DOI: 10.2507/33rd.daaam.proceedings.068

ONLINE MULTI – SENSOR PROCESS MONITORING DURING ROBOTIC SANDING OF THIN-WALLED STRUCTURES

Dora Bagaric*, Tomislav Staroveski, Miho Klaic & Damir Ciglar

This Publication has to be referred as: Bagaric, D[ora]; Staroveski, T[omislav]; Klaic, M[iho] & Ciglar, D[amir] (2022). Online Multi – Sensor Process Monitoring during Robotic Sanding of Thin-Walled Structures, Proceedings of the 33rd DAAAM International Symposium, pp.0490-0495, B. Katalinic (Ed.), Published by DAAAM International, ISBN 978-3-902734-36-5, ISSN 1726-9679, Vienna, Austria
DOI: 10.2507/33rd.daaam.proceedings.068

Abstract

The goal of the proposed research is the development of indirect sanding paper wear level and surface quality estimation models for sanding of thin-walled structures. The models should be applicable in robotic sanding systems in real time. Since the dynamics of tool wear appears highly nonlinear even in the conventional machining processes, it can be assumed that an array of impacting factors will occur due to lower rigidity of the robot, elastic deformation of the thin-walled workpieces, and due to a damping effect of the tool interface. Additionally, it can also be expected that the factors will have a negative influence on the development of the models. Therefore, to realize the research, a number of experiments will be conducted in order to determine the effect of machining parameters on the sanding paper wear dynamics. Subsequently, determination of the process parameters sensitive to change in tool state and/or workpiece surface quality will be conducted. Lastly, design of the sanding paper wear and workpiece surface quality estimation models will be carried out. By successfully realizing the aforementioned models, preconditions for achieving higher autonomy in automated robotic sanding systems will be established.

Keywords: sanding; tool condition; surface quality; multi-sensor monitoring; artificial intelligence

1. Introduction

Application of robots in finishing processes is one of significant trends in the development of state-of-the-art machining systems, and sanding processes are among the most performed finishing processes. Such systems are, in most cases, equipped with an axial force control drive, on which a main drive with a sanding tool with an elastic interface is mounted. Sanding tools are subjected to intensive wear resulting from mechanical, thermal, and chemical loads during sanding. Negative impact of tool wear on the workpiece surface quality is noticeable even in the early stages of tool wear. Consequently, sanding paper is frequently replaced, potentially causing unnecessarily frequent process interruptions and hence, unnecessary costs.

The moment in which the tool needs to be replaced is, in most cases, determined based on human experience. Nevertheless, today, when the highest possible level of machining process autonomy is sought for, such type of estimation is unacceptable for a number of reasons. If a certain amount of tool wear is exceeded, workpiece surface quality will deteriorate.

On the other hand, if the maximum threshold value of tool wear is not achieved, sanding paper is going to be prematurely discarded and the manufacturing process frequently interrupted. For that reason, a reliable and efficient method of indirect process monitoring, applicable during the process in real time, is of great importance for achieving high productivity, as well as high product quality [1], [2].

Although research done so far in the field of indirect process monitoring showed that robust tool wear models are attainable, the studies were often conducted on machining processes with geometrically defined cutting tools, and with the interfaces of tool, machine tool, and workpiece being rigid [3]. Even in those conditions, achieving a universal and generally applicable model for tool wear or surface quality monitoring was not possible due to the highly nonlinear and stochastic nature of tool wear. For that reason, such monitoring systems are almost always developed according to the specific characteristics of a machining process [1].

There are two main approaches in machining process monitoring – monitoring based on direct and indirect methods [4]. In direct methods, the information on tool wear level or state of the surface in acquired by directly measuring the tool or the machined surface features. Even though the accuracy of the measured value is the advantage, the main disadvantage of the method is the inability to be used during machining [5]. In other words, frequent interruptions to the machining process are caused in order to carry out the measurements.

