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Nicholas, Paul; Zwierzycki, Mateusz; Clausen Nørgaard , Esben ; Leinweber, Scott; Stasiuk, David; Ramsgaard Thomsen, Mette; Hutchinson, Christopher

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Paul Nicholas
Royal Danish Academy of Fine Arts, Schools o…

Mateusz Zwierzycki
Royal Danish Academy of Fine Arts, Schools …

Mette Ramsgaard Thomsen
KADK

Christopher Ross Hutchinson
Monash University (Australia)

ADAPTIVE ROBOTIC FABRICATION FOR CONDITIONS OF MATERIAL INCONSISTENCY
INCREASING THE GEOMETRIC ACCURACY OF INCREMENTALLY FORMED METAL PANELS

PAUL NICHOLAS / MATEUSZ ZWIERZYCKI / ESBEN CLAUSEN NØRGAARD / DAVID STASIUK / METTE THOMSEN
CITA | Centre for Information Technology and Architecture, The Royal Danish Academy of Fine Arts, Copenhagen
CHRISTOPHER HUTCHINSON
Monash University

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, were 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

1

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

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, including 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.

2

3

1 & 2. *A Bridge Too Far*, at the Royal Danish Academy of Fine Arts, School of Architecture, 2016. Image: © Anders Ingvartsen.

3. Double point incremental forming. Image: © CITA.

4. The pre-calculation of material thinning is materially informed (AL5005-H14 is shown here) and used to prevent tearing during the forming process. Image: © CITA.

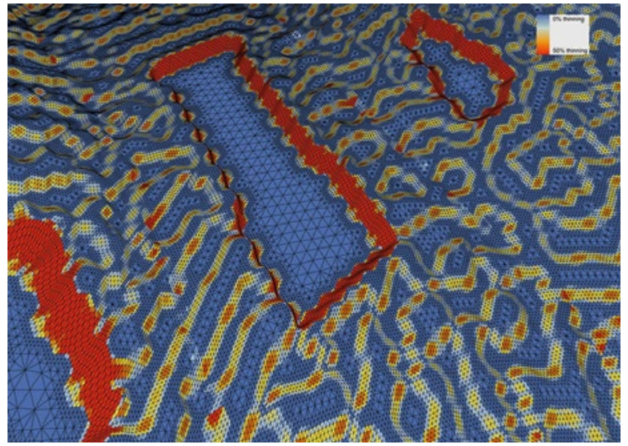
Transferred into architecture, ISF moves from a prototyping technology to a production technology. Within the context of mass customisation, it provides an alternate technology through which to incorporate, exploit and vary material capacities within the elements that make up a building system. Potential architectural applications have been identified in folded plate thin metal sheet structures (Trautz & Herkrath, 2009) and customised load-adapted architectural designs (Brüninghaus et al., 2012). Recent research has established ISF as structurally feasible at this scale (Bailly et al, 2014) and has explored the utilisation of forming cone geometries as a means to reach from one skin to another (Kalo & Newsum, 2014).

The DPIF set-up used to fabricate panels for *A Bridge Too Far* incorporates two ABB industrial robots working on each side of a moment frame that allows for a working area of approximately 1,000 x 1,000mm. Working with DPIF requires a precise positioning of two tools, one that works as a forming tool and one as the local support. The supporting tool can be positioned in two different ways, following the top perimeter of the feature or following the forming tool down the geometry (Paniti, 2014). Early investigation of both methods showed that, for our set-up, moving the supporting tool only along the feature perimeter quickly led to tearing of the metal, due to the repeated tooling of the same area.

Material considerations

The DPIF 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



4

initial hardness. In comparison to previous research demonstrators (Nicholas et al., 2016), 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 fabrication pass. 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 16mm 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

5

5. Points connecting the upper and lower skins provide local rigidisation capable of sustaining significant point loads. Image: © Anders Ingvartsen.

behaviour and forming parameters than subtractive or additive approaches. Research into resultant incrementally formed geometries has shown significant deviations from the planned geometries (Bambach 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 deterrent from the widespread take-up of the process (Jeswiet et al., 2008).

