Adaptive Linear Span Network for Object Skeleton Detection

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Abstract—Conventional networks for object skeleton detection are usually hand-crafted. Although effective, they require intensive priori knowledge to configure representative features for objects in different scale granularity. In this paper, we propose adaptive linear span network (AdaLSN), driven by neural architecture search (NAS), to automatically configure and integrate scale-aware features for object skeleton detection. AdaLSN is formulated with the theory of linear span, which provides one of the earliest explanations for multi-scale deep feature fusion. AdaLSN is materialized by defining a mixed unit-pyramid search space, which goes beyond many existing search spaces using unit-level or pyramid-level features. Within the mixed space, we apply genetic architecture search to jointly optimize unit-level operations and pyramid-level connections for adaptive feature space expansion. AdaLSN substantiates its versatility by achieving significantly higher accuracy and latency trade-off compared with state-of-the-arts. It also demonstrates general applicability to image-to-image tasks such as edge detection and road extraction. Code is available at [github.com/sunsmarterjie/SDL-Skeleton].

Index Terms—Skeleton Detection, Linear Span Network, Neural Architecture Search, Genetic Algorithm.

I. INTRODUCTION

SKELETON is a kind of representative visual descriptor, which contains rich information about object topology, constituting an explicated abstraction of object shape. Object skeletons can be converted to descriptive features and/or spatial constraints, promoting computer vision tasks such as human pose estimation [1], hand gesture recognition [2], text detection [3], and object localization [4], in an explainable fashion.

In the deep learning era, object skeleton detection using convolutional neural networks (CNNs) has made unprecedented progress. State-of-the-art approaches commonly utilize side-output architectures to integrate feature pyramid as a countermeasure for variations from object appearances, poses, and scales. This is intrinsically based on the observation that low-level features focus on detailed structures while high-level features are rich in semantics [5].

As a pioneer work, the holistically-nested edge detection (HED) [6] used a deeply supervised strategy to take full use of the hierarchical multi-scale features in a parallel manner. Fusing scale-associated deep side-outputs (FSDS) [7] adopted a divided-and-conquer approach to supervise network side-outputs given scale-associated ground-truth. SRN [8] and RSRN [9] investigated the multi-layer association problem by utilizing side-output residual units to pursue the complementarity among multi-scale features in a deep-to-shallow fashion. HiFi [9] introduced a bilateral feature integration mechanism to incorporate the low-level details and high-level semantics.

Despite the encouraging progress, one limitation lies in that most of the existing network architectures for skeleton detection are hand-crafted and lack the theoretical backup. Although such networks incorporating rich human knowledge are somewhat effective, they experience difficulty in maximizing representation complementarity for objects/parts in different granularity. This hinders further performance optimization of object skeleton detection in complex scenes.

In this paper, we formulate the pixel-wise binary classification tasks as linear reconstruction problems within the linear span framework [10] and conclude that the key for network design is to perform feature space expansion. Accordingly, we propose a systematical approach, termed adaptive linear span network (AdaLSN), to transform and integrate hierarchical scale-aware features for object skeleton detection. Fig. 1 AdaLSN is driven by neural architecture search (NAS), which optimizes the network operations and connections to push the features towards scale-aware configuration. This improves the feature versatility towards higher accuracy and latency trade-off compared to the state-of-the-arts.

Under the guidance of the linear span theory [11], we find out that not only should we expand feature subspace in each stage, but also adaptively reduce structure redundancy to compress their intersection space. Specifically, we design the linear span unit (LSU) to explicitly transform the input features towards complementary with customized operations. Based on LSUs, we construct an explainable search space, termed the linear span pyramid (LSP), to perform subspace and sum-space expansion. LSP is a unit-pyramid mixed search space, which pursues feature complement spaces with a complementary learning strategy. At the unit level, the feature space is expanded by the LSU. At the pyramid level, we progressively pose intermediate supervision to each expanded feature subspace to reduce their semantic overlap and expand the sum-space. With a genetic search algorithm, AdaLSN automatically optimizes the network operations and connections in each area of the search space, including multiple side-outputs, short connections, feature transform, and intermediate supervision, to push the features towards scale-aware configuration.

Linear Span Network (LSN) was proposed in our previous study [10], while is promoted by introducing a well-designed architecture search space and the adaptive search algorithm. The contributions of this paper are summarized as follows:
We propose the adaptive linear span network (AdaLSN), opening up a promising direction to learn complementary scale-aware features within the framework of linear span.

- We design a unit-pyramid mixed search space, where competitive network architectures evolve via properly defined genetic operations for search.
- We improve the state-of-the-arts of object skeleton detection, and demonstrate the general effectiveness of AdaLSN to image-to-mask tasks including edge detection and road extraction.

II. RELATED WORK

Object skeleton detection has attracted much attention in computer vision community for its significance: elaborating object skeleton facilitates image understanding. Existing works typically perform geometric modeling or multi-scale feature fusion to improve the skeleton detection performance, while, to the best of our knowledge, NAS methods have not been considered in this area.

