More steps towards process automation for optical fabrication

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ABSTRACT

In the context of *Industrie 4.0*, we have previously described the roles of robots in optical processing, and their complementarity with classical CNC machines, providing both processing and automation functions. After having demonstrated robotic moving of parts between a CNC polisher and metrology station, and auto-fringe-acquisition, we have moved on to automate the wash-down operation. This is part of a wider strategy we describe in this paper, leading towards automating the decision-making operations required before and throughout an optical manufacturing cycle.

Keywords: optics, fabrication, automation, CNC, robot, artificial intelligence

1. INTRODUCTION

Our long-term research strategy is to develop an autonomous manufacturing cell for high- and ultra-high-precision surfaces. This embraces manufacture of optics, molds & dies, prosthetic joint implants, turbine blades etc. Hand-work is still common in these industries, for example hand-fettling of molds and dies and local figuring of challenging optics. Even using modern CNC machines, craft-expertise is usually required for their effective operation.

Compared with many process-automation projects, the development of an autonomous cell is complicated by the combination of several factors, such as:-

1. surface tolerances from sub-micron down to nm regimes in different spatial wavelengths and different applications
2. limited determinism of the processes themselves, requiring iteration with metrology
3. wide variety of materials in routine use, both brittle and ductile – glasses, ceramics, crystals, metals etc.
4. wide variety of surface-forms required, from simple spherical/flat, through aspheres to complex freeforms
5. circa 10^6 dynamic range from raw surface to finished part
6. complex relationships between metrology and process.

We have previously drawn attention [1] to the order-of-magnitude faster speeds and accelerations of robots compared with equivalent CNC machines, but the substantially lower robot positioning accuracy, larger deflections under load, and lower first resonant frequencies. This has led us to combine robots with CNC polishing machines, where the former provides higher-end processing, and a robot a smoothing function, and a capability to automate manual operations on the CNC machines [2,3,4].

We have reported [3] on combining an industrial robot with a Zeeko CNC polishing machine, to automate placement of parts on the machine, and transfer parts to an interferometric metrology station with auto-alignment / fringe-capture. Nevertheless, in this work previously reported, the part still needs to be washed-down manually between processing and metrology.

In this paper, we first describe our vision of the autonomous manufacturing cell, present our proposed practical physical layout, and some of the practical issues to be overcome. We then report on a new auto-wash-down and dry capability, its installation on a Zeeko machine, and first experience using it. We then describe possibilities for implementing auto-tool-changing using a robot. Finally, we consider the prospects for artificial intelligence to automate the overall process-chain, each process-step, and decision-making along the way.

2. AUTONOMOUS MANUFACTURING CELL

The ultimate Autonomous Manufacturing Cell delivers a finished part, taking as input:-

- a blank of a specified material (glass, ceramic, crystal, metal etc), sawn to near net dimensions
- a specification with tolerances for the finished part

For processing brittle materials, the Cell will need a complement of workstations, and an indicative layout is shown in Figure 1. This has a robot mounted centrally, with radially-distributed work-stations. Part In-Out is an auto-loading bay to accept raw, and dispatch finished, parts. The ultrasonic bath provides optional post-cleaning after a wash-down on-machine. The 3D printer makes specialized tools and fixtures within the Cell. The Robot Processing Station supports the robot itself in conducting optional smoothing operations, intermediate between CNC grinding and polishing.

This overall robot-centric configuration can be adapted for other process-chains, utilizing single-point diamond turning, ion figuring, atomic plasma etching, etc., with some functions stacked vertically if required.

