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Learning to Assemble Geometric Shapes

Jinhwi Lee*[1,2] Jungtaek Kim*[1] Hyunsoo Chung[1] Jaesik Park[1] Minsu Cho[1]

[1]POSTECH [2]POSCO * Equal contribution

Introduction

- Human can assemble a geometric shape with fragments after analyzing the shapes and structures of them
- Assembling the fragments into the target shape is a *combinatorial problem.*
- Previous work focuses on tackling limited cases such as primitive fragments of identical shapes or jigsaw-style fragments of textured shapes.
- We introduce a challenging problem of shape assembly with textureless fragments of arbitrary shapes and also propose a learning-based approach.

Geometric Shape Assembly

- The goal is to reconstruct the target object using all the fragments.
- In this work, we create a dataset by partitioning a shape into multiple fragments using binary space partitioning (BSP) algorithm.

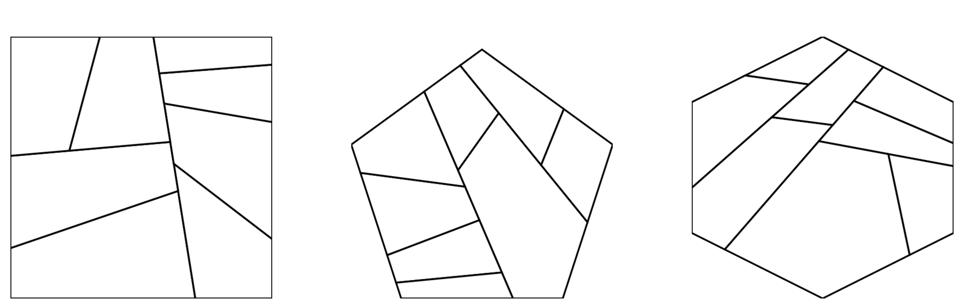
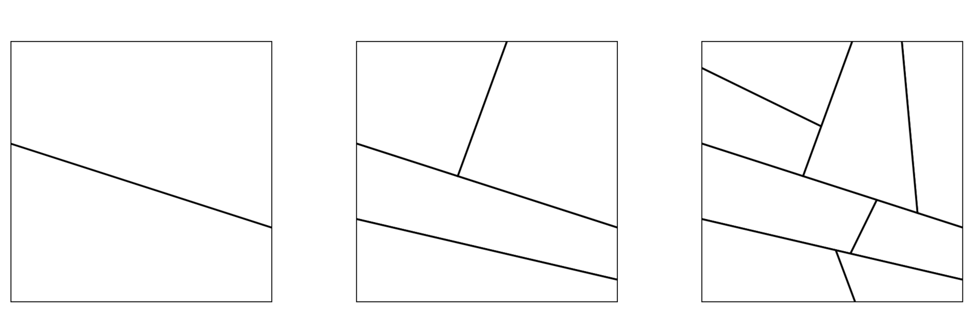


Figure 1: Textureless fragmentation examples



(a) Partitioning 1 (b) Partitioning 2 (c) Partitioning 3

Figure 2: Fragmentation examples on `Square` by partitions.

