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A Novel Local Time-Frequency Domain Feature Extraction Method for Tool Condition Monitoring Using S-Transform and Genetic Algorithm

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Abstract: This paper investigates an online effective method for tool condition monitoring. Acoustic emission signal of a system which is acquired by a sensor mounted to the spindle of the milling machining center is used as the fault indicator because it is easily to be installed, inexpensive and practical for use in industrial environment. Time-frequency analysis is selected for signal processing step based on its ability to reveal time and frequency variant characteristics of faulty signal. S-transform is used as a powerful time-frequency method for this purpose. Because of the high dimension of the time-frequency results, it is desirable to use a local region of interest in time-frequency domain instead of using the entire information, for fast and accurate monitoring and detection when any abnormal/fault operating condition might occur. Such a strategy also helps to reduce the computation cost which is necessary for online applications and improves the interpretation resolution for law quality signals. An optimization method based on genetic algorithm is used for finding the most discriminative local area as the region of interest in time-frequency domain. For feature generation step, a correlation coefficient between each signal and the healthy signal is assigned to the signal using a 2-D correlation analysis. Curve fitting approach is then used to determine a function to approximate the fault value based on the correlation coefficients. Experimental results based on a milling machine under different operating conditions show that this method has a high accuracy for fault detection. It is also concluded that the accuracy of the local feature extraction is higher than the conventional ways.

1. INTRODUCTION

Turning, milling, and drilling are examples of conventional machining operations which are among the most common activities in the manufacturing industry. Tool failure is one of the probable faults during machining process. The high temperature of tool cutting edge, generation of built-up-edge resulting in higher cutting force and temperature and other possibilities in industrial environment may cause tool failure/damage (Landers et al., 2001). Tool failure can cause unscheduled down-time which is costly in terms of time lost. Furthermore, it may increase the production cost because of the damages of tools, machines and work pieces. The amount of down-time due to the tool breakage is about 20% of machine down-time based on some researches (Camci, 2010 and Rehorn et al., 2005). Moreover, cutting tools should be maximally utilized to reduce manufacturing costs as tooling is quite expensive. Another issue is that excessive tool faults such as wear can affect the accuracy of cutting and surface finishing quality significantly. Therefore, it is in high demand to automatically monitor and diagnose tool wear, tool fault, or tool damage during machining to increase efficiency and product quality and reduce production cost (Landers et al., 2001).

Methods used for tool condition monitoring (TCM) can be classified as either direct or indirect. Direct methods are generally more reliable, although they are not convenient for in-process use in a harsh manufacturing environment and they are still very expensive or not possible to be used online. On the other hand, indirect methods estimate the tool fault by relating it to a measured variable such as the change in the size of the workpiece, cutting force, temperature, vibration, acoustic emissions etc. (Danai, 2010 and Abellan-Nebot & Romero Subirón, 2010). Most indirect methods use signal processing algorithms as well as artificial intelligence (AI) techniques to detect the faults according to abnormality occurs to the signals because of the faults.

Many signals have been used for tool condition monitoring in the field of machining monitoring. Cutting force signal can reflect different features of the cutting. It is considered to be the variable that best describes the cutting process and it is widely used in TCM systems (Abellan-Nebot & Romero Subirón, 2010). For example Liu, et al. (2012) has developed a tool wear monitoring algorithm based on the cutting force signals. One drawback of cutting force signal is that increase in the cutting force due to a fault is strongly dependent on other cutting conditions. Furthermore, force signal based monitoring systems are very difficult to apply in industry in terms of cost and applicability. Vibration and acoustic emissions (AE) signals are also widely used in TCM systems (Zhang & Chen, 2008 and Mathew et al., 2008). Using vibration signals has the advantage of simplicity and low cost, but is not reliable (Abellan-Nebot & Romero Subirón, 2010). AE sensors are also easy to install and inexpensive, but they should be located in an appropriate position and carefully calibrated (Abellan-Nebot & Romero Subirón, 2010). Current and power sensors, temperature sensors, optical sensors and ultrasonic sensors are among others

Fig. 1. Steps to design a TCM system

that can be used for monitoring purposes (Abellan-Nebot & Romero Subirón, 2010).