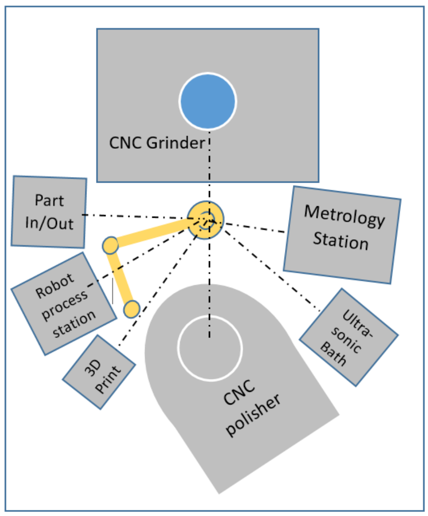


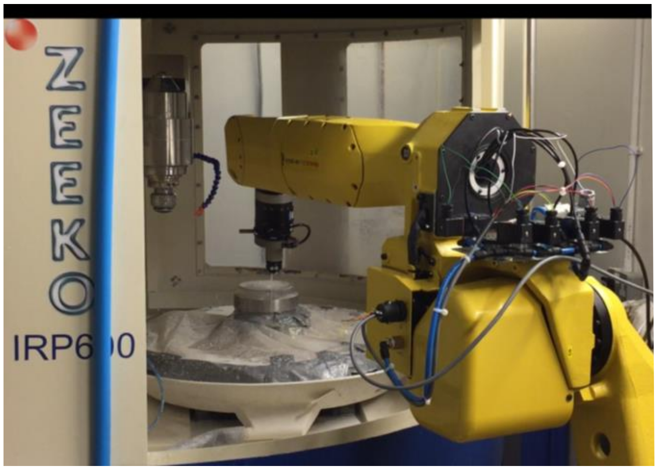
Figure 1 One possible schematic layout of the proposed Autonomous Manufacturing Cell

Compared with many process-automation projects, the development of an autonomous cell for generalized ultra-precision surfaces is complicated by several factors, such as:-

- limited determinism of the processes themselves, this being dependent on other factors below:-
- wide variety of materials in routine use, both brittle and ductile – glasses, ceramics, crystals, metals etc.
- wide variety of surface-forms required, from simple spherical/flat, to complex freeform
- use of loose-abrasive slurries, which introduce complex hydro-dynamical effects
- requirement for surface tolerances well below a micron, and down to nm levels
- huge dynamic range from raw surface to finished part
- complex relationships between metrology and process.

3. AUTOMATING ON-MACHINE WASH-DOWN

The Cell has been developed further by incorporating a wash/dry facility in a prototype Cell with Zeeko machine, Fanuc robot and interferometer metrology station (Figure 2 a,b). The robot lifts and tilts the part to drain bulk slurry, and inserts it back in the machine chuck. The robot then automatically picks up a wash/dry head from the tool storage-rack, and proceeds to raster-scan the part with a water-jet under solenoid control. The slurry drainage system has been modified to include solenoid-valves to direct drainage to waste, or recirculated to the slurry management system, as appropriate. The wash-down water-supply is then automatically exchanged for pressurized conditioned air, which is sufficient to expel wash-down water from the concavity of a concave part, and leave a clean dry surface which has proved directly measurable by interferometry. The robot relinquishes the wash-dry head, and using a gripper, transfers the part to the metrology station, where interferometer-alignment and fringe-acquisition is conducted automatically.



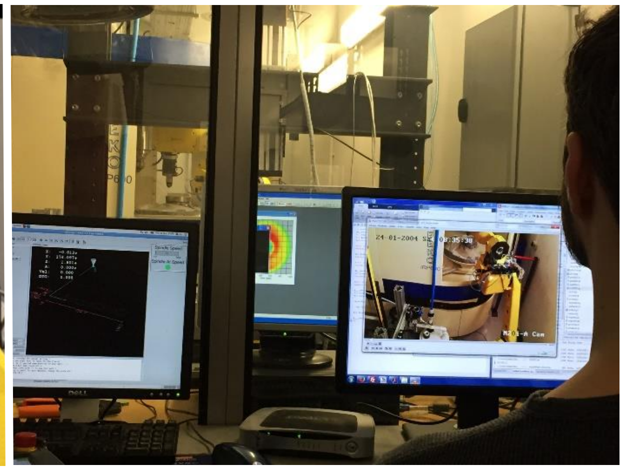


Figure 2a (left) Wash-down cycle in progress on IRP600 machine

Figure 2b (left) Prototype Cell:- control desk (front), looking through metrology station, to Zeeko IRP600 (rear)

