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Process-parallel quality estimation

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Abstract
The currently available CAD-CAM-NC process chain involves design data to be passed from CAD environment to CAM, where an operator's empirical knowledge is used to select optimal cutting parameters. At this stage the operator has only qualitative information of the cutting forces and the machine's dynamic behaviour, and safe cutting parameters are a result of the operator's accumulated experience. Once this part programme is executed on the machine, it is difficult to provide quality-related indicators. Thus, most of the produced parts, especially in performance- or safety-critical applications, pass through the CMM. For larger components, the post-process metrology cost can be up to 25-50 % of the total cost of the part.
The availability of better computing and possibility to run digital-twin models presents an opportunity to estimate the quality of the metal cutting in parallel to the real process. The present work investigates an approach for virtual real-time quality estimation in metal cutting. A digital-model of the machine tool is created to realize this. For the current study, this digital-model incorporates a stiffness map of the machine tool augmented with models of various tools and tool holders. When this digital-model is simulated with the real-time data of the process—obtained from the machine controller and additional sensors—it estimates the tool deflection. The real-time data consists of the compensated tool position from the machine tool controller, cutting forces, and the tool table from the machine controller. Collectively, such data is called 'digital-fingerprint' or 'digital-shadow' of the process. This data is then used to generate a faceted body in real-time, called 'in-progress digital workpiece', which can be easily compared to the target CAD of the part to estimate the quality of machining. This type of workflow provides better information on the process quality in real-time, thereby eliminating or reducing the CMM time for manufactured parts.

Process monitoring; Virtual metrology; Virtual quality control; Edge computing; Process parallel quality estimation; Digital shadow; Digital twin; Closed-loop manufacturing

1. Introduction

To date, the conventional CAD-CAM-NC process chain relies heavily on an operator's empirical knowledge to select the safe cutting parameters. His decisions are based on accumulated experience that is guided by qualitative information regarding cutting forces and the machine's dynamic behaviour, and by information provided by cutting tool and machine tool manufacturers on safe cutting parameters.

Research efforts over the last few decades have been aiming to decrease the impact of the operator and consequently increase machining quality. Similarly, the existing techniques that are used to make predictions about the process performance rely on accurate model-based simulations [1-4], where the quality of the prediction can be directly linked to the quality of the model, e.g. [5]. While modern CAM simulations include the physical behaviour of a given machine tool—like NC controls, servo motor—to verify and optimise toolpaths, they have a built-in flaw—they cannot model and are hence unable to predict the effect of randomness of the process e.g. variation in process forces, tool wear, clamping conditions, etc. [6, 7]. As these disturbances are unknown in a-priori simulations, their influence on process performance can only be assessed using real-time process data captured during machining.

With the availability of affordable and powerful industrial computers, better process monitoring is now possible by analysing real-time data from the machine tools. This opens up the avenue for the analysis of the effect of random errors on machining operation [3, 8]. Besides collecting data generated by the machine tool itself, it has been observed that by adding additional sensors, knowledge about random errors of the process can be gathered [8, 9]. However, the question remains on how this information can be linked to the quality of the produced part.

To achieve this, a virtual machine tool model is set up, which contains physical models based on simulation and measurements (refer figure 1). This digital-model is run on an Edge computer and is fed by the data from the machine controller, like current tool position, measured tool dimensions from the tool table and, if possible, updated data from the in-situ tool setter. The digital-model also receives additional data from added sensors including cutting forces and vibration. Resultant output is then fed to a real-time material removal simulation, which is similar to the material removal simulation routines available in commercial CAM packages. The material removal simulation produces a high-fidelity 3D mesh of the part being produced on the machine. This 3D mesh includes process randomeness resulting from relative displacement of the tool and workpiece. As a final step of the quality estimation, this 3D mesh can be analysed against the target CAD of the part. With an automated comparison of the target CAD's geometric dimensions and tolerances (GD&T) data and produced 3D mesh, an early detection of failure or process control can be achieved, as opposed to delayed detection after a direct measurement on a CMM. This workflow is outlined by Kushwaha et al. [10].

