Tool Wear Condition Monitoring Using Emitted Sound Signals By Simple Machine Learning Technique

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Abstract— as a continuous enhancement to the tool wear monitoring using non-disturbing method of sound wave analysis, a simple machine learning technique enhances the prediction to better levels and reduces the procedures. A simple linear regression Algorithm was used to train and predict the trends of various degrees of tool wear to distinguish them from each other. The results based on this simple linear regression were successful in showing the difference of sound patterns and are reported.

Keywords— Tool wear monitoring, industry 4.0, non-disturbing testing, Machine Learning.

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1.Introduction

Using the pressure difference in sound that is arising from an ongoing machining job to find the degree of tool wear is a good method followed by the recent advancements in automation. As the Industry 4.0 compliance giving continuous demands for machine learning and perfect automation, there is always an opportunity for improvement in this work. This challenging task of knowing the degree of tool wear without stopping the process was dealt differently by different researchers. Usually the conventional methods fix sensors and cameras to get tool wear conditions and the parameters drawn are used to decide the action. This happens in the production process using CNC machine that highly depends on the tool condition involved in the job work. It is important to ensure the good quality of tool to get the genuine quality in end product. In such turning process an automated conditional monitoring of an active and effective tool, involved in drilling and milling requires a mechanism that works without hindrance of the operation sequence is highly productive.

A very useful method of drawing sound information from the evaluated feed motor current, force of feed, cutting, are the parameters suggested by Alonso et al. [3] suggested a guessing method of tool flank wear a ANN. The directional proportional connection between the maximum extend of vibration with the increasing tool wear was found by Sadettin et al [4]. The sound that is created during the machine cutting process is used as the unique parameter for monitoring the degree of tool flank wear from the research of Ming-Chyuan et al [5] and Alonso F.J et al. [6]. A much simpler and cost effective mechanism following the methods of [5] and [6] is developed by sound converting process to estimate the tool flank wear swiftly via dynamic assessment group technique through just a portion of discharged noise instead of a big piece of sound wave by A Samraj et al. [7]. The distinctive signal is handled in the form of linear and not permanently immobile; or else the result deriving Fourier spectrum may produce significantly lower physical sense was suggested by Peng et al [8]. In following the Fourier transformation leads the world wide properties of the signal rather than local properties according to the direction of Huang et al [9]. Hilbert-Huang transformation also helps to estimate the results to a good extent.[10] A continuous enhancement of the process leads to much simpler method and effective results and is presented by Prakash & A.Samraj [11,12,13]

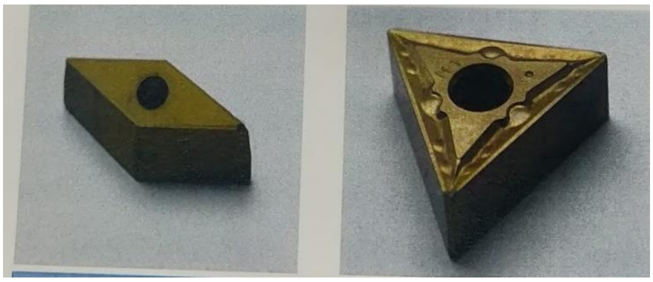

Figure1: Different types of tool bits used in the cutting process

In alignment to Industry 4.0 automation a Machine learning approach seems to be appropriate to address this problem. Hence we started a basic ML approach using a simple Linear Regression and found the approach results in fruitful but different way of representations.

This initiative is to change the direction of tool wear monitoring from conventional and basic techniques to advanced and compatible technique of ML. A refined approach which will be more adoptive to any Industrial 4.0 systems would be the ML technique. Here we started it with the first ML technique on the emitted sounds and found it as a competent method that augments any efficient automated manufacturing. The old alternative such as image capturing in videos and other monitoring devices causes expenses and erroneous predictions. In this paper we presented the possible results with the estimation of wear in single point cutting tools by the displays of Linear Regression estimations and their convergence styles.

2.Methodoloy

2.1 Eqipment and setup

The setting up of equipment for this sound capturing experiment due to the noise created out of the vibration involve a sensitive micro phone which has a size of ¼" in diameter and its market identification name is PCB 130 D20. The capacity of this microphone is to record a vital extent of noise till 12dB. Hence PCB 130 D20 becomes the most appropriate microphone to capture and record the sound created during turning process with a reaction to the frequency between the extend of 20Hz to 20 kHz with the precision of noise variations of ±0.5dB. This microphone is using a BNC connector and a high temperature resistant material made by polymer, for removing the requirement of external polarization, which include freeze concerned with charges, implemented on the back platys top. In general this PCB 130 D 20 microphone has records of being widely used in the measuring of noise in multi-channel machinery as well as sound power measurements.

