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Dynamic Clustering Estimation of Tool Flank Wear in Turning Process using SVD Models of the Emitted Sound Signals

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***Abstract*—**Monitoring the tool flank wear without affecting the throughput is considered as the prudent method in production technology. The examination has to be done without affecting the machining process. In this paper we proposed a novel work that is used to determine tool flank wear by observing the sound signals emitted during the turning process. The work-piece material we used here is steel and aluminum and the cutting insert was carbide material. Two different cutting speeds were used in this work. The feed rate and the cutting depth were constant whereas the flank wear was a variable. The emitted sound signal of a fresh tool (0 mm flank wear) a slightly worn tool (0.2 -0.25 mm flank wear) and a severely worn tool (0.4mm and above flank wear) during turning process were recorded separately using a high sensitive microphone. Analysis using Singular Value Decomposition was done on these sound signals to extract the feature sound components. Observation of the results showed that an increase in tool flank wear correlates with an increase in the values of SVD features produced out of the sound signals for both the materials. Hence it can be concluded that wear monitoring of tool flank during turning process using SVD features with the Fuzzy C means classification on the emitted sound signal is a potential and relatively simple method.

***Keywords*—**Fuzzy c means, Microphone, Singular Value Decomposition, Tool Flank Wear.

I. INTRODUCTION

THE state of a cutting tool is a crucial factor in the process of metal cutting as the increase in expenses in terms of scrapped components, machine tool fissures and unscheduled downtime result from worn tool usage [1].

Tool wear is directly connected in making the quality surface finish, dimensional precision and ultimately the costs of the parts produced. If the status of the tool wear is available during the running time, it is effective in establishing a tool change policy, adaptive control, economic optimization of machining operations and full automation of the same [2].

Flank wear arises due to both the adhesive and abrasive wear mechanisms from the intense abrasion action of the two surfaces in contact, i.e. the clearance face of the cutting tool and the newly formed surface of the work piece. Its rate of increase at the beginning of the tool life is rapid, settling down to a steady state then accelerating rapidly again at the end of tool life. Flank wear is directly proportional to the surface quality. The wear gradually leads to a deterioration, by increased contact area and consequently to increased heat generation [1]. Recent technical approaches in the area of tool wear monitoring typically measure several process parameters which are indirectly correlated with tool wear such as force, vibration and sound signals which are measured on-line, i.e. during an ongoing cutting process [2]. Close monitoring of the vibration signal of the machine during the machining operation is considered as a common practice for distinguishing the status of the tool wear [4]. Modeling of features using singular value decomposition (SVD), is one of the most basic and important method of numerical linear algebra, is finding increasing applications in digital signal processing [5]-[7]. The singular values of a matrix play a role similar to that played by the power density spectrum of a signal [9]. In this proposed research work, we used this modeling to estimate the flank wear of a tool from the emitted sound during the turning process. This was done on-line machining process for tool inspection. Our findings resulted in discriminated SVD feature values that correlates with the tool flank wear produced out of the sound signals.

II. METHODOLOGY

A. The microphone

The vibration of the work-piece and machine tool during the turning process produces the noise. It is expected that the intensity of this noise depends on the flank wear (VB) of the cutting insert. [3] The other vibrations from surroundings represent disturbances in the tool condition monitoring system. But this disturbances are only significant in the low frequency range (between 0 and 2 kHz) but the influence of the turning process is significant and dominating over this disturbances above the 2 kHz frequency level [3]. To measure the sound pressure features in a sound wave a condenser microphone was used.Please submit your manuscript electronically for review as e-mail attachments.

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Fig. 1 The PCB 130D20 is a pre-polarized condenser microphone coupled with ICP sensor powered preamps.

The micro phone used to record this vibration noise is the PCB 130 D 20 microphone which is ¼” in diameter, with a dynamic range up to 122dB. It is more suitable to record the machinery sound since it has a frequency response range of 20Hz to 20 kHz at a noise accuracy of ±0.5dB. It utilizes a BNC connector and the need for external polarization is eliminated by utilizing a high temperature polymer material, which contains frozen electrical charges, applied to the top of the back plate. It has been widely used in multi-channel sound power measurements and multi-channel machinery noise measurements.

B. The experiment

The position of the microphone and the measurement equipment are shown in Fig. 2.