4. AUTOMATING TOOL-CHANGING

Auto-tool-changing for the Zeeko machine has some particular requirements. Currently, the centres of curvatures of the bulged (inflated or elastomer) ‘bonnets’ are co-located on the virtual pivot defined by the intersection of the machine A and B axes. The bonnet is advanced towards the part, and touch-on established by a sensitive load-cell in the polishing head. The tool is then advanced by a specified ΔZ to create the contact spot of required size. With an auto-tool-changer, virtual pivot registration, and sensing of first-contact, must be retained. Many other types of tooling are also used with Zeeko machines, for use with particular materials, or process steps (e.g. pitch tooling to smooth mid spatials). In our scheme, tools will stored in a fixture outside the machine, accessible by the robot. Each tool will be encoded with its type and setup conditions. The main outstanding issue is to adapt the current head where the spindle ‘floats’ to support an auto-change capability.

5. ARTIFICIAL INTELLIGENCE

There are various sources of information available in principle to an AI decision-making system for processing surfaces:-

- Captured craft expertise (choice of tooling, speeds, feeds, pressures, tool-paths, pads, abrasives…)
- In-process monitoring of key variables (forces, slurry-conditions …)
- Metrology data acquired between process-steps

We have previously considered the problem from the perspective of “Process” being central, with “Automation” as a bolt-on accessory. We now see “Artificial Intelligence” (AI) as the core of the system. This should be capable of deep learning from digitized libraries of process data (including both good and bad results), as well as continuously improving decision-making, based on its own performance. This, in turn, demands attention to the **fidelity of the information** on which the AI core makes decisions, and the **fidelity of the processes** which execute the decisions. The latter acknowledges i) that each process-step aims to remove signatures of its predecessor, but leaves its own, and ii) no process is fully deterministic. These conspire to reduce overall process-convergence and increase cost and time. Clearly tradeoffs could be performed, such as trading a fast but lower-quality grind followed with more post-polishing, or the imposition of an intermediate robotic smoothing step. The ultimate vision is for AI to perform the following operations, as also shown in Figure 3:-

6. Decide the optimum strategy for the overall process-chain for the specific part's geometry, material, initial surface condition, and target specification. In a production environment, this will need to take account of the overall flow of work through the Cell, trading resource to optimize throughput.
7. Monitor accessible physical parameters of processes in real-time and adjust key variables
8. Supervise metrology and data-analysis between process-steps, and feed process-instructions back
9. Recover from unexpected process events, such as:-
    a. process-interruptions due to issues with machines or services
    b. unexpected surface-features such as mid spatial frequencies, edge-roll, form-anomalies, digs and scratches
10. Terminate the process at the appropriate stage, requiring interpretation of metrology data in the context of:-
    a. the specification of the part, including tolerances
    b. uncertainty of measurement (systematic and random effects)
    c. the relative risks in i) performing one or more additional process-steps, compared with ii) early termination, leading to a non-conformance and potential need to seek a concession
11. Archive process parameters and results for use in future data-mining

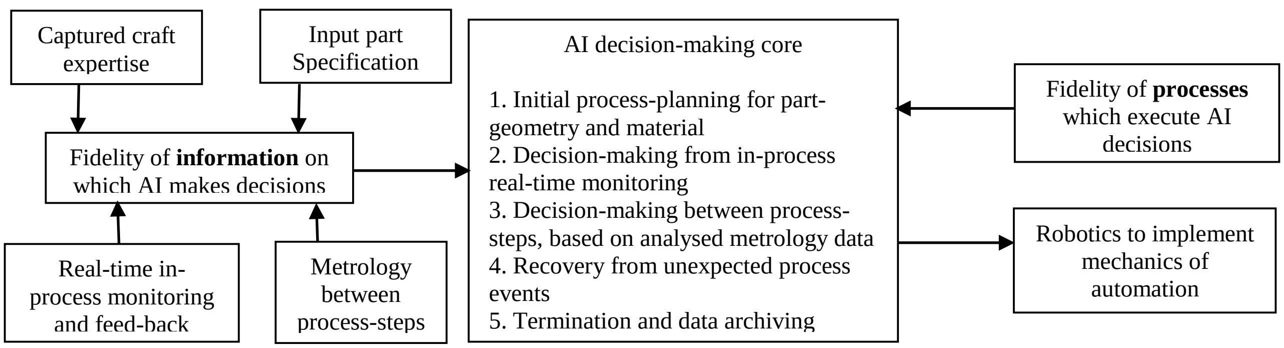


Figure 3 Outline of information-flow through Cell

The ultimate vision of totally autonomous operation is most certainly a long way off. Therefore, our strategy is to make *incremental* advances, each of which can be delivered to the user community:-

