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Digital Twin Based Online Material Defect Detection for CNC-Milled Workpieces

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Abstract

Reliable lot-size-one compatible online quality monitoring for CNC machined parts remains elusive. To address this challenge, our approach aims to bridge the current gap in research by developing a cost-effective and reference-independent monitoring concept for material defect detection in CNC-machined parts. This paper presents a novel digital twin-based method, utilising machining vibrations and a g-code-based encoding of the cutting process. The objective is to detect material defects, such as blowholes, without the need for individual workpiece references. The proposed method aims to reduce barriers to entry, minimise waste, and enhance machine productivity by enabling automated early online quality control. To develop and validate the model, we generate a new dataset combining machining vibration with technological context data such as chip-shape. We demonstrate the feasibility and potential of the approach in a job shop setting on a 3-axis CNC mill.

Keywords: Online process monitoring; Material defect detection; Digital Twin; Lot size one; Vibration monitoring

1. Introduction

The manufacturing industry is undergoing a paradigm shift, transitioning from a focus on *responsiveness* to a *market-of-one*, deemed *Mass Individualisation* [1] or *Mass Personalisation* [2]. This entails the production of custom-made products while maintaining the low unit costs traditionally associated with mass production. In response, there has been a global push towards smart manufacturing characterized by autonomous operations enabled by advanced sensing, data processing, and decision-making technologies. [3, 4]

Within this context, reducing lot sizes in job-shop settings becomes imperative, and additive manufacturing (AM), particularly 3D printing, emerges as a promising solution due to its autonomy and versatility. However, despite its advantages, AM still falls short compared to traditional techniques like CNC milling in aspects such as dimensional accuracy, mechanical properties, material variety, and surface quality [5, 6, 7]. CNC milling, therefore, remains pivotal, presenting not only significant potential but also high necessity for optimisation due to its complex nature of underlying processes that result in lower process resilience and robustness compared to AM.

Nomenclature

CNC	Computerised Numerical Controled (machine tool)
AM	Additive Manufacturing
CCC	...

A monitoring system that utilises deep process context (e.g. technological, geometric, or material property data) to generate reference agnostic (= lot size one capable) process status insights, would ready CNC mills for the Mass Personalisation paradigm shift.

Such a workpiece-centred monitoring system, which detects material defects or user (=operator) errors (e.g. wrong material, or part clamping errors) during normal machining, can increase

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process efficiency & reliability, reduce waste, and enable higher product quality.

To achieve economic efficiency and general market accessibility, this system must be easy to integrate, machine-agnostic, and relatively low-cost.

Requirements: workpiece quality monitoring system that is:
- lot size one capable
- machine agnostic
- easy to integrate
- cost effective

2. Related work

Predominantly, CNC monitoring is focused on tool condition monitoring, particularly detecting tool wear and breakage, ensuring surface finish quality, including mitigating chatter, and monitoring machine health for predictive maintenance purposes [8, p.2727]. The following sensors are in use for CNC monitoring and are rated by investment cost and information value (see: Table 1).

Table 1. Sensors according to signals and properties [according to 8, p.2725]

Sensor	Level of investment cost	Extent of signal accuracy and information value
Dynamometer	•••••	•••••
Accelerometer	••••	•••
AE	••••	•••
Current/power	•	•
Temperature	•••	••
Sound	•	•

Dynamometers commonly utilise all six spatial axes (three translatory and three rotatory) to capture force profiles at high sampling rates, with higher rates correlating with increased cost. Vibrations measured by accelerometers refer to the oscillatory motion of an object or system around an equilibrium position ($f_{acc} \lesssim 10$ kHz). AE refers specifically to the release of stress waves or energy due to internal changes or deformation within a material. AE is difficult to measure in lower frequencies. Usual frequencies are: 20 kHz $\lesssim f_{AE} \lesssim$ 500 kHz. [9, 10]

Current/power is measured from the drive unit of the spindle (and translates ruffly into spindle tourque) and is therefore extremely cost effective. Temperature, mostly measured via thermal imaging cameras, lack high sample rates (due to low frame rates), and suffer from delays and perspective obstacles.