Indirect methods can be applied in real time, during the machining process but the correlation between process parameters and tool or surface state must be established beforehand. Any machining process characteristic measurable or determinable during machining can be considered as a process parameter. These methods generally facilitate multiple different types of sensors. Amongst most commonly used are force [6], [1], [7], current [8], vibration [9], [1], acoustic emission [10], [1], and sound [11], [7], [1] sensors. After the signal acquisition, a number of features sensitive to change in tool state and/or workpiece surface quality, are extracted and used in tool wear and surface quality estimation models. Unlike direct, indirect methods do not require a disruption to the machining process and can in some cases significantly shorten overall machining time, which makes them suitable for industrial environments.

When it comes to tool condition monitoring in robotic finishing processes, research has been mostly done on belt grinding and polishing. Ren et al. [7] developed a method for machine learning based workpiece heat input monitoring in robotic belt grinding of Inconel 718 using force and sound sensors. They concluded that the heat input is influenced by grinding parameters and the state of the grinding tool. Between the state of the grinding tool and the force and sound signals, a clear correlation was discovered. The result of work done in [12] is a robust method of grinding belt condition monitoring in a robotic grinding system of superalloys, accomplished by utilizing sound signals and a machine learning method. An evaluation of the grinding belt condition was successfully performed by a neural network based multi-sensor system developed in [1], in which vibration, force (F_x and F_z) and acoustic emission sensors were used. In a study done by Chen et al. [13] a grinding belt condition monitoring system was proposed. The system uses a model based on random forest (RF) classifier and multiple linear regression (MLR) which use acoustic emission signal features as input data. Acoustic emission signals and tool condition revealed considerable correlation. Pandiyan et al. [6] have suggested a method of identifying the compliant belt grinder condition by means of force, acoustic emission, and vibration signals whose features were employed to train the support vector machine algorithm. As a result, a high-accuracy tool condition prediction model was attained. Meier et al. [14] developed a model for polishing stone breakage detection and determination of the optimal time for tool replacement in robotic polishing based on acoustic emission and force sensors. In [15] acoustic emission, force and current sensors were used in a robot-assisted polishing process to estimate the correct time for tool replacement (end-point detection), in order to maintain the desired surface roughness. A robust surface roughness classification model based on an artificial neural network was obtained.

In [16] a parameter optimization for manual sanding of black pine was conducted based on the relationship between process parameters (feed rate, grit size, spindle speed), and the achieved surface roughness. Motivated by the exposure of workers to harsh working environments (orbital sanding tool simultaneously executes rotary and eccentric motion to attain better surface quality and consequently, produces dust, noise, and vibrations), Nagata et al. [17] developed a robotic system for sanding furniture with free-formed surfaces. Robotic sanding systems were also utilized in naval industries [18] as a solution to problems with large, stationary parts. In research by Putz et al. [19] a step closer to an autonomous robotic system has been made by presenting a successful method of automated tool alignment, necessary for automated sanding paper replacement.

The industry has shown considerable interest in robotic machining despite the challenges they pose [20], [21]. Robotic machining systems have considerably lower rigidity compared to machine tools. However, due to their ability to perform complex tool paths in a relatively large working area they are facilitated in finishing processes that require lesser forces and accuracies during machining. Such systems are also commonly utilized in sanding of large, thin-walled structures.

The sanding process is performed with a geometrically undefined tool with an elastic interface that, on one hand, allows for better adherence to the workpiece surface, but on the other, causes a dampening effect. In addition, workpieces such as thin-walled structures are prone to elastic deformation. Therefore, despite the many advantages robotic cell application offers, it is expected that the aforementioned disturbances (e.g. vibration signals that could result from change in tool and/or surface quality state, would be dampened by the elastic interface) may make the existing process monitoring models difficult to apply. Additionally, even though machining process monitoring has been widely studied, not many have dealt with robotic finishing, and hardly any research has been done on robotic sanding. Hence, research on the possibility of attaining sanding paper wear level and workpiece surface quality estimation models specifically designed for the robotic sanding process of thin-walled structures is proposed. The goals of the research would be:

1. To determine the effect of cutting parameters (spindle speed, feed velocity, and axial force) on the dynamics of the sanding paper wear.
2. To determine the effect of cutting parameters and level of sanding paper wear on workpiece surface quality.
3. To determine the process parameters (sensor signal features) sensitive to changes in the sanding paper wear level.
4. To determine the process parameters (sensor signal features) sensitive to changes in workpiece surface quality.
5. To develop robust sanding paper wear level and workpiece surface quality estimation models applicable in real time during the sanding process.