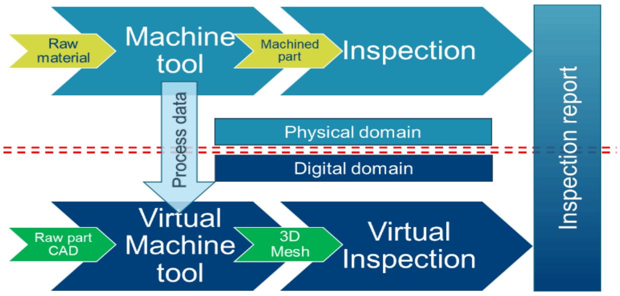

Figure. 1. Concept of in-process virtual quality inspection

However, authors have also outlined the limitations associated with high computation loads associated with the high-fidelity material removal simulation.

This article improves the workflow in [10], and reduces the reliance on the material removal simulation while producing a high-resolution profile of the machined surface. For completeness, the original workflow and improvements are described in the next section. The final section of the article shows the results obtained on machining prismatic parts. Concluding remarks are discussed thereafter.

2. Digital model

The presented in-process quality estimation on an Edge computer requires a digital-model of the machine tool, a communication topology with the machine tool, and a material removal simulation. This section describes these constituent parts in the successive sub-sections.

The commercial quality-predictive simulation routines available as CAD-CAM plugins can be improved by feeding a live stream of data from machine encoders. Nevertheless, this kind of simulation fails to quantitatively identify the random deviation of the tool centre point from the programmed position due to effects like finite stiffness of the structure, thermal deformation and uncaptured volumetric errors. This article deals with the identification of the tool centre point deviation due to the finite stiffness of the machine tool and machining forces. To incorporate the information of the stiffness of the machine tool, a digital-model of the machine tool is created. Along with other dimensional parameters of the machine tool, this model includes the machine calibration (volumetric error compensation table, a look-up table) and a dynamic compliance map of the machine [11].

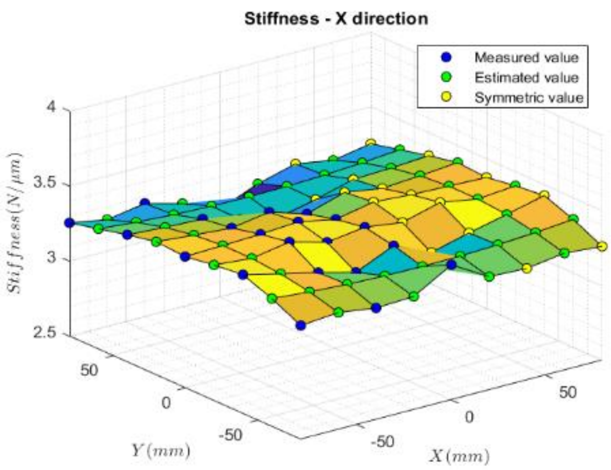

Figure 2. Static stiffness map

In order to reduce the total number of measurements required to obtain the frequency response function of every tool in the machine magazine, a compliance map of the machine is characterised by the receptance coupling method [12, 13]. A static compliance map in the x-direction of the machine tool with a 3 mm tungsten carbide tool shank and 8 mm overhang is shown in figure 2. This method of characterisation captures the model of every joint and coupling present in the machine structure with just one measurement, and approximates it as a linear time-invariant system. This compliance map is analogous to the volumetric error compensation table, except this map contains compliance of the machine tool.

Referring to figure 3, this digital-model when fed with the tool position from the machine controller and measured process forces—the 'digital-shadow'—generates the actual tool position during the process.

A data exchange stream is required to feed the digital-model of the machine tool and the process running on an Edge computer, this communication is set up by industrial communication protocols like PROFINET. This data stream comprises of events on the machine tool, like the start and stop of the programme, coolant status, current tool number, controller error status etc. Event-based data is also used to synchronise the data stream from various data sources.

