Tracking Operation Status of Machines through Vibration Analysis using Motif Discovery.

Yon-Qing Lee¹, Woan-Lin Beh² and Boon-Yaik Ooi³

¹, ²Faculty of Science, ³Faculty of Information and Communication Technology, Universiti Tunku Abdul Rahman, Malaysia.

E-mails: ¹leeyonqing@utar.my, ²behwl@utar.edu.my; ³ooiby@utar.edu.my

Abstract. Industrial revolution 4.0 is inevitable for developing countries and created an urgency for many small and medium enterprises (SME) manufacturers to modernize their operations. Unfortunately, the process of modernization is expensive and it may not be justifiable for SMEs. This work is part of our existing effort in developing retrofitting sensors solution to help in reducing the cost and risk of SMEs moving towards Industry 4.0. This work focuses on tracking operation of machine through vibration data. Vibration analysis is not new and there are many existing works especially in the area of machine condition monitoring. This work is different from machine condition monitoring because the aim of this work is to track operation status of machines. The operation status of machines are crucial for manufacturers to manage maintenance and estimate the throughput of their operation. However, the main challenge of tracking operation status is that there are no prior knowledge on the machine’s vibration. The success of Motif Discovery has provided an opportunity to distinguish and identify the operation status of a machine from its vibration with minimal interference to the machine’s operation. This work puts Matrix Profile to test; using 15 sets of vibration data from 2-speed (high and low speed) industrial fan and exhaust hood, with the period for each collection at 10 minutes. From the experimental results, this work showed that it is possible to track the operation status of a machine through its vibration data and the accuracy can be as high as 99%.

1. Introduction

One of the key-advantage of industry 4.0 is the ability collect operation data and allows data driven decision to be made to improve the overall manufacturing performance [1]. Unfortunately, many SME manufacturers do not have the capital to do the transition. Therefore, in our previous work [2], we designed a retrofitting sensors solution to provide an affordable approach for SME to perform transition at lower risk. The operation status tracking information can be used to help manufacturers to manage maintenance, estimate yields and plans operations [3], [4]. Vibration analysis has been around for several decades and the development of vibration measuring instrumentation now able to determine the deteriorating condition of equipment or machine before it leads to a breakdown [5]. Unfortunately, many of these vibration analysis techniques are machine dependent and it requires intensive vibration profiling before prognosis can be carried out. Vibration profiling is not only a time consuming process but also costly because it involves interruption on the manufacturing process. It is
not suitable for many SME. Therefore, a least intrusive method is needed. This work was inspired by the success of Matrix Profile technique and attempt to use it to analyze real vibration data.

Vibration analysis methodology could be subdivided into four principal domains: time domain, frequency domain, joint domain and modal analysis. Each domain gives specific information on the working conditions and features of the vibrating part [6]. However, industry is facing challenges while using vibration data to conclude their operation status of a manufacturing machine. One of the main issue is how to interpreted the raw vibration data meaningfully [2]. Many manufacturing machines are custom made without prior knowledge on the machine’s vibration and the right to interrupt the process for classifying the machines’ vibration [2]. Therefore, the objectives of this work is to distinguish and identify the operation status of a machine from its vibration with minimal interference to the machine’s operation and the operators using a time series motif discovery approach.

This study discovery the motif of the vibration data by using Matrix Profile, a novel algorithm developed by the Keogh research group at UC-Riverside [7]. This algorithm is a powerful tool to help solve the dual problems of anomaly detection and motif discovery [7]. This approach is simple and perform well with parameter-free compare to others existing methods [7], [8].

The paper is organized as follows: Section 2 summarizes the related work. Section 3 describes the proposed method in details. Section 4 shows the findings of the work, and we conclude our work in Section 5.

2. Related work

Vibration analysis is a very broad and complicated domain which make uses of several aspects of the testing and diagnosis disciplines, from condition monitoring to defect detection. There are many ways to collect, process and analyse on the vibration data. Caesarendra and Tjahjowidodo [9] summarized six categories of methods based on certain characteristic of the features to extract the vibration data in slew bearing vibration signal. Zvokelj et al. [10] presented the condition monitoring method utilizing vibration signal based on ensemble empirical mode decomposition and principal component analysis (PCA). There are few studies of slew bearing condition monitoring and life prediction utilizing vibration signal with different methods [11], [12].

Single spectrum analysis (SSA) is one of the well-known data analysis tools that has been successfully applied in analysing vibration data [13], [14]. PCA and SSA are found successfully used to analyse short and nonstationary time series data; however, majority of the vibration data are found as nonstationary in mean and variance. There were few significant algorithms were introduced in discovering the variable length of the time series motif [15], [16], [17]; however, majority of the existing algorithms required the prior information of the parameter.

