Adaptive Robotic Training Methods for Subtractive Manufacturing

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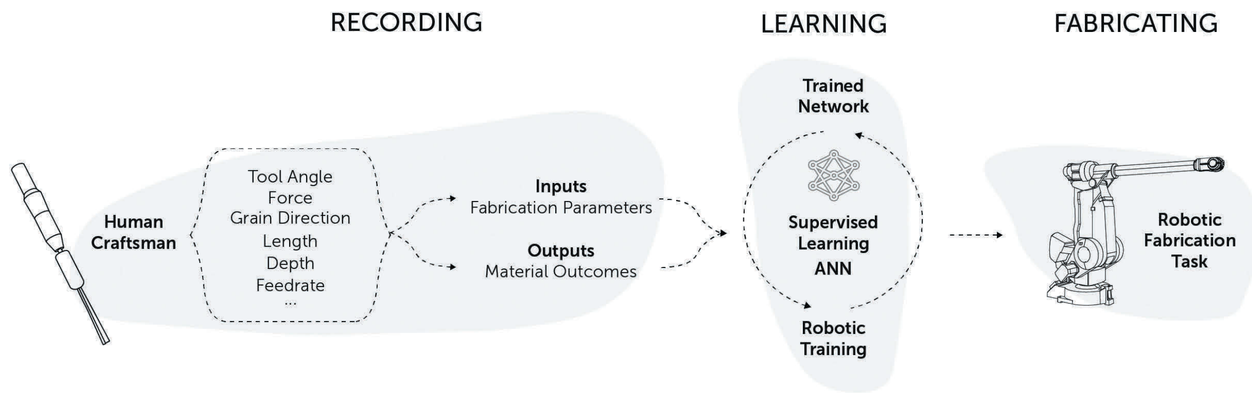
ABSTRACT

This paper presents the initial developments of a method to train an adaptive robotic system for subtractive manufacturing with timber, based on sensor feedback, machine-learning procedures and material explorations. The methods were evaluated in a series of tests where the trained networks were successfully used to predict fabrication parameters for simple cutting operations with chisels and gouges. The results suggest potential benefits for non-standard fabrication methods and a more effective use of material affordances.

1 Based on the networks trained with the information gathered by the human craftsman, robotic explorations of the narrowed-down parameter space are performed to increase the prediction abilities of the system.

2 The training methods for an adaptive framework for subtractive fabrication processes are structured and evaluated in three main stages: Recording, Learning, Fabricating.



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INTRODUCTION

In contemporary practice, designers are required to encapsulate all the information necessary for a project in a digital notational form, such as a CAD/CAM model. The entire fabrication process is calculated in advance before moving on to the production. As a consequence, the range of possible materials that could be used for construction is restricted to homogenous materials with standard shapes and well-known properties. For instance, many CNC operations require homogeneous materials that can be systematically carved, while the overall process is driven by tolerances measured against the initial digital notation, leaving no room for any material agency (Fure 2011). Many materials, like timber, are heterogeneous in nature and undergo heavy industrial processing before becoming suitable for a standard fabrication environment. This is inefficient and results in material waste.

This research investigates an alternative approach. If materials are not conceived of as inert receptacles for an imposed form, but are instead understood as active participants in its genesis, it follows that fabrication strategies cannot be routinized or pre-calculated (DeLanda 2004). Therefore, the initial digital model, rather than operating as mere notational mean, is required to act as a flexible framework for design exploration, finding its completion in the fabrication stage and directly informed, through sensor feedback, by tools, materials and design affordances.

The proposition is that digital processes can more closely resemble traditional craftsmanship and human making, in the sense that design intent "evolves concurrent with [...] production" (Sharif and Gentry 2014), or what Ingold (2013) terms "thinking through making." While digital software regularly encapsulates explicit knowledge such as calculus-based mathematics (Witt 2010), the important tacit dimension of making and materials that is typically acquired through participation rather than formal inquiry (Eraut 2000) is difficult to capture, formalize and share (Polanyi 1967).

