ADAPTIVE ROBOTIC FABRICATION FOR CONDITIONS OF MATERIAL INCONSISTENCY INCREASING THE...

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This paper describes research that addresses the variable behaviour of industrial quality metals and the extension of computational techniques into the fabrication process. It describes the context of robotic incremental sheet metal forming, a freeform method for imparting 3D form onto a 2D thin metal sheet. The paper focuses on the issue of geometric inaccuracies associated with material springback that are experienced in the making of a research demonstrator. It asks how to fabricate in conditions of material inconsistency, and how might adaptive models negotiate between the design model and the fabrication process? Here, two adaptive methods are presented that aim to increase forming accuracy with only a minimum increase in fabrication time, and that maintain ongoing input from the results of the fabrication process. The first method is an online sensor-based strategy and the second method is an offline predictive strategy based on machine learning.

Rigidisation of thin metal skins

Thin panelised metallic skins play an important role in contemporary architecture, often as a non-structural cladding system. Strategically increasing the structural capacity – particularly the rigidity – of this cladding layer offers a way to integrate enclosure, articulation and structure, but requires a consideration of scale and fabrication that lies outside a typical architectural workflow. Thin sheets can be stiffened via isotropic or anisotropic rigidisation techniques that selectively move local areas of the sheet out of plane, with the effect of increasing structural depth. The use of these techniques marked the early development of metallic aircraft, seen pioneered by Junkers and LeRicolais within architecture and are currently applied within the automotive industry.

This research takes inspiration from Junker’s proposition, made through the transfer of these techniques into building, of thin-skinned metallic architectures. A Bridge Too Far (Fig. 2) presents as an asymmetric bridge. The structure consists of 51 unique planar, hexagonal panels, arranged into an inner and outer skin. The thickness of each panel varies locally, though it is at maximum 1mm thick. Excluding buttresses, the bridge spans 3m and weighs 40kg. Geometric features for resisting local footfall, buckling within each panel and structural...
Robotic incremental sheet forming

The incremental sheet forming (ISF) method imparts 3D form onto a 2D sheet, directly informed by a 3D CAD model. A simple tool, applied from either one or two sides, facilitates mouldless forming by moving over the surface of a sheet to cause localised plastic deformation (Bramley et al., 2005). A double-sided robotic approach provides further flexibility for forming out of plane in opposing directions (Fig. 3). Moving from SPIF (single point incremental forming) to DPIF (double point incremental forming) removes the need for any supporting jig. This allows for more freedom and complexity in the formed geometry, making features that it would be difficult or impossible to create supports for. A second advantage is the creation of a hydrostatic pressure between the two tools, which has been found to delay the initiation of necking for any strain path.

Connections – for managing shear forces across inner and outer skins – are produced through the custom robotic forming of individual panels.

Incremental forming of individual panels.

The ISF process has effects that are both geometrically and materially transformative. Geometric features locally stretch the planar sheet to increase structural depth or to provide architectural opportunities for connection and surface expression. Depending on the geometric transformation, the effects of the material transformation are locally introduced into the material to different degrees according to the depth and angle attained. Calculation in advance to inform generative modelling and fabrication is important, as local thinning of the stretched metal can lead to buckling or tearing when approaching zero thickness (Fig. 4). Work hardening during the forming process also induces different yield strengths, and even strain softening, depending on the base materials.

The choice of material for A Bridge Too Far was a negotiation between formability and yield strength to ensure a stable structure but not exceed the force capability of our robotics set-up. Aluminium 5005H14 was chosen, as it provided a good balance between formability, forming speed, initial thickness and initial hardness. In comparison to previous research demonstrations (Nicholls et al., 2017), a higher fixed speed could be used in order to ensure faster production without risking a significantly higher amount of material failures. This choice of material also impacted the design, where the average wall angle of the rigidisation pattern and other geometries was increased from previous prototypes. Because AL5005H14 is pre-hardened, forming at low wall angles softens the metal, while higher wall angles harden it again.

Robotic fabrication

Toolpaths for 51 panels were generated automatically from a 3D mesh using HAL and a custom toolpathing algorithm based on the creation of spirals. The main parameters of this algorithm were the grouping and positioning of features. Because the pattern of rigidising points at which the upper and lower skins connected (Fig. 5) had not yet been designed or located, these geometric features were not included in the initial fabrications. However, leaving the formed panels in their frames provided a means to exactly relocate them in the moment frame for continued forming at a later point. Panel fabrication times for 51 panels varied between 4 hours and 8.5 hours. After fabrication, the panels were measured for accuracy, where tolerances of up to 0.1mm from the digital geometry were found.

The problem of accuracy

Incremental forming is a formative fabrication process, in which mechanical forces are applied to a material so as to form it into a desired shape. A characteristic of formative fabrication processes, particularly mouldless, freeform approaches, is that their positional accuracy is more highly dependent upon a combination of material...
There are several approaches to improving geometric accuracy, the most direct of which is reprogramming. This approach simply re-runs the whole, or significant parts, of the original toolpath. It has been shown to achieve considerable improvement, but can potentially double the amount of fabrication time. A second approach is to use a sensor-based measuring strategy, where the local deviation is measured, at each cone centrepoint, the local deviation to supports and formed geometries has shown significant deviations from additive approaches. Research into resultant incrementally formed geometries has shown significant deviations from the planned geometries (Rambach et al., 2009), and that parameters including the forming velocity, the toolpath, the size of material and distance to supports and particularly the material springback of the sheet during forming all affect the geometric accuracy of the resulting shape. These geometric deviations are a key determinant from the widespread take-up of the process (Sanner et al., 2008).