The Matrix Profile algorithm is an approach to determine likeness in time series data which is introduced by Yeh et al. in 2016 [7]. Matrix Profile is robust [7], [8], scalable [8], [18] and largely parameter-free [19], [20]. Matrix Profile algorithm does not require the user to set a similarity threshold [20]. This algorithm has time complexity that is constant in subsequence distance [21], [22]. Matrix Profile algorithm is works for range of metrics [20], including website user data [23], DNA [24], music analysis [25] and other business-critical applications. This study is different from existing vibration analysis which focused on identifying the status of a manufacturing system based on the system vibration by using Matrix Profile algorithm and then uses the identified status for further analyse usage such as Overall Equipment Effectiveness (OEE).

3. Methodology

The Matrix Profile algorithm is introduced in 2016 and is an approach to discovered the likeness in the time series. An order from a data is compared to each single order of the identical distance within the series, then the gaps are calculated and stored. This gap is a metric for likeness. If that series has a minimum length, then another series with same feature is presented in that series. If the minimum length of a series is relatively high, it is special in the series [8].
Matrix Profile used a novel Euclidean distance similarity search algorithm called Mueen’s algorithm for similarity search (MASS) for time series data [26]. This algorithm computes the distance profile by using the fast Fourier transform (FFT). This algorithm is unlike the k-nearest neighbors (KNN) search algorithm [27], it calculated the distance to every subsequence in the series.

STUMPY is the algorithm used in this study in order to discover the length-invariant motif with the measurement distance [27], [28]. STUMPY is a sturdy and robust library that accurately computes a vector that represents the intervals between all sub-sequences within a time series and their closest neighbors [7], [27]. STUMPY is the predecessor to Scalable Time series Anytime Matrix Profile (STAMP) and Scalable Time series Ordered-search Matrix Profile (STOMP). STAMP helps on allocate memory of the two different matrix profiles and then performed pairwise minimum search operation and matching. Meanwhile STOMP performs an ordered search of the distance of the series. The goal of STUMPY is to speed up the time for pattern discovery.

4. Results

This vibration data obtained in this study is collected from a 20 inch, 2-speed (high and low speed) industrial exhaust fan. The exhaust fan blowing duration and speed are deliberately controlled in order to obtain vibration datasets with a known ground truth. A total of 15 sets of vibration data were obtained from the fan and exhaust hood, with the period for each collection at 10 minutes. There are 5 different duration ratio of vibrations with 3 different samples in each dataset (i.e. 10:90, 20:80, 30:70, 40:60 and 50:50). Figures 1-5 visualize the data for each duration ratio of different vibrations.

Figure 1. The plot of the vibration of the 2-speed industrial exhaust fan (ratio 10:90; Sample 1).

Figure 2. The plot of the vibration of the 2-speed industrial exhaust fan (ratio 20:80; Sample 1).

Figure 3. The plot of the vibration of the 2-speed industrial exhaust fan (ratio 30:70; Sample 1).
Figure 4. The plot of the vibration of the 2-speed industrial exhaust fan (ratio 40:60; Sample 1).

Figure 5. The plot of the vibration of the 2-speed industrial exhaust fan (ratio 50:50; Sample 1).

Figures 6-8 illustrate the zoom in samples of the vibration motifs discovered by the proposed method. The two different motifs in the series are differentiate in blue and red colors. From the figure, we are able to reveal how similar to each other of the subsequence are for different ratio of the samples. Table 1 shows the experimental setting and results of the proposed technique in monitoring the operation status of the industrial exhaust fan. The results in Table 1 show that the duration ratio discovered from the proposed method is about same as the actual duration ratio of different vibrations.

Figure 6. The motif of the vibration visual representation of the ratio 30:70 (Sample 1).

Figure 7. The motif of the vibration visual representation of the ratio 40:60 (Sample 1).

Figure 8. The motif of the vibration visual representation of the ratio 50:50 (Sample 1).
Table 1. Experimental Results.

| Actual ratio of different vibrations | Sample | Ratio obtained from the proposed method |
|-------------------------------------|--------|----------------------------------------|
| 10:90                               | 1.     | 10:90                                   |
|                                     | 2.     | 10:90                                   |
|                                     | 3.     | 10:90                                   |
| 20:80                               | 1.     | 20.6:79.4                               |
|                                     | 2.     | 20.1:79.9                               |
|                                     | 3.     | 20.1:79.9                               |
| 30:70                               | 1.     | 30:70                                   |
|                                     | 2.     | 29.9:69.1                               |
|                                     | 3.     | 29.9:69.1                               |
| 40:60                               | 1.     | 40:60                                   |
|                                     | 2.     | 39.7:60.3                               |
|                                     | 3.     | 40.1:59.9                               |
| 50:50                               | 1.     | 50:50                                   |
|                                     | 2.     | 49.9:50.1                               |
|                                     | 3.     | 49.9:50.1                               |

