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• **Supplementary File** •

Indoor Layout Programming via Virtual Navigation Detectors

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Appendix A Layout programming results

Figure A1 illustrates the indoor scenes whose layouts are programmed via the virtual navigation detector. In the top two cases, we change the shape of the input room from (a) to (b). The different suggested layouts show that our method is adaptive to the room shape. In the cases of (c) and (d), we show that merging small rooms whose layouts are programmed by our method, can synthesize more complex large-size indoor scenes. In the cases of (e) and (f), layouts of multiple core furniture for single rooms are programmed by our method. It shows that the layout programming by our system is also adaptive to the object categories.

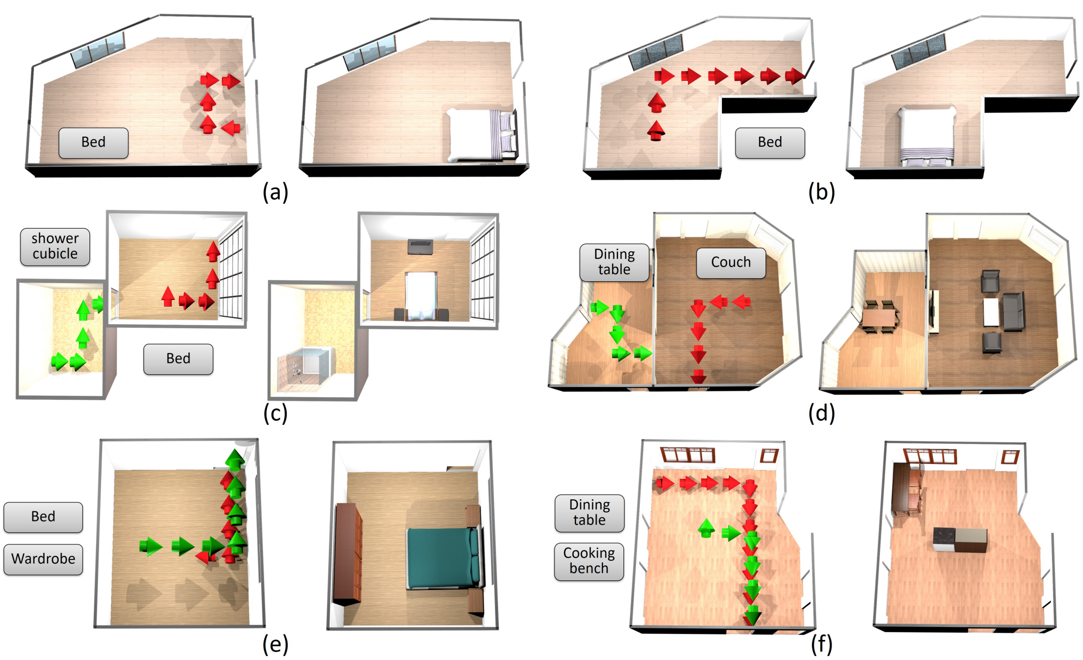

Figure A1 Gallery of synthesized indoor scenes with the indoor layouts programmed by our approach.

Appendix B Comparisons

In Figure B1, we show two groups of indoor scenes synthesized by our method and methods of [1] and [2]. The top cases show that all these methods perform well in layout creation for a rectangle input room. For the bottom cases with non-rectangle room inputs, the method of [1] needs additional information (the red dotted line in Figure B1) to separate a rectangle sub-room first aiming at exploring similar references, while the method of [2] needs a very large indoor scene database to train a CNN-based model in order to handle non-rectangle rooms.

We conducted a user study to compare the scenes synthesized by these three methods (e.g., cases in Figure B1). In this blind evaluation, five graduated students who majored in art and design were invited to compare pairs of indoor scenes, and vote to their preferred ones (the participant can also vote both scenes). The user study had two stages: the first one is to compare 10 pairs of scenes synthesized by method [1] and our method; the second one is to compare 10 pairs of scenes synthesized by method [2]

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Figure B1 Comparisons between our method and data-driven indoor synthesis methods (including [1] and [2]) on layout programming, given rectangle and non-rectangle rooms.

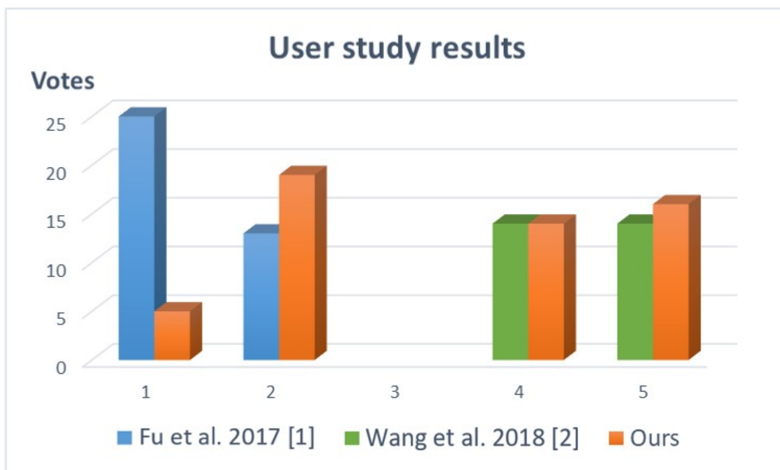

Figure B2 The comparison results of the user study. We show the votes between [1] & ours, and [2] & ours. For the two comparison results of each stage, the left one is for rectangle rooms and the right one is for non-rectangle rooms.

and our method. In both stages, 10 scene pairs included 5 pairs of rectangle rooms and 5 pairs of non-rectangle rooms. Figure B2 illustrates the results of the user study. We can see that benefited from the navigation model which makes our method adaptive to the non-rectangle room inputs, our method performs better on non-rectangle rooms compared with [1,2]. On the other hand, [1] is much better than ours for rectangle room inputs. This is mainly because our method considers less about the global layout of the room which always involves the relative positions/directions of objects in different groups, while [1] can generate the global layout by merging multiple reference floor plans. For the same reason, [2] which even though can place lots of furniture in the given room, still got a similar evaluation result as ours. Despite that, we must admit that [2] can generate much more indoor scene variations than ours due to their large-scale training data. Even though the local features we adopt can extend the usage of lightweight datasets, the size of the database is still important for the data-driven indoor scene synthesis methods.

References

1 Qiang Fu, Xiaowu Chen, Xiaotian Wang, Sijia Wen, Bin Zhou, and Hongbo Fu. 2017. Adaptive synthesis of indoor scenes via activity-associated object relation graphs. ACM Transactions on Graphics (TOG) 36, 6 (2017), 201.

2 Kai Wang, Manolis Savva, Angel X Chang, and Daniel Ritchie. 2018. Deep convolutional priors for indoor scene synthesis. ACM Transactions on Graphics (TOG) 37, 4 (2018), 70.