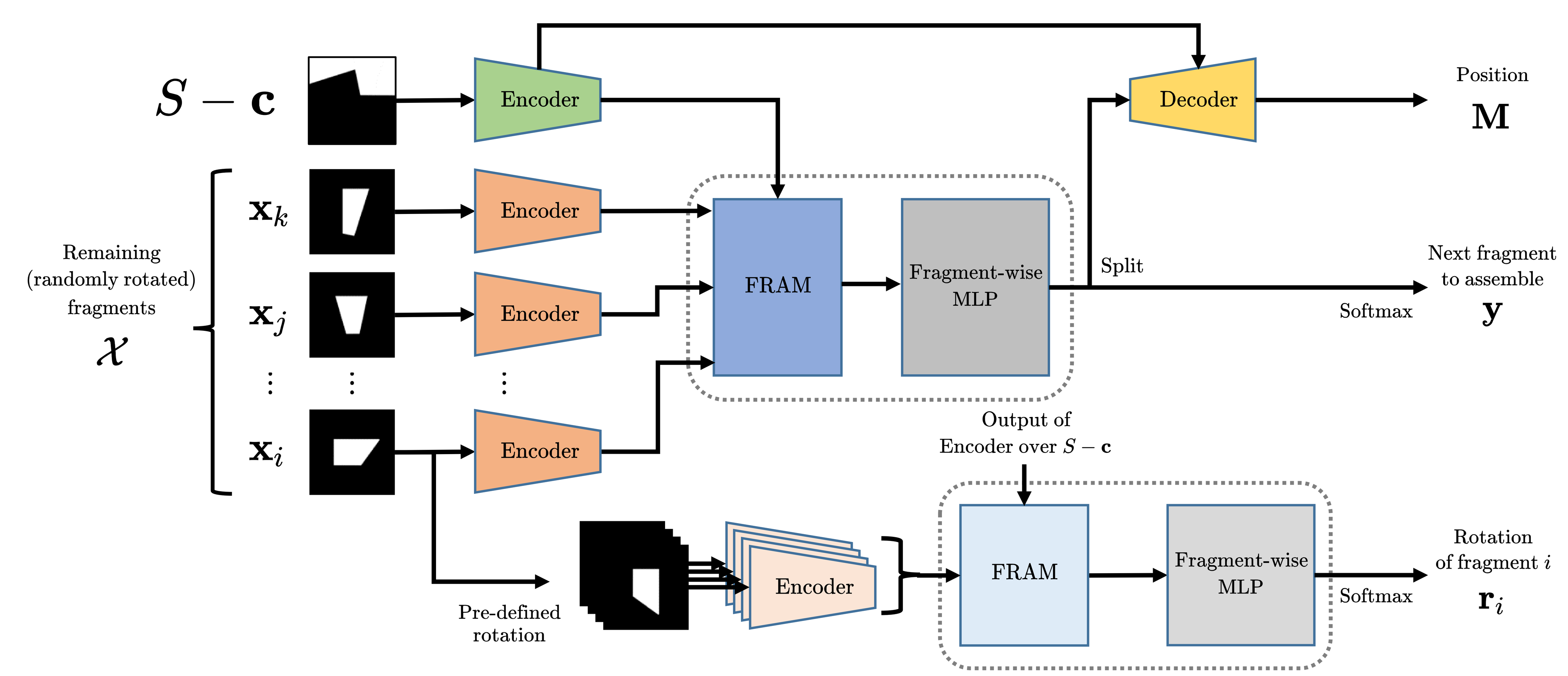


Figure 3: Our architecture overview

Fragment Assembly Networks

- FAN contains two branches for the selection and the placement.
- Both operations are determined by the probability of $\mathbf{x}$ with the remaining shape $S - \mathbf{c}$, which is the result of assembled fragments at the previous steps.
- The fragment selection network and placement network share many learnable parameters that are parts of encoders, fragment relation attention module (FRAM), fragment-wise MLP.
- We assemble all the fragments by iteratively running our model until no candidate remains.

Experimental Results

- We compare our approach to other baseline methods.

Table 1: Quantitative results on three shapes.

		Cov	IoU
`Square`	SimAnneal	0.720	0.655
	BayesOpt	0.730	0.664
	V-GAN	0.720	0.562
	Ours	**0.914**	**0.882**
`Pentagon`	SimAnneal	0.697	0.581
	BayesOpt	0.710	0.660
	Ours	**0.922**	**0.884**
`Hexagon`	SimAnneal	0.711	0.608
	BayesOpt	0.727	0.674
	Ours	**0.916**	**0.882**