A. Hand-crafted Method

Early skeleton detection methods were usually performed on binary images by geometric modeling, e.g., morphological image operations. One approach is to treat object skeleton as line subsets which connect super-pixels’ center points. Such line subsets were explored from the super-pixels and extract skeleton paths using a sequence of disc models [12]. The smoothness of the skeleton can be enforced with spatial filters, e.g., a particle filter, which link local skeleton segments into continuous curves [13]. When being applied on color images, an image segmentation procedure for contour extraction was first performed as pre-processing. The segmentation procedure tended to produce multi-scale super-pixels, which are converted to skeleton pixels using geometric models.

In the deep learning era, object skeleton detection has been formulated as an pixel-wise binary classification problem with multi-scale feature integration. For clarity, the characters of several typical methods are summarized in Table I. The HED [6] developed parallel multiple side-outputs to produce edges, which can be also used for skeleton detection. Fusing scale-associated deep side-outputs (FSDS) [7] learned skeleton representations with specific scales across multiple network stage given scale-associated ground-truth.

Side-output residual network (SRN) [8] leveraged the side-output residual units to build short connections between adjacent side-output branches for complementary feature utilization. In this way, SRN progressively expand the feature space to fit the errors between the object skeleton/symmetry ground-truth and the multiple side-outputs. To take full use of richer scale-aware features, RCF [14], RSRN [5], and HiFi [9] establish dense side-output branches for smooth multi-scale feature integration.

In the linear span view [10], the feature integration actually aims at spanning larger feature spaces for complementary feature extraction and fusion. With this aim, DeepFlux [15] utilize the ASPP module [16] to enrich the semantic level and scale granularity of the feature space. Further, DeepFlux [15] contributed a novel strategy by training a network to predict a vector field, which corresponded each image pixel a skeleton/background pixel, in the fashion of flux-based skeletonization. This flux-based skeletonization explicitly encodes the skeleton pixel positions to contextually meaningful entities. Share the same network architecture, GeoSkelNet [17] also used the region-based vector field to model object parts at multiple scales. By designing Hausdorff distance inspired objective function, both global and local contours were detected...
through an end-to-end network.

The conventional hand-designed skeleton networks, although incorporating rich prior knowledge, have obvious limitations. With elaborately designed feature integration mechanisms, they are somewhat competent to capture rich representation but still experience difficulty when configuring representation for objects/part in different scale granularity.

### B. Neural Architecture Search

NAS targets at optimizing network architectures under the driven of data without human intervene. Early NAS methods formulated network designs using reinforcement learning [18]–[20], evolutionary algorithms [21], [22], or random search approaches [23].

To reduce the time cost, one-shot search methods employed weight-reusing [24] and weight-sharing [25], [26] strategies, which fusing the architecture search procedure with network weight optimization. A special family of one-shot architecture search, which adjusted itself in continuous spaces, formulated the search space as a super-network [27]. This leads to the differentiate search method where the network and architectural parameters are jointly optimized [28]–[30]. Recent EfficientNet [31] defined a scaling method that uniformly searches network depth, width, and resolution by introducing the compound coefficient.

To automatically fuse multi-scale features, NAS-FPN [32] defined a search space where the hierarchical side-output features can be optimally combined based on reinforcement learning. NAS-Unet [33] has the similar idea to fuse hierarchical side-output features by defining primitive operation sets on search space to automatically find cell architectures. For the image segmentation task, Auto-DeepLab [34] designed a search space including popular hand-designed networks. In the networks, the scale of the convolutional features can be up-sampled, down-sampled or not changed. Driven by gradient-based searching algorithm, Auto-DeepLab found the novel architectures which significantly improved the segmentation performance.

In this paper, we propose using NAS to define a general feature integration method. By introducing linear span units upon side-output features, we provide the foundation to define operations and connections for feature space expansion. By introducing linear span pyramid, we defines a more complete space for complementary feature extraction and architecture optimization in the linear span framework.

### III. Rethinking Skeleton Network Design

#### A. Problem Retrospect

With cascaded convolution and down-sampling operations, CNN backbones typically generate the feature pyramids where features in deeper layers have richer semantics and larger receptive fields, yet fewer fine-details and smaller spatial resolutions. In the pyramid, the semantic levels, scale granularity, and resolution variation of the extracted features tangle together, which raise the following challenges to scale-aware feature integration.

1. How to tackle the large variations of appearance, shape, pose, and scale of objects while depressing cluttered backgrounds with limited convolutional layers?
2. How to balance the benefit of complementary features and the degradation caused by up-sampling in the resolution alignment for feature integration?
3. How to explicitly enrich the semantic hierarchy and scale granularity of the convolutional features?
4. How to find out the hierarchical scale-aware features of the largest complementary?

To tackle these challenges, existing methods typically employed the techniques including multiple side-outputs, short connection, feature transform and intermediate supervision.