The next step, after signal acquisition, is signal processing and feature extraction which is needed for automated TCM. The nature of faulty signals in TCM is often non-stationary and contains rich information about machinery health conditions (Feng et al., 2013). Time domain, frequency domain, and conventional time-frequency domain analysis have been widely used in the literature in this context. Nevertheless, there is still a lack of using advanced time-frequency analysis in this area (Rehorn et al., 2005). Time-frequency analysis has the potential to reveal the time-varying features of the signal which makes it an effective tool to extract machinery health information contained in non-stationary signals since fault will induce significant time-varying behaviours (Feng et al., 2013). S-transform is such a modern time-frequency analysis method. It has shown great applicability in many research fields such as medical and electrical engineering. The performance of this method is higher than short-time Fourier transform (STFT) because of using a progressive frequency resolution and maintaining a clear relationship to the Fourier spectrum which is its paramount advantage in comparison to Wavelet transform (WT) (Stockwell, 2007). Therefore, it has a great potential for TCM applications and it can improve the interpretation accuracy from a low quality signal and reveal the specific signature of different faults in time-frequency domain (Rad et al., 2013).

Time-frequency representation of a signal should be converted to feature vectors ideally containing only relevant information in order to make the fault detection problem solvable (Avendaño-Valencia et al., 2011). It is possible to use linear transform methods directly, such as principal component analysis (PCA) or partial least squares (PLS), to decrease the time-frequency information dimension and construct a feature vector. However, for high dimension datasets, it becomes time consuming to compute the feature vectors and the obtained components are not always representative of the most discriminative information. One way to conquer this issue is to form the feature vector using local regions of time-frequency domain instead of the entire time-frequency plane. The significantly unsolved issue associated with local-based analysis, is the selection of the size and location of relevant area which is highly dependent on the final application (Avendaño-Valencia et al., 2011). Rehorn et al. (2006) investigated the detection and diagnosis of brush seizing faults in the spindle positioning using selective regional correlation (SRC) which is a local time-frequency analysis method. However, to the authors' best knowledge, effective local time–frequency feature generation issue still has not been addressed in the field of TCM.

In this study, spindle acoustic emissions signal is used for tool wear detection due to its applicability and ease of use in industrial environments. S-transform is selected for time-frequency analysis as an advanced and powerful transformation method. A local region of interest with most discriminative information of fault is obtained using genetic algorithm (GA). A 2-D correlation coefficient between each faulty signal and the healthy signal is calculated on the region of interest in time-frequency domain and is assigned to each signal as a representative of tool wear intensity for fault detection purpose. Genetic optimization algorithm is employed to find the most informative area with respect to fault. In the next step, a curve fitting approach determines a function between the correlation coefficients and tool wear value which is used for tool wear detection. Finally, the accuracy of the proposed fault detection scheme with natural integration of the above components is evaluated by testing a number of faulty signals from a milling machine system and its accuracy is compared to the scheme without using a local region of interest.

2. STEPS TO DESIGN A TOOL CONDITION MONITORING SYSTEM

In this paper a TCM system is designed using indirect method. Figure 1 shows the steps of designing a TCM system. The first step is to capture an indicator signal from appropriate sensor(s) for fault detection purpose. In the next step, signal processing and feature generation methods are needed to convert the signal to features vector with a more clear relation to the faults. Final step is to learn a model and determine the fault value based on the model for faulty signals in industrial environment.

2.1 Acoustic emission as the fault indicator signal

The data set of the BEST lab at UC Berkeley (Agogino & Goebel, 2007) is used for fault detection. This dataset contains experimental results measured from a milling machine under different operating conditions and the flank wear (Vb) is measured as a generally accepted parameter for evaluating tool wear. The insert of milling machine is of the type of KC710 grade and the work piece is made of cast iron. A high speed data acquisition board sends data with maximal sampling rate of 100 KHz. Figure 2 represents the spindle AE signals for healthy case as well as the signals associated with the flank wears $Vb = 0.24$ and $Vb = 0.50$ in time domain with 0.5 mm/s feed rate and 1.5 mm depth of cut as the operation conditions. It can be implied from Figure 2 that the fault existence and intensity is not clear in time domain analysis and it is not possible to realize whether the change is because of cutting condition alternation or different kind of faults.