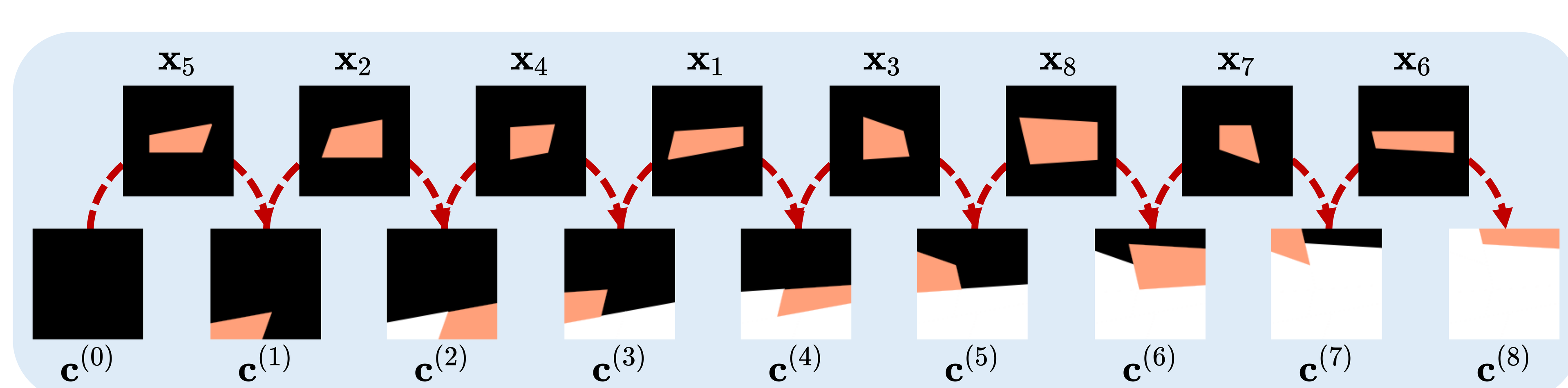


Figure 4: Assembly scenario

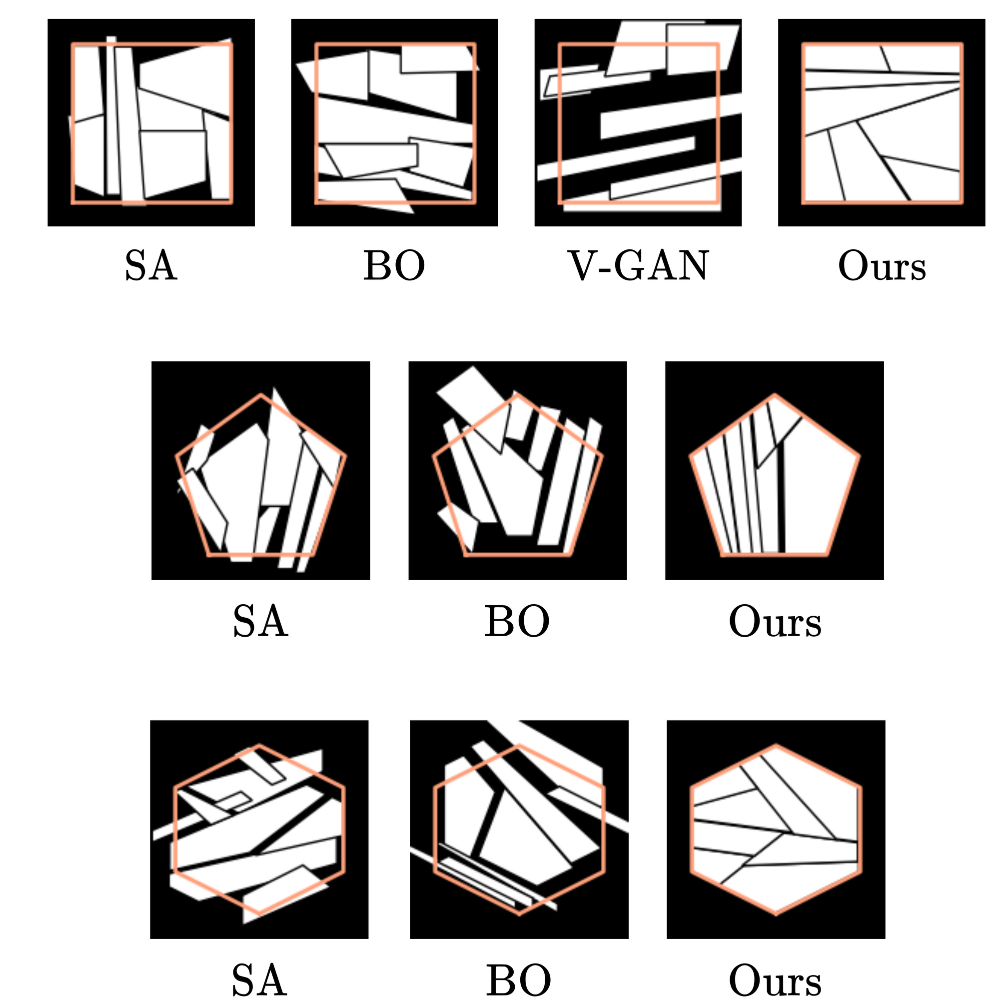


Figure 5: Shape assembly results for `Square`, `Pentagon` and `Hexagon` shape. The results of simulated annealing (SA), Bayesian optimization (BO), V-GAN (only for `Square`), and ours are compared.

Conclusion

- We solve a two-dimensional geometric shape assembly problem with our proposed neural network FAN.
- It predicts the next fragment and its pose where fragemnts to assemble are given, with an attention-based module, FRAM.

Available on the code below

Contact Information

- **Email**: jinhwi@postech.ac.kr