#### Table I

| Method          | Year | Multiple Side-outputs | Network Architecture | Feature Transform | Intermediate Supervision | Multi-scale Annotation | Geometric Modeling |
|-----------------|------|------------------------|----------------------|-------------------|--------------------------|-----------------------|-------------------|
| HED [6]         | 2015 | ✓                      | ✓                   | ✓                 | ✓                        | ✓                     | ✓                 |
| FSDD [7]        | 2016 | ✓                      | ✓                   | ✓                 | ✓                        | ✓                     | ✓                 |
| RCF [14]        | 2017 | ✓                      | ✓                   | ✓                 | ✓                        | ✓                     | ✓                 |
| SRN [15]        | 2017 | ✓                      | ✓                   | ✓                 | ✓                        | ✓                     | ✓                 |
| HiFi [9]        | 2018 | ✓                      | ✓                   | ✓                 | ✓                        | ✓                     | ✓                 |
| LSN [10]        | 2019 | ✓                      | ✓                   | ✓                 | ✓                        | ✓                     | ✓                 |
| Deepflux [15]   | 2019 | ✓                      | ✓                   | ✓                 | ✓                        | ✓                     | ✓                 |
| GeoSkelNet [17] | 2019 | ✓                      | ✓                   | ✓                 | ✓                        | ✓                     | ✓                 |
| AdaLSN (ours)   | 2020 | ✓ (adaptive)           | ✓ (adaptive)        | ✓ (adaptive)      | ✓ (adaptive)             | ✓                     | ✓                 |

#### B. Linear Span View

In the deep learning era, object skeleton detection is typically performed with a pre-trained CNN backbone for feature extraction and $1 \times 1$ convolutional layers in the side-output branches for skeleton pixel detection.

Given an input image $X$, we denote the extracted features as $V_c^{W \times H} = (v_{c, i,j})_{c \times W \times H}$ and the $1 \times 1$ convolutional
layer as \( \Lambda_{C \times 1} = (\lambda_c)_{C \times 1} \), where \( C \), \( W \), and \( H \) respectively represent the channel number, feature map width, and feature map height. Skeleton detection is usually formulated as a pixel-wise classification problem \( [6] \) as

\[
\sum_{c=1}^{C} \lambda_c \cdot v_{c,i,j} = \hat{y}_{i,j} \approx y_{i,j},
\]

where \( \hat{y}_{i,j} \) and \( y_{i,j} \) are respectively the pixel values of the output image \( \hat{Y} \) and the ground-truth mask \( Y \) at location \((i, j)\).

Regarding each feature map as a vector \( v_c \), where \( c \) indexes feature channels, Eq. [2] is rewritten from the perspective of linear reconstruction, as

\[
\sum_{c=1}^{C} \lambda_c v_c = \hat{Y} \approx Y.
\]

Based on Eq. [2], we introduce the linear span concepts and space decomposition theorems \([11]\), which lead to the vector set

\[
\{ v_1, v_2, \ldots, v_C \}
\]

is also a linear space, termed the sum-space of \( V \). The linear span concepts of each feature subspace towards complementary subspace of the other, which guides the complementary feature learning. In specific, we propose to progressively force the feature subspaces from the shallow stages to fit the complementary subspace of the deep stages \([8]\). Numbering the \( S \) stages from shallow to deep, we denote the features extracted from the \( s \)-th stage as \( V_s \), \( s = 1, 2, \ldots, S \), the spanned feature subspaces as \( V_s = \text{Span}(V_s) \), and the corresponding subspace after transform as \( V_s' \), such that \( V_s' = \text{Span}(O(V_s)) \), Eq. [3] is restated as

\[
\text{Span}((v_1, v_2, \ldots, v_C)) \ni \hat{Y} \approx Y.
\]

The complementary learning strategy is concluded as

\[
\begin{align*}
V'_{1} \ni \hat{Y}_1' & \approx Y'_{1} & V'_{2} \ni \hat{Y}_2' & \approx Y'_{2} \\
V'_{S} \ni \hat{Y}_S' & \approx Y'_{S} & V'_{S-1} \ni \hat{Y}_{S-1}' & \approx Y'_{S-1} & \ldots & \\
& \vdots & & & & \\
& \vdots & & & & \\
& \vdots & & & & \\
& \vdots & & & & \\
V'_{S} + \cdots + V'_{2} + V'_{1} & \ni \hat{Y}_1 & \approx Y
\end{align*}
\]

Theorem 2 (Space Dimension). Supposing \( V \) is a finite dimensional linear space, \( V_1 \) and \( V_2 \) are two subspaces of \( V \) such that \( V = V_1 + V_2 \), and \( V_{12} \) is the intersection of \( V_1 \) and \( V_2 \), i.e., \( V_{12} = V_1 \cap V_2 \). Then \( V_{12} \) is a linear space, and

\[
\text{dim} V = \text{dim} V_1 + \text{dim} V_2 - \text{dim} V_{12}.
\]

Theorem 2 uncovers that smaller dimension of the intersection space implies bigger dimension of the sum-space. This again supports us to perform feature space expansion in the subspace level while compressing their intersection space in the sum-space level. Note that the intersection space of feature subspaces is actually the semantic overlap of multi-stage features, which is mainly caused by architecture redundancy. We propose to utilize architecture encoding and neural architecture search (NAS) to solve these issues.

