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Learning to Floorplan like Human Experts via Reinforcement Learning

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***Abstract*—Deep reinforcement learning (RL) has gained popularity for automatically generating placements in modern chip design. However, the visual style of the floorplans generated by these RL models is significantly different from the manual layouts' style, for RL placers usually only adopt metrics like wirelength and routing congestion as the reward in reinforcement learning, ignoring the complex and fine-grained layout experience of human experts. In this paper, we propose a placement scorer to rate the quality of layouts and apply abnormal detection to the floorplanning task. In addition, we add the output of this scorer as a part of the reward for reinforcement learning of the placement process. Experimental results on ISPD 2005 benchmark show that our proposed placement quality scorer can evaluate the layouts according to human craft style efficiently, and that adding this scorer into reinforcement learning reward helps generating placements with shorter wirelength than previous methods for some circuit designs.**

***Index Terms*—Floorplan, Reinforcement Leaning, Abnormal Detection, Placement Scorer**

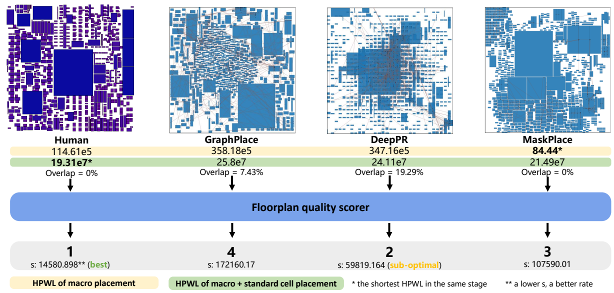

Fig. 1. Different placements of $adaptec3$ and the corresponding scorers of floorplan quality scorer.

I. Introduction

As a crucial and time-consuming step in modern chip design, quality of floorplanning directly affects the routability in routing stage, time convergence, power supply stability and yeild rate, etc. Throughout the physical design process, a high quality floorplan normally brings designs with better power, performance, and area (PPA).

Series research of automated placer has emerged for the past few years, however, visual styles of output floorplan images for previous RL placers [2] [3] [5] have intuitive differences with that of human experts shown as Fig. 1. Unlike neatly arranged human layouts, RL placers prefer to place macros on the center of the canvas, make macros overlapping with each other, gathering in clusters or mixing up together. While wirelength metrics of placers surpass the human benchmark in some samples during the early floorplanning stage, this advantage fades with the following placement step. To overcome the difficulty of expressing experts' layout principles mathematically, we construct a placement scorer to learn hardware experts' experience from layout images and to predict floorplan quality according to the learned human standards.

Our contributions are summarized as follows:

- We adopt Transformer-based abnormal detection model to learn distribution patterns of normal (manual) data by feature reconstruction. This work is the first to use unsupervised abnormal detection in floorplanning task.
- We integrate the quality score generated by the trained layout scorer into deep RL-based chip floorplanning training process to help generate layouts like experts.
- Experimental results show that our proposed method can evaluate quality of layout and shorten the wirelength in the placement stage.

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II. Methodology

As shown in Fig. 2, we cast the placement quality evaluation as unsupervised abnormal detection. Inspired by previous work [4], we treat different circuits as different classes and assume that human-crafted placements share similar characteristics so that they can be considered as the same class of images. we build a model to capture the distribution of all circuits at the same time (Fig. 2(a)), and detect anomalies for images of chip placements (Fig. 2(b)). Finally, the model produces an abnormal value to quantitatively measure the deviation of the layout's style from human standards (Fig. 2(c)).

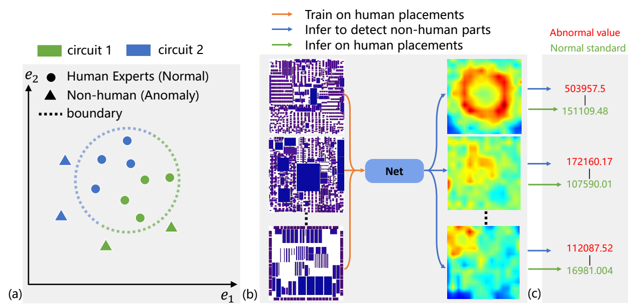

Fig. 2. Task explanation of anomaly detection in floorplanning.

