ADeLA: Automatic Dense Labeling with Attention for Viewpoint Adaptation in Semantic Segmentation

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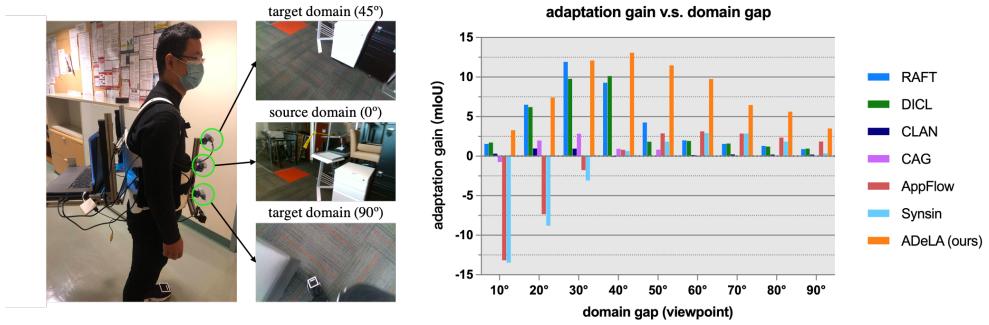
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Figure 1: Left: An assistive exoskeleton with multiple cameras towards different viewpoints can be used to improve the user mobility. However, the performance of the semantic segmentation network trained on the forward viewpoint (typical view of existing datasets) drops sharply when tested on different viewpoints (Tab. 2). Right: Adaptation gain obtained by state-of-the-art methods for adapting between viewpoints. Our method consistently achieves positive adaptation gain and works robustly towards substantial viewpoint change, *e.g.*, perpendicular viewing angles.

Abstract

We describe an unsupervised domain adaptation method for image content shift caused by viewpoint changes for a semantic segmentation task. Most existing methods perform domain alignment in a shared space and assume that the mapping from the aligned space to the output is transferable. However, the novel content induced by viewpoint changes may nullify such a space for effective alignments, thus resulting in negative adaptation. Our method works without aligning any statistics of the images between the two domains. Instead, it utilizes a view transformation network trained only on color images to hallucinate the semantic images for the target. Despite the lack of supervision, the view transformation network can still generalize to semantic images thanks to the inductive bias introduced by the attention mechanism. Furthermore, to resolve ambiguities in converting the semantic images to semantic labels, we treat the view transformation network as a functional representation of an unknown mapping implied by the color images and propose functional label hallucination to generate pseudo-labels in the target domain. Our method surpasses baselines built on state-of-the-art correspondence estimation and view synthesis methods. Moreover, it outperforms the state-of-the-art unsupervised domain adaptation methods that utilize self-training and adversarial domain alignment. Our code and dataset will be made publicly available.

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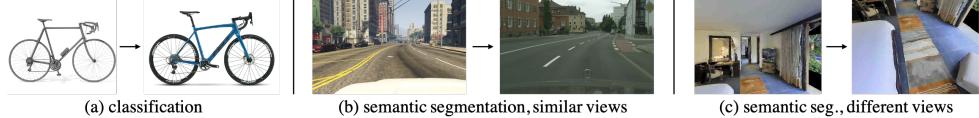(a) classification   (b) semantic segmentation, similar views   (c) semantic seg., different views

Figure 2: (a): image classification where image style and viewpoint are nuisances [35, 38]. (b): semantic segmentation at similar views where image style is the major nuisance for domain gaps [34, 20]. (c): semantic segmentation with changing view (*e.g.*, forward to downward), a nuisance that should not be aligned away. We focus on UDA for viewpoint change in semantic segmentation.

1 Introduction

Parsing the environment from multiple viewing angles to arrive at a comprehensive understanding of the surroundings is critical in many settings for autonomous agents or assistive robots. An example is the case of a human exoskeleton instrumented with multiple cameras as shown in Fig. 1, where training a scene parsing network that performs well at multiple viewpoints is key to estimating the walkable floor surface and preventing falls and other accidents. However, viewpoint changes across cameras induce significant domain gaps – as a result, a scene parsing network trained with annotations in only one view usually encounters a large performance drop on another (Tab. 2). We aim at reducing this domain gap by adapting the network from the view with rich annotations (source) to views where no annotation is available (target), i.e., unsupervised domain adaptation (UDA).

Most UDA methods build on the idea that an alignment in a shared latent space helps the task-specific network trained in the source domain generalize to the target. Despite its effectiveness in practice, domain alignment generally assumes (sufficient) invariance exists for the task, which can be computed through the alignment, so that the mapping from the aligned space to the output is transferable across domains. For example, if one converts the images in Fig. 2 (a) and (b) into edge maps, the discrepancy between domains may diminish, so the task networks trained on the source edge maps would also work on the target. However, the domain discrepancy we are considering here is mainly the content shift caused by the viewpoint change. As dense scene parsing (semantic segmentation) is viewpoint elevation-dependent, any alignment that learns away viewpoint will result in (insufficient) invariances which are not adequate or suitable for the task, thus inducing negative adaptation (Fig. 1).