2.2 Signal processing

2.2.1 S-transform (ST)

The S-transform is an advanced time-frequency transformation with a great ability of interpretation from low quality of signals. It can be assumed to be an extension of the continuous wavelet transform (CWT) concept known for its local spectral phase properties. It works based on a moving and scalable localizing Gaussian window in a way that the modulating sinusoids are fixed with respect to the time axis while the localizing scalable Gaussian window dilates and translates (Stockwell, 2007).

The window function in S-transform is a function of both time and frequency which is the advantage of S-transform in comparison to STFT. Therefore, the window is wider in the time domain for lower frequencies, and narrower for higher frequencies. As a result, the window provides good localization in the time domain for high frequencies, while it provides good localization in the frequency domain for low frequencies (Djurovi et al., 2008).

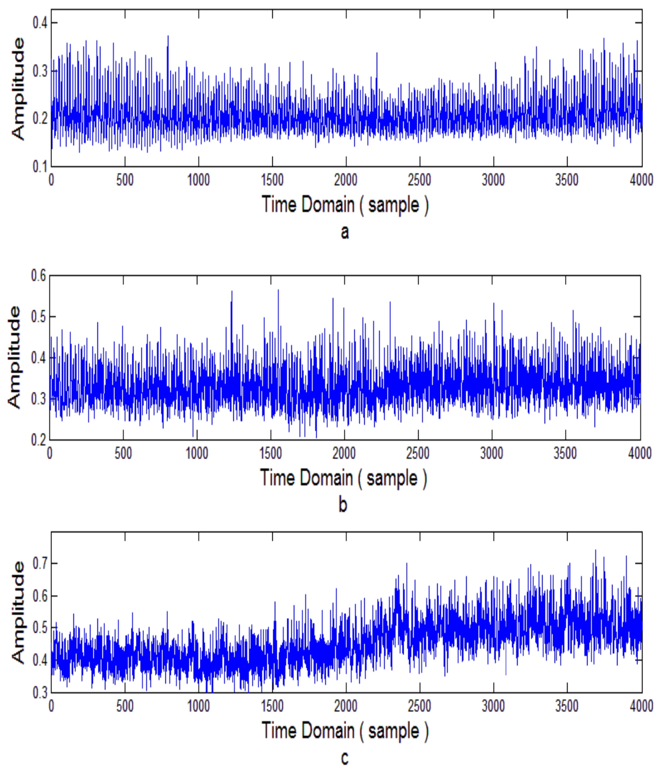

Fig. 2. Spindle AE signal in time domain: a) Vb = 0, b) Vb = 0.24, and c) Vb = 0.50

Continuous S-transform of a time dependent function of $h(t)$ is defined as follows (Stockwell, 2007):

$$S\,(\tau, f) = \int_{-\infty}^{\infty} h(t)\, \frac{|f|}{\sqrt{2\pi}}\, e^{-(\tau-t)^2 f^2/2}\, e^{-i2\pi f t}\, dt \tag{1}$$

Using the equivalent frequency domain definition of the S-transform for the discrete case has computational advantages. It can be represented as (Stockwell (2007)):

$$S\left[jT\,, \frac{n}{NT}\right] = \sum_{m=0}^{N-1} H\left[\frac{m+n}{NT}\right] e^{-2\pi^2 m^2/n^2} e^{i2\pi m j/N}, \; n \neq 0$$

$$S[\,jT\,, 0\,] = \frac{1}{N}\sum_{m=0}^{N-1} h[mT], \; n = 0 \tag{2}$$

where $H\,[\frac{n}{NT}]$ is the Fourier transform of the N-point time series $h[kT]$ and j, m, and $n = 0, 1, ..., N–1$.

