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Student Project Proposal

Generative Design of Kirigami Patterns on Elastic Sheets

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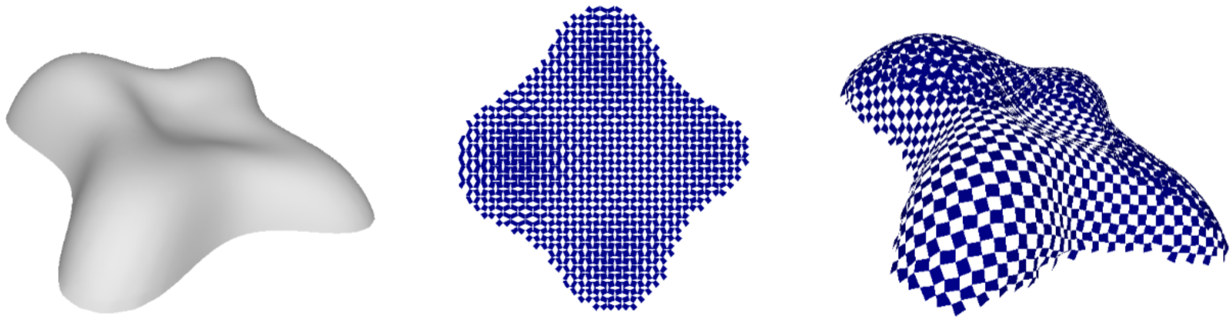

Figure 1: Given a target shape, we intend to design a cut-pattern optimal according to user-designed performance criteria which when deployed under a particular actuation closely approximates the target shape.

Description

Generative modeling has a gain of attention in the past few years thanks to the impressive performance of Generative Adversarial Networks (GAN) [3], or Variational AutoEncoders (VAEs) [4] in creating high quality portraits for instance. Both frameworks aim at training a generative model (mapping a latent space to an output space) for the task of learning a target distribution.

Deployable structures are physical systems that are fabricated in one state - preferably planar - and can be deployed into a prescribed target shape. This naturally gives rise to the inverse-design problem: Given a desired fabrication space and a target shape, encode the target deployment into the fabricated shape such that under a chosen actuation, the shape deformation favours conforming to the desired target shape.

We are particularly interested in the shape space of cut-patterns on an elastic sheet which demonstrate low energy deformations called *mechanisms*. One characteristic of them is that there is no significant elastic deformation in the interior of the sheet but localized at tiny regions/hinges around which the sheet elements rotate. Previous works do forward design of parametric non-periodic cut-patterns [1] or do a simplistic inverse design with an initialization strategy independent of the input shape making it unlikely to generalize to complex shapes [2].

General inverse-design of cut-patterns is shown [5] to be highly non-convex, and, without good initialization, often converges to sub-optimal local minima. Furthermore, the design optimization process is computationally heavy as it involves forward simulation of the deployment in each of the optimization steps. GCM's recent efforts in finding better local minima and mitigating this computational burden consist in finding a better way to initialize solutions using simple geometric abstractions. However, the underlying assumptions appear to be too coarse for some cases.

This motivates the use of generative models to capture design-space distributions that provide better and diverse initial designs. In turn, this could open directions towards having a better understanding of the more general problem of arbitrary cut-design for shape-transformations.

The project's primary goal is to design a neural network "SimNet" to approximate the deployment of cut-patterns. Once trained, SimNet can be leveraged to have a generative model learn a better initialization for the inverse-design. Further goals would involve either extending the family of cut-patterns from regular grid topology to curvilinear grids, and finally to incorporate topological singularities. Alternate directions would involve actual implementation of the computational design optimization using the adjoint method over the forward simulation gradients.

Prerequisites

Good knowledge of linear algebra and machine learning is required; familiarity with generative models and physics is preferred. Good coding skills in Python and one of PyTorch or Tensorflow is expected. C++ skills will be useful but not required.

Remarks

The scope of the project can be adapted for semester projects at the master level, for one or two students working as a team, as well as a master thesis project.

References

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[2] Gary PT Choi, Levi H Dudte, and L Mahadevan. Programming shape using kirigami tessellations. *Nature materials*, 18(9):999–1004, 2019.

[3] Ian Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio. Generative adversarial nets. In *Advances in neural information processing systems*, pages 2672–2680, 2014.

[4] Diederik P Kingma and Max Welling. Auto-encoding variational bayes. *arXiv preprint arXiv:1312.6114*, 2013.

[5] Mina Konaković, Keenan Crane, Bailin Deng, Sofien Bouaziz, Daniel Piker, and Mark Pauly. Beyond developable: computational design and fabrication with auxetic materials. *ACM Transactions on Graphics (TOG)*, 35(4):1–11, 2016.