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# Moving Soon? Rearranging Furniture using Mixed Reality

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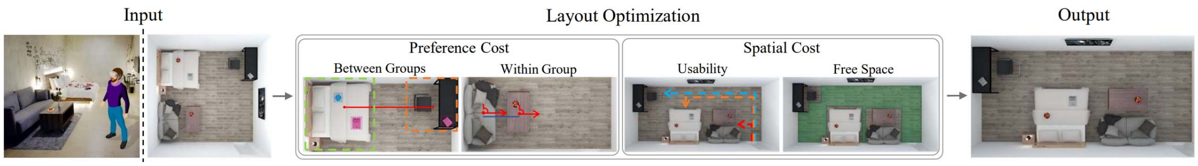


Figure 1: We propose a pipeline to rearrange furniture in a new scene according to a previous layout. A real scene is captured by a Mixed Reality device to form a top-down view layout. Then, the new layout generation problem is formulated as an optimization process with two cost terms, considering the user's preferences analyzed from the previous layout and the spatial rationality.

## Abstract

We present a mixed reality (MR) system to help users with a houseful of furniture moving from an existing home into a new space, inheriting the preferences of furniture layout from the previous scene. With the RGB-D cameras mounted on a mixed reality device, Microsoft HoloLens 2, our system first reconstructs the 3D model of the existing scene and leverages a deep learning-based approach to detect and to group objects, *e.g*., grouping the bed with nightstand. Then, our system generates a personalized furniture layout by optimizing a cost function, incorporating the analyzed relevance of between and within groups, and the spatial constraints of the new layout. The experiment results show that our system can transfer furniture layout to new spaces automatically, keeping the user's preferences well.

**Index Terms:** Human-centered computing—Visualization—Visualization design and evaluation methods

## 1 Introduction

People moves to a new home from time to time due to job changes, wanting to bringing something new, or upgrading. Interior designers found that two main strategies can enhance our living experience [2]: i) improving space utilization as reasonably as possible, ii) designing a new furniture layout according to that of the previous home. However, rearranging furniture is a challenging task, especially when we want to keep most furniture items from previous house.

Considering the interior design is costly, many researchers explored algorithms to generate scene layout automatically, meeting the requirements of aesthetics and functionality. Yu *et al*. [6] proposed automatically synthesizing the interior furniture layout following the optimization strategy. Wang *et al*. [4] used deep learning-based techniques to iteratively insert objects into the scene and achieved virtual indoor scene generation. Liang *et al*. [3] rearrange the scene layout by personal preference learned from activities. In this paper, we focus on exploring the user's preferences reflected by the existing home furniture layout to guide the layout generation for new space consequently.

## 2 System Framework

For the furniture rearrangement task, our system aims to generate a new layout for the user according to the analysis of the input scene. As shown in Fig. 1, with the wearable MR device, Microsoft HoloLens, the real scene is captured and the corresponding 3D model is automatically reconstructed. We apply a state-of-the-art object detector [1] to detect all furniture objects in the scene and mirror a virtual home accordingly. Our system then performs layout analysis and formulates the layout generation in new spaces as an optimization with various constraints, including furniture layout preference and spatial constraints.

The layout of a scene with $N$ objects is defined as $\mathscr{L} = \{\mathscr{L}_i | \mathscr{L}_i. = (x_i, y_i, \theta_i), i \in \{1, 2, \ldots, N\}\}$. For the $i$-th object, $(x_i, y_i)$ and $\theta_i$ are the center of the furniture and its orientation from the top view.

**Cost Function.** We define a cost function to consider the spatial and the user's preference constraints accordingly:

$$C_{total}(\mathscr{L}_0, \mathscr{L}) = \omega_p C_p(\mathscr{L}_0, L) + \omega_s C_s(\mathscr{L}), \tag{1}$$

where $\mathscr{L}_0$ and $\mathscr{L}$ are the original and the current layout, respectively. $C_p(\cdot)$ models how well the layout fits the user's preference obtained from the original layout; $C_s(\cdot)$ models how rational the current layout is. $\omega_s$ and $\omega_p$ are the weights, being set as 0.5 by default.