IV. ADAPTIVE LINEAR SPAN NETWORK

Based on the linear span theory \([11]\), AdaLSN is materialized by defining a mixed unit-pyramid search space to perform both subspace and sum-space expansion, Fig. [2]. To fulfill feature subspace expansion, we design the linear span unit (LSU) which transforms the input feature vectors towards complementary by adaptively selecting proper operators and connections. Based on the LSU and the complementary learning strategy, we establish the pyramidal architecture search space, which is referred to as the linear span pyramid (LSP). On the pyramid, short connections are utilized to merge the spanning set of each feature subspace towards complete. To reduce the architecture redundancy, we encode the LSP to gene segments for genetic architecture search. The searched AdaLSNs comprehensively integrate the techniques about multiple side-outputs, short connection, feature transform and intermediate supervision with less human experience.

A. Unit-Pyramid Space for Linear Span

Linear Span Unit (LSU). An LSU can be regarded as a directed acyclic graph, which consists of an input node, an output node, and \( P \) intermediate nodes, each of which represents a set of feature vectors, Fig. [2]. The nodes are denoted as \( n_i, i = 0, 1, \ldots, P + 1 \). Each pair of nodes has an edge \( e_{i_{1}i_{2}} \) connecting the lower-numbered node \( n_{i_{1}} \) with
the higher-numbered node $n_{i+s}$, which consists of an operator $O_{i+s}$ selected from a pre-defined operator set $O$. The node $n_{i+s}$ is then calculated as $n_{i+s} = O_{i+s}(n_{i})$.

To reduce the searching complexity, we set each immediate node to keep only a single edge and the output node $n_{P+1}$ to be the sum of all other $P + 1$ nodes. Denote the path from the input node $n_0$ to the $i$-th intermediate node as $P_i$ and the node index at $k$-th step in the $i$-th path as $P_i(k)$. Suppose $P_i$ has $K_i$ steps, such that $P_i(0) = 0$ and $P_i(K_i) = i$.

We construct a side-output branch by attaching an LSU $U_s$ to the last convolutional layer of the $s$-th network stage, where the input node $n_{0}^s$ and output node $n_{P+1}^s$ are actually aforementioned $V_s$ and $V_i$ in Eq. 5. Thereafter, the $s$-th LSU can be formulated as

$$V_s' = \sum_{i=0}^{P} O_{P_i}(V_i)$$

$$= \sum_{i=0}^{P} O_{P_i}(V_i) \in \text{Span}(O^s(V_s)),$$

where $O_{P_i} = \prod_{k=1}^{K_i} O_{P_i(k-1), P_i(k)}(k)$ denotes the composite of operators in the path $P_i$ and $O^s = \sum_{i=0}^{P} O_{P_i}$ the transformation posed on the input node $n_0$, which is defined by the combination of operators at all paths.

According to Eq. 4 we conclude that, by selecting proper operators and edges, the unit can transform the input nodes to facilitate feature space expansion. Accommodating the third challenges defined in Sec. III-A, we add skip, convolutions and dilated convolutions with various kernel sizes and dilation coefficients in $O$ to pertinently enrich the semantic hierarchy and the scale granularity of feature vectors.

**Linear Span Pyramid (LSP).** To tackle the challenges in multi-stage feature integration, we materialize the complementary learning strategy by stacking LSUs to construct the pyramid search space with intermediate supervisions.

In specific, according to Eq. 5 we add short connections among LSUs in a deep-to-shallow fashion to merge the spanning sets of the corresponding feature subspaces. Each LSU accepts and accumulates input features from the backbone and/or the output of LSUs from deeper stages, the channels and resolutions of which are respectively aligned to those of the current stage by $1 \times 1$ convolution and upsampling. To ease the noise caused by feature upsampling, we restrict the upsampling rate to $4 \times$ at most, and each LSU only accepts features from two adjacent deeper stages. With intermediate loss layers, LSUs are assigned with different supervision priority to progressively force the feature subspaces to expand towards complementary with each other. We additionally use a fuse LSU ($U_{S+1}$) to accept the outputs from all other LSUs, which further expands the feature sum-space, Fig. 2.

**B. Adaptive Linear Span by Architecture Search**

Regarding the LSP as a sup-network, Fig. 2 we aim at instantiating an AdaLSN in the architecture search space to perform linear span. To fulfill this purpose, we propose to encode the LSP into a chromosome matrix and use the genetic algorithm for adaptive architecture search.

**Architecture Encoding.** LSP consists of a set of operators and connections, which are divided to four encoding areas, Fig. 2. These four encoding areas are respectively defined to handle the four challenges aforementioned in Sec. III-A.