The rate of reading data from the machine depends on the required resolution of the resultant 3D mesh from the material removal simulation and is bottle-necked by available computing power on the machine controller and the Edge computer. As an example, a programmed feed rate of 100 mm/min and tool position sample rate of 200 samples/second will result in a spatial resolution of 8.3 µm. On the machine controller, this sample rate is limited by the machine's NC controller, as for an example, a machine running on a Sinumerik 840d SL, with an interpolator cycle (IPO) time of 2 ms can provide position data at a maximum of 500 samples/second.

The data rate from the analog sensors and subsequent data processing is also performed in real-time. The cycle rate and data resolution should be set so that it sufficiently captures the required dynamic behaviour of the tool.

The material removal routine then uses the consecutive actual tool centre point position and tool geometry (tool's outer profile, and not cutting edge information) and runs it over a 3D mesh of the workpiece. A Boolean operation on geometry where tool-swept geometry is subtracted from the workpiece mesh results in the final 3D mesh of the machined part. This is the most expensive computation step, as the generation of high-fidelity stl mesh demands high memory usage. It should be noted that improving the 3D mesh precision also increases the memory requirement by a power of two, along with more computation load. In order to reduce the reliance on the

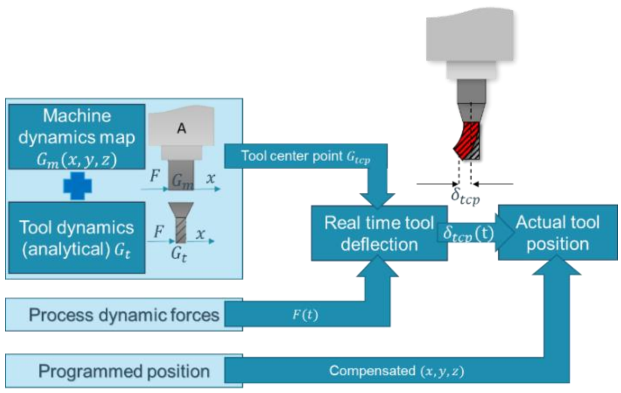

Figure 3. Proposed model to obtain actual tool position

material removal simulation to calculate the profile of the prismatic parts, the calculated tool path is offset by the measured tool radius. The known problem associated with offsetting a curve and arising singularities is solved by the method described in [14]. This method completely eliminates the need to run the material removal simulation to calculate the profile of the manufactured part, thereby reducing the computation load.

3. Experimental validation

The methodology described in the previous section is employed on a DMG Sauer US 20—a five-axes milling machine—run by Siemens Sinumerik® 840d SL controller. An industrial computer—Beckhoff® CX2062 powered by an eight core Intel® Xeon® processor and 32 GB of RAM—is added as an Edge computing device to the existing machine controller to receive the process data and run the material removal simulations.

An adapted ISO 10791-7 2014 part as shown in figure 4 is machined from Titanium alloy Ti6Al4V. The cutting parameters and tool description are listed in Table 1. Down milling was employed unless specified otherwise.

Table 1 Employed tool and cutting parameters

Parameter	Value
Tool	DIXI 7242, φ 6 mm, two teeth (z=2)
Cutting speed V_c	30 m/min
Feed per tooth f_z	0.02 mm/tooth (max)
Depth of cut a_p	1 mm
Width of cut a_e	20 % tool diameter (max.)

Process forces were measured using a Kistler dynamometer 9119AA1 (figure 4 inset). Analog data is collected at 1 kHz, as the dynamic compliance model of the tool is validated only for the first 200 Hz. The tool was measured by an on-machine Renishaw® NC4 tool setter. It was measured before and after finishing every feature. Cutting conditions of the features shown in figure 4 are listed in Table 2.

The material removal simulation was run with a precision of 7.6 µm. This 3D mesh is generated as an stl file and can be compared against the available geometric dimensioning and tolerancing data from the design and quality requirements (ISO 1101). In the current case, GOM Inspect is used to post-process the data and create an inspection report. In table 2, the results of the quality estimation by material removal simulation are listed and compared against the measurements on a Werth VideoCheck® CMM. The effect of tool wear is also shown by machining with and without cutter compensation.