There are several approaches to improving geometric accuracy, the most direct of which is reforming. 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 deviations are detected and accounted for on the formed shape. After forming, new adjustment lengths for the next forming cycle can be calculated from accurate measurement of the formed shape. This workflow can again lead to considerably longer fabrication times and also requires sophisticated machine vision and path offsetting approaches. A third approach is to use a model-based technique, in which a finite element model of the material and a model of the compliant robot structure are coupled together (Meier et al., 2009). The forces in the tool tip are computed by the FEA, while the path deviations due to these forces can be obtained using the MBS model. Coupling both models gives the true path driven by the robots. While predictive, and therefore minimising the time used to increase fabrication accuracy, this approach is entirely dependent on simulation, which may not accurately represent the reality of fabrication.

In contrast to these approaches, we have investigated two methods 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: an online sensor-based strategy and an offline strategy based on machine learning.

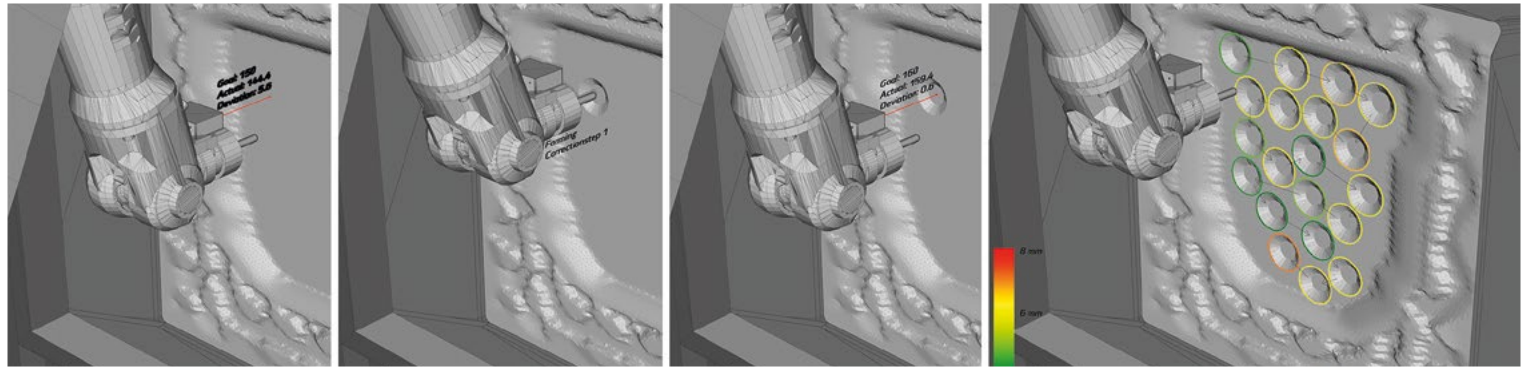
Sensor-based strategy to increase accuracy

The first method for increasing forming accuracy during forming was implemented on the rigidising cones that connect the upper and lower skins. A single point laser distance measure was mounted to the robot arm and used to measure, at each cone centrepoint, the local deviation between actual formed depth and ideal geometry. This deviation was then automatically added to the target depth for a given cone, and from this combined target depth an appropriate cone was chosen from a series of toolpaths pre-programmed into the controller, with depths of 20mm, 23mm, 26mm and 30mm.

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 5mm off the target geometry, the cone was reformed. If it was between 5 and 2mm 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 for the machine learning algorithm, a load transducer was attached to the forming tool to register changing forces on the tool tip during the fabrication process. A live stream of read-outs



6

6. Single point distance sensor mounted to the robot arm. Image: © CITA.

(approximately one per 50ms, 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 as a material behaviour model. Visualising this information revealed relationships between the fabricated shape 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 set-up 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 understood 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. With the 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 9 x 9 pixel – 81 dimensional – heightmap.

The network consists of an input layer with 82 neurons (81 + 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. Back-propagation-based learning was performed on a set of ~1600 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 the forming process result upfront, and with multiple queries the resulting panel surface can resemble the target much more precisely.

The training set is a set of randomly distributed fragments on the surface of the panel. The training set output is a heightmap based on a 3D scan of the formed panel (the ground truth), and is used as the training set output.

As the training process might end up with function overfitting, a comparison is made on another panel to assure the network's versatility.

The values obtained from prediction were used to adjust the fabrication geometry. The method for adjusting the geometry is straightforward: the input mesh heightmap values are increased by the difference between the target and prediction heightmaps. While this method yields a substantial increase in precision, more advanced methods will be a subject of future research.