But because of springback during the forming process, a cone that has the same forming depth as the combined target depth is not the correct choice – the forming depth needs to be larger than the target depth. To determine the correct amount, curve fitting was used to model the relationship between target depth and forming depth. After each cone was formed, the resultant depth was scanned and this data was used to refine the curve-fitting model, allowing a continued improvement in accuracy across the course of fabrication (Fig. 6). After forming and scanning, two further automated correction methods could be triggered. If the formed cone geometry was greater than the target depth, the cone was reformed. If it was between 3mm and 5mm off the target geometry, the tip of the cone was extended by 2mm. Tolerances below 2mm were considered acceptable.

Force feedback

While tolerances could be adequately corrected for using the sensor-based strategy outlined above, this method did not provide any deeper understanding of the forming process and the resulting imprecisions. To establish meaningful input parameters required, a local transducer was attached to the forming tool to register changing forces on the tool tip during the fabrication process. A low stream of read-outs (approximately one per 20ms, or every 2cm along the toolpath) was established and the data was stored directly in a binary file. This data was used to identify the right type and amount of data for the training of a neural network to map a material model.

This information revealed relationships between the fabricated shapes and forces acting on the sheet, and showed the following parameters to be significant:

- Local feature.
- Distance to fixed panel edge.
- Current depth of the shape.

A ‘local feature’ is understood to be a small fragment of the shape being currently formed. It informs the model about edges, ridges and other small-scale geometry of the panel.

Distance to the edge of the panel is the parameter describing the distance to the closest point on the edge of the formed geometry. It is a result of the physical setup and how the panel was placed in the forming frame (pinned to the underlying MDF board with a panel-specific cut-out). Current depth of the shape is the distance from the initial sheet plane to the current position of the tool tip. It is directly dependent on the material properties and their change over deformation depth. Other parameters – such as the slope angle – are not provided directly to the model. Instead, the local feature is used as an indirect provider of such information.

Network architecture and learning process

The information gained from the force gauge read-outs was overlaid with a 3D scan of the fabricated panels. This coupling of input and output parameters (local feature, distance to the edge, depth vs. formed shape) constitutes the input and output set for the supervised learning process. Given that the output of the network is the depth of the analysed point after forming, the problem is substantially a regression analysis.

The local feature and current depth are encoded as a heightmap, with a real-world size of 5 x 5cm and a resolution of 1 pixel per millimetre, without pre-processing the input vector would have to have 2,500 dimensions, making the training process unnecessarily detailed and slow. To reduce its dimensionality, a max pooling technique was applied, resulting in a 2 x 2 pixel – 81 dimensional – heightmap.

The network consists of an input layer with 81 neurons (R1 + 1 additional for edge-proximity parameter), a hidden layer with 30 neurons and an output layer with 1 neuron indicating the depth of the resulting point. Bagging propagation-based learning was performed on a set of 10,000 samples and took approximately an hour on a regular desktop computer.

Results

The network is able to predict, to some extent and resolution, the resulting geometry based on an input heightmap of the target piece. The authors find the network unexpectedly accurate, given that the training was based only on data gathered from a small number of panels. Additionally, the exploration of the network predictions gave more information on the trained model itself, showing that material behaviour isn’t strictly linear – therefore it would be reasonably more challenging to find appropriate functions and ways to encode shape information with a curve-fitting approach (although the neural network is function-fitting as well).

With this neural network based model, it is possible to predict from full forming process and multiple queries the resulting panel surface can resemble the target much more precisely.
is a combination of multiple functions. making, especially where the material behaviour model could provide new bridges between designing and the authors believe that machine learning processes itself enough to achieve accurate forming. On this basis, information contained within the design model is not by because, for the incremental forming process, the achieve the desired design. These models are necessary changes the fabrication geometry prior to fabrication to from the desired design, while the second method parametrically during the fabrication process, diverging fabrication process. The first method changes the design Both models negotiate between the design model and the adaptation and the second based on offline prediction. methods have been presented, the first based on online feedback to manage springback and to reduce geometric inaccuracies within the forming process. Two different approaches exist for this method: the first is based on online adaptation and the second based on offline prediction. Bird models negotiate between the design model and the fabrication process. The first method changes the design-parametrically during the fabrication process, diverging from the desired design, while the second method changes the fabrication geometry prior to fabrication to achieve the desired design. These models are necessary because, for the incremental forming process, the information contained within the design model is not by itself enough to achieve accurate forming. On this basis, the authors believe that machine learning processes could provide new bridges between designing and making, especially where material behavior models are a combination of multiple functions.

Conclusion

This paper has addressed the issue of material springback and geometric inaccuracy in the incremental forming process. It has demonstrated the use of sensing and feedback to manage springback and to reduce geometric inaccuracies within the forming process. Two different methods have been presented, the first based on online adaptation and the second based on offline prediction. Both models negotiate between the design model and the fabrication process. The first method changes the design-parametrically during the fabrication process, diverging from the desired design, while the second method changes the fabrication geometry prior to fabrication to achieve the desired design. These models are necessary because, for the incremental forming process, the information contained within the design model is not by itself enough to achieve accurate forming. On this basis, the authors believe that machine learning processes could provide new bridges between designing and making, especially where material behavior models are a combination of multiple functions.