The experimental setup and the research method will be described in the following section. Lastly, in section 3., a conclusion will be given.

2. Experimental system

The research will be carried out in three phases. In the first phase, the experimental setup (Fig. 1) will be developed. The setup will consist of two industrial robots of which the first one (ABB 6660) is equipped with a main drive for sanding.

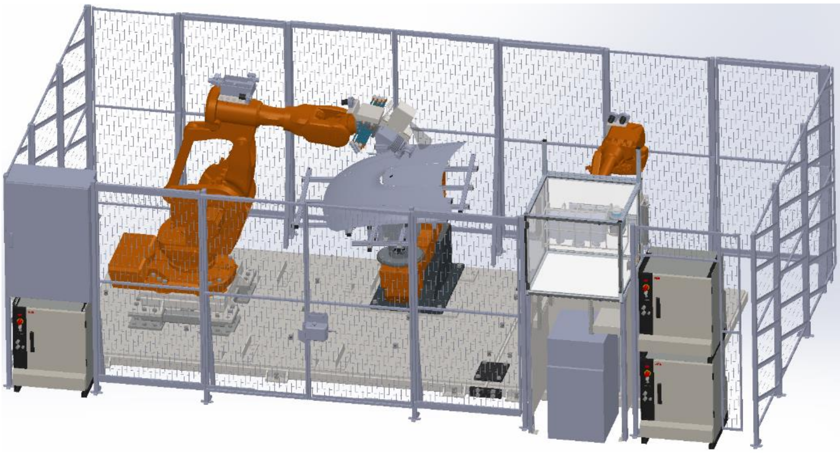

Fig. 1. Robotic sanding cell (left: ABB 6660, middle: IRBP A with the clamping system, right: ABB 4600)

The main drive for sanding is realized through a precise force control unit with a mounted orbital sander (Fig. 2). The orbital sander includes an elastic interface pad for the sanding paper. Different sorts and granulations of sanding paper will be used.

Fig. 2. Mirka® AIROS 650CV orbital sander for industrial robots [22]

Vibration (Fig. 3, left), acoustic emission (Fig. 3, right), and sound sensors (Fig. 4), as well as a thermal imaging camera (Fig. 5) will be mounted in proximity to the main drive.

Fig. 3. KISTLER triaxial accelerometer [23] (left), and acoustic emission sensor [24] (right)

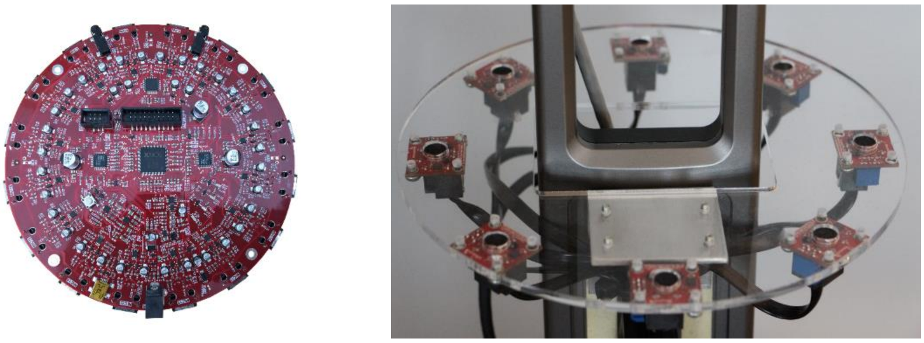

Fig. 4. 16SoundsUSB sound card [25] (left); example of an 8SoundsUSB system microphone array [26] (right)

Fig. 5. Teledyne thermal imagining camera Flir A700-EST, 24° Lens [27]

In between the two robots, a rotary-swivel table (IRBP A) with a suitable clamping system for the workpiece will be placed. This research will be conducted on relatively large and thin-walled composite structures. On the second robot (ABB 4600), an optical 3D measurement instrument for automated form and roughness measurements (Alicona IF-SensorR25) (Fig. 6) will be mounted.

