Boundary Conditioned Floor Layout Generation with Diffusion Model

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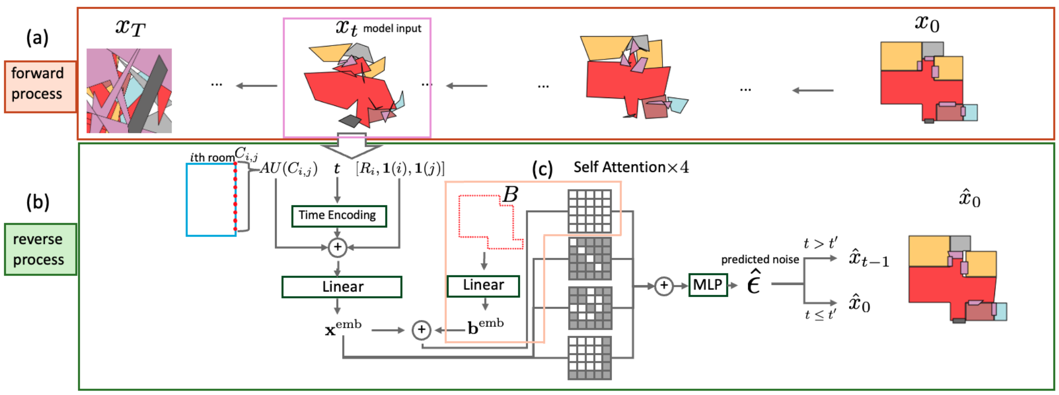

Figure 1: Overview of the proposed method. (a) Adding noise T times to the training data x_0 to create pure Gaussian noise x_T. (b) Predicting noise $\hat{\epsilon}$ with x_t as input. (c) Self-attention between boundary coordinates and room corner coordinates.

Abstract

Automated floor plan generation that aligns with exterior wall boundaries is crucial in architectural design. Existing methods using GANs lack accuracy and require raster-to-vector conversion. Our study employs Diffusion Models and Transformers, incorporating self-attention mechanisms between exterior wall coordinates and room corners. This approach effectively generates diverse, accurate floor plans in vector format conditioned on exterior boundaries, addressing key challenges unmet by previous methods.

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1 INTRODUCTION

In architectural design, the initial conceptualization phase is labor-intensive, making automated floor plan generation highly advantageous. Predetermined the exterior wall boundary is common in practical scenarios, and methods that cannot incorporate the boundary are impractical. Some methods have been proposed to predict the boundary and subsequently generate floor plans [Hu et al. 2020; Upadhyay et al. 2022]. However, methods employing CNNs often exhibit low generation accuracy. Additionally, they necessitate the conversion from raster to vector formats, entailing significant pre- and post-processing efforts. House Diffusion [Shabani et al. 2023] improves generation accuracy using Diffusion Models and Transformers but cannot condition floor plans on the boundary. While House Diffusion generates the coordinates of room corners as fixed-length vectors, it is not straightforward to determine which corner corresponds to which boundary coordinate, necessitating additional refinement.

This study introduces a method that successfully generates floor plans conditioned on an arbitrary boundary by employing self-attention on vectors that combine the coordinates of the boundary and room corners. Our method overcomes three key challenges that existing methods have been unable to address simultaneously: 1) generating floor plans conditioned on exterior boundaries, 2) maintaining the floor plan in vector format, and 3) producing diverse room shapes.

2 METHOD

2.1 Floor Plan Representation

Figure 1 shows an overview of the proposed method. In this study, we represent a floor plan as a vector. The coordinates of the j-th corner of the i-th room or door are denoted as $C_{i,j} = (x_{i,j}, y_{i,j})$. These are combined into a single vector $P = (C_{1,1}, C_{1,2}, ..., C_{i,j})$ representing one floor plan. The coordinate values are integers in

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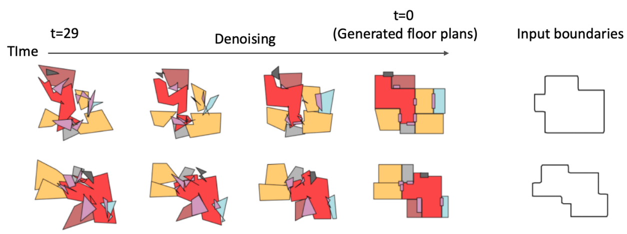

Figure 2: Examples of generated floor plans and the input boundaries

the range of $[0, 255]$. In the forward process, this range is affine-mapped to $[-1, 1]$ and mixed with Gaussian noise $N(0, 1)$, treating $\{C_{i,j}\}$ as continuous values. In the reverse process, when $t \le t'$, coordinate values are represented as discrete integers in binary form to capture geometric relationships.

2.2 Model Architecture

We utilize a Diffusion Model for floor plan generation. A Transformer-based neural network estimates the noise $\epsilon_\theta(x_t, t)$. The input to the model includes a vector that combines the floor plan P^t at step t, the step t itself, the room type R_i, the room index i, the corner index j, and the boundary vector B.