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 the material behaviour model is a combination of multiple functions.

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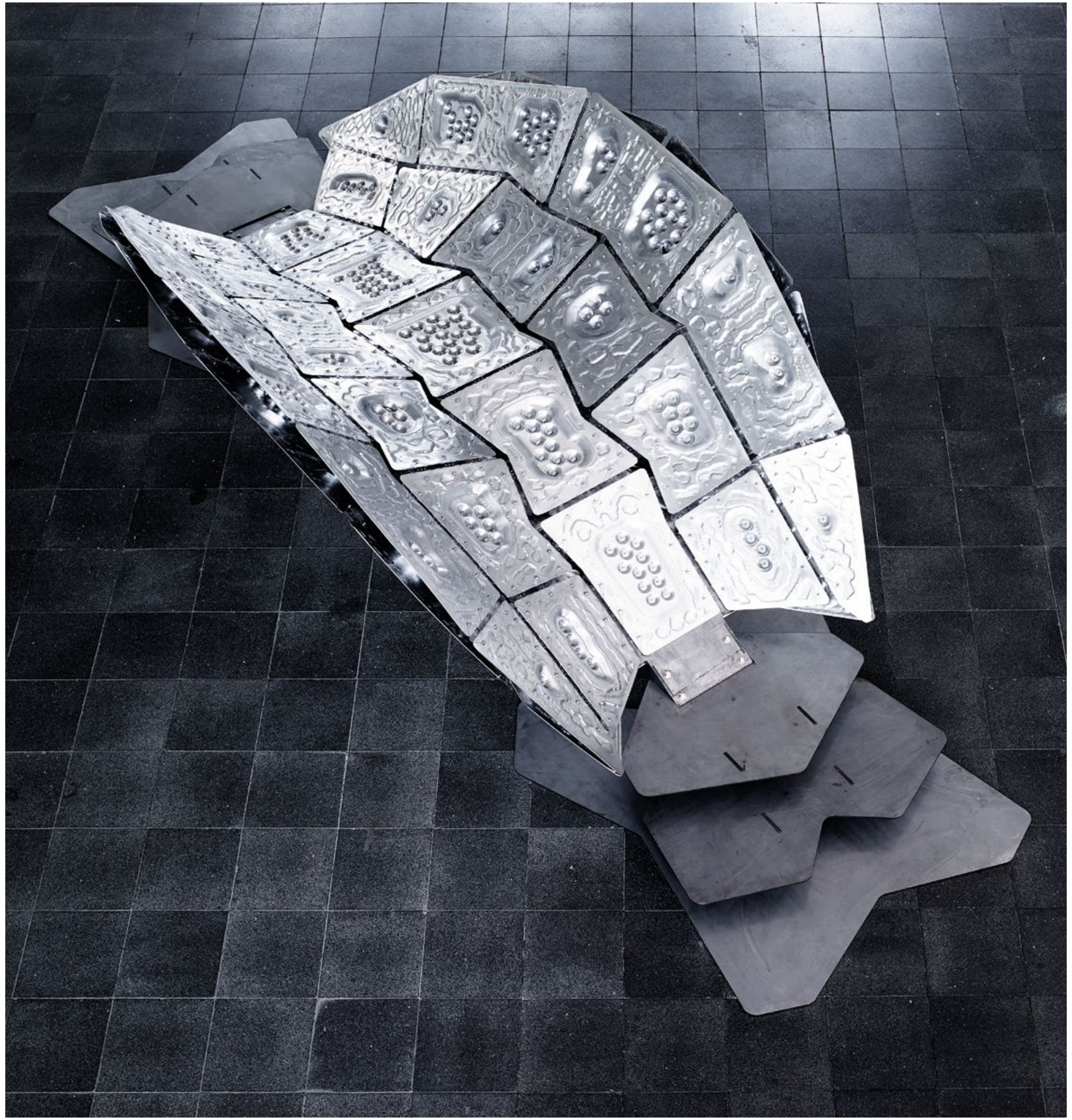

7. *A Bridge Too Far*, at the Royal Danish Academy of Fine Arts, School of Architecture, 2016. Image: © Anders Ingvartsen.