Fig. 6. Alicona IF-SensorR25 [28]

The experiment will cover a large number of sanding cycles including different:

a. combinations of cutting parameters (feed velocity, spindle speed, axial force),
b. types of sanding papers (at least three different granulations) – that will be worn out to different degrees (at least three levels of wear),
c. types of workpieces with dissimilar geometrical features (at least two types of workpieces – homogenous and composite).

Tool wear level and workpiece surface quality will be determined with the Alicona optical sensor, before and after each cycle of sanding. Vibration, acoustic emission, sound signals, and a thermal image of the workpiece surface will be recorded during the sanding cycles. In the second phase (after completing all tests) the acquired information will be processed and analysed. Features will be extracted from recorded signals and images and examined to determine their sensitivity to changes in tool wear and/or workpiece surface quality. In the third phase, a portion of the extracted features will be used for the tool wear estimation model formation, and the rest will be used to obtain the workpiece surface quality estimation model. In the proposed research the estimation models will be based on artificial intelligence algorithms since the high complexity of the tool wear process makes statistical models unsuitable for this application [29].

3. Conclusion

Machining process monitoring models are not universal and generally applicable, and their successful implementation depends on specific process characteristics. Although robotic machining process monitoring has been studied, research on robotic sanding is quite scarce. Therefore, the formation of sanding paper wear level and workpiece surface quality estimation models would be conducted for the set process – robotic sanding. Robotic sanding has its advantages, but problems such as: lower rigidity of the machine performing the process, commonly used large, thin-walled workpieces prone to elastic deformation, undefined geometry of the sanding paper, and the dampening effect of the sanding paper elastic interface are expected to contribute to the difficulty of applying the existing models obtained so far and are also expected to be a challenge in obtaining the new models.

In the proposed research the possibility of developing a multi-sensor based sanding paper wear level and workpiece surface quality monitoring system will be studied. The aim is to determine the effect of cutting parameters on sanding paper wear and the effect of cutting parameters alongside the level of sanding paper wear on workpiece surface quality. Lastly, the objective would also be to determine the process parameters sensitive to change in sanding paper and/or workpiece surface quality and to develop robust sanding paper wear level and workpiece surface quality estimation models applicable during sanding process in real time. The suitability of signal features extracted from vibration, acoustic emission, and sound signals, along with the thermal image would be investigated and potentially used for the formation of estimation models based on artificial intelligence.

Successful realization of the proposed models would create preconditions for development of a robotic sanding monitoring system in real time. By obtaining the models, the level of robotic sanding system autonomy would be significantly increased and a foundation for adaptive control of cutting parameters (feed velocity, cutting speed, and axial force) would be established.

4. Acknowledgements

This research is supported by the European Regional Development Fund (ERDF) through the grant KK.01.1.1.07.0016 (ARCOPS).

5. References

[1] Qi. J.; Chen, B. & Zhang, D. (2020). Multi-information fusion-based belt condition monitoring in grinding process using the improved-Mahalanobis distance and convolutional neural networks, Journal of Manufacturing Processes, vol. 59, pp. 302-315, ISSN 1526-6125, DOI: 10.1016/j.jmapro.2020.09.061.

[2] Kuntoğlu, M.; Aslan, A.; Pimenov, D. Y.; Usca, Ü.A.; Salur, E.; Gupta, M.K.; Mikolajczyk, T.; Giasin, K.; Kapłonek, W. & Sharma, S. (2021). A Review of Indirect Tool Condition Monitoring Systems and Decision-Making Methods in Turning: Critical Analysis and Trends, Sensors 2021, Vol. 21, No. 1: 108, DOI: 10.3390/s21010108

[3] Klaic, M.; Staroveski, T. & Udiljak, T. (2014). Tool Wear Classification using Decision Trees in Stone Drilling Applications: a Preliminary Study, Proceedings of the 24th International DAAAM Symposium "Intelligent Manufacturing & Automation", ISSN 1877-7058, Katalinic, B. (Ed.), pp. 1326-1335, Published by Elsevier Ltd., Oxford, UK, DOI: 10.1016/j.proeng.2014.03.25.