For each corner $C_{i,j}$, the AU function [Shabani et al. 2023] is employed to uniformly sample $L(= 8)$ points along the wall to the next corner, extending the point information to wall information. The extended $AU(C_{i,j})$, along with the one-hot encoded room type (R_i), room index ($\mathbf{1}(i)$), corner index ($\mathbf{1}(j)$), and encoded step t, is passed through a fully connected layer to obtain the embedding vector $\mathbf{x}^{\text{emb}}$. The boundary information is treated as a single closed polygon loop around the entire floor plan. From this loop, 100 coordinate points are uniformly sampled in a clockwise direction (=B), and passed through a fully connected layer to obtain an embedding vector $\mathbf{b}^{\text{emb}}$. Building on House Diffusion [Shabani et al. 2023], this study adds self-attention to account for the relationship between corner coordinates and the boundary. By passing the vector $\mathbf{x}^{\text{emb}}$ augmented with $\mathbf{b}^{\text{emb}}$ through the self-attention layer, we align corner information with exterior boundary coordinates, enabling the generation of floor plans that conform to the input boundaries.

3 EXPERIMENTS

3.1 Implementation Details

We implemented the proposed method using PyTorch and optimized the model on a single NVIDIA GeForce RTX 3090. The batch size was set to 256, with an initial learning rate of 1e-3, which was reduced by a factor of 0.1 every 100k steps. The number of diffusion steps T was set to 1000, and during training, t was uniformly sampled. We used Adam as the optimization method and trained for a total of 250k steps. We used the RPLAN dataset [Wu et al. 2019], sampled 30,000 floor plans from RPLAN into vector format for training. In this experiment, we focused only on floor plans with 8 rooms. The threshold t' for using discrete regression was set to 20, and during inference, we used discrete regression for $t < 32$, having the model output $\hat{C}^0_{i,j}$.

Table 1: Results for diversity and exterior wall consistency.

	FID ↓	IoU ↑
Ours	**10.56**	**0.93**
FLNet [Upadhyay et al. 2022]	19.42	0.87
Graph2Plan [Hu et al. 2020]	23.82	0.67

3.2 Evaluation Metrics

We evaluate our proposed method using two metrics: diversity and exterior wall consistency. For diversity, we use the Frechet Inception Distance (FID), which is standard for evaluating generative deep learning models. FID measures the distance between the distributions of generated floor plans and actual floor plans, with lower values indicating that the distribution of generated floor plans is closer to that of actual floor plans. Boundary consistency is calculated using the Intersection over Union (IoU) between the input boundary and the boundary of the generated floor plan. IoU takes values in the range of [0, 1], with higher values indicating better consistency with the input boundary.

4 RESULTS

The boundaries used for evaluation were randomly sampled from the training data set. Figure 2 shows samples generated from pure Gaussian noise X_T and the input boundaries. Table 1 shows the evaluation results for diversity (FID) and boundary consistency (IoU). We used 2,560 evaluation samples for quantitative evaluation. For comparison, we used FLNet [Upadhyay et al. 2022] and Graph2Plan [Hu et al. 2020], which predict exterior wall boundaries and generate floor plans. The proposed method outperforms the other methods in both metrics. The values for FLNet [Upadhyay et al. 2022] and Graph2Plan [Hu et al. 2020] are quoted from the results reported in FLNet [Upadhyay et al. 2022].

5 CONCLUSION

In this study, we proposed a method for automatic floor plan generation that incorporates exterior wall boundaries as conditions by integrating the embedding vector of exterior wall boundaries into the self-attention within a framework using Diffusion Models and Transformers. We experimentally verified the effectiveness of automatic floor plan generation conditioned on arbitrary boundaries and confirmed results that surpass existing methods in evaluation metrics.

References

Ruizhen Hu, Zeyu Huang, Yuhan Tang, Oliver Van Kaick, Hao Zhang, and Hui Huang. 2020. Graph2Plan: Learning Floorplan Generation from Layout Graphs. *ACM Transactions on Graphics* 39 (7 2020). Issue 4. https://doi.org/10.1145/3386569.3392391

Mohammad Amin Shabani, Sepidehsadat Hosseini, and Yasutaka Furukawa. 2023. Housediffusion: Vector floorplan generation via a diffusion model with discrete and continuous denoising. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. 5466–5475.

Abhinav Upadhyay, Alpana Dubey, Veenu Arora, Suma Mani Kuriakose, and Shaurya Agarawal. 2022. Flnet: graph constrained floor layout generation. In *2022 IEEE International Conference on Multimedia and Expo Workshops (ICMEW)*. IEEE, 1–6.

Wenming Wu, Xiao Ming Fu, Rui Tang, Yuhan Wang, Yu Hao Qi, and Ligang Liu. 2019. Data-driven interior plan generation for residential buildings. *ACM Transactions on Graphics* 38 (11 2019). Issue 6. https://doi.org/10.1145/3355089.3356556