to class ‘a’ were misclass class ‘a’ were misclassified as class ‘b’.

Table 5: Confusion matrix of artificial neural network for fused data in frequency domain

a	b	c	Tool condition	Classification efficiency, %
40	5	0	a	94.80
2	43	0	b	
0	0	45	c	

Feature level fusion in wavelet domain

The wavelet coefficients were extracted from the vibration and AE signals to obtain the time frequency resolution of the signal using wavelet transforms. The extracted wavelets are Haar, biorthogonal (bior 3.9, bior 4.4 and bior 5.5), Daubechies (db11, db12, db13 and db 14) and reverse biorthogonal (rbio 4.4, rbio 5.5 and rbio 6.8). From the extracted wavelets best performing wavelets are identified.

Wavelet selection

The best performing wavelets identified are Haar wavelet from vibration signature and the bior 4.4 wavelet from acoustic emission signals. The wavelet coefficients are fused together to form a single data set. The fused data set is used for tool condition classification.

Tool condition classification

The selected fused discrete wavelet coefficients were used to classify the tool condition using decision tree algorithm, Naive Bayes, support vector machine and artificial neural network.

Decision tree

The combined wavelet data set (Haar wavelet from vibration and the bior 4.4 wavelet from acoustic emission signals) is presented to decision tree for tool condition classification.

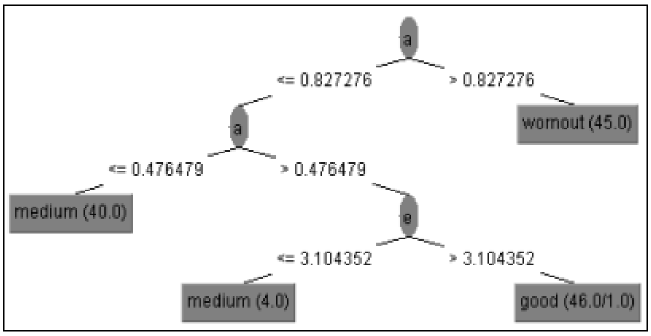

Fig 5: Decision tree for fused data in wavelet domain

At various degrees of decomposition, the dominant coefficients in tool condition categorization are illustrated by the root nodes in the decision tree depicted in Figure 5. Signifying the first and fifth level decompositions of the vibration signal, respectively, are 'a' and 'e' in Figure 5. Table 6. displays the decision tree's classification performance as a confusion matrix. Of the 135 pieces of data fed into the decision tree, 5 were incorrectly classified. Class 2 'a' in cw 1 in class 'c' is the owner of the three data points. There are two pieces of data that contribute to the categorization efficiency of 96.29%.

Table 6: Confusion matrix of decision tree algorithm for fused data in wavelet domain

a	b	c	Tool condition	Classification efficiency, %
42	2	1	a	96.29
2	43	0	b	
0	0	45	c	

Naïve Bayes

Next, Naïve Bayes is used to assess the chosen discrete wavelet features for tool condition categorisation. The results of the Naïve Bayes classifier are shown in Table 7. Five points from class 'a' were mistakenly placed in class 'b,' four points from class 'b' were mistakenly placed in class 'a,' and two points from class 'c' were mistakenly placed in both 'a' and 'b,' respectively. A 91.85% effectiveness rate in categorisation

Table 7: Confusion matrix of Naïve Bayes for fused data in wavelet domain

a	b	c	Tool condition	Classification efficiency, %
40	5	0	a	91.85
4	41	0	b	
1	1	43	c	

Support vector machines

As inputs to support vector machines, vibration and AE signal wavelet coefficients are used as predictors. We want to determine the tool wear state. This research makes use of a c-SVC support vector machine trained with an RBF kernel function. You can get the equivalent confusion matrix in Table 8, and the classification effectiveness of this support vector machine is 95.56%. The data shown by the confusion matrix are as follows: Four data points from class 'a' were mistakenly placed in class 'b,' four data points from class 'b,' and two data points from class 'b,' were mistakenly placed in class 'a,' and one data point in class 'c,' respectively.

Table 8: Confusion matrix of support vector machine for fused data in wavelet domain

a	b	c	Tool condition	Classification efficiency, %
41	4	0	a	95.56
1	43	1	b	
0	1	45	c	

Artificial neural network

The research team has decided to use a three-layer feedforward artificial network once again. The artificial neural network (ANN) was fed the combined discrete wavelet coefficients of the vibration and AE signals. In the intermediate layer ten hidden neurones are located. All of the data points were properly identified in the network simulation using the V-fold cross validation model; the results are reported in Table 9 as a confusion matrix.

Table 9: Confusion matrix of artificial neural network for fused data in wavelet domain

a	b	c	Tool condition	Classification efficiency, %
45	0	0	a	100
0	45	0	b	
0	0	45	c	

From the results presented, it can be observed that ANN gives the maximum classification efficiency of 100%.

Conclusion

We were able to record the vibration and AE signals' time-frequency resolution by using the discrete wavelet transform to extract wavelets. Eleven wavelets were considered, belonging to the bi-orthogonal, reverse bi-orthogonal, daubechies, and haar families. In every case where vibration data was examined with wavelets, SVM proved to be the most successful classifier. There is no better ML approach than ANN, which achieves a classification performance of 100% for all wavelets using AE data. Using AE signals rather of vibration signals improves the performance of machine learning algorithms in the wavelet domain. Machine learning techniques employ these wavelet coefficients to categorize tool situations. To get the frequency content of the original AE and vibration signals, Fast Fourier Transform is used to convert them from time domain to frequency domain. Machine learning techniques' categorization performance was enhanced by using AE and vibration data at the feature level. In the temporal domain, feature level fusion outperforms both frequency domain and wavelet treatments.

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