The central question of this paper is whether it is possible to encapsulate, at least partially, this instrumental knowledge in the technological means for fabrication currently available. An adaptive framework for subtractive robotic timber fabrication, using a set of traditional carving tools (chisel and gouges), is used to investigate whether this knowledge can be captured and transferred from the domain of human craftsmanship to robotic manufacturing. Sensor feedback and machine learning are tested as methods to train the robot to replicate, and potentially augment, the actions of the skilled human (Figure 2).

A number of related precedents attest to the relevance of the approach in more conventional industrial manufacturing, such as the use of artificial neural networks (ANNs) to optimize cutting force or tool wear (Al-Zubaidi et al. 2011), and the use of supervised learning and scanning to improve accuracy in incremental sheet forming (Nicholas et al. 2017). The specific emphasis on human action follows recent work such as the analysis of stonemasons' mallet strikes (Steinhagen et al. 2016), and the robotic reconstruction of ancient hide-scraping gestures to investigate the link between tools and cognitive functions (Pfleging et al. 2015).

METHODS

The first stage of the training method for an adaptive robotic process for subtractive manufacturing focuses on capturing, with different types of sensors, a series of carving operations with a set of chisels and gouges as performed by human experts on a series of wooden boards (Figure 3). A system of motion-capture cameras (OptiTrack mocap) is arranged around the workpiece and used to track the position of spherical reflective markers in the recording space with a high-degree of precision (~0.2 mm) (Figure 4). Within this setup, a series of 3D-printed custom markers have been designed and applied as rigid bodies directly on the carving tools themselves in order to reconstruct their orientation at any moment, streaming the results into the digital design environment (Rhino3D/Grasshopper) in real time.


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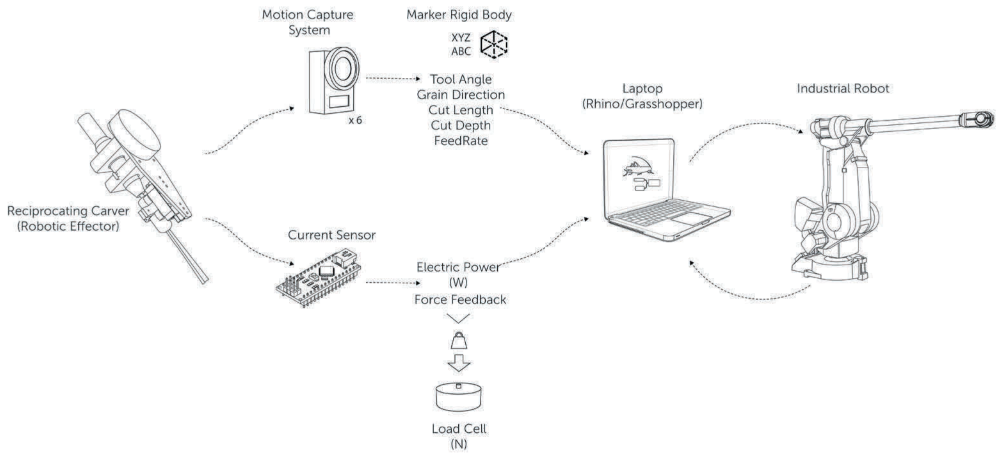
The chisels and gouges, integrated with the MOCAP markers, are mounted on a reciprocating electric tool already used by professional craftsmen as an augmenting device that allows them to be more efficient and reduce fatigue, therefore not altering the way they use traditional carving tools (Figure 5). The reciprocating mechanism works proportionally to the material resistance and the force that the craftsman applies to overcome it. In this way, it not only allows the more efficient performance of subtractive operations; within this research context, it becomes a sensor device that acts as a “probe” during the fabrication process and returns continuous feedback about the relation between the tool and the material it cuts. Through a load cell is then possible to create a conversion scale between the electric power feedback and its respective force amount in Newtons.

The combination of these sensing strategies allows the collection of information simultaneously with the performing of the carving operation, which is compiled into an ongoing dataset for that recording session (Figure 6). The recorded parameters could be divided in two categories: first, those related to the interaction of the tool with the material, such as its angle orientation in relation to the wooden surface and grain direction, the feed rate or the force used to cut through it, and second, the effects that these parameters have on the material itself, measured through the length and depth of the cut or the removal volume. The recorded information is also used to generate a geometric reconstruction of the cut in the digital design environment through a sequence of oriented planes embedding the respective recorded parameter values.