We break this conundrum by hallucinating the target semantic images using their source counterparts. Instead of aligning features between domains, our method employs a view transformation network that outputs the target semantic image, conditioned on a source semantic image and a pair of regular color images. The hallucinated semantic images are then converted to semantic labels to adapt the task network. Since semantic images in the target domain are missing, the only supervision for the view transformation network is the color images. One can train a network to hallucinate using the color images and apply it to the semantic images. However, without a proper inductive bias, the view transformation network would completely fail on semantic images due to their different structures. We propose that the right inductive bias is to encourage learning *spatial transportation* instead of transformation in color space. Further, we introduce a novel architecture for view transformation where the desired inductive bias is injected via an attention mechanism. To combat noise in the hallucination and better decode the semantic labels, we treat the view transformation network as a functional representation of an unknown mapping signified by the color images. Accordingly, we propose a functional label hallucination strategy that generates the soft target labels by taking in the indicator functions of each class. The proposed decoding strategy improves the label accuracy by a large margin and makes the labels more suitable for adaptation by incorporating uncertainties.

Due to the lack of datasets in semantic segmentation whose domain gaps are mainly from viewpoint change, we also propose a new dataset where the viewpoint is varied to simulate different levels of content shift. We perform an extensive study of the state-of-the-art UDA methods, and show that the adaptation gain of domain alignment vanishes quickly when the viewpoint-induced domain gap increases. Moreover, we show that the soft labels from our method are superior to those from the state-of-the-art dense correspondence estimation and view synthesis methods, even if the ground-truth camera poses are made available to them. Our method consistently achieves the best adaptation gains across different target domains, even for perpendicular viewing angles, demonstrating the effectiveness of the proposed architecture (inductive bias) and functional transportation strategy.
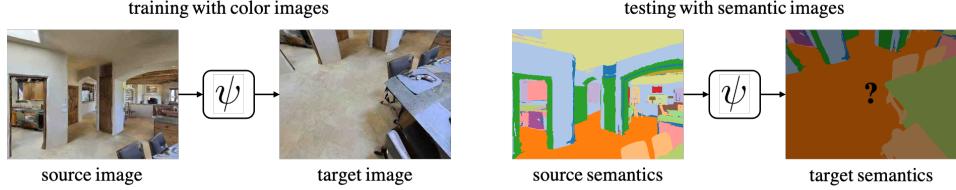
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training with color images · testing with semantic images

source image · target image · source semantics · target semantics

Figure 3: Left: a network ψ is trained to hallucinate color images from the source to the target and is never exposed to semantic images; Right: ψ is directly applied on the corresponding source semantic image to hallucinate the target semantic image to provide training labels for the target domain.

2 Related work

We focus on unsupervised domain adaptation (UDA) methods for the pixel-level prediction task of semantic segmentation. The core ingredient of unsupervised domain adaptation is to reduce the domain shift between the source and the target data distributions [33, 9, 54, 18, 14, 2], where the domain shift can be measured by maximum mean discrepancy [17, 27] or central moment discrepancy [61]. Deep learning based methods resort to adversarial measurements, where discriminator networks are used to confuse the two domains [42, 50, 30, 39, 43, 23] in a shared feature space. In contrast to classification, feature space alignment is much less effective for pixel-level prediction tasks like semantic segmentation [28, 40], due to the difficulties in keeping the aligned features informative about the spatial structure of the output.

The recent success of unsupervised domain adaptation for semantic segmentation mainly relies on image-to-image translation [71, 26, 60] where the goal is to reduce the style difference between domains while preserving the underlying semantics [66, 20, 25]. Multi-level feature alignment is proposed in [57] and [19] introduces intermediate styles that gradually close the gap. A disentanglement of texture and structure is also beneficial [4], and [22] performs style randomization to learn style invariance. To ease the difficulty in adversarial training, [59] proposes a style transfer via Fourier Transform, which enforces semantic consistency, and [58] directly regularizes the image translation module using a phase preserving constraint. On the other hand, [65, 13, 29, 55, 12] propose class-wise alignments, given that each of the semantic classes may possess a different domain gap. Similarly, [48] proposes patch-wise alignment, and [21] utilizes local contextual-relations for a consistent adaptation. The alignment can also be performed in the output space [52], or in a curriculum manner. For example, [32] employs inter and intra domain adaptation with an easy-to-hard split, and [24] pre-selects source images that share similar content with the target. With aligned domains, self-training using pseudo labels can be utilized to further close the gap [64, 25, 59].