The first encoding area corresponds to connections between the backbone network and the LSUs, which are denoted as a string $g_00 = g_{S1} \delta_{S2} \delta_{S3} \cdots \delta_{S6}$. $\delta$ is a 0-1 binary variable where $\delta_{S_s} = 1$ ($1 \leq s \leq 6$) means that $U_s$ is connected with the $s$-th stage, otherwise to be discarded. The shallow network stages output high resolution features, which require larger memory but have low representation capability, while deep stages output low resolution features with coarse scale granularity, which require smaller memory. Within the first
encoding area, we require to adaptively determine connections between the backbone network and the LSUs so that features of shallow and deep stages can be optimally selected.

The second encoding area corresponds to the connections among LSUs, which are represented as a string $g_{s0} = \delta_{s+1} \cdots \delta_{S+1}$ and $g_{s1} = \delta_{U_1} \delta_{U_2} \cdots \delta_{U_S}$. $\delta_{s+1} \cdots \delta_{S}$ $(1 \leq s \leq S)$ denotes the connection states of unit $U_s$ with $U_{s+1}, \cdots, U_S$ and $\delta_{U_s}$ denotes the connection states of $U_s$ with $U_{S+1}$. This encoding area aims to balance the advantage brought by feature complementarity and the degradation caused by the up-sampling operation during multi-stage feature integration.

The third encoding area contains operators and edges in each LSU to enrich the semantic hierarchy and scale granularity of the feature subspace, which should be adaptive to the characteristics of each stage. This encoding area is denoted as a string $g_p = e_1^p e_2^p \cdots e_p^p o_1^p o_2^p \cdots o_p^p$, $1 \leq s \leq S + 1$. $e_p$ ($p = 1, 2, \cdots, P$) denotes the index of the node connected to the $p$-th node and $o_p$ the corresponding operator on it. $e_p$ varies from 0 to $p - 1$ and $o_p$ varies from 0 to $|O|$. Based on the above three encoding areas, the LSUs are defined as $U_s = (\delta_{S_s}, g_{s0}, g_{s1})$ $(1 \leq s \leq S)$ and $U_{S+1} = (g_{S+1}, \delta_{S+1})$.

The fourth encoding area is about the intermediate supervisions, which are denoted as string $g_{00} = \delta_{L_1} \delta_{L_2} \cdots \delta_{L_S}$, where $\delta_{L_s}$ $(1 \leq s \leq S)$ indicates the connection state of the $U_s$ with the $s$-th loss layer. The adaptive architecture search in this encoding area facilitates balancing advantages brought by linear span and the disadvantages (e.g., error accumulation) of intermediate supervisions.

Combining the four encoding areas, we have the architecture search space for AdaLSN. The search space is formulated as a matrix $(G = (g_{s1})_{(S+2) \times 2})$ with dimensionality $(S + 2) \times 2$ where the elements in $G$ are denoted as

$$
\begin{align*}
g_{00} &= \delta_{S_1} \delta_{S_2} \cdots \delta_{S_S}, \\
g_{01} &= \delta_{L_1} \delta_{L_2} \cdots \delta_{L_S}, \\
g_{s0} &= \delta_{s+1} \cdots \delta_{S+1}, \\
g_{s1} &= e_1^s e_2^s \cdots e_p^s o_1^s o_2^s \cdots o_p^s, \\
g_{(S+1)} &= \delta_{U_1} \delta_{U_2} \cdots \delta_{U_S},
\end{align*}
$$

where $g_{00}$ corresponds to the multiple side-outputs, $g_{01}$ the intermediate supervision, $g_{s0}$ $(1 \leq s \leq S)$ the short connection, and $g_{s1}$ the feature transform. The search space covers most side-output network architectures. For example, the well-designed SRN [8] falls into this space. SRN contains manual design of multiple side-outputs, short connections between adjacent side-output branches, and intermediate supervisions, which can be represented as

$$
G_{SRN} = \begin{bmatrix}
11111 & 11111 \\
01000 & - \\
00110 & - \\
00010 & - \\
- & - \\
- & - \\
11111 & -
\end{bmatrix}.
$$

**Architecture Search.** Architecture search aims to find out sub-structures in the search space for adaptive linear span. Considering the large dimensionality of the search space, a genetic algorithm is employed for architecture search. In the searching procedure, AdaLSN is defined as a chromosome $G$, the element $g_{ij}$ in the character string matrix $G$ as a gene segment, and each byte in encoded strings as a gene, Eq. 7 A chromosome is an individual in the population. Genes and gene segments are the smallest unit for mutation and crossover, respectively. The initial population size is set to 24. Half of the population is randomly selected from all possible chromosomes with equal probability. The other 12 individuals are initialized by mutating the ASPP-like module [35] once for LSUs and randomly sampling for the rest structures.

To select superior individuals for evolution, the prediction performance with sufficient training is accurate and reliable but too time-consuming. We resort to sort the loss at one thousand training iterations of the population in each generation and update the 8 individuals with the smallest loss value among all historical generations. The selected top-8 individuals will survive and generate the next generation.