The microphone and its arrangement with position and connection for measuring sound intensity are shown in Figure. 2 suitable to be deployed in the machining process.

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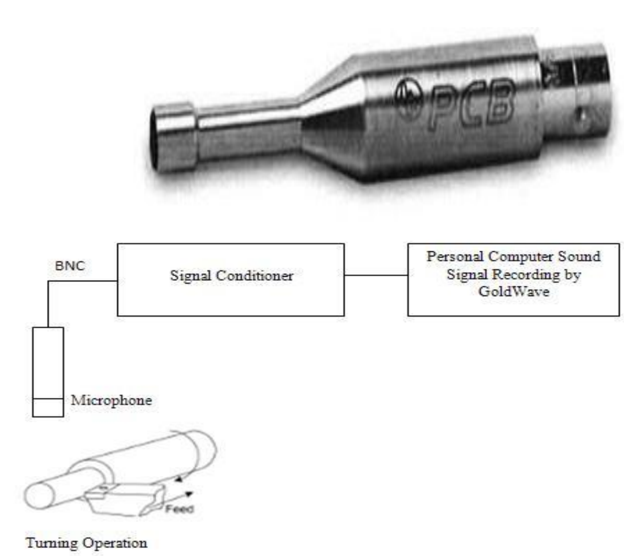

Figure. 2 The Microphone used to record the cutting sound and its setup

2.2 Simple Linear Regression:

One of the basic ML technique adopted is this statistical model to predict the relationship between independent and dependent variable. Linear regression has to be applied on a 1000 point statistical model of the acoustic signal captured during the machining process with Fresh, Slightly worn tool and Severely worn tool as three different categories.

The simple linear regression is to find the relationship between two variables with a linear trend of the future values of these variables. So the regression is a process of estimating the value of one variable using another variable.

2.3 The mechanics

A substantial quantity of sound is constantly produced during the turning process due to the vibration produced from the work machine tool and the work-piece. This produced noise during the machining process is anticipated according to the intensity and the size of surface of contact to which the insertion of cutting flank were occurred. Along with that the other assorted vibrations produced from the tool helps us in the tool wear estimation process. But some vibration interruptions from the environment spoil the quality. Hence they should be separated using appropriate filters since they appear in the less than average frequency ranges of null point [0] and 2 kHz. But the effect of the conversion procedure is important when these interruptions over the 2 kHz frequency measure.

Out of many materials like Steel Aluminum, and alloy, the Aluminum work-piece material is selected for this experiment. The work piece was having a diameter around 50 mm. The cutting insert tool bit used here was a carbide insert NR9. Throughout this experiment the micro phone's output varies according to the sounds pressure on the time discipline proportionally changes.

A PCB 130 D20 associated software was used for the recordings, which has the commercial name called 'Gold Wave' , and was very helpful to do the recoding of sound signal with the modal rate of 44100 points/sec using the pre polarized condenser microphone. The sampling rate of 44100/sec is high and the resulted data due to this high sampling rate is a challenging and is an over head for processing. We designed the Experiments with few constant cutting parameters like depth of the cut, cutting speed as well as feed rate and kept them the same throughout the experiment. We recorded emitted sound waves during 15 trials during the turning operation. Three sessions of recordings were done for all the three status conditions of the aluminum tool bit. (Fresh tool without any flank wear- 15 trials, slightly worn tool – 15 trials which is having an approximately 0.2- 0.25 millimeter flank wear also severely worn out tool of approximately 0.4 millimeter flank wear – 15 trials). A free run sound was also recorded to have it as a base reference in the start of the experiment while the machine is operated freely without touching the work piece by the tool bit. This particular measurement is then labeled as no control run. Subsequently tools of experiments like Fresh tool, slightly worn tool and severely worn tool were used in recordings and are labeled it their names after the sound waves are recorded.

2.4 Experiments with 1000 data points of the sound signal

The data involved in this experiment contains a sequence of 1000 data points of acoustic signal for 3 different categories. The signal recorded during the job work when a fresh tool bit was used, when a slightly worn tool bit was used and a severely worn tool bit was used are the three different data used in this experiment.

The sequence of 1000 data values are converted from 1000 X 1 array form to 10 X 100 array form by splitting the data in to 100 data points. Then the dataset posses the dependent and independent variables 'x' and 'y' respectively with the time stamps. Then once again these 10 X 100 data set array is split into training and testing set , by using the ML framework software as the training size of 70% of the given data and 30% as the test data out of the 1000 data points.

The next step is to build the ML model by using Linear Regression function. Create an object of ML as 'regress' to fit the trained data as x_train and y_train in the regress object.