***Preference cost.*** The goal of this cost term is to encourage the solution which keeps the user's preferences reflected by the original layout well. For a scene, furniture items usually perform functions in the form of a group. For example, a bed often goes with nightstand.To make the optimization tractable, it makes sense for us to divide the layout into groups, which can be realized by user manually or by a cluster with distance and category constraints automatically. We consider two aspects of the user's preferences over the divided groups. One is the relative position between groups; the other is the relative position and angle among furniture items within one group. The preference cost is defined as:

$$C_p(\mathscr{L}_0, \mathscr{L}) = \omega_b C_b(\mathscr{L}_0, \mathscr{L}) + \omega_w C_w(\mathscr{L}_0, \mathscr{L}). \tag{2}$$

The first term is modeled by the neighborhood relationships among groups which is expected to be as consistent as possible. That is, if two groups are with a tight relationship, they are expected to be closer in the space, and vice versa. To this end, this term is defined as $C_b(\mathscr{L}_0, \mathscr{L}) = \sum_i \sum_j (S_{i_0 j_0} - 0.5) \times (d_{ij} - 0.5) + 0.5$, where $d_{ij}$ is the distance between $i$-th and $j$-th region normalized by the largest distance and $S_{ij}$ is their neighborhood relationship.

For the neighborhood relationship of two furniture items, it is defined as $S_{i_0 j_0} = d_{i_0 j_0} \times (1 - o_{i_0 j_0})$. $d_{i_0 j_0}$ is the distance of two regions in the original scene normalized by the largest distance. We use the central position of the largest furniture in each region to calculate the distance. $o_{i_0 j_0} = \frac{N_o}{N_w}$ is the overlap ratio of the objects' categories in two regions, where $N_o$ is the number of the objects appearing in both two regions and $N_w$ is the total number of all objects in two regions. Totally, the smaller the value is, the tighter the neighborhood relationship is.

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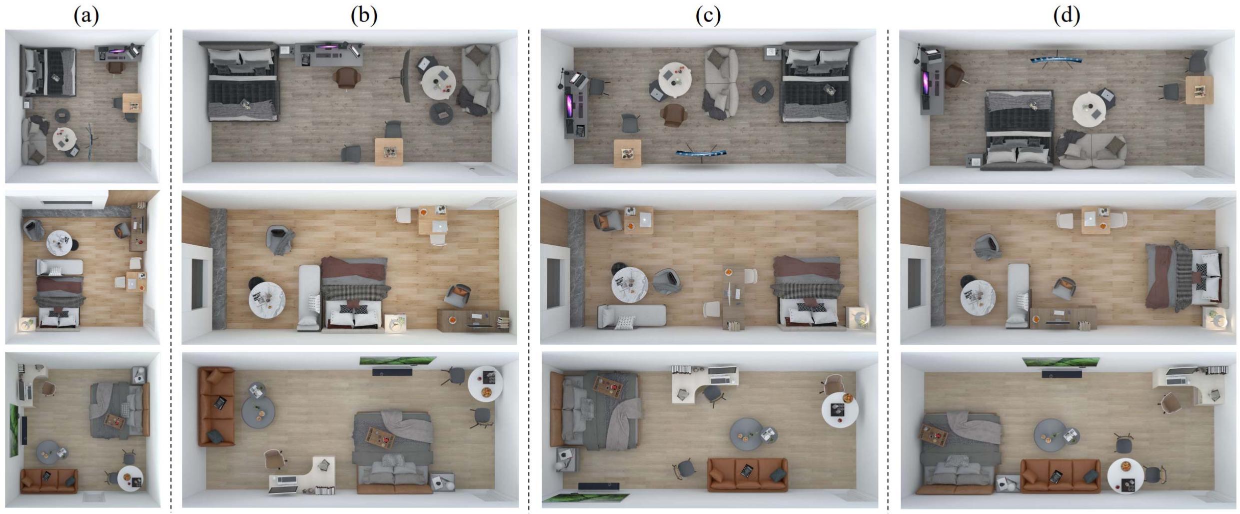


Figure 2: The layout generation results. (a) Input scenes, different layouts of different users' exiting home. (b) Layouts generated by our approach. (c) Layouts generated by conventional approach, *i.e.* no user preference considered. (d) Layouts designed by professionals.

