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Fragment Relation Networks for Geometric Shape Assembly

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[1]POSTECH [2]POSCO * Equal contribution

Introduction

- 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.
- We also propose a learning-based approach to solve it.

Geometric Shape Assembly

- The goal is to build the target object using all the fragments with the constraint from bottom to top, and from left to right.
- In this work, we create a dataset by partitioning a shape into multiple fragments using binary space partitioning (BSP) algorithm.
- The BSP algorithm is used to the partitioning process.

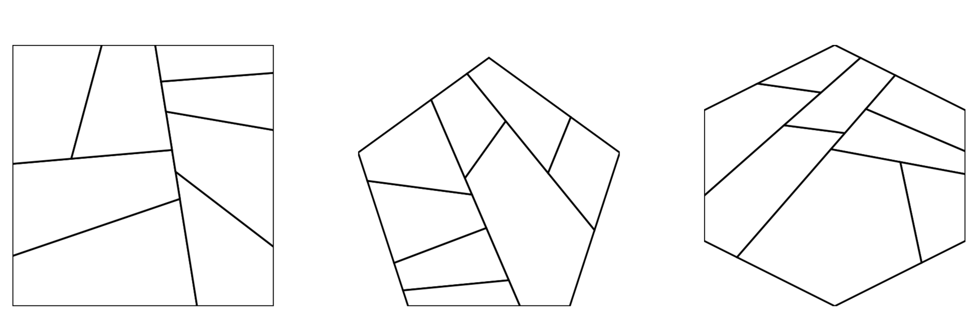
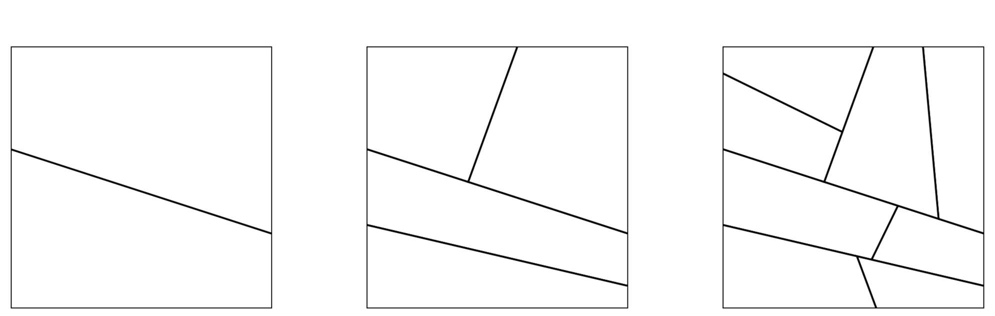