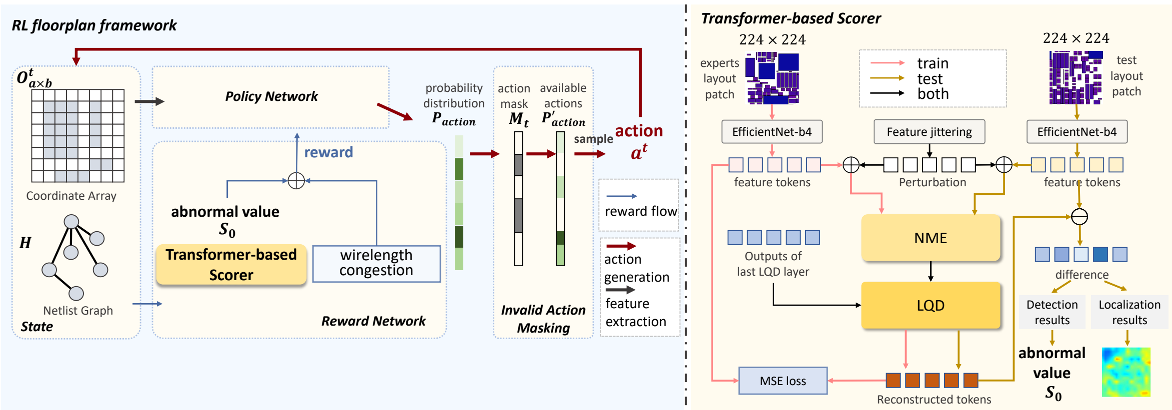

Fig. 3. Overview of RL floorplan framework and transformer-based scorer.

TABLE I
HPWL OF PLACEMENT BY DIFFERENT PLACERS ($\times 10^7$).

Placer	ad1	ad2	ad3	ad4	bb	bb3
Human	**7.28**	**8.19**	19.31	**17.38**	**8.93**	**30.40**
DREAMPlace [1]	12.89	15.27	**17.55**	28.10	10.38	42.69
GraphPlace [2]	8.67	12.41	25.80	25.58	16.85	46.00
MaskPlace [5]	7.93	9.95	21.49	22.97	9.43	37.29
Ours	8.35	9.59	19.85	20.48	9.74	38.76

Overall Framework. As depicted in Fig.3, our overall deep RL framework includes a policy network and a reward network, the latter includes the constructed Transformer-based scorer. In RL floorplan flow, given a placement coordinate array $O^t_{a\times b}$ (a and b are the size of the canvas) and a netlist graph H, the policy network maps them into probability distribution P_{action}. An action mask M_t generate available actions probability distribution, from which an action a^t is sampled. The architectures of policy network follows [3].

Transformer-based Scorer. As Shown in Fig. 3, Our Transformer-based scorer receives the observation of a complete macro placement, converts it into an image, and extracts feature tokens using EfficientNet-b4. The Neighbor Masked Encoder (NME) integrates feature tokens and derives the encoder embeddings, after which the Layer-wise Query Decoder (LQD) outputs the reconstructed features. The training and testing framework follows UniAD [4].

Inference results. The localization result s is generated from the reconstruction differences, and the anomaly value result: $S_o = \sum_{i=0}^{W} s(p_i)$, if $s(p_i) > \tau$, where p_i is the position of pixel i, and τ is an empirical constant.

III. RESULTS

We choose ISPD 2005, ISPD 2006, ISPD 2011 and DAC 2012 benchmark suites to construct a new dataset for the scorer. Placers' performances are evaluated by six of ISPD 2005.

Transformer-based Scorer. As illustrated in Fig.4, anomaly localization is represented by a heatmap image. High anomaly values displayed as colors that near the red in color spectrum. The ranking of floorplan quality according to the anomaly value s is different with that sorted by the wirelength metric. Abnormal value assesses floorplan quality in more comprehensive perspective.

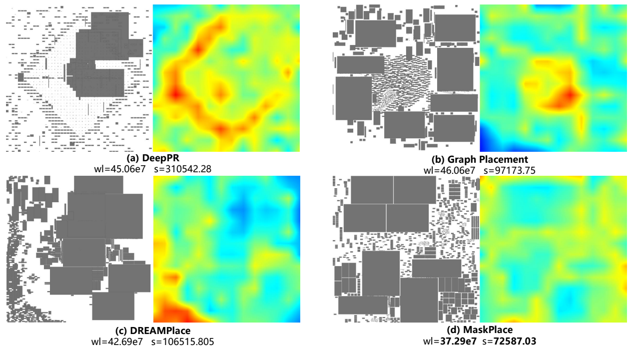

Fig. 4. Anomaly localization and anomaly value results for different placements of $bigblue3$, wl is HPWL of the mixed-size placement, and s is anomaly value, $*$ indicates the best performance.

RL Chip Floorplanning. Table I compares the HPWL results after placing standard cells using DREAMPlace [1], where "ad" means "adaptec", "bb" means "bigblue". The second-best and the third-best outcomes are marked with underlines and double underlines respectively. Our outcomes rank within the top three, outperform the others except human baseline.

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