[4] Zhou, Y. & Xue, W. (2018). Review of tool condition monitoring methods in milling processes, The International Journal of Advanced Manufacturing Technology, vol. 96, pp. 2509-2523, DOI: 10.1007/s00170-018-1768-5

[5] Jourani, A.; Hagege, B.; Bouvier, S.; Bigerelle, M. & Zahouani, H. (2013). Influence of abrasive grain geometry on friction coefficient and wear rate in belt finishing, Tribology International, vol. 59, pp. 30-37, ISSN 0301-679X, DOI: 10.1016/j.triboint.2012.07.001.

[6] Pandiyan, V.; Caesarendra, W.; Tjahjowidodo, T. & Tan, H. H. (2018). In-process tool condition monitoring in compliant abrasive belt grinding process using support vector machine and genetic algorithm, Journal of Manufacturing Processes, vol. 31, pp. 199-213, ISSN 1526-6125, DOI: 10.1016/ j.jmapro.2017.11.014.

[7] Ren, X.; Chai, Z.; Xu, J.; Zhang, X.; He, Y.; Chen, H. & Chen, X. (2020). A new method to achieve dynamic heat input monitoring in robotic belt grinding of Inconel 718, Journal of Manufacturing Processes, vol. 57, pp. 575-588, ISSN 1526-6125, DOI: 10.1016/ j.jmapro.2020.07.018

[8] Tian, Y.; Liu, F.; Wang, Y. & Wu, H. (2017). Development of portable power monitoring system and grinding analytical tool, Journal of Manufacturing Processes, vol. 27, pp. 188-197, ISSN 1526-6125, DOI: 10.1016/j.jmapro.2017.05.002.

[9] Wu, D.; Jennings, C.; Terpenny, J.; Gao, R. X. & Kumara, S. (2017). A comparative study on machine learning algorithms for smart manufacturing: tool wear prediction using random forests, Journal of Manufacturing Science and Engineering, vol. 139, no. 7, DOI: 10.1115/1.4036350

[10] Liao, T. W. (2010). Feature extraction and selection from acoustic emission signals with an application in grinding wheel condition monitoring, Engineering Applications of Artificial Intelligence, vol. 23, no. 1, pp. 74-84, 2010., ISSN 0952-1976, DOI: 10.1016/j.engappai.2009.09.004.

[11] Ghosh, N.; Ravi, Y. B.; Patra, A.; Mukhopadhyay, S.; Paul, S.; Mohanty, A. R. & Chattopadhyay, A. B. (2007). Estimation of tool wear during CNC milling using neural network-based sensor fusion, Mechanical Systems and Signal Processing, vol. 21, no. 1, pp. 466-479, ISSN 0888-3270, DOI: 10.1016/j.ymssp.2005.10.010.

[12] Zhang, X.; Chen, H.; Xu, J.; Song, X.; Wang, J. & Chen, X. (2018). A novel sound-based belt condition monitoring method for robotic grinding using optimally pruned extreme learning machine, Journal of Materials Processing Technology, vol. 260, pp. 9-19, ISSN 0924-0136, DOI: 10.1016/ j.jmatprotec.2018.05.013.

[13] Chen, J.; Chen, H.; Xu, J.; Wang, J.; Zhang, X. & Chen, X. (2018). Acoustic signal-based tool condition monitoring in belt grinding of nickel-based superalloys using RF classifier and MLR algorithm, The International Journal of Advanced Manufacturing Technology, Vol. 98, pp. 859-872, DOI: 10.1007/ s00170-018-2270-9

[14] Meier, N.; Papadoudis, J. & Georgiadis, A. (2020). Prediction of the tool change point in a polishing process using a modular software framework, Proceedings of the 13th CIRP Conference on Intelligent Computation in Manufacturing Engineering, ISSN 2212-8271, ISBN 978-1-713814-59-7, Teti, R. & D'Addona, D.M. (Ed.), pp. 341-345, Published by Elsevier B.V., Amsterdam, Netherlands, DOI: 10.1016/j.procir.2020.05.059.