In specific, we apply the crossover and mutation operation on the selected 8 individuals to generate another 8 individuals. To perform crossover, we randomly select a pair of chromosomes and randomly exchange one of their gene segments in the same position. In this way, excellent sub-structures can be probably preserved and evolve to optimal architectures. To avoid local optimum and increase the gene diversity of the population, we randomly change the value of every byte of all gene segments of the chromosomes in the current generation for mutation operation. Every gene in the chromosome has a chance to be changed and excellent gene combinations are compete to be survived and passed to the next generation. In this way, the individuals evolve to adaptively perform feature space expansion for complementary feature learning.

All individuals in the current generation are trained for evaluation and the surviving (selected) individuals will be encoded for the next generation search. After tens of generations, the search procedure stops and the individual with the smallest training loss outputs as the optimal architecture and will be retrained to learn the final model.

**V. EXPERIMENTS**

In this section, the experimental settings are first described and the modules of AdaLSN are analyzed with ablation studies. The performance of AdaLSN is then presented and compared with the state-of-the-arts. Finally, we apply AdaLSN on edge detection and road extraction to validate its general applicability to image-to-mask tasks.

**A. Experimental Setting**

**Datasets.** Five commonly used skeleton datasets, including SK-LARGE [36], SK-SMALL [37], SYM-PASCAL [8].
SYMMAX300 [38], and WH-SYMMAX [39], are used to evaluate AdaLSN. SK-LARGE involves skeletons from about 16 classes of objects, and contains 746/745 training and test images sampled from MS-COCO [40]. SK-SMALL (SK506) is sampled from MS-COCO but contains fewer images. SYMPASCAL contains 648/797 training and test images annotated from the segmentation subset of PASCAL VOC 2011 [41]. SYMMAX300 has 200 training images and 100 test images, which are annotated on BSDS300 [42]. WH-SYMMAX is developed for skeleton detection with 228/100 training and test images.

Implementation details. AdaLSN is implemented using PyTorch and runs on NVIDIA TITAN RTX GPUs (with 24 GB of memory). In the search phase, the raw training set without pre-processing is used to train the architectures in each generation, and fifty valid images are used for evaluation. In both the search and retraining phases, we use the Adam optimizer [43] with the initial learning rate 1e-6, a momentum (0.9, 0.999), and a weight decay 0.0005. The batch size is set as 1 while network parameters are updated every 10 times of forward propagation. In the retaining phase, we train the searched architecture for 25 epochs to obtain the final model. The learning rate is fixed during searching and reduced a magnitude after 20 epochs while retraining. We use multiple data augmentation techniques, including resizing to 3 scales (0.8x, 1.0x, and 1.2x), rotating for 4 directions (0°, 90°, 180°, and 270°), flipping in 2 orientations (left-to-right and up-to-down), and resolution normalization [17].

Evaluation protocol. Following the settings in [38], the F-measure score (F-score) and Precision-Recall (PR) curves are used as the evaluation metrics. While PR curves diagnose the binary classification results under different thresholds, F-score provides a single score weighting both precision and recall.

B. Ablation Study

Ablation studies are performed on SK-LARGE [38], which is the most used benchmark for object skeleton detection. In the search phase, by default, we set the index of side-outputs as \{1, 2, 3, 4, 5\}, the channel number of the nodes (Channel Number) as 32, the intermediate node number (Intermediate Node) as 4. The kernel size and dilation rate of the convolution layers in the alternative operator set (Operator) vary in \{1, 3, 5\} and \{1, 2, 4, 8\}, respectively.

Architecture Search. In Table III one can see that the searched AdaLSNs significantly outperform the randomly sampled architectures by \sim 3\% F-score. AdaLSNs also demonstrate robustness to search initializations.

In Table [IV] we re-train the most excellent individual selected in each population iteration, and report the performance every ten generations. It can be seen that the top-1 individuals evolve quickly and the F-score increases significantly from 0.727 to 0.751, and slightly improves to 0.753 after 20 epochs while retraining. We use multiple data augmentation techniques, including resizing to 3 scales (0.8x, 1.0x, and 1.2x), rotating for 4 directions (0°, 90°, 180°, and 270°), flipping in 2 orientations (left-to-right and up-to-down), and resolution normalization [17].

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In Table IV we re-train the most excellent individual selected in each population iteration, and report the performance every ten generations. It can be seen that the top-1 individuals evolve quickly and the F-score increases significantly from 0.727 to 0.751, and slightly improves to 0.753 after 30 more generations. We search fifty generations by default. These results verify the effectiveness of the proposed approach.

In Table V we validate the effectiveness of the encoding areas including multiple side-outputs (A1), short connection (A2), feature transform (A3), and intermediate supervision (A4). Specifically, we compare the performance of partial search by screening an encoding area (w/o) and randomly sampling the corresponding area after complete search (Rand.).
Experiments show that the encoding areas can boost the performance significantly, validating that the search space is more complete.