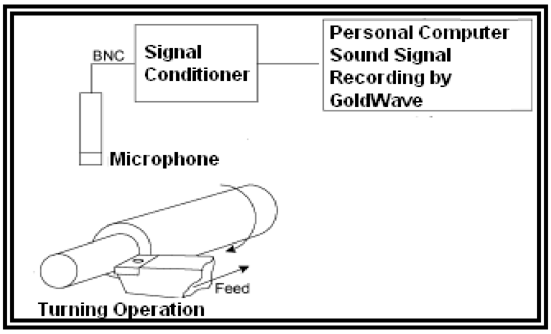


Fig. 2 The tool wears data collection arrangement.

Its output is proportional to the alterations of the sound pressure in the time domain. The materials of the selected work-piece were aluminium and steel with a diameter of about 50 mm. The cutting insert was *Carbide Insert NR9.* The sound signal recoding was done using *GoldWave* software at the sampling rate of 44100 by the PCB micro phone. With constant cutting parameters (depth of cut, cutting speed, feed rate) 15 trials of the emitted sound were recorded during the turning operation each in 3 sessions and each session uses 1 second, 2 seconds and 7 seconds as the duration of recording. This process is repeated for all the three types of tools and for both the materials of steel and aluminium; fresh tool with no flank wear, slightly worn tool with a flank wear of approximately 0.2- 0.25 mm and a severely worn tool with a flank wear of approximately 0.4 mm. A free run sound is recorded when the machine is running without any contact between the tool bit and the work-piece. These measurements were labelled as free run, Fresh, Slight wear and severe wear.

The analysis of the experiment is conducted with the 15X4 samples for each category of tool wear were digitized using *waveread* function for aluminium. The same quantity of data with the same procedures was repeated for steel too. The digitized signals were in array form and raw to do any further analysis as it was. To condense the dimensionality and to reduce the effects of overlapping spectral information between noise and vibration features, Singular Value Decomposition (SVD) approach was applied to all the vibration signal arrays of size of *n* rows and *m* columns.

C. Singular Value Decomposition of Sound Signals

Since there is a real factorization for any real n X m arrays, The SVD of any array **A**, is given by

$$A = USV^{t} \tag{1}$$

Where **U**(m by m), and **V**(n by n) are orthogonal matrices and **S** (m x n) is the diagonal matrices [8]. The columns, u_i and v_i of **U** and **V** are the left and right singular vectors respectively, and the diagonal elements of σ_i of **S** are called the singular values. The columns, r_i and q_i of **R** and **Q** are the left and right singular vectors respectively, and the diagonal elements of σ_i of **S** are called the singular values.

Next, the singular values for each sound signal are arranged on the main diagonal in such an order:

$$\sigma_1 \geq \sigma_2 \geq \sigma_3 \cdots \geq \sigma_{r+1} = \cdots = \sigma_p = 0 \tag{2}$$

The singular values calculated from the Matrix A are considered as the total Energy of matrix A.[2], and are measured in the direction of i^{th} left singular vector of the matrix A.

$$E[A] = \|A\|_F^2 = \sum_{i=1}^{n}\sum_{j=1}^{m} a_{ij}^2 \tag{3}$$

Similarly through SVD, the diagonal entries σ_i are the singular values of any matrix A, A can be written as the sum of rank one matrices as r= rank (A).

$$A = \sum_{i=1}^{r} ui.\sigma i.v_i^t \tag{4}$$

Where (u_i,σ_i,v_i) is the i^{th} singular triplet of matrix A [5]. The Oriented Energy of matrix A, E_q is measured in direction q is delineated as

$$E_q[A] = \sum_{k=1}^{n} (q^T . a_k)^2 \tag{5}$$

In general the energy E_Q measured in subspace Q $\in$ R^m is given as

$$E_Q[A] = \sum_{k=1}^{n} \|P_Q(a_k)\|^2 \tag{6}$$

The SVD can be related to the minima or maxima of the oriented energy distribution as follows.

$$\max_{q \in UB} E_q[A] = E_{u1}[A] = \sigma_1^2 \quad (7)$$

$$\min_{q \in UB} E_q[A] = E_{un}[A] = \sigma_n^2 \quad (8)$$

From equation 8 it is proved that the oriented energy measured in the direction of the i^{th} left singular vector of the matrix A is equal to the square of i^{th} singular value. Hence it is determined that the singular value decomposition protects the characteristics of the source sound signal matrix given by the *m* signal samplings from 1 x 44100 for 1 second signal. After the application of SVD the features are reduced to a singular value feature.