[15] Segreto, T. & Teti, R. (2019). Machine learning for in-process end-point detection in robot-assisted polishing using multiple sensor monitoring, The International Journal of Advanced Manufacturing Technology, vol. 103, pp. 4173-4187, DOI: 10.1007/s00170-019-03851-7.

[16] Hazir, E.; Koc, K. H. & Hiziroglu, S. (2017). Optimization of sanding parameters using response surface methodology, Maderas. Ciencia y tecnologia, Vol. 19, pp. 407-416, ISSN 0717-3644, DOI: 10.4067/S0718-221X2017005000034.

[17] Nagata, F.; Kusumoto, Y.; Fujimoto, Y. & Watanabe, K. (2007). Robotic sanding system for new designed furniture with free-formed surface, Robotics and Computer-Integrated Manufacturing, vol. 23, pp. 371-379, ISSN 0736-5845, DOI: 10.1016/ j.rcim.2006.04.004.

[18] Subrin, K.; Garnier, S.; Bressak, T. & Furet, B. (2019). Digital chain development for sanding application with a kinematically redundant robotic system, Proceedings of the 17th CIRP Conference on Modelling of Machining Operations, ISSN 2212-8271, ISBN 978-1-7138-0094-1, Ozturk, E.; Mcleay, T. & Msaoubi, R. (Ed.), pp. 515-520, Published by Elsevier B.V., Amsterdam, Netherlands, DOI: 10.1016/J.PROCIR.2019.04.063.

[19] Putz, V.; Stangl, M; Kohlberger, C. & Naderer, R. (2019). Computer Vision Approach for the Automated Tool Alignment of an Orbital Sanding Robot, Proceedings of the 8th IFAC Symposium on Mechatronic Systems, ISSN 2405-8963, ISBN 978-1-7138-0790-2, Jadachowski, L. (Ed.), pp. 19-24, Published by Elsevier Ltd., Oxford, UK, DOI: 10.1016/J.IFACOL.2019.11.643.

[20] Nam, H. H.; Verlinden, O. & Rivière-Lorphèvre, E. (2017). Robotic Machining Simulation using a Simplified Multibody Model, Proceedings of the 28th International DAAAM Symposium "Intelligent Manufacturing & Automation", ISSN 1726-9679, ISBN 978-3-902734-11-2, Katalinic, B. (Ed.), pp. 0885-0894, Published by DAAAM International, Vienna, Austria, EU, DOI: 10.2507/28th.daaam.proceedings.123.

[21] Pérez, R.; Gutiérrez, S. C. & Zotovic, R. (2018). A Study on Robot Arm Machining: Advance and Future Challenges, Proceedings of the 29th International DAAAM Symposium "Intelligent Manufacturing & Automation", ISSN 1726-9679, ISBN 978-3-902734-20-4, Katalinic, B. (Ed.), pp. 0931-0940, Published by DAAAM International, Vienna, Austria, EU, DOI: 10.2507/29th.daaam.proceedings.134.

[22] https://www.mirka.com/en/p/MIA6502012. Mirka®. Accessed on: 2022-9.

[23] https://www.kistler.com/en/product/type-8763b/. KISTLER. Accessed on: 2022-9.

[24] https://www.kistler.com/en/product/type-8152c/. KISTLER. Accessed on: 2022-9.

[25] https://github.com/introlab/16SoundsUSB/blob/master/README.md. github. Accessed on: 2022-9.

[26] https://introlab.3it.usherbrooke.ca/sam/ca/description-du-projet/hardware/8soundsusb/. github. Accessed on: 2022-9.

[27] https://www.flir.eu/products/flir-a700-est/. TELEDYNE FLIR. Accessed on: 2022-9.

[28] https://www.alicona.com/en/products/if-sensorr25/. Bruker alicona. Accessed on: 2022-9.

[29] Lv, L.; Deng, Z.; Liu, T.; Li, Z. & Liu, W. (2020). Intelligent technology in grinding process driven by data: A review, Journal of Manufacturing Processes, vol. 58, pp. 1039-1051, ISSN 1526-6125, DOI: 10.1016/ j.jmapro.2020.09.018.