1. Introduction

Computer aided design (CAD) technology is indispensable for architectural design, but current CAD tools require high-level design specifications from architects. It would be fantastic to construct an intelligent CAD system performing automatic architectural layout parsing (AutoALP), which allows to generate candidate designs or predict architectural attributes without much user intervention. It would not only inspire creation of architects, but also reduce tedious adjustment. Recently, AutoALP has attracted ever-growing research interests [1]–[8].

From a computational perspective, AutoALP has two subtasks. One is for prediction task, whose goal is to predict some architectural attributes [1]–[3]; the other is for generation task, which aims to generate candidate designs for the users [4]–[8], [10].

AutoALP is a challenging problem involved with the formulation of visual representation, generation and predic-

\begin{table}[h]
\centering
\begin{tabular}{|c|c|c|c|c|c|c|}
\hline
\textbf{Dataset} & \textbf{Num.} & \textbf{App.} & \textbf{Label} & \textbf{Pre.} & \textbf{Gen.} & \textbf{Pub.} \\ \hline
2015 [9] & 122 & FP & LA & - & $\checkmark$ & $\checkmark$ \\ \hline
2016 [10] & 80 & UP/FP & LA/AT & - & $\checkmark$ & - \\ \hline
2017 [8] & 870# & FP & LA & - & $\checkmark$ & - \\ \hline
2017 [11] & 300 & FP & LA & $\checkmark$ & $\checkmark$ & - \\ \hline
2018 [5] & 1.1K# & FP & LA & - & - & - \\ \hline
2018 [6] & 200 & FP & LA & - & - & - \\ \hline
2018 [7] & 115 & FP & LA & - & - & - \\ \hline
2018 [3] & # & UP & AT & $\checkmark$ & - & $\checkmark$ \\ \hline
2019 [4] & >80K & FP & LA & - & $\checkmark$ & $\checkmark$ \\ \hline
2019 [2] & 5K# & FP & AT & $\checkmark$ & - & $\checkmark$ \\ \hline
2020 [1] & 150K & FP & AT & $\checkmark$ & $\checkmark$ & - \\ \hline
\textbf{Ours} & 602 & UP/FP & LA/AT & $\checkmark$ & $\checkmark$ & $\checkmark$ \\ \hline
\end{tabular}
\caption{Representative datasets for AutoALP, where “Num.” is for sample numbers, “App.” for application, “Pre.” for prediction task, “Gen.” for layout generation task, “Pub.” for publicly released; “FP” is for floor plan, “UP” for urban plan, “LA” for layout labels, “AT” for attribute labels; “#” means it is built by modification or expansion of previous dataset.}
\end{table}
lected and reviewed 5000 floorplans from a larger dataset of Finnish floorplan images; [5] use the SUNCG dataset, a large database of virtual 3D scenes created by users of the online Planner5d interior design tool, to train the deep convolutional model. Many datasets have not been released publicly yet, which makes the comparison difficult. Recently, Wu et al. [4] constructed a large-scale dataset containing over 80K real floor plans with dense layout annotations, and proposed a two-stage method with deep neural networks to generate floor plans for residential buildings with given boundaries. Kato et al. [1] built a predictor for user preference of real estate properties based on a dataset containing 1.5K samples with 10 classes. Both of these works would greatly advance the studies of AutoALP.

Table 1 indicates that AutoALP is intrinsically a multi-paradigm problem with diverse tasks (prediction/ generation), labels (layout/attribute) and applications (floor plan/urban plan). Building a dataset under specific paradigm would limit the performance and flexibility of the computational model trained on the dataset, and it would be difficult to make comparison with the models trained by the dataset with specific constraints. Therefore, we argue that AutoALP is a multi-paradigm computational problem, and propose a new diverse benchmark dataset, called SCUT-AutoALP, to achieve multi-paradigm ALP.

SCUT-AutoALP contains two subsets, where Subset-I is for floor plan design containing 300 residential floor plan layouts with boundary, layout and attribute labels (apartment area); Subset-II is for urban plan design containing 302 campus plan layouts of primary school with boundary, layout and attribute labels (like building area and building density), as shown in Fig. 1. With different combinations of samples and labels, SCUT-AutoALP is available for different applications. For example, boundary label (Fig. 1 (b)) and layout label (Fig. 1 (c)) allow interior plan generation as in [4]; samples (Fig. 1 (a)) and layout labels (Fig. 1 (c)) allow image-to-image layout recognition as in [7]. We analyzed the samples and labels statistically, and evaluated SCUT-AutoALP for different image parsing tasks, including boundary-to-layout (B2L) generation, layout recognition/generation. The results illustrate the effectiveness and indicate the potential applications of SCUT-AutoALP.

The main contributions of this article can be summarized as follows:

1. **Dataset:** We propose a new benchmark dataset SCUT-AutoALP containing 602 samples and dense labels, which is flexible for multi-paradigm AutoALP with diverse tasks (prediction/generation), labels (layout/boundary/attribute) and applications (floor plan/urban plan).

2. **Benchmark Analysis:** We analyze the samples and labels of SCUT-AutoALP statistically, and visualize some properties of SCUT-AutoALP.

3. **Layout Parsing:** Evaluation experiments were conducted for different layout parsing tasks for floor plan or urban plan, including boundary-to-layout (B2L) generation and layout recognition/generation. The results indicate the effectiveness and potential applications of SCUT-AutoALP, and can be used as baselines for the following research.

2. **Construction of SCUT-AutoALP**

SCUT-AutoALP Dataset contains totally 602 samples with dense labels (annotated by architectural designers), which can be divided into two subsets.