2.1. Similar monitoring solutions

Matta's Grey-1 model as shown in their paper [11] demonstrates AM process monitoring on fused layer deposit 3D printers, based on an automated deep process understanding. They trained a multi head transformer model on labeled images; labels such as: extrusion speed, layer thickness and hotend temperature. They are able to detect extrusions errors (which translate into material defects), or adjust printing parameters fully autonomously for unseen material. [11] This study serves as a substantial inspiration and influence for the present work.

Another noteworthy study [12] investigates the cutting forces measured by a (6-axis) dynamometer in the micromanufacturing of Ti6246 alloy by comparing them with theoretically calculated forces, to detect material defects such as blowholes. This approach is in theory lot size one capable because the force measurement is not compared to a previsouly manufacured 1:1 reference, but rather is based on experimental measurements and a geometric physics-based process simulation. It is concluded that the accuracy of the calculated force and the insufficient change in amplitude between normal and defect machining are too low to achieve automated detection. [12, p.169]

While dynamometer force measurements offer the highest signal accuracy and information value due to their direct measurement method and process proximity [13], they are expensive (multiple 10s of thousands of euros), difficult to set up, and usually not feasible for production environments (see Table 1).

Qass's Optimizer 4D, an off-the-shelf AE-based general-purpose inspection system, addresses the problems of dynamometers described above, at the cost of reduced signal accuracy. The system is still expensive, but it comes with out-of-the-box spectral pattern recognition, which enables reference-dependent material defect detection, thus is not lot size one capable. [14, p.5]

Research gap:
- research in online CNC workpiece quality monitoring remains relatively underexplored
- material defect detection represents a particular under-researched subfield
- only a single paper has been identified thus far that addresses reference-independent defect monitoring within this domain

2.2. ML usage in CNC monitoring

- DBN (deep belieef network) feature reduction/extraction
- SVM (support vector machine) classification

Sensor products employed in research:

- Acoustic Emission via Optimizer 4D by Quass; powerful AE monitoring employed in tool condition monitoring and tested (sci) on chatter detection (Szulewski.Sniegulska-Gradzka2017)

- multi axis Force Dynanometers by Kistler; most direct process monitoring (most powerful); material defects monitoring in micro milling Ti(Pfirrmann.Baumann.ea2021)

- Contact Microphone (Gitarrenabnehmer) for chatter detection

- ML: was machen andere paper mit ml, allgemein time-series analysis...

optional: –¿ research gap

3. Aproach

The general aproach to fullfill the requirements from Section 1 in the scope of the research gap concluded in Section 2, is to use cost effective sensors that are easy to retro fit and don't disturb machining, and to contextualise sensor data with machining-specific information, to enable effective lot-size one monitoring.

3.1. Physical quanitity to monitor

Vibrations measured via accelerometers or Acoustic Emission (AE) sensors form a great compromise between ease of installation & cost, and signal accuracy & information value. While Dynamometers entail greater information value, their high cost and poor mountability don't make them viable for general monitoring. Other options such as "current/power" "temperature" or "sound" hold lower information value and are therefore not considered. Additionaly are the relatively easy

The easily and cheaply achievable high sampling rates of vibration measuremnts are an enormous advantage when zooming in and analysing each cutting event (cutting edge engagement). As the paper [12] shows that especially smaller/micro material defects affect machining forces for just a few edge engagements, lasting in total a few microseconds.

3.2. Machining-context features

(context architecture) - process descriptive parameter

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welche gren nehmen einfluss auf den schneidprozess?

wie kann der der prozess mglichst allgemeingltig beschrieben werden? -mglichst prozess beschreibende parameter

wie knnen diese parameter mglichst unabhngig von einander dargestellt werden? (-¿ dimensionslos), als Koefizient darstellen

—

Key aspect of our aproach is to substitute a 1:1 reference of the same part manufactured prior, by general machining and cutting conditions and circumstances for each time in the manufacturing process, we call this data: context. To design our context features, we followed 3 questions.