Where 'regress' object is representing the linear regression of the training and test data using the function. The prediction based on the training occurs as the best fitting line on the given test data. To visualize the output, the predictions are plotted with variables x_train and y_train as the x and y axis of the graph along with the predicted best fitting regression line of test data.

3.Results and Findings

Fresh Data:

The plot in figure 3 shows the time in the x axis and wave pressure value in the y axis plotted into the graph. It consists 1000 Data points out of which a random 70% (700) is chosen as a training set, and the remaining 30% (300) is the test set. The regression line is plotted for the test set and the predicted values show the regression line.

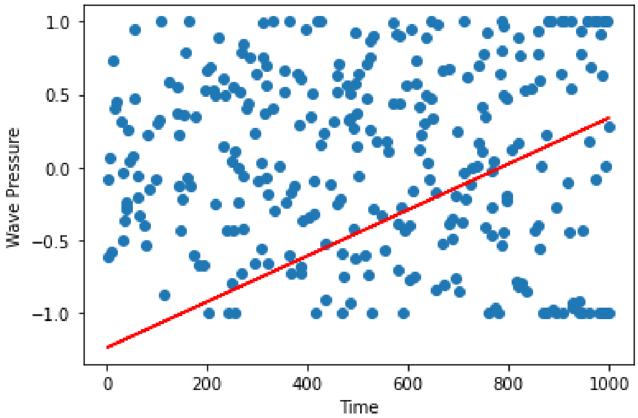

Figure 3: Linear Regression of 1000 data points in sound signal from Fresh category Tool.

The plot in figure 4 shows the time in the x axis and wave pressure value in the y axis plotted into the graph. But it consists 300 Data points out of which a random 70% (210) is chosen as a training set, and the remaining 30% (90) is the test set. The regression line is plotted for the test set and the predicted value shows the regression line.

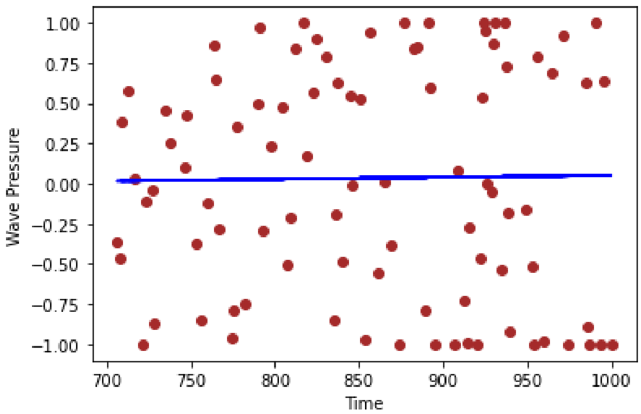

Figure 4 : Linear Regression of 300 data points in sound signal from Fresh Category Tool.

Severe Data:

The plot in figure 5 with same axis legends is showing the change in wave pressure value depicted in the y axis of the graph. It is due to the worn out tool that is being used changes the aquostic noise. Here too a 1000 data points out of which a random 70% (700) is chosen as a training set, and the remaining 30% (300) is the test set. The regression line is plotted for the test set (30%) and the predicted values show the regression line.

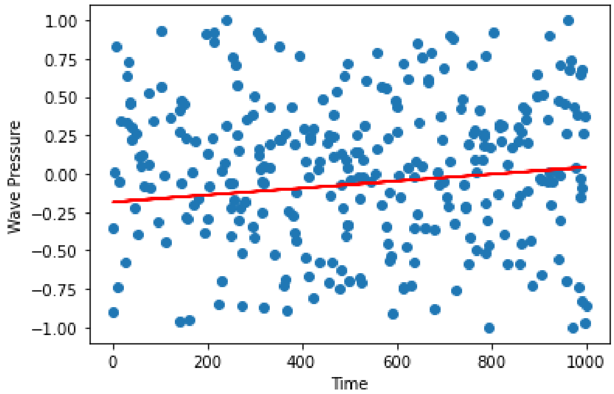

Figure 5: Linear Regression of 1000 data points in sound signal from Severe Category Tool.

The plot in figure 6 shows the time in x axis and wave pressure value in the y axis plotted into the graph. It contains 300 Data points out of which a random 70% (210) is chosen as a training set, and the remaining 30% (90) is the test set. The regression line is plotted for the test set and the predicted values show the regression line..