1. Provide mechanical sub-systems to deliver practical automation functions
2. AI in its first implementation purely advises a skilled operator for limited cases
3. AI to take control of simple functions under the watchful eye of a skilled operator
4. AI progressively extends its spread of capability under the watchful eye of a skilled operator
5. Skill-requirement for operator is progressively reduced
6. Ultimately, fully autonomous operation for a specified range of materials

6. The MANUFACTURING CELL AS AN AUTONOMOUS INTELLIGENT SYSTEM (AIS)

Our aim is to create a Manufacturing Cell as a cyber-physical autonomous intelligent system (AIS), which will receive as input a requirements specification for the finished part and a blank of a specified material, and will produce as output a finished product to meet the specification. The intelligent characteristics of the Manufacturing Cell will include the capability of the Cell to synthesize descriptions of chains of behaviour for the Cell's tools to meet the requirements specifications; to explain its behaviour and the rational for its construction, and thus increase the confidence of the decisions made; to perform diagnostic reasoning on any failures and avoid repeating the same mistakes in the future; to perform automated acquisition of causal operators, and adapt and improve itself through experience. The architecture of the AIS, given in Figure 4, will consist of two levels: the deliberative, and the operational level. The main processes and data in the architecture are shown by ellipses and rectangles, respectively.

The components of the AIS architecture are described in Figure 4. The role of the deliberative level is to synthesize descriptions of chains of behavior in the form of an abstract process description, using the causal definitions of the operations available, the AIS's situational awareness and any available manufacturing constraints. The operational level provides a support to decision making to respond to i) in-process real-time monitoring, ii) measurement data collected between process-steps and eventually iii) to re-planning recovery from unexpected process events. This support will evolve from an assistance to the machine operator, towards the fully automated support. Data and Knowledge definitions, and information and constraints about the components of the Cell will be shared between the two levels in the Domain Model component shown in Figure 4. The two level architecture has advantages not only from the functional but also maintenance perspective. It also makes the overall system more generic if ported to other manufacturing scenarios.

