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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 conclusion: 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 band is: 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 conclusion:

- 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

ML: was machen andere paper mit ml, allgemein timeseries analysis...

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

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 point in time in the manufacturing process, we call this data: context. To design our context features, we came up with 3 questions.

1. *What factors influence the cutting process?*
   - workpiece -geometry, -clamping, -material characterstics (e.g. e-module)
   - tool -type (shape), -coating (surface), -cutting fluid
   - machine -kinemantics, -stiffness, -sub componenent noise
   - cutting process on chip level (e.g. rake angle)
   - generall milling process (e.g. cutting speed: v_c)
   - others: temperature, chip extraction, direction, etc.

   The above factors affect the cutting process, some directly by influencing the load on the material being removed, ultimately resulting in a change in the virbation pattern. Others affect the process indirectly through resonance, e.g. slender workpiece geometries are excited at their natural frequency.

2. *How can the process be described as universally as possible by these factors?*
   Some factors can't be generalised, or are not feasable to do so. Those factors stay as static features that need specific learning later. Incomprhesible features e.g. "specific machine" can't be generalised because of their complex nature, therefore each machine needs custom learning. Other features are not feasable to generalize because they would make the medel too complex: e.g. material characterisitcs can be explained by more general features such as hardness, tensile strength, etc. Due to the high number of material features, we decided to custom train each material. We have identified the following static features on which later learning is based: material, machine, clamping/fixture, tool type, and cutting fluid.
   Factors that are generalisable - where comprehensible and detachable features with general predication can be derived from - are prefered and form the backbone of deep process insights. E.g. cutting speed v_c, is machine, material and tool independent while having substantial influence on the cutting process, ultimatly influencing sensor signal patterns.
   Factors that require specifc sensors in order to be captured, such as temperature, are excluded from the model to keep complexity manageable.

3. *How can these factors be modelled as mathematically independent (uncoupled, lower-dimensional) coefficients?*
   To achieve high quality training data interdependence or correlation among features is to be avoided. Most classical technological paramters are interdependent: e.g. infeed $a_p[mm]$ is dependent on tool diamter $d[mm]$, that means by changing the tool to a bigger diameter, the ratio from a_p and d changes. To fix this a_p needs dimensional reduction: from $a_p[mm]$ to $a_p/d[\%]$ removing the interdependence of d. Feed rate f is dependent on cutting speed v_c and tool diameter d. Uncoupled f translates into feed rate per tooth f_z.
   We found the following independent coeffiecients: tool diameter d, cutting speed v_c, infeed percent $a_{p\%}$, cutting depth a_e, tool edge number z, direction, milling mode (climb or up-cut), spindle speed n
   Additional features are modelled to better describe the cutting context such as: contact arc (angle of attack where tool is in contact with workpiece), arc direction (direction vector of contact arc), chip volume, cutting frequency,
   Not all the considered factors can be fully modelled, so there is always some loss of information. Whether the remaining information is sufficient to model the cutting context is analysed in our proof-of-concept implementation.

The final context features are a mix of static features concluded in question 2 (e.g. material), independent coefficients (e.g. feed rate per tooth), as well as additionally modeled features (e.g. contact arc) from question 3.

3.3. Concept architecture

The general aproach to the lot size one capable material defect monitoring integrates dirctly into common pre-existent production interfaces to enable easy machine agnostic retrofitting. The wohle concept architecure is shown in Fig. 1. The whole diagram centers around the "CNC Mill" including its "CNC Controler" in the bottom center. The process steps highlighted in bright green colour represent the standard information flow on the shop floor for CNC machines - no monitoring -just the preexistent "Conventional Shop Procedure". The monitoring system integrates right on top of this procedure which can be subdiveded into four "Monitoring Procedures" (grey boxes): "Signal Acquisition & Preperation", "Context Acquisition & Generation", "Signal Context Overlay", and "Contextualised Classification".

Inside those procedure boxes (bright green and grey) are dark blue coloured "Process Steps", specific functions that process information. Information flows in and out of these dark blue "Process Steps", this flow and exchange of information is visualised with arrows and rounded boxes in turquoise colour, we called them "Exchanged Inforamtion". See the diagram for details.

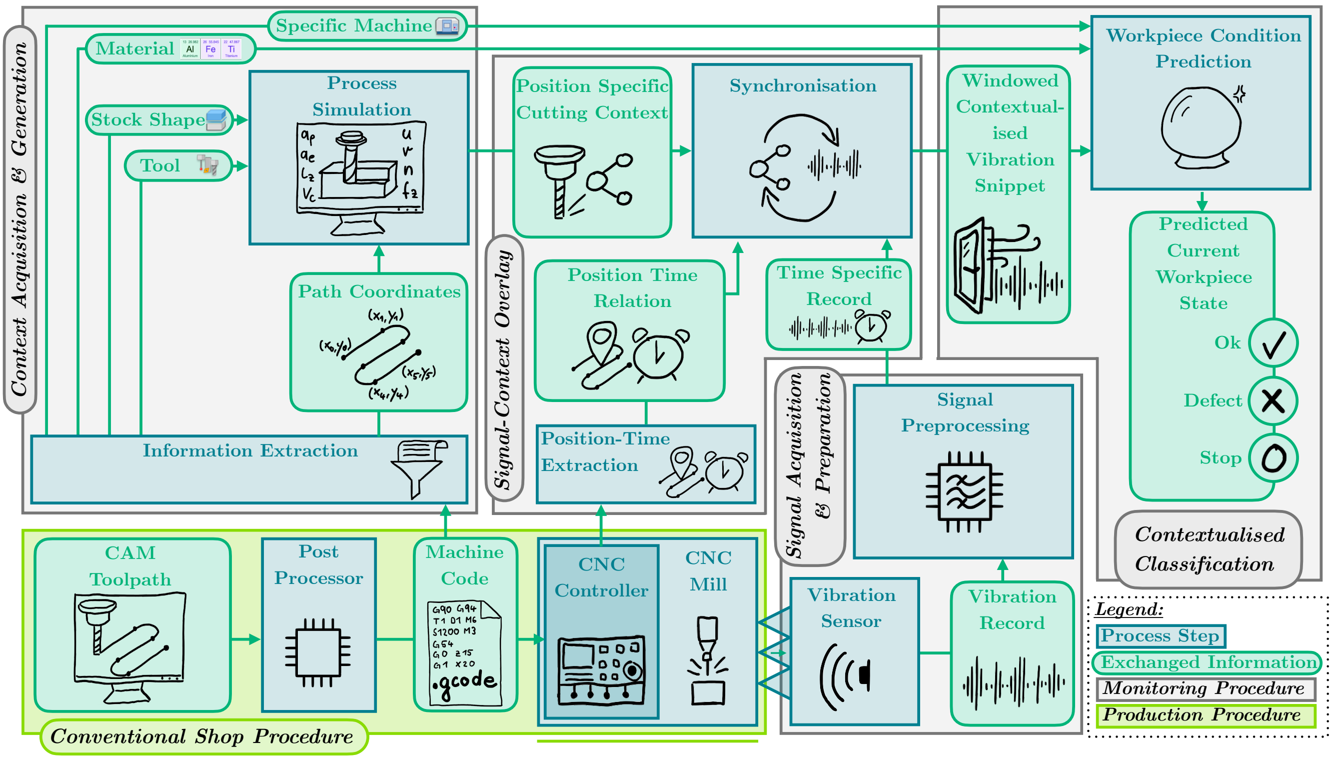

Fig. 1. High-Level Concept

3.4. *ML architecture ???*

- 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)

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