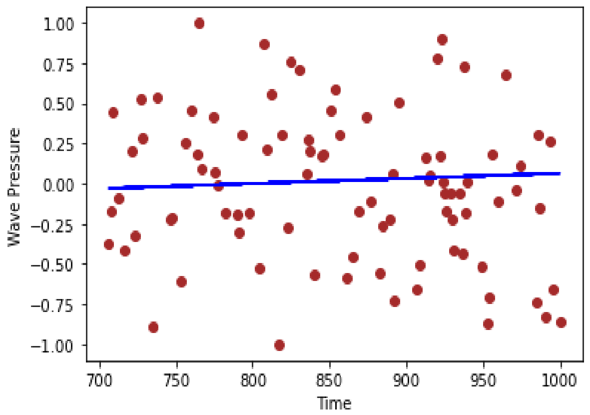

Figure 6 : Linear Regression of 300 data points in sound signal from Severe Category Tool.

Slight Data :

The plot in figure 7 shows the time in the x axis and wave pressure value in the y axis plotted into the graph. It consists 1000 Data points out of which a random 70% (700) is chosen as a training set, and the remaining 30% (300) is the test set. The regression line is plotted for the test set and the predicted values show the regression line.

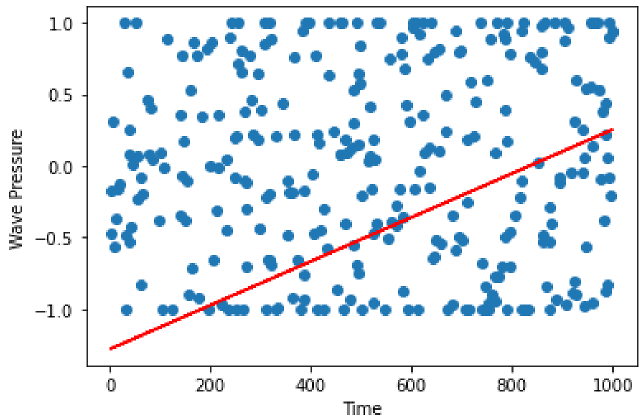

Figure 7 : Linear Regression of 1000 data points in sound signal from Slight Category Tool.

The plot in figure 8 shows the time in the x axis and wave pressure value in the y axis plotted into the graph. But it consists 300 Data points out of which a random 70% (210) is chosen as a training set, and the remaining 30% (90) is the test set. The regression line is plotted for the test set and the predicted values shows the regression line.

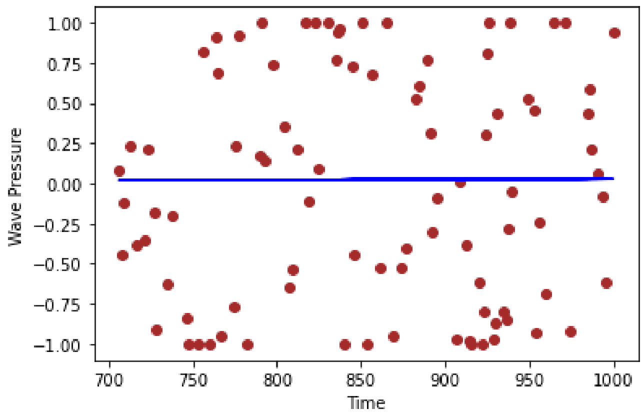

Figure 8 : Linear Regression of 300 data points in sound signal from Slight Category Tool.

4. Results & Discussions

The identification of degree of tool wear can be identified by the proposed machine learning technique without any complex transformations. The signal samples taken over the period of time is reduced and analysed for the quality of prediction and found unaffected. It means that a very small piece of sound signal is enough to identify the degree of tool wear by this technique. There are some specific features patterns are found for different category of the signals which are clearly grouped down by our simple ML techniques. The accumulation of processed data points over a particular area can be found in the figures 3 to 8 . Especially in figures 5 and 6 the intensification of data points near 0 could be found.

5. Conclusion

The simple features constructed using simple machine learning technique used for identifying the degree of tool wear is found suitable in different categories. On observing the table 1 the change in linear regression for fresh , slight and severe tool categories are found in perfect intonations. It is found that the proposed approach is simple, easier and does not involve any complex mathematical derivations or transformations. The features based on the sound pressure represented by the data points are only considered for decision making. This, valid contribution to this particular research area will definitely contribute to save cost and time.

Table 1: Start and end points of linear regression for three Different categories

data	*fresh*		*slight*		*severe*	
	start	**end**	**start**	**end**	**start**	**end**
1000	**0 , -1.25**	**1000 , 0.4**	**0 , -1.25**	**1000 , 0.2**	**0 , -0.2**	**1000 , 0.0**
300	**700 , -0.12**	**1000 , 0.3**	**700 , -0.22**	**1000 , 0.25**	**700 , 0**	**1000 , 0.0**

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