Averaging the S-transform over time to get the Fourier transform spectrum, and inverting to the time domain gives the discrete inverse of the S-transform as follows (Stockwell, 2007):

$$h\,[kT] = \sum_{n=0}^{N-1} \left\{\frac{1}{N}\sum_{j=0}^{N-1} S\,\left[jT, \frac{n}{NT}\right]\right\} e^{i2\pi n k/N} \tag{3}$$

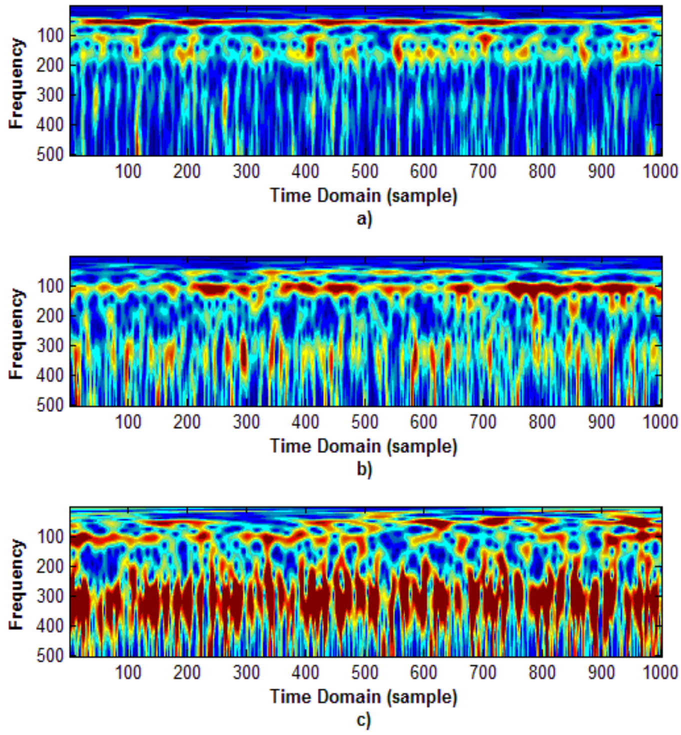

Fig. 3. Spindle AE signals in time-frequency domain: a) Vb = 0, b) Vb = 0.24, and c) Vb = 0.50

2.2.2 Time-frequency analysis using S-transform

In this step a time-frequency analysis of the AE signals is performed by S-transform because time-frequency representation has the potential to clarify the abnormality of signals and the fault state. Figure 3 demonstrates the AE signals for three set of signals with different fault values. As it is visible from the figures, S-transform has great capability to signify the changes associated with the abnormality in the system caused by the fault. For each particular point in time-frequency domain the colours show the value of S-transform at that point. Red colour shows higher intensity in comparison to blue colour. This variety between each faulty case gives us the necessary information for the fault estimation and fault state interpretation.

3. FEATURE GENERATION, SELECTION/EXTRACTION

3.1 2-D correlation analysis

In order to make the fault detection problem solvable, the time-frequency domain information of each signal needs to be converted to features which represent a specific fault in the system. As the fault value increases in the system, the indicator signals show more deviations from the corresponding healthy signal. Therefore, a correlation analysis between each signal and the healthy signal with the same operating conditions determines intensity of abnormality in the system. In this paper, a 2-D correlation coefficient between the time-frequency representation of each signal and the healthy signal is generated as the detection feature for each faulty state. The 2-D correlation coefficient for 2-D signals *A* and *B* can be calculated as follows:

$$r = \frac{\sum_m \sum_n (A_{mn} - \bar{A})(B_{mn} - \bar{B})}{\sqrt{(\sum_m \sum_n (A_{mn} - \bar{A})^2)(\sum_m \sum_n (B_{mn} - \bar{B})^2)}} \quad (4)$$

where

$\bar{A}$ and $\bar{B}$ are the mean value of A and B, respectively.

3.2 Local feature extraction in the time-frequency domain

After transferring the faulty signals to time-frequency domain, the fault existence and its growth trend is clear. However, the dimension of the time-frequency representation is extremely high which makes an interpretation time consuming and inappropriate for online application. Furthermore, for low quality signals, there may be some noise in the time-frequency domain representation of the signals which deteriorate the fault detection performance. Employing a local region of interest of time-frequency domain rather than using the whole information can be a suitable approach to overcome the aforementioned issues. The most informative region of interest which reflects the fault characteristics and intensity accurately will improve the signal resolution as well as reducing the calculation cost.