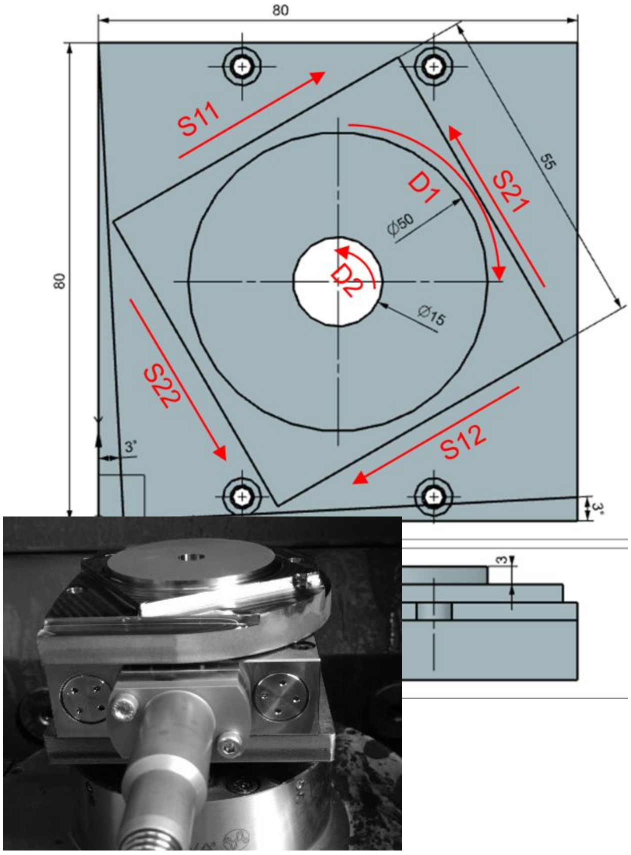

Figure 4. Machined workpiece, red arrows show the feed direction for the feature, inset: workpiece mounted on dynamometer on machine.

Table 2 Process parallel quality estimation results

Feature	Nominal dimension [mm]	Cut type (cutter compensation)	CMM [mm] (deviation from nominal)	Virtual measurements [mm] (deviation as compared to CMM)
S1 (S11to S12)	55	Down (On)	55.0289 (+0.0289)	55.037 (+0.0081)
S2 (S21 to S22)	55	Up (Off)	54.9901 (-0.0099)	55.001 (+0.0109)
D1 (dia.)	50	Down (On)	50.0311 (+0.0311)	50.038 (+0.0069)
D2 (dia.)	15	Down (On)	14.9659 (-0.0341)	14.958 (-0.0079)
Mean error as compared to CMM [mm]				0.0085

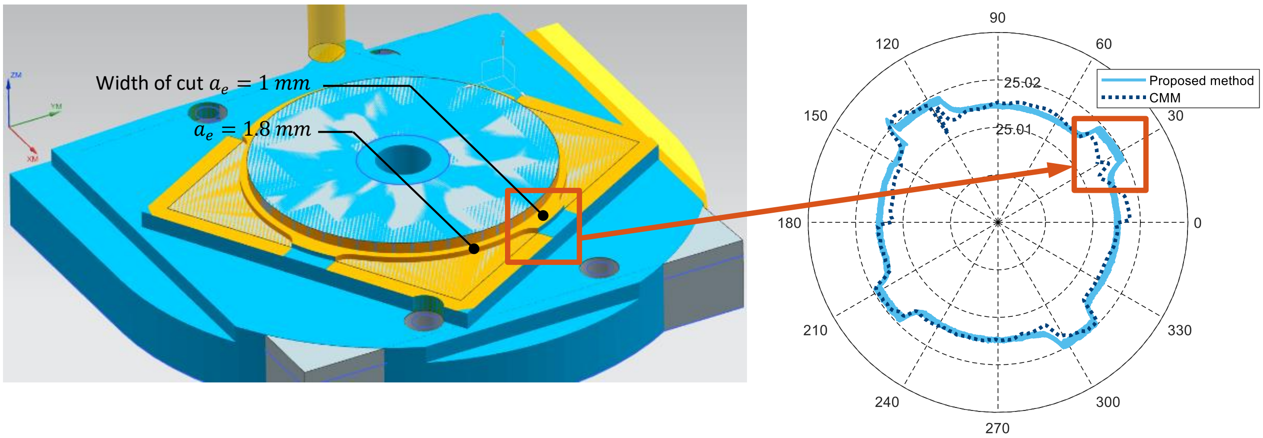

Figure 5. Geometric deviation showing the effect of local variation of cutter engagement on the quality; left: tool path simulation performed in Siemens NX®, right: comparision of virtual estimation of the profile against the profile measured on CMM.