3.2.1. What factors influence the cutting process?

blub

3.2.2. How can the process be described as universally as possible by these factors?

blub

3.2.3. How can these factors be modelled as mathematically independent (non-dimensional) coefficients?

blub

3.3. Concept architecture

- concept diagram Figure 1

- center: CNC - conventional procedure - grey, the four monitoring procedures, explain them - legend: process step, exchanged information

3.4. ML architecture ???

hhh - diagram mit high level ML (konzeptionell)

4. Implementation

4.1. Proof of concept

from full design concept to simplified proof of concept. DoE, welche context feature knnen heraus vereinfacht werden? - Maschinentyp=1, Werkstoff=1 ...

4.2. Dataset design

Datensatz dimension und umfang

4.3. Experiment pipeline

hhh

4.4. Experiment setup

DoE -¿ static gocode lines (drawing) in python, auf emco, ...

5. Validation

...and evaluation

6. Conclusion

and futere recommendation (halbe seite)

References

[1] Y. Lu, X. Xu, L. Wang, Smart manufacturing process and system automation – A critical review of the standards and envisioned scenarios, Journal of Manufacturing Systems 56 (2020) 312–325. doi:10.1016/j.jmsy.2020.06.010.

[2] Z. Qin, Y. Lu, Self-organizing manufacturing network: A paradigm towards smart manufacturing in mass personalization, Journal of Manufacturing Systems 60 (2021) 35–47. doi:10.1016/j.jmsy.2021.04.016.

[3] X. Gu, Y. Koren, Mass-Individualisation – the twenty first century manufacturing paradigm, International Journal of Production Research 60 (24) (2022) 7572–7587. doi:10.1080/00207543.2021.2013565.

[4] Y. Lu, K. C. Morris, S. P. Frechette, Current Standards Landscape for Smart Manufacturing Systems, NIST.

[5] T. Chen, Y.-C. Lin, Feasibility Evaluation and Optimization of a Smart Manufacturing System Based on 3D Printing: A Review, International Journal of Intelligent Systems 32 (4) (2017) 394–413. doi:10.1002/int.21866.

[6] 3D printing vs. CNC machining: Which is better for prototyping and end-use parts?, https://www.hubs.com/knowledge-base/3d-printing-vs-cnc-machining/.

[7] CNC vs. 3D Printing: What's the Best Way to Make Your Part?, https://markforged.com/resources/blog/cnc-vs-3d-printing.

[8] M. Kuntoğlu, E. Salur, M. K. Gupta, M. Sarıkaya, D. Y. Pimenov, A state-of-the-art review on sensors and signal processing systems in mechanical machining processes, The International Journal of Advanced Manufacturing Technology 116 (9) (2021) 2711–2735. doi:10.1007/s00170-021-07425-4.

[9] J. Józwik, D. Mika, DIAGNOSTICS OF WORKPIECE SURFACE CONDITION BASED ON CUTTING TOOL VIBRATIONS DURING MACHINING, Advances in Science and Technology Research Journal 9 (2015) 57–65. doi:10.12913/22998624/2365.

[10] S. Sun, X. Hu, W. Zhang, Detection of tool breakage during milling process through acoustic emission, The International Journal of Advanced Manufacturing Technology 109 (5) (2020) 1409–1418. doi:10.1007/s00170-020-05751-7.