Architecture Adaptability. In Fig. 3, we validate the adaptability of the four encoding areas using statistics figures. In A1, Fig. 3(a) shows that the side-output numbers in deep stages are significantly larger than those in shallow stages. This is because the features from deep stages have small resolutions yet coarse-scale granularity and strong representation capability. More deep stage features imply higher accuracy. The adaptive configuration of multi-stage features greatly eases the scale variation problem. In $A_2$, we divide the short connections adjacent ones and cross-stage ones, Fig. 3(b). Considering the degradation caused by feature upsampling, the adjacent connections are preferred.

In $A_3$, we compare LSU operator distributions, including skips and convolutions with different kernel sizes, Fig. 3(c). For the moderate performance gain (0.750 vs 0.753) with dilated convolutions, we calculate the average number of different convolutions in an LSU according to their kernel size only. It can be seen that the $Conv_3$ and $Conv_5$ are more preferred than $Conv_1$. This is because they correspond to stronger representation capability and larger receptive fields to ease the imbalance of semantic level and scale granularity. In the early search phrase, the number of $Conv_3$ is noticeably larger than that of $Conv_5$ while the gap reduces when search goes on. The reason lies in that with less parameters, $Conv_3$ layers are easy to be optimized. When sufficient evolution takes place, $Conv_5$ with large receptive field and representation capability show its advantages. This validates AdaLSN’s adaptability on network architecture configuration.

In $A_4$, we calculate the ratio of intermediate supervision, Fig. 3(d). It can be seen that in the early phase, the architecture is more dependent on intermediate supervision because intermediate supervision can force the feature subspaces to expand to fit the ground-truth. With sufficient training after tens of generations, architectures with less intermediate supervision can ease the error accumulation issue while fulfilling complementary learning for feature space expansion.

AdaLSN Exemplars. The computational cost and the prediction accuracy of AdaLSNs largely depend on the search space settings, Table V. Specifically, we explore the effect of the injected channel number into each LSU with the VGG backbone. The circle size indicates the channel number. (Best view in color and zoom in.)
of “channel number”, “intermediate node”, and “operator” ({kernel size}×{dilation rate}) at the unit level; and the effect of “side-output” at the pyramid level.

When the channel number increases from 2 to 64, the memory cost increases from 8.1G to 24.0G. The parameters and runtime of the searched network in the retraining phase increase moderately from (14.7M, 12.52ms) to (16.1M, 14.21ms), while the F-score increases significantly from 0.726 to 0.759. Table VII We conclude the channel number is an important factor in balancing the computational cost and accuracy for our approach.

When adding intermediate nodes in each LSU from 0 to 4, one can see that the computational cost in both phases increases moderately, while the F-score greatly increases from 0.704 to 0.753. It is worth noting that comparing LSUs without any intermediate node, the F-score increases impressively from 0.704 to 0.740 with only 1 intermediate node used in each LSU. This validates the importance of operators and their combinations in the explicit feature transform for feature space expansion. However, when the intermediate node number increases to 5, the F-score of AdaLSN falls to 0.749. This is because the more intermediate nodes means higher search complexity, which significantly improves the difficulty to search optimal architectures.

We evaluate the convolution operators with different kernel sizes larger than 1 have superiority for feature space expansion, e.g., the F-score increases from 0.713 to 0.750 with negligible computational cost. When the dilation rate enlarges properly as {1, 2, 4, 8}, which enriches the scale granularity, the performance improves up to 0.753. Nevertheless, the F-score falls upon larger dilation rates, because convolution operators with large dilation tend to missing feature details. Accordingly, the kernel sizes and dilation rates are set as {1, 3, 5} – {1, 2, 4, 8}.

As features from shallow stages are less representative but have high resolution, we gradually reduce the shallow side-outputs in the search phase to figure out the effect of each side-output. As shown in the bottom row of Table VII without $S_1$ and $S_2$, the memory cost reduces significantly from 19.8G to 11.3G and the search time decreases from 47.5h to 39.5h, while the F-score reduces slightly. In Fig. 4 we visualize the figures of ablation on channel number and side-output in Table VII and Table VII using the VGG backbone. One can find that when reducing the shallow network stages \{1, 2\} while increasing the channel number from 32 to 128, the F-scores of the searched architectures increase significantly. When we reduce the deep stages with medium channel numbers, the F-score significantly drops. For instance, with the channel number 32, the F-score drops from 0.746 to 0.723 when the side-outputs reduce from \{4, 5\} to \{5\}.

Empirically, we set the side-output as \{2, 3, 4, 5\} and change
the channel number and intermediate node to (2, 1) for a small AdaLSN(S), while (64, 4) for a medium AdaLSN(M). By increasing the channel number to 128 while reducing the side-output to {3, 4, 5}, we have a large AdaLSN(L). The detailed structures of three versions of AdaLSN with VGG [44] are depicted in Fig. 5. Comparing to the state-of-the-art approaches, such as HED [6], SRN [8], and LSN [10], AdaLSN(S) has significant accuracy improvement (about 0.056 ∼ 0.227 F-score gain) with negligible parameter cost. Comparing with DeepFlux [15], AdaLSN(M) achieves better F-score (0.760 vs 0.724) with less params (16.6 M vs 18.3 M). In Table VI, we can find that with the InceptionV3 [45] backbone, AdaLSN(L) achieves 0.786, improving the state-of-the-art with a large margin.