Figure 4 depicts a local region in time-frequency domain with the $\tau1$ and $\tau2$ boundaries in time domain and $\gamma1$ and $\gamma2$ boundaries in frequency domain. Let us assume that the time-frequency transforms of the healthy signal and faulty signal are Sh(t, f) and Sf(t, f) respectively. It is proposed that for the correlation evaluation, only the region of interest ($t \in [\tau1, \tau2]$ and $f \in [\gamma1, \gamma2]$) will be taken into account. Then, the key question related to this approach is how to find the most informative local area.

The possible solution for finding the most discriminative local area for fault detection purpose is to use an optimization algorithm. Genetic algorithm is selected as the optimization method based on the nonlinear nature of the problem. The variables aimed to be optimized are the boundaries of the region of interest ($\tau1$, $\tau2$, $\gamma1$, $\gamma2$). Therefore, both the size and location of the region can be changed within the time-frequency domain until the best solution is found. The first constraint of the optimization is that the variables should be within the time-frequency matrix range and a minimum length and width size is set as the constraint for region of interest to increase the reliability of system.

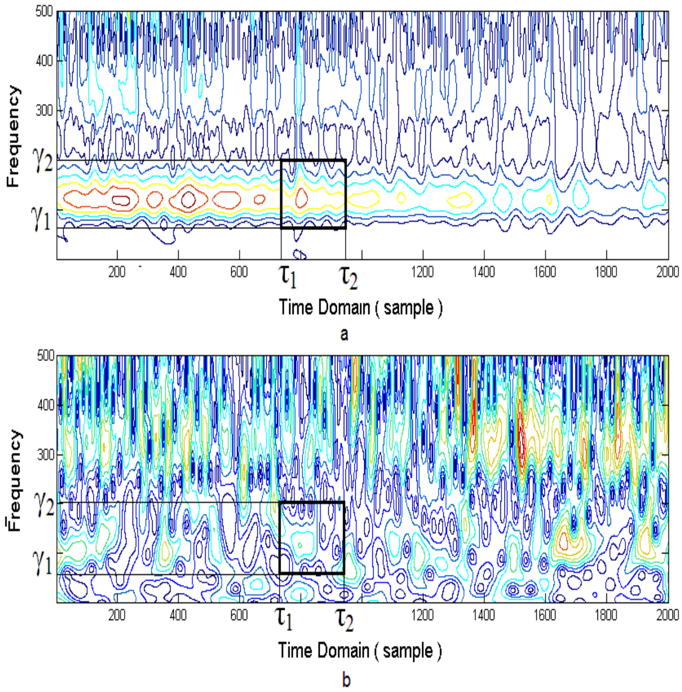

Fig. 4. A local area in time-frequency domain: a) Vb = 0 and b) Vb = 0.50

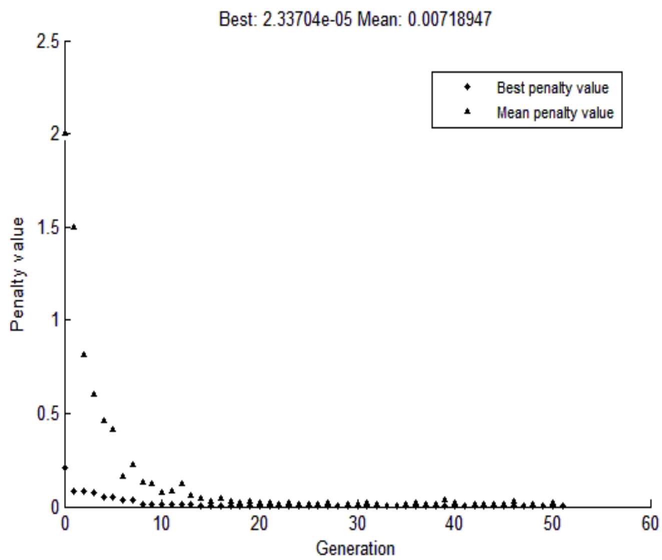

Fig. 5. GA optimization trend

The objective of this optimization problem is to find the region that best describes the trend of change in the signal with the changes in fault values. A sequence of faulty signals is used to define to define an appropriate objective function to better notify the trend of changes in the signals as faulty situation changes. Signal dataset samples are divided into two categories of training and test. The training data itself is divided to subcategories of training and validation data to determine a function between the correlation coefficients of faulty signals and their fault values. A curve fitting approach is employed for this purpose. A curve is fitted by around 70% of training data and then the 30% validation data is fed into system and the fault value is calculated for each iteration. Minimizing the mean error of fault estimations for validation dataset is the objective of this optimization. In other words, the region of interest is the one which gives less mean value of error for fault estimation of the validation dataset. Figure 5 shows the trend of GA optimization.

Finally, the test group of data which was not used in the optimization process will be fed into scheme based on the local region of interest obtained in the optimization step and the fault value will be estimated for this data. This error is considered as an evaluation of the accuracy of the local feature generation method.

4. EXPERIMENTAL RESULTS AND VALIDATION