During the following stage, a supervised machine-learning procedure is used to extract relevant correlations within the recorded dataset, and uses these to inform the robotic manufacturing process. Before the training process, different features of the dataset are plotted against each other to visually check for possible correlations between them. Considering the sequential arrangement of recorded data along individual cut sequences, it’s possible to observe, for instance, that the tool angle tends to decrease along the progression of the cut or that the highest amount of force is required when the tool is deeper into the wood board (Figure 7). The importance of these trends is that they are not only qualitative evaluations but they could be quantified and therefore processed to be used in a further stage.

The prediction of fabrication parameters combinations, which constitutes a regression problem, is performed through the training of an artificial neural network (ANN) with backpropagation-based learning. The network topology not only determines the performance of the system, but its configuration of inputs and outputs also needs to be arranged considering the intended use of the trained network in the fabrication stage. For instance, given an arbitrary toolpath and a desired force graph profile, the network should be able to predict the variation of the tool angle and depth along the path itself.

The evaluation of the training process is performed with a train/test split validation method (on an 80/20 split), where part of the recorded dataset is used to train the network, while another smaller portion is used to test its prediction rate (Figure 7).



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3 During a recording session, several training boards are carved to capture the combination of parameters involved and extract relevant correlations among them.

4 A system of motion-capture cameras is arranged around the workpiece and used to track the position of spherical reflective markers in the recording space.

5 The gouges are mounted on a reciprocating electric tool and tracked with 3D-printed MOCAP markers.

6 The fabrication parameters are recorded with different types of sensors and collected into an ongoing dataset.

The final stage of the training is articulated via robotic explorations directly interacting with tools and material affordances without human intervention. While learning only through robotic self-exploration would be both dangerous and inefficient given the large dimension of the parameter space considered, the trained network, drawing on human expertise, is used to provide guidance, narrowing down the search. This allows for more thorough exploration; in an interpolated series of cuts, the combination of parameters that have been derived from the human expert map the narrowed-down search space in greater detail to build better parameter correlations (Figure 1).

RESULTS

The first full iteration of the training methods has been evaluated through the design and realization of a series of design probes in the shape of different circular design patterns, aiming to showcase the potentials and limits of the current developments (Figures 8 and 9).

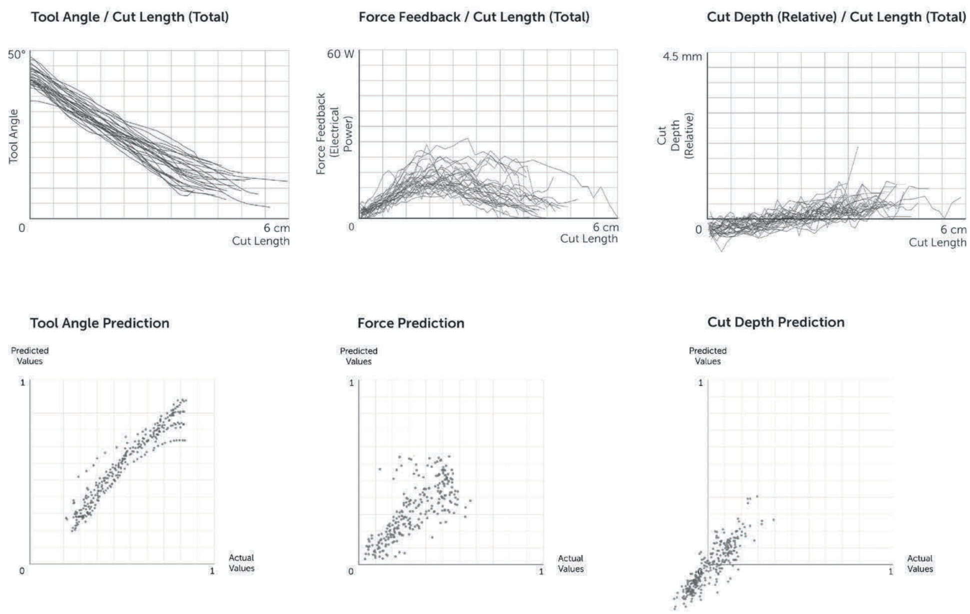
In the initial stage, a series of lime wood boards (30 x 30 x 4 cm) were carved with carving gouges (Stubai 9/20 and 9/30) by a novice craftsman. The carving operations were devised as linear sequences of cuts of different lengths and orientations in respect to the wood grain. In each session, simultaneously with the craftsman's action, a dataset (averaging 1500 entries) was compiled, with the following recorded parameters for each frame composing a cut sequence: tool/surface angle, tool/grain angle, force feedback, feed rate, cut length, cut depth. Given a series of desired toolpaths with a predetermined length describing the circular patterns, the network topology was configured to output the prediction of (1) the tool angle variation and (2) the cut-depth profile along the cut itself for each pass of the carving process. The mean absolute error (MAE) for the two parameters prediction was, respectively, 2.12° and 0.31 mm.