**Linear Span.** In Fig. 6, we compare the skeleton predictions of the state-of-the-art approaches about a dog. It can be seen that with only parallel side-outputs for scale-aware feature utilization, the predictions of HED [6] suffer background noise in shallow network stages and mosaic effects in deep stages. With adding short connections among side-outputs for feature integration, SRN [8] purses the residual between adjacent stages to progressively improve the predictions in a deep-to-shallow manner so that the predictions in shallow stages are greatly improved. To learn more complementary features and span a larger feature space, LSN [10] builds dense short connections among side-outputs for feature space expansion. However, without explicitly feature transform, LSN only moderately improves the result comparing with SRN. DeepFlux [15] generates a slim skeleton with manually designed ASPP modules [16] and the context flux constrain. However, the prediction is also barely satisfactory.

AdaLSN incorporates these advantages in the linear span view and updates them with the adaptive architecture search algorithm. As the searched architectures are adaptive to the skeleton characteristics, feature subspaces are adaptively expanded while forced to be complementary with each other. This explains why the prediction results at all stages are more precise, clear, and consecutive.

### C. Performance and Comparison

The proposed AdaLSN approach outperforms the CNN based state-of-the-art methods in terms of F-score, Tab. VII. The results of AdaLSN is reported by the architecture searched in the SKLARGE with the large version setting of the inceptionV3 [16] backbone and retrained on each dataset.

With the SKLARGE dataset, one can find that Hi-Fi [9] with additional scale-associated ground-truth achieves the F-score of 72.4%; DeepFlux [15] with skeleton context flux reports the highest skeleton detection performance up to date of 73.2%. Without additional supervision information and explicitly geometric modeling, AdaLSN achieves greatly high F-score of 78.6%, which outperforms DeepFlux by significant margins of 5.4%. When comparing to DeepFlux with transferring the architecture to other skeleton\symmetry datasets,
AdaLSN respectively improves the F-score by 4.5%, 1.1% and 0.4% on SK-SMALL, WH-SYMMAX, and SYMMAX300, and achieves comparable performance on SYM-PASCAL.

The detected skeleton results are shown and compared in Fig. 7, where our method can extract the skeleton maps of different granularity with better continuity and higher accuracy. In specific, HED produces skeletons with lots of noise. SRN and LSN predict relatively clearer skeletons which are not smooth. Deepflux reports clearer and slimmer results, while remains some false positive points and dis-continual segments. Incorporating complementary features rich in semantic hierarchy and scale granularity, AdaLSN produces more precise skeleton masks similar to the groundtruth.

D. Other Image-to-Mask Tasks

AdaLSN can be directly applied in other image-to-mask tasks such as edge detection and road extraction. In this section, we compare the edge detection and road extraction performance of the proposed AdaLSN with some other state-of-the-art methods. The good performance of the proposed AdaLSN in these two tasks demonstrates its general applicability to image-to-mask tasks.

**Edge Detection.** To demonstrate the general applicability of AdaLSN, we directly apply the model searched on the skeleton dataset to edge detection and report the edge detection performance on the BSDS500 dataset [37], which is composed of 200 training images, 100 validation images, and 200 testing images. The F-score used as evaluation metrics is chosen an optimal scale for the entire dataset. As shown in Fig. 8, all the CNN-based approaches achieve good performance, which is comparable to human performance. AdaLSN reports the highest F-score of 0.798, which has a very small gap (0.002) to human performance.

**Road Extraction.** We also test our AdaLSN for road extraction in aerial images, using the dataset from the Deep-
As the ground-truth annotations of the test dataset are not published, we randomly select 100 images from the training dataset as a test dataset and cut the rest images to $512 \times 512$ sub-images for training. AdaLSN slightly outperforms DLinkNet (0.6354 vs 0.6321 mAP), which is one of the state-of-the-art approaches for road extraction. The multi-scale feature integration in a data-adeptive fashion. The significant higher accuracy compared with the state-of-the-arts and the general applicability to image-to-mask tasks demonstrated the effectiveness of the proposed AdaLSN approach. The NAS-driven feature space expansion provides a fresh insight for feature representation learning.

VI. CONCLUSION

Object skeleton detection is a representative image-to-mask task in computer vision yet remains challenged by objects in different granularity. In this paper, we proposed adaptive linear span network (AdaLSN), with the aim to automatically configure and integrate scale-aware features for object skeleton detection. Following the linear span theory and driven by neural architecture search (NAS), AdaLSN configured complementary features for subspace and sum-space expansion. It thus optimized the multi-scale feature integration in a data-adeptive fashion. The significant higher accuracy compared with the state-of-the-arts and the general applicability to image-to-mask tasks demonstrated the effectiveness of the proposed AdaLSN approach. The NAS-driven feature space expansion provides a fresh insight for feature representation learning.

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