Subset-I is for floor plan design, which contains 300 residential floor plan images. The original samples were collected from “LianJia” website, and that with obvious drawing errors has been eliminated. All the cleaned samples were resized by 1: 100, and the final samples were placed on 20cm×20cm white background images. For layout parsing, we use different RGB color blocks to denote different regions for boundary labels and layout labels, as shown in Fig. 2 (a). Since all the drawing images were resized with the same scale, each of the region was labelled with the corresponding area for attribute prediction.

Subset-II is for urban plan design, which contains 302 urban plan images of primary school campus. The original samples were collected from the Internet, like websites of architectural design or government. Urban plan design is influenced by many factors, like climate or topography. To reduce the unwanted variances, we selected the samples with similar climatic and topographical conditions. All the cleaned samples were resized by 1: 1800, and the final samples were placed on 24cm×24cm white background images. For layout parsing, we use different RGB color blocks to denote different regions for boundary label and layout label.
as shown in Fig. 2(b). For attribute prediction, we annotate each region with building area, and estimate building density and floor area ratio for attribute prediction.

3. Benchmark Analysis

We analyzed the visual variances of different samples and labels in SCUT-AutoALP.

Figure 3 shows boundary labels and layout labels for floor plan and urban plan. It shows that these labels cover diverse visual properties with variances of boundary shape, region size, region location and orientation.

To illustrate the sample variances, we tried to visualize the variances of the label images. Since the visual diversity of different regions in the labels are encoded in the corresponding images with different texture properties, we can obtain the visual feature by local binary patterns (LBP) [14], which is one of the most powerful texture descriptors for textual representation. Then, we projected the extracted high-dimensional LBP features of these labels into a 2D space by t-SNE [15], as shown in Fig. 4. It can be observed that the data of SCUT-AutoALP have good visual diversity for both floor plan and urban plan, and it seems that the visual variances of Subset-I is larger than Subset-II.

For more direct illustration of the variances, we visualized the pixel-wise standard deviation of the layout labels for floor plan and urban plan, as shown in Fig. 5. The layout labels were first normalized, and then standard deviation of each pixel in R, G, B channel is computed, respectively. Larger value of standard deviation would obtain higher intensity value. It can be seen that the labels of floor plan have more pixels with higher standard deviation, which further indicates larger visual variances of Subset-I than Subset-II.

Since each layout sample consists of many smaller color blocks and corresponding attribute labels (as in Fig. 1), we also analyze the distribution of different block types and region area for layout labels, as shown in Table 2 and Fig. 6 respectively. It shows that some kinds of block types (like living room) exist in most of the samples, while some are not (like study room), which is consistent to practical architectural design logic of floor plan or urban plan.

4. Layout Parsing of SCUT-AutoALP

4.1 cGAN-Based Model for Layout Parsing

Based on SCUT-AutoALP, different combination of samples or labels can be used for different layout parsing tasks. Since all the inputs and outputs of these tasks are images, we regard layout parsing as an image-to-image translation problem. We formulate AutoALP tasks using the cGAN-based pix2pix model [12], whose generator has a U-Net structure as shown in Fig. 7.

In the experiments of this paper, all the images were resized to 256 × 256. For Subset-I and Subset-II, we used 290 pairs for training and the rest for testing, respectively.
The original pix2pix model is trained with data augmentation that uses cropping + resizing [12]. However, B2L generation and layout generation in AutoALP require global constraint on boundary, directly applying the original pix2pix model for AutoALP would cause region missing or isolation artifacts, as shown in Fig. 8 (a). To tackle this problem, we use horizontal flipping for data augmentation, which obtain better generation results in Fig. 8 (b).

4.2 Evaluation and Analysis

We evaluated SCUT-AutoALP for different layout parsing tasks, including boundary-to-layout (B2L) generation, layout recognition and layout generation.

Figure 9 shows the results of B2L generation for floor/urban plan, which takes layout label as output ground-truth, boundary label as input condition, just as the problem setting of interior plan generation in [4]. Figure 10 shows the results of layout recognition for floor plan, which takes layout label as output ground-truth and sample as input condition, just like the architecture drawing recognition settings in [7] that marking rooms with different colors. Figure 11 shows the results of layout generation for floor plan, which takes sample as output ground-truth and layout label as input condition, just like the architecture drawing generation setting in [7] that generating apartment plans with the input layout blocks. More results can be found in the website of the dataset [16].

The evaluation illustrates that SCUT-AutoALP is flexible for multi-paradigm layout parsing tasks with different combination of labels and samples. It can be observed that the results produced by our modified pix2pix model are globally consistent to the ground-truth for B2L generation and layout recognition/generation, which indicates that it is suitable to formulate AutoALP as an image-to-image translation problem. The results also indicate that the pix2pix model can be a good baseline for AutoALP, and more sophisticated prior can be integrated into the model to obtain results with better local consistency.

5. Conclusion

This paper proposes a SCUT-AutoALP dataset for multi-paradigm applications, which has totally 602 samples and labels with diverse boundary, layout and attributes. It allows to achieve different architecture layout parsing tasks for floor plan or urban plan. We analyzed the samples and labels statistically, and made evaluation of B2L generation, layout recognition and layout generation for floor plan/urban plan based on the pix2pix model. The results verify the effectiveness and indicate the potential applications of SCUT-AutoALP.

In our future works, SCUT-AutoALP can be further extended in some directions. Firstly, more types, labels and
amounts of sample could be added in the dataset. Secondly, more sophisticated models could be used with SCUT-AutoALP, like GNN-based models for image analysis and editing [13].

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