In the final step of this research, two online fault detection systems are designed and evaluated. Both systems use the spindle AE signals for fault detection purpose. In the first fault detection system, signals are transformed to time-frequency domain using S-transform as the first step. In the second step, a correlation coefficient with the healthy signals is assigned to each signal using the whole time-frequency output band. In this system the dataset is divided to two subsets. The first one is used for curve fitting and determining a function between the fault values and correlation coefficients and the second subset is used for test. In this scheme there is not any optimization and therefore not validation data is required. Finally test data which is not seen in curve fitting step is used for accuracy evaluation and scheme error calculation.

Table 1. Fault estimation example for two case (Depth of cut = 1.5 mm and feed = 0.5 mm)

Case number	1	2
Actual value	0.24	0.43
Estimated value by system using the entire time-frequency information	0.2755	0.4559
Estimated value by system using the local feature extraction	0.2521	0.4519

The first step of the second fault detection system is the same as the previous system by transferring the signals to time-frequency domain. Then a GA optimization approach provides the coordinates of the most informative local area and the system uses this region instead of the entire time-frequency information for the test section. It should be noted that the test data is not seen by the optimization method and the training data itself is divided to curve fitting and validation in the optimization algorithm. This approach guarantees that the local area gives accurate result for new signals in the industrial environment and provides realistic circumstances for comparing two systems. It should be noted that the selected local area in time frequency-domain has less dimensions and therefore less calculation is needed in the correlation coefficients evaluation step. Table 1 represents the actual value and the estimated tool wear value by each system for two example cases.

Table 2. Designed systems accuracy results

System number	Mean error	Maximum error
System using the entire time-frequency information	10.40%	14.80%
System using the local feature extraction	5.00%	5.10%

Table 2 demonstrates the accuracy results of the system without and with using local features. As it is interpreted from the results in the table, the combination of S-transform correlation analysis and curve fitting approach has promising results for fault detection with mean errors of 10.40% and 5% in two systems. Furthermore, using a local region in time-frequency domain and GA optimization approach to find this region is made the system more accurate by decreasing both mean error value and maximum error from 10.4% to 5% and 14.8% to 5.10% respectively. Moreover, the second system has the important advantage of less computing cost which makes it more suitable for online application.

5. CONCLUSIONS

This paper investigates a new online monitoring method for tool wear estimation in milling process. Acoustic emission signal acquired by an acoustic emissions sensor mounted to the spindle of the milling machining centre is used as the fault indicator signal. Based on the non-stationary nature of the faulty signals a time-frequency analysis is performed using S-transform to provide clear and accurate information of signal and clarify the fault effect. It can be concluded from the time-frequency results that S-transform has great potential to reveal the fault signature and can reflects the fault nature more significant.