Figure 1: Textureless fragmentation examples



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

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

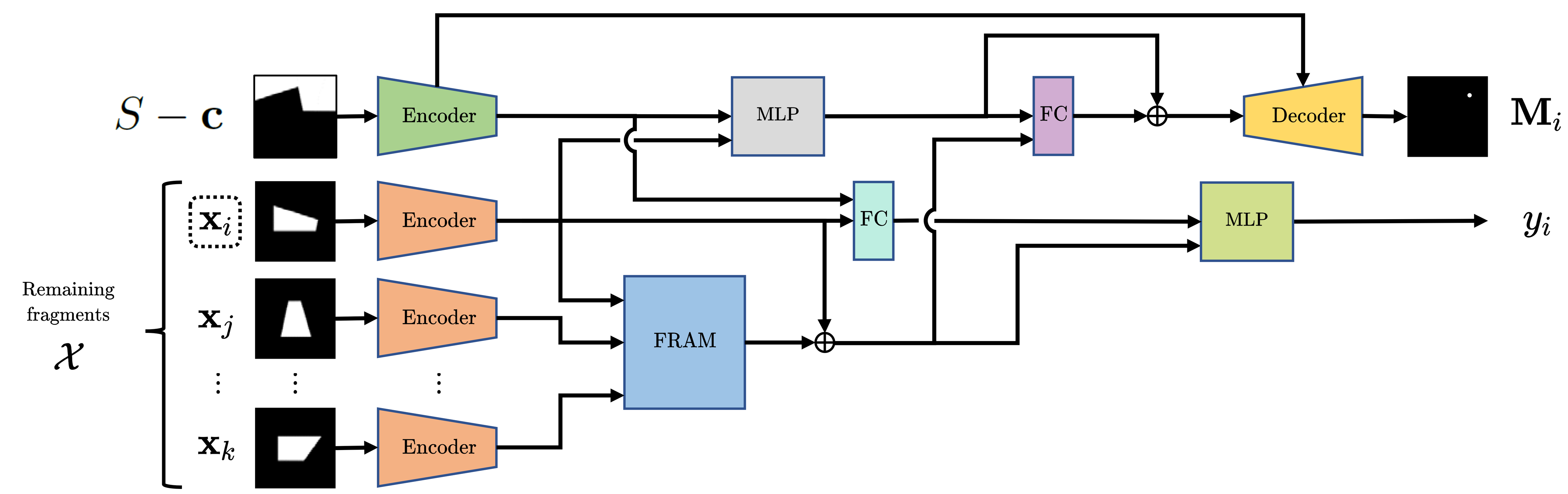


Figure 3: Our architecture overview

Fragment Relation Networks

- FRN contains two branches for the selection and the placement.
- Both operations are determined by the probability of $\mathbf{x}$ with the remaining shape $S - \mathbf{c}$ for the target object, which is the result of assembled fragments at the previous steps.
- The fragment selection network and the fragment placement network share many learnable parameters that are parts of two encoders and fragment relation attention module (FRAM).
- 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.

		mIoU	Time
`Square`	SA	0.8524	2,700 sec.
	BayesOpt	0.8329	1,180 sec.
	V-GAN	0.5615	**< 1 sec.**
	Ours	**0.8938**	**< 1 sec.**
`Pentagon`	SA	0.8349	2,584 sec.
	BayesOpt	0.7812	1,240 sec.
	V-GAN	N/A	
	Ours	**0.9262**	**< 1 sec.**
`Hexagon`	SA	0.8230	2,520 sec.
	BayesOpt	0.7745	1,210 sec.
	V-GAN	N/A	
	Ours	**0.9323**	**< 1 sec.**