We used the arrived singular values of sound signals captured during the turning process of materials Aluminum as well as Steel in three different categories say fresh, slightly worn and severely worn. The selected features were ***A(l), B(q)*** and **C(r)** representing the sound signals obtained from respective tools. These *l*, *q and r* are the largest singular value features of ***A, B*** and ***C*** represent the feature component of the tools' unique vibrations that discriminates the tools from each other since each tool produce the sound differently according to their degree of freshness. To minimize computational complexity, we set the *l, q and r* value without modification throughout the experiments. These calculations were repeated three times for each metal for duration of 1 second, 2 seconds and 7 seconds on the emitted sound signals.

D. Classification of SVD features

The classifications of the SVD features were carried out by Fuzzy C Means (FCM) Clustering developed to the present stage by J.Bezdek, 1981 as an unsupervised clustering method. This FCM calculates the centroid as the mean of all points weighted by their degree of belongingness to their clusters. The degree of membership of a point in a cluster is related to the inverse of its distance to the centroid of the cluster. The centroid is dynamic rather static, as more points coming in for classification. This iterative calculation process of centroid moves the cluster centre to its appropriate and accurate positions [10].

Given a set of n data patterns, X=x1, . . .,xn, the FCM algorithm minimizes the weighted within group sum of squared error objective function J(U, V)

$$\text{J(U,V)} = \sum_{k=1}^{n}\sum_{i=1}^{c} u_{ik}^{m} d^2(x_k, v_i) \quad (9)$$

where x_k is the kth *p*-dimensional data vector, v_i is the prototype of the centre of cluster i, u_{ik} is the degree of membership of x_k in the *i*th cluster, m is a weighting exponent on each fuzzy membership, $d(x_k, v_i)$ is a distance measure between object x_k and cluster centre v_i, n is the number of objects and c is the number of clusters. A solution of the objective function J(U, V) can be obtained through an iterative process where the degrees of membership u_{ik} and the cluster centers v_i are updated through:

$$u_{ik} = \frac{1}{\sum_{j=1}^{c}\left(\frac{d_{ik}}{d_{jk}}\right) 2/m-1} \quad (10)$$

with d_{ik} as the distance between object k and cluster i, d_{jk} as the distance between object k and cluster j,

$$vi = \frac{\sum_{k=1}^{n} u_{ik}^{m} xk}{\sum_{k=1}^{n} u_{ik}^{m}} \quad (11)$$

With the constraints of $u_{ik} = \in [0,1]$, $\sum_{i=1}^{c} u_{ik} = 1 \forall k$,

$$0 < \sum_{k=1}^{n} u_{ik} < N \forall i$$

According to the update formula for the cluster prototypes (Eq. (11)), objects with minor membership values for that particular cluster have a small contribution to the final position of that particular cluster prototype. This is the general principle on which csiFCM is based: by weakening membership values of objects that belong to the larger cluster, the contribution of those weakened objects to the cluster centres of the smaller clusters will be small. As a result, the cluster centres of the smaller clusters will not drift to the larger adjacent cluster.

We used FCM due to its characteristics of preserving more information than its variants and its simplicity [11], [12].

Fig.3 The different stipulated tools used in this experiment

III. The Results and Discussions

The observation of results show that the SVD features created from the emitted noise signals clearly determines the flank wear condition of the tool. The comparisons were performed among the SVD features for free run with differently worn out tools sounds. The comparisons were repeated for the features of 1 second signals, 2 second signals and seven second signals as well as for both the different materials. The features of fresh tools in the case of aluminum as well as steel were found high in deviation from the free run in all the three cases and with the comparatively noisier worn tool sounds.