As compared to the CMM, the process parallel quality estimation has a mean error of 8.5 µm, it should be noted that geometry discretisation of the 3D mesh was set to 7.6 µm. The total CPU time to simulate the material removal is only 0.4 hours, whereas the machining time was 3.25 hours. Any further improvement would quadratically increase the memory requirement. To overcome this, the recorded tool path is offset by the known tool radius while removing the singularities associated with the curve offsetting. This method directly results in the locus of cutter engagement points.

The change in cutter engagement results in variation of cutting forces, which in turn results in variation in tool displacement. A similar tool path with varying width of cut a_e was designed while machining feature D1. As shown in figure 5, this variation in cutter engagement effects the roundness of the machined feature. As can be seen, the proposed method is in agreement with the measurements on CMM (fibre probe on Werth VideoCheck®). This method also has a better estimation of the feature diameter—50.034 mm—a deviation of only 2.9 µm as compared to 6.9 µm by material removal simulation.

Based on the same methodology, a spur gear was machined using the machining parameters as listed in table 1. The profile of the face and flank of one of the gear teeth is measured by the fibre probe of the Werth VideoCheck®. Figure 6 shows the profile of the gear tooth estimated from the data obtained while machining, as compared to the same measured on CMM. As the worst case estimation error is only 3.6 µm, the proposed method can be employed for in-process quality estimation.

4. Conclusion

An in-process quality estimation method is described. This method is based on a digital-model constructed from measuring the compliance map of the machine tool. Being analogous to the volumetric error compensation table, this map has to be contructed only once during the machine calibration. Measurement efforts are further reduced by employing receptance coupling. The improvement over quality estimation methods based on material removal simulation is also shown.

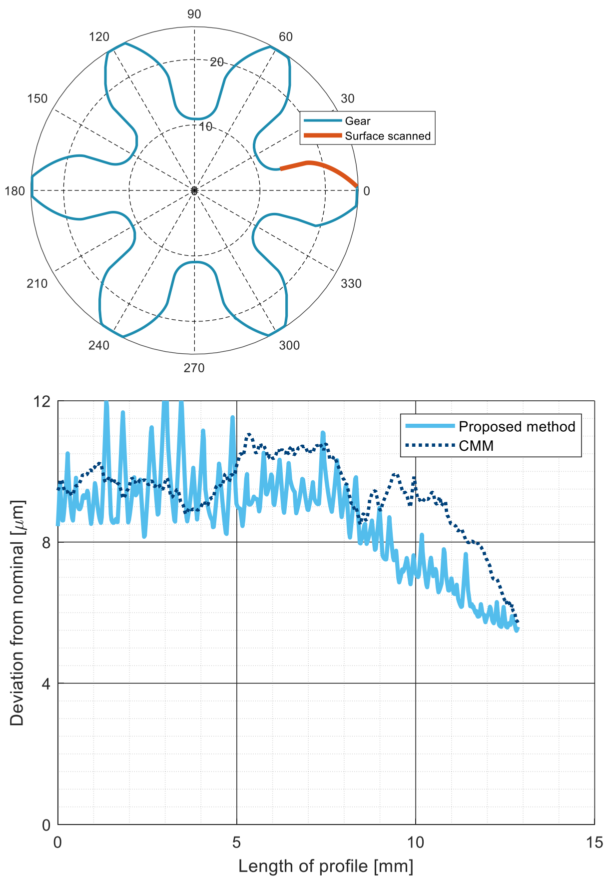

Figure 6. Top: machined spur gear outline; bottom: measured profile

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