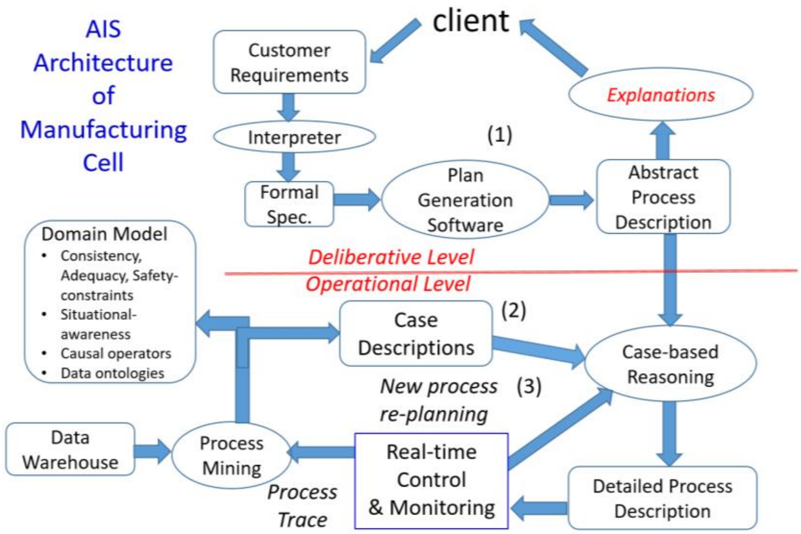


Figure 4. A two-level architecture of the AIS

Figure 4 shows an interpreter process, inputting the requirements specification of the job, performing consistency, adequacy and completeness checks, and extracting the characteristics of the customer requirements in a machine-understandable form called a 'formal specification'. Plan generation software (1) will then decide on and synthesize the optimum abstract strategy for the overall process-chain, and produce an abstract process description and explanations of its decisions. Case-based Reasoning (2) drives the scheduling and optimization operation, mapping the abstract process description into a detailed process description with all required parameters, such as a tool to be used, its path, etc. Utilising existing and operational data, the Process Mining function (3) automatically acquires cases for the CBR and casual connections for the domain model. Below we elaborate on the three main processes in the AI architecture (1) – (3).

6.1 Plan Generation

Plan generation software will reason with the formal specification of the customer requirements, and elements of the domain model, and output an abstract process chain for the part in question. The causal operators that capture the dynamic capabilities of components (e.g. polishers) within a formal description language will be assembled by the software into a process chain using techniques from the area of automated planning [9]. Such software has been used in a number of real applications (e.g. Urban Traffic Control [10]). The planning process will require factual descriptions from the Cell's situation awareness (including the status of the part and the status of tools and equipment), the requirement's formal specification, and information from the domain model, forming an 'initial world state'. The description of the process chain generated will be able to generate a prediction of the world state of the part over time (the part's geometry, material, surface condition), and the state of the environment (position / condition of tools etc). Thus predicted states can be matched with real states to monitor the progress of a job against predicted, and to inform a client of the rationale behind the process plan chosen.

6.2 Case-based reasoning (CBR)

Craft-expertise or know-how knowledge and experience is crucial in the operational level. Significant decision making is required from an operator during each process-step and also between them. There is a wide range of parameters to be considered when deciding how to configure each process-step and then when and how to change them. Case-based Reasoning (CBR) will provide support to the required decision making, by using the accumulated experience of operators gained in dealing with similar situations in the past [11]. CBR has been successfully used in a wide range of domains including health care [12], traffic management [13], machine diagnosis, [14], signal analysis [15], etc. However, it has not been applied in optical fabrication yet. A case-base, which will contain cases describing specific knowledge/experience of operators applied in a specific context in order to achieve a specified goal, will be formed. CBR offers learning capabilities and thus can adapt to changing process requirements and environmental conditions. A wide range of sources will be used to construct cases including available digitised data and data which are unavailable but identified to be important are possible to collect, expertise that is in the operator's head which they employ during operating a machine, textual descriptions of workflows of frequently occurring situations, etc.

6.3 Automated Acquisition of Causal Definitions using Process Mining

The first step when considering deep mining of manufacturing process data consists of defining a method for classifying and searching information gained from past, current, and future manufacturing runs. These may include process development, prototyping, as well as "monitored" production. The concept of process signature has been proposed in previous research to address this classification problem [6,7]. Machining processes can be abstracted to numerical "causal operators" that convert inputs (materials + process conditions) into outputs (modified materials + functional surface properties) in a manner reminiscent of a "black box", as shown in Figure 5. An expandable structure must be implemented for data storage, such that ancillary information like energy transfer, material modification/wastage, or machining mode (brittle-to-ductile transition [8]) can also be accounted for in the causal operator, should it become available from a certain point in time.

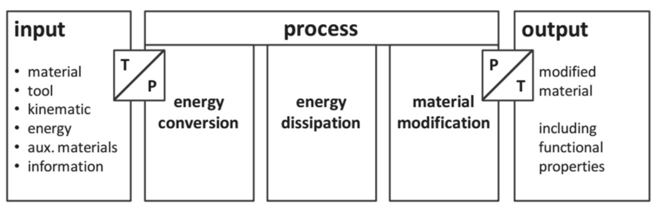


Figure 5. Abstraction of physical process as causal operator [6]

The information related with causal operators should be formatted to fit a SQL/MySQL type database, which may only accommodate 2 dimensional tables. Figure 6 shows a possible scheme for such process database: On the left hand-side, a "master process table" contains the list of causal operators identified to date (which may grow indefinitely). The columns of the process operators table link to sub-tables, where detailed information is provided for material, shape, tool, influence, roughness, and so on… Some of these sub-tables can also provide a column for "linking-back" to the process operators table.