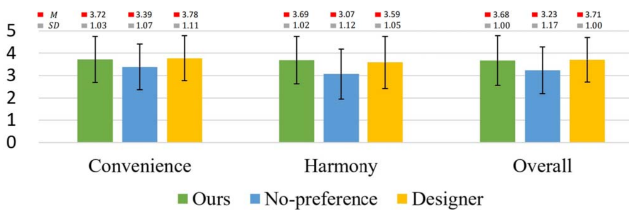


Figure 3: Statistics of average rating of our approach, no-preference approach, and professional designs.

Another term is the constraints within one group, defined by $C_w(\cdot) = \sum_{ij}(\frac{1}{Z_d}|d_{ij} - d'_{ij}| + \frac{1}{Z_\theta}|\theta_{ij} - \theta'_{ij}|)$. $d$ and $\theta$ represent the relative distance and orientation of two furniture item; $\frac{1}{Z_d}$ and $\frac{1}{Z_\theta}$ are their corresponding normalization parameters.

***Spatial cost.*** We consider two factors for the rationality of the layout. One is the usability of each furniture, that is, whether there is an available route from the door to the furniture. The solution with inaccessible furniture items will be penalized. This term is defined by $C_{s1}(\mathscr{L}) = 1/R$, where $R$ represents the amount of furniture items with available route. Another is the size of free space, measuring the enclosed area by furniture and walls. Since the enclosed area cannot be used, the solution with bigger enclosed area will be penalized during the optimization. This term is defined by $C_{s2}(\mathscr{L}) = A$, where $A$ represents the size of the enclosed area. Finally, the spatial cost is defined as $C_s(\mathscr{L}) = \omega_{s1}C_{s1}(\mathscr{L}) + \omega_{s2}C_{s2}(\mathscr{L})$, where $\omega_{s1}$ and $\omega_{s2}$ are factors to balance these terms, they are set to 0.5 by default.

**Scene Generation.** We use the simulated annealing algorithm to iteratively explore the layout of the scene. The algorithm can accept the non-optimal choice by Metropolis criterion, for avoiding coming stuck at the local minima. The scene layout is alternately changed by $(x_i + \Delta x, y_i + \Delta y) \rightarrow (x'_i, y'_i)$ and $(\theta_i + \Delta\theta) \rightarrow (\theta'_i)$, where $(x_i, y_i)$ and $(\theta_i)$ represent the current position and orientation of the $i$ item; $(x'_i, y'_i)$ and $(\theta'_i)$ represent the new position and orientation of the $i$ item, the amount of change $(\Delta x, \Delta y)$ and $(\Delta\theta)$ is sampled by a Gaussian distribution. The optimization will be terminated if the total cost value variation is less than 5% over the past 30 iterations.

## 3 Experiment

We implement our system using C# in Unity 5.6 and deploy it to the Hololens platform. As shown in Fig. 2(a), we reconstructed three 3D models of different users' home and compared three approaches of furniture layout generation for new space: i) our optimized layout (Fig. 2(b)); ii) conventional generated layout [5], *i.e.* no user preference considered (Fig. 2(c)); iii) professionally designed furniture layouts (Fig. 2(d)).

We recruited 30 participants to rate the convenience, harmony, and the overall experience of the layouts, using a 1-5 Likert scale, with 1 meaning bad experience and 5 meaning the opposite. Fig. 3 shows the mean $(M)$ and standard $(SD)$ deviation statistics of ratings. Take the overall ratings as an example, our approach $(M = 3.68)$ is 13.93% higher than the conventional approach $(M = 3.23)$. The difference is statistically significant $(\chi^2 = 8.97, p < .05)$ at the $\alpha = 0.05$ significance level. The results do not show significant difference between the method of ours and of professional designs $(M = 3.71)$.

## 4 Conclusion

In this paper, we introduce an approach of personalized furniture layout generation with the help of MR device, help users when moving to new homes. The layout generated by our approach could meet the requirements of both user preference and spatial rationality. Through the user study, we validate the effectiveness of our approach. Moreover, our approach could be easily extended to solve the furniture rearrangement in stores or workspaces.

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