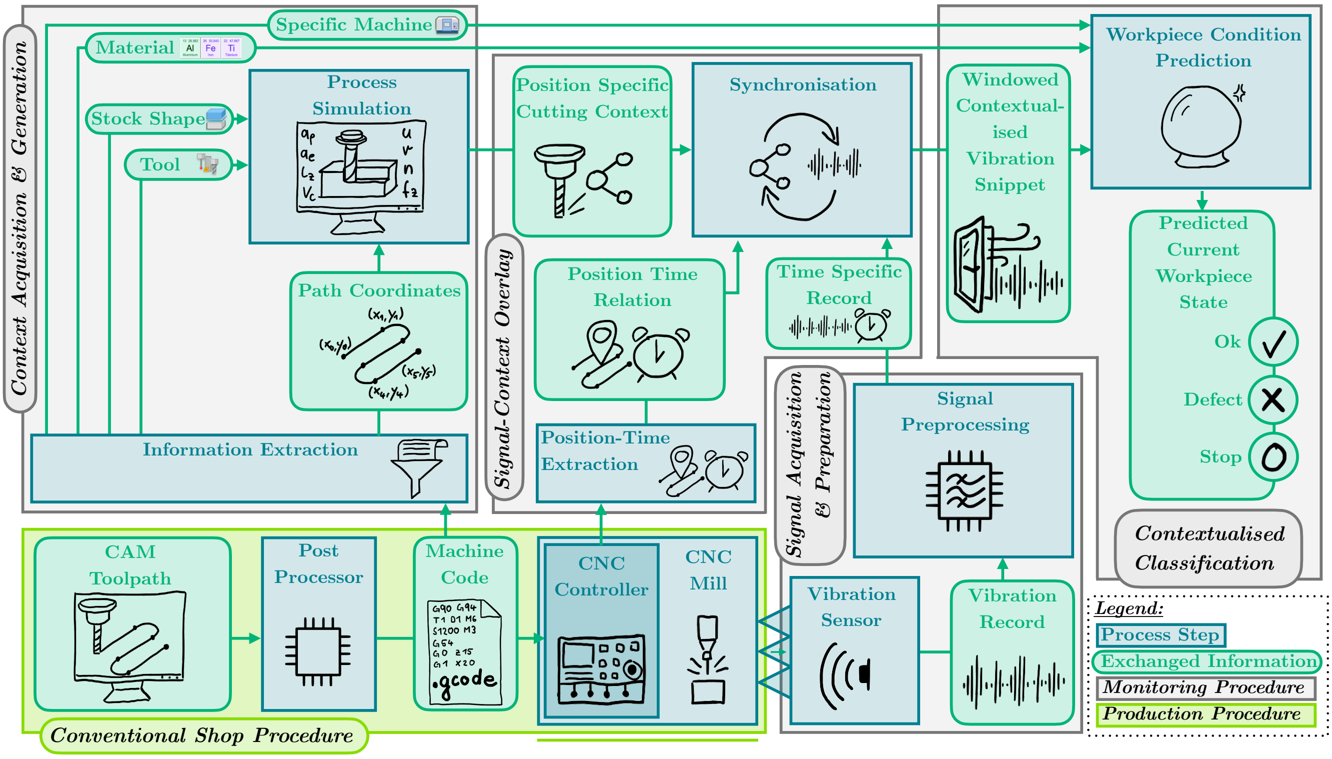

Fig. 1. High-Level Concept

[11] D. A. J. Brion, S. W. Pattinson, Generalisable 3D printing error detection and correction via multi-head neural networks, Nature Communications 13 (1) (2022) 4654. doi:10.1038/s41467-022-31985-y.

[12] D. Pfirrmann, J. Baumann, E. Krebs, D. Biermann, P. Wiederkehr, Material defects detection based on in-process measurements in milling of Ti6246 alloy, Procedia CIRP 99 (2021) 165–170. doi:10.1016/j.procir.2021.03.023.

[13] M. E. Korkmaz, N. Yaşar, M. Günay, Numerical and experimental investigation of cutting forces in turning of Nimonic 80A superalloy, Engineering Science and Technology, an International Journal 23 (3) (2020) 664–673. doi:10.1016/j.jestch.2020.02.001.

[14] P. Szulewski, D. Śniegulska-Gradzka, Systems of automatic vibration monitoring in machine tools, Mechanik 90 (3) (2017) 170–175. doi:10.17814/mechanik.2017.3.37.