The causal operator model offers the possibility of modelling process chains by stacking operators (see Figure 7). From the start condition of a workpiece, the stack model may evaluate the end-condition and predict the energy use and material waste. Furthermore, the numerical nature of the operators makes them ideal for automated optimization of process chains, using such methods as genetic algorithms.
A search algorithm for surface condition may function as follow:

(1) Material identification: scan the material table to identify entries that either correspond to the current material, or offer a close match (based on a comparison of material properties such as elasticity, hardness, brittleness…).
(2) Roughness data gathering: Query the roughness table for entries associated with the materials identified in (1).
(3) Identification of logical paths: find overlap regions within the roughness values, in order to find all possible logical paths linking a specific input condition (based on surface measurement) with a desired output condition (based on user input).
(4) Optimize the process chain: using the "link-back" column provided in the roughness data, the algorithm can recover the associated causal operators, and their sub-entries such as tools. The optimum process chain may then be identified as a function of several objectives such as: (1) using the least possible amount of different machines/tools, (2) minimizing the overall process time.

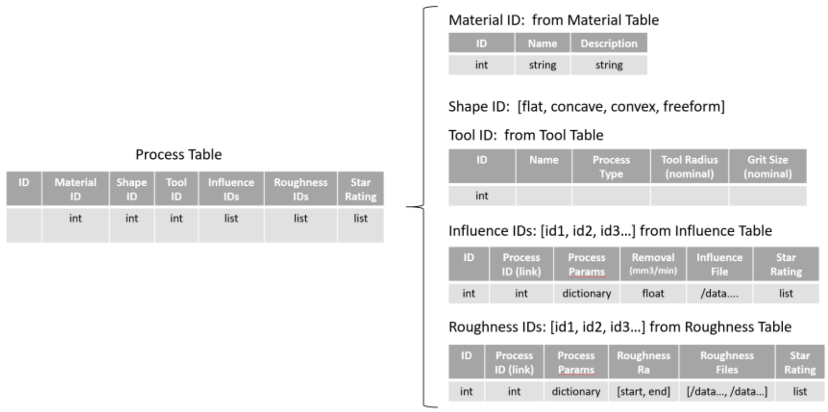


Figure 6. Formatting of process data into a series of interlinked tables

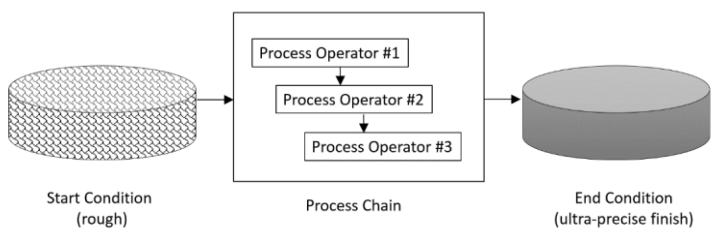


Figure 7. Stacking operators into a process chain

7. CONCLUSION

We have developed our previous experimental work to include an effective auto-wash-down and dry, with the part in-situ on the Zeeko machine. This has enabled us to demonstrate for the first time a complete automatically-executed procedure to follow CNC polishing, involving tipping the part to drain surplus slurry, wash, dry, un-load from Zeeko machine, load onto the interferometer work-station, align, null and acquire fringes, and re-mount the part on the Zeeko machine turntable ready for the next run. The next stage is to meld this with the Zeeko corrective polishing algorithms, to enable a full series of corrective polishing / metrology runs to be conducted with no human intervention. In parallel, we have brought together the optical processing and AI communities to develop the strategy for automating the decision-making processes required in real life. This encompasses methods to i) configure an optimum process-route in advance, ii) utilize real-time diagnostic monitoring of process variables, iii) make decisions at metrology steps which may change the strategy deployed and iv) interpret metrology in the context of the specification, to decide when to terminate the process. We have reported on the results of a preliminary study as to how this could be implemented in practice.

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