5. Conclusions
In this paper, we explored the industrial vibration data using the Matrix Profile algorithm. This approach is searching the similarity motif based on the novel Euclidean distance and is parameter free. From the experimental results, this work showed that it is possible to track the operation status of a machine through its vibration data and the accuracy can be as high as 99%. This proposed algorithm does not need the legacy manufacturing system operation to be interrupted for vibration profiling. In future work, we plan to check on the status for vibration data with 3 different states (low, medium and high speed). We may consider other waveform analysis apart Matrix Profile in future which may help to further improve the performance of the proposed solution.

Acknowledgement
This research is supported in part by UTAR Research Fund IPSR/RMC/UTARRF/2019-C2/003 from the Universiti Tunku Abdul Rahman, Malaysia.

References
[1] Kagemann H, Wahlster W, and Helbig J Recommendations for implementing the strategic initiative INDUSTRIE 4.0 Final report of the Industrie 4.0 Working Group
[2] Ooi BY, Beh WL, Lee WK, and Shirmohammadi S 2019 IEEE International Instrumentation and Measurement Technology Conf. (I2MTC) May 20-23 Auckland New Zealand p 1-6
[3] Perera C, Liu CH, Jayawardena S, and Chen M 2015 IEEE Access 2 p 1660-1679
[4] Perera C, Liu CH, and Jayawardena S 2015 IEEE Trans. Emerg. Top. Comput. 3(4) p 585-598
[5] Nakajima S 1988 Introduction to total productive maintenance (TPM) Productivity Press Cambridge
[6] Larizza P 2015 Micromanufacturing engineering and technology 2 Ed ScienceDirect
[7] Yeh et al. 2016 IEEE International Conf. on Data Mining (ICDM) Dec 12-15 Barcelona
[8] Anton et al. 2018 IEEE International Conf. on Data Mining Workshops (ICDMW) Nov 17-20 Singapore
[9] Caesarendra W and Tjahjowidoo T 2017 Machines 5(21) p 1-28
[10] Zvokelj M, Zupan S and Prebil I 2010 Mech. Syst. Signal Process 24 p 1049-1067
[11] Zvokelj M, Zupan S and Prebil I 2011 *Mech. Syst. Signal Process* **24** p 2631-2653
[12] Hua W, Yan T and Rongjing H 2016 *J. Vibroeng* **18** p 4340-4353
[13] Vautard R, Yiou P and Ghil M 1992 *Physica D* **58** p 95-126
[14] Vitanov NK, Sakai K and Dimitrova ZI 2008 *Chaos Solitons & Fractals* **37** p 187-202
[15] Staden R 1989 *Computer Applications in Biosciences* **5** p 293-298
[16] Tanaka Y, Iwamoto K and Uehara K 2005 *Mach. Learn* **58**(2-3) p 269-300
[17] Guyet T, Garbay C and Dojat M 2007 *Journal of Biomedical Informatics* **40**(6) p 672-687
[18] Yoon et al. 2015 *Sci Adv* **1**(11) e1501057
[19] Ma Y, Meng X and Wang S 2016 *Concurr Comput* **28**(1) p 166-183
[20] Yeh et al. 2017 *Data Min Knowl Disc* DOI 10.1007/d10618-017-0519-9
[21] Ding et al. 2008 *Proc. of the VLDB endowment (VLDB)* **1**(2) p 1542-1552
[22] Mueen et al. 2009 *Proc of the 2019 SIAM International Conf. on Data Mining (SDM)* p 473-484
[23] Morales GDF and Gionis A 2016 *Proc. of the VLDB endowment (VLDB)* **9**(10) p 792-803
[24] Agrawal R, Faloutsos C and Swami AN 1993 *Proc. of the 4th International Conf. on foundations of data organization and algorithms (FODO’93)* p 69-84
[25] Silva et al. 2015 *IEEE Transactions on Multimedia* **14**(8) p 1-10
[26] Mueen et al. 2017 [http://www.cs.unm.edu/~mueen/FasterstSimililaritySearch.html](http://www.cs.unm.edu/~mueen/FasterstSimililaritySearch.html)
[27] Zhu et al. 2016 *IEEE International Conf. on Data Mining (ICDM)* Dec 12-15 Barcelona
[28] Law SM 2019 *Journal of Open Source Software* **4**(39) p 1-2