Our method tackles the domain gap caused by different camera views, which renders the image space alignment ineffective as the domain gap is mainly content shift but not the style difference. Unlike cross-view image classification [36, 63, 10, 1, 16], aligning domains of different viewpoints for pixel-level prediction tasks is ill-posed, since the task is indeed view dependent [7]. The most relevant are [11, 8], which again resort to adversarial domain alignment. Additionally, [8] requires known camera intrinsics and extrinsics. Note, both assume the viewpoint change is small or there is a large overlap between the two views, therefore the applicability to a broader setting is limited, whereas our method is not constrained by any of these assumptions. Also related is novel view synthesis [69, 45, 15, 6], particularly, single view synthesis [70, 49, 56], where multiple posed images of the same scene are needed during training. Hence, if the goal is to synthesize semantic images of a different view, the target domain's semantic images are needed, which, however, are not available in our problem setting. Another related topic is dense correspondence estimation [47, 53, 67], which can be used to warp labels to help adaptation between domains.

3 Method

Let $\mathcal{D}^s = \{(x_i^s, y_i^s)\}_{i=1}^n$ be the source dataset collected at the source viewpoint s, where $x_i^s \in \mathbb{R}^{h \times w \times 3}$ is an RGB image, and $y_i^s \in \mathbb{R}^{h \times w \times 3}$ is the corresponding semantic image that is color coded according to the semantic labels for visualization[3]. Further, let $\mathcal{D}^\tau = \{x_i^\tau\}_{i=1}^n$ be the target dataset collected at the target viewpoint τ, whose semantic label/image y_i^τ is to be predicted. In

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[3]One can always convert the semantic image to integer semantic labels using nearest neighbour search.

Figure 4: Left to right: source and target color images (1st,2nd) for training the view transformation. During testing, source semantic images (3rd) are inputs to the network. The hallucinated semantic images by the network without attention (4th) are inaccurate and not consistent with the target images; however, the hallucinations from the network with attention (5th) are sharp and more precise.

order to make our method generally applicable, we assume no knowledge about the viewpoints s, τ except that $x_i^s \in \mathcal{D}^s$ and $x_i^\tau \in \mathcal{D}^\tau$ are synchronized. Therefore, the domain gap between $\mathcal{D}^s$ and $\mathcal{D}^\tau$ comes from the viewpoint difference in our problem setting. Moreover, the synchronized source and target view images may or may not share co-visible regions, which is determined by the difference between the two views. Please see Fig. 7 for examples of the source domain and target domains with increasing viewpoint changes.

Similar to unsupervised domain adaptation, our ultimate goal is to train a semantic segmentation network $\phi : \mathbf{x} \to \mathbf{y}$ given only the annotations from the source dataset $\mathcal{D}^s$ so that ϕ can perform well on the target dataset $\mathcal{D}^\tau$ with the presence of domain gaps. The domain gap we are considering here is mainly the content shift induced by different viewing angles, *i.e.*, the discrepancy in the output structures, which violates the assumptions made by most unsupervised domain adaptation methods that rely on either image space alignment or feature space alignment, or both [64, 29, 65, 59, 22, 24, 52]. Instead of aligning distributions of any kind between the two domains, which may result in negative adaptation gains (Fig. 1, right), we resort to a network that can hallucinate the target view semantic images (y^τ) from the source (y^s) guided by the color images (x^s, x^τ). Specifically, we want to have a network $\psi : \mathbf{y} \times \mathbf{x} \times \mathbf{x} \to \mathbf{y}$, whose output $\psi(y_i^s; x_i^s, x_i^\tau)$ can be used as pseudo ground-truth for improving ϕ to make better predictions on $\mathcal{D}^\tau$.

3.1 Auto-labeling with attention

Looking at a pair of color images x_i^s, x_i^τ shown in Fig. 3, one could hallucinate to some extent the target semantic image y_i^τ associated with x_i^τ given the source semantic image y_i^s. On the other hand, if a network learns how to hallucinate the target image x_i^τ from the source image x_i^s, we would expect it to make a reasonable hallucination of the target semantic image y_i^τ from the source semantic image y_i^s, since x_i^s and y_i^s are simply two different appearances of the same geometry. However, without a proper inductive bias, a network trained to hallucinate color images between different views may fail completely when tested on semantic images due to their statistical difference.

To validate, we train a UNet [37] ψ^{unet}, which is widely used for image transformation and dense prediction, to hallucinate x_i^τ from x_i^s, with τ fixed and L1 loss as the training objective, *i.e.*, $\hat{x}_i^\tau = \psi^{unet}(x_i^s)$. After training, we directly test ψ^{unet} on the semantic images to check if $\psi^{unet}(y_i^s)$ is similar to y_i^τ. As shown in Fig. 4, the UNet trained on color images for view transformation does not generalize well to semantic images, which confirms the difficulties to perform novel appearance hallucination of a seen view, even if the geometry is unchanged.