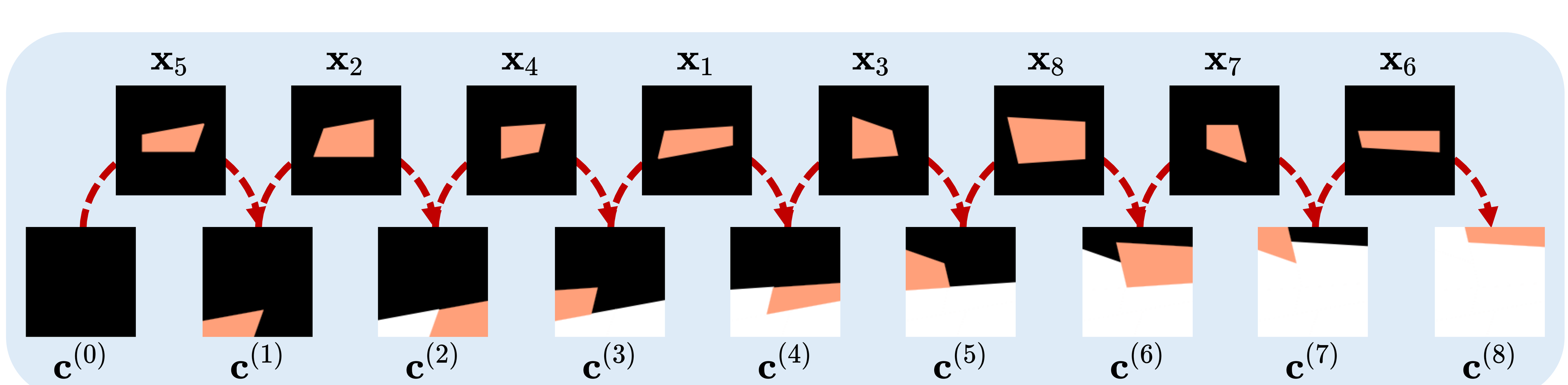


Figure 4: Assembly scenario

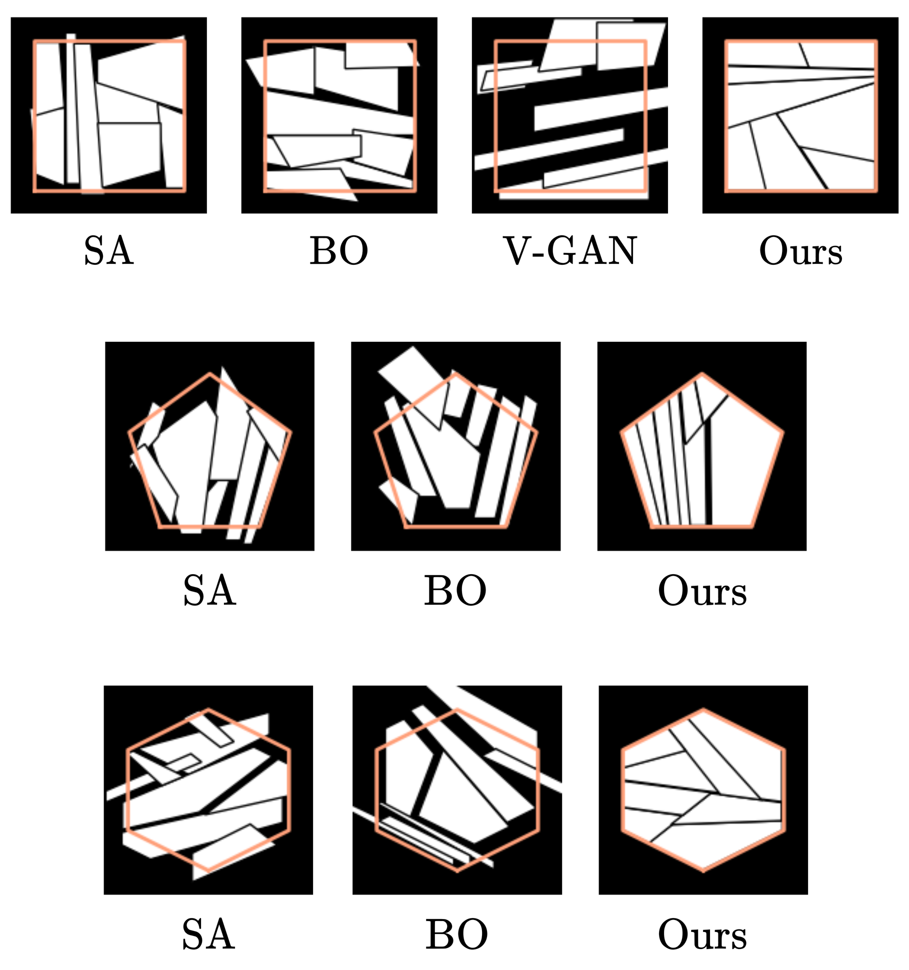


Figure 5: Shape assembly results for `Square`, `Pentagon` and `Hexagon` shape. The results of simulated annealing (SA), Bayesian optimization (BO), V-GAN (only for `Square`), and ours are compared.

Conclusion

- We solve a two-dimensional shape assembly problem with our proposed neural network FRN.
- It predicts the next fragment and its corresponding position by considering fragments relations with FRAM.

Available on the code below

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