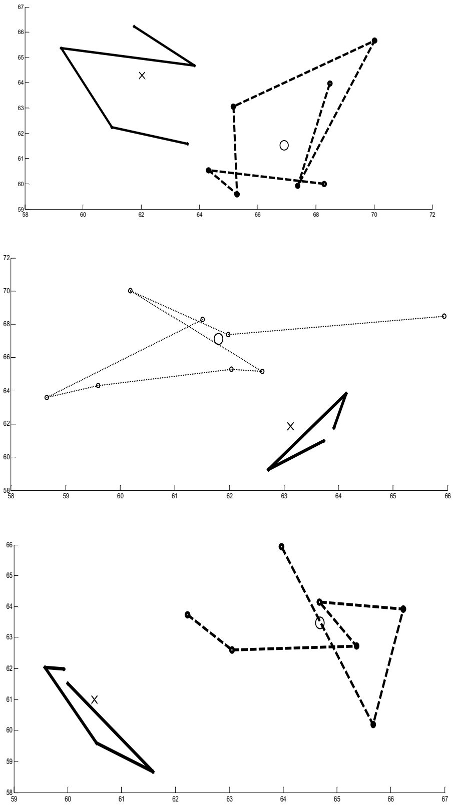
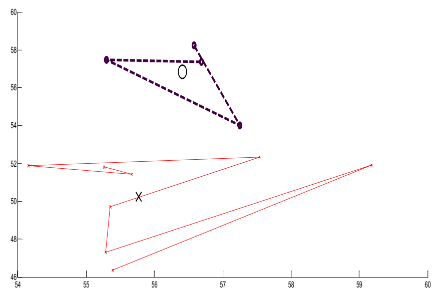


Fig. 4 Fuzzy clustering of tool bit sounds. a) Fresh and slightly worn, b) Slight and severly worn, c) Fresh and severly worn (1 Second High speed signals , Aluminium Job)

The FCM clusters of SVD features calculated for each tool bit signals against the SVD features of free run also reiterate the findings that the noise level is directly proportional to the wear in tool bits. This finding also shows that only when the wear is significant the differences in the sound intensity could be felt completely and in the case of slight wear, the noise is more complex in behaviour and it the clustering is found messy and overlaps on both the fresh and wornout tool characteristics. This character of sounds can be obsereverd from the FCM clusters in figure 4 and 5.



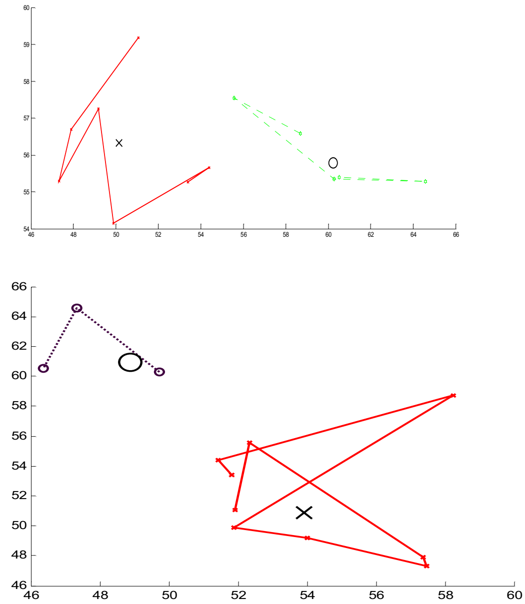


Fig. 5 Fuzzy clustering of tool bit sounds. a)Fresh and slightly worn, b) Slight and severly worn, c) Fresh and severly worn (1 Second Medium speed signals , Steel Job)

An additional observation was made to reinforce the decision making by calculating the center point values obtained from the different FCM clusters including the noisy free run. The fresh tool sound clusters converge in far distance from the free run clusters and the severly worn out tool sound is very high and it appears similar to the free run, and the slightly worn out tool sound lies in between the fresh and severly worn out tool sounds. The centre point of FCM clustering from the aluminium job and steel job is given in table X.

IV. Conclusion

It is clear that there is an increase in the SVD features as the tool flank wear increases. It is evident that the SVD features of the emitted sound can be utilized to ascertain the condition of the tool flank wear during turning process. In conclusion it is found that the condition monitoring of tool flank wear by the emitted sound is proven possible and relatively a simple process. The significant advantage of this sound wave analysis is the duration of decision making on the condition of the tool is very little like 1 second. The analysis and observation of recorded sound for 7 and 2 seconds correlates to a very high degree of resemblance with the 1 second signal observation outputs; hence it is good enough and highly reliable and appropriate to subject the signal piece of one second using our proposed method.

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