The output of time-frequency analysis has high dimensions and is costly for further investigations. This paper proposed a new method for dimensionality reduction of the transmitted signal and also obtain more resolution with focusing on the most relevant data to faulty situation for signal representation. It is concluded that a local region of time-frequency domain has more resolution for the fault detection purpose especially for low quality signals. It is also important to conclude that the selected local area in time frequency-domain has less dimensions and therefore less calculation is needed in the correlation coefficients evaluation step that reduces the calculation cost significantly, which is desirable for online applications. A genetic algorithm optimization approach is employed for finding the local region with the most discriminative information. Then, a 2-D correlation analysis between each faulty signal and the corresponding healthy signal in the region of interest is used and a coefficient is assigned to each signal. In the next step, a function is determined between the fault values and their corresponding signal correlation coefficients using curve fitting. Finally a group of test signals are fed into the system and the method accuracy is evaluated. Table 2 shows that for the system with local feature in time-frequency domain the mean and maximum errors are 5% and 5.1% respectively. The results imply that the local area in time-frequency domain perfectly represents the fault situation and intensity of the system. This system accuracy is compared to the accuracy of a system using the entire information of time-frequency domain with the mean error of 10.40% and maximum error of 14.80%. It is clear from comparing the results that the local feature extraction in time-frequency domain outperforms using whole information of time-frequency domain for feature generation from the accuracy and online applicability point of view.

REFERENCES

Abellan-Nebot, J.V. and Romero Subirón, F. (2010). A review of machining monitoring systems based on artificial intelligence process models. *International Journal of Advanced Manufacturing Technology*, 47 (1-4), 237-257.

Agogino, A. and Goebel, K. (2007). Mill Data Set. *BEST lab, UC Berkeley. NASA Ames Prognostics Data Repository,* NASA Ames, Moffett Field, CA.

Avendaño-Valencia, L. D., Acosta-Medina, C. D. and Castellanos-Domínguez, G. (2011). Time-Frequency Based Feature Extraction for Non-Stationary Signal Classification. *Applied Biomedical Engineering, In Tech,* 289-312.

Camci, F. (2010). Process Monitoring, Diagnostics and Prognostics in Machining Processes. *LAP Lambert Academic Publishing.*

Danai, K. (2001). Machine Tool Monitoring and Control Chapter 5 of Mechanical Systems Design Handbook: Modeling, Measurement, and Control. *CRC Press*, 75-84.

Djurovi, I., Sejdi, E. and Jiang, J. (2008). Frequency-based window width optimization for S-transform. *AEU - International Journal of Electronics and Communications,* 62 (4), 245-250.

Feng, Z., Liang, M. and Chu, F. (2013). Recent advances in time–frequency analysis methods for machinery fault diagnosis: A review with application examples. *Mechanical Systems and Signal Processing*, 38 (1), 165-205.

Landers, R. G., Ulsoy, A. G. and Furness, R. J. (2001). Process monitoring and control of machining operations Chapter 6 of Mechanical Systems Design Handbook: Modeling, Measurement, and Control. CRC Press, 85-104.

Liu, T.-I., Song, S.-D., Liu, G. and Wu, Z. (2012). Online monitoring and measurements of tool wear for precision turning of stainless steel parts. *International Journal of Advanced Manufacturing Technology*, 65 (9-12), 1-11.

Mathew, M.T., Pai, P.S. and Rocha, L.A. (2008). An effective sensor for tool wear monitoring in face milling: acoustic emission. *Sadhana - Academy Proceedings in Engineering Sciences*, 33 (3), 227-233.

Rad, J.S., Hosseini, E., Zhang, Y. and Chen, C. (2013) Online tool wear monitoring and estimation using power signals and S-transform. *Control and Fault-Tolerant Systems (SysTol) Conference,* 234-238.

Rehorn, A.G., Sejdić, E. and Jiang, J. (2006). Fault diagnosis in machine tools using selective regional correlation. *Mechanical Systems and Signal Processing,* 20 (5), 1221-1238.

Rehorn, A.G., Jiang, J. and Orban, P.E. (2005). State-of-the-art methods and results in tool condition monitoring: A review. *International Journal of Advanced Manufacturing Technology*, 26 (7-8), 693-710.

Stockwell, R.G. (2007). A basis for efficient representation of the S-transform. *Digital Signal Processing*, 17 (1), 371-393.

Zhang, J.Z. and Chen, J.C. (2008). Tool condition monitoring in an end-milling operation based on the vibration signal collected through a microcontroller-based data acquisition system. *International Journal of Advanced Manufacturing Technology*, 39 (1-2), 118-128.