The first stage of the training, based on human expertise, has been used to set up a second stage, where the gradual interpolation of the parameters of tool angle and depth has been tested by the robot itself, collecting force feedback data for each cutting operation. This allowed it to train the network with the same topological configuration as the first stage, but integrated more in-depth data about the narrowed-down search space extracted from the skilled human's actions.

The trained network, applied to the specific task of the circular patterns (Figure 10), has been used successfully to generate the sequence of robotic target frames composing each individual cut carved into lime wood boards, using a small industrial robot (KUKA KR6) equipped with the same reciprocating carving tool used by the human craftsman during the recording session. As a first complete iteration of the training cycle, the carving operations, set up as a series of radially arranged short cuts (4 to 10 cm) , were quite simple and similar to each other. Nevertheless they offered a good opportunity to test the system throughout its different stages. Overall, the carved circular shapes showed, to a varying extent, local deviations from the ideal digital models, measured through photogrammetric reconstruction, due to the local interaction between the carving tool and wood material behavior with its grain arrangement (Figure 11).

CONCLUSION

The trained networks successfully predicted fabrication parameters for simple cutting operations, demonstrating the feasibility of encapsulating tacit, instrumental knowledge of specific tools



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7 Above: Before the training process, the recorded features are analyzed against each other to visually check for possible correlations. Below: Train/test split validation plots for the prediction of individual features (tool angle, force and cut depth) with ANN (5-30-1).

8, 9 The trained networks are evaluated at the fabrication stage, where they are required to provide the prediction of relevant fabrication parameters such as the tool angle variation or depth of cut.

10 The initial fabrication outcomes are in the shape of circular design patterns carved by the robotic arm.

11 The carved circular patterns showed local deviations from the initial digital model due to the interaction between the cutting tool and local material properties such as the wood grain structure. (Left: Photo, Right: Photogrammetric Reconstruction)

and materials in the robotic system. These results suggest two main potential roles for the use of machine-learning strategies for design applications with subtractive robotic fabrication:

- Encapsulating knowledge and using it as part of a predictive strategy to train the fabrication process and optimize it to operate with a specific set of carving tools and wood type.
- Capturing and manipulating instrumental knowledge across distinctly operating domains such as human making and industrial robotic manufacturing.

The application to carved circular patterns was effective, but measurements of geometric deviations suggest that further work is needed to increase predictive abilities and accuracy in relation to shape generation. The next steps in the research will (a) use the system in more challenging design tasks, focusing on the variation occurring throughout diverse types of wood and carving tools, and (b) extend the capturing of instrumental knowledge to a wider range of craftsmen with different levels of expertise and measure how that affects the training process.

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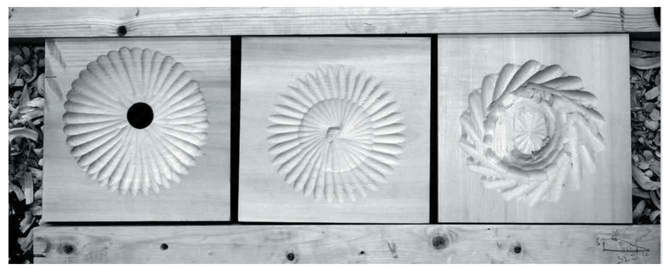

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IMAGE CREDITS

Figures 1–11: Giulio Brugnaro, The Bartlett School of Architecture, UCL.

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