We propose that the key to generalizing to novel appearance is to bias the network towards learning spatial transportation instead of color transformation. For example, the network needs incentives to learn where the color should be copied to in the target view instead of how the color should change to form the target view. If so, the view hallucination should generalize to any novel appearance since the color transformation may depend on domains while the spatial transportation conditioned on the same views and geometry is invariant.
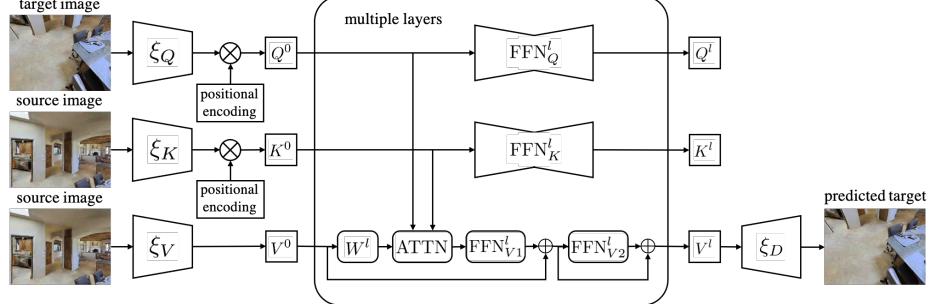
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Figure 5: The proposed architecture for hallucinating arbitrary target domains, which is specified by the input target image (top left). During testing, the input to the value encoder ξ_V (bottom left) is replaced by the source semantic image. Please refer to Sec. 3.2 for detailed explanations.

Biasing towards transportation with attention. The self-attention mechanism proposed in [51] represents a layer that processes the input by first predicting a set of keys (K) and a set of queries (Q), whose dot-products are then used to update a set of values (V) to get the output (updated values):

$$\text{ATTN}(Q, K, V) = softmax(\frac{QK^T}{\sqrt{d_k}})V$$

By examining how a single output value v'_i is computed, we can see why attention helps to bias towards spatial transportation that facilitates the generalization of the hallucination. Let q_i be the corresponding query for v'_i, and $[k_1, k_2, ..., k_m]$ be the keys, then $v'_i = \sum_{j=1}^{m} \alpha_j \cdot v_j$, with α_j's the elements of $softmax([k_1 q_i^T, k_2 q_i^T, ..., k_m q_i^T])$ (scaling factor omitted for simplicity). Note if q_i is extremely similar to a certain key, *e.g.*, k_{j*}, but dis-similar to the other keys, we may write $v'_i \approx v_{j*}$. This signals that the attention is transporting values from different locations to i through the weighted summation. In the extreme case, it can even stimulate point-wise transportation of the values.

To verify the effectiveness of attention in hallucinating labels (novel appearance), we simply reorganize the tunable parameters in the UNet ψ^{unet} such that the convolutional layers near the bottleneck are now replaced by attention layers of the same capacity. We term it as ψ^{attn} and train it to hallucinate the target color images from the source color images, *i.e.*, $\hat{x}_i^\tau = \psi^{attn}(x_i^s)$, and test it on the semantic images. As shown in Fig. 4 (5th column), ψ^{attn} can hallucinate reasonable target semantic images even it is only trained on color images. Given the effectiveness of the inductive bias introduced by the attention mechanism in label hallucination for a single target view, we now detail our view hallucination network for multiple target views and the technique that we propose to generate soft labels for adaptation to different target domains.

3.2 Labeling multiple target domains

Here we specify the proposed network architecture that can seamlessly work for different target views, *e.g.*, the target domain is a mixture of views, which eliminates the need to train separate networks. Again, the view hallucination network $\psi(x_V; x_K, x_Q)$ takes in a pair of color images, which guide ψ to predict the target view from the source whose appearance is determined by either the source color image or the source semantic image, *i.e.*, $\hat{x}_i^\tau = \psi(x_i^s; x_i^s, x_i^\tau)$ during training or $\hat{y}_i^\tau = \psi(y_i^s; x_i^s, x_i^\tau)$ during testing. As illustrated in Fig. 5, we let $x_Q = x_i^\tau$, $x_K = x_i^s$ and $x_V = x_i^s$, which are lifted to query, key and value features through the following procedure:

$$Q^0 = \xi_Q(x_Q)[\mathbf{1}; u_{pos}; v_{pos}]$$
$$K^0 = \xi_K(x_K)[\mathbf{1}; u_{pos}; v_{pos}]$$
$$V^0 = \xi_V(x_V)$$

here ξ_Q, ξ_K, ξ_V are separate encoders with strided convolutions to reduce the spatial dimensions of the features, and u_{pos}, v_{pos} are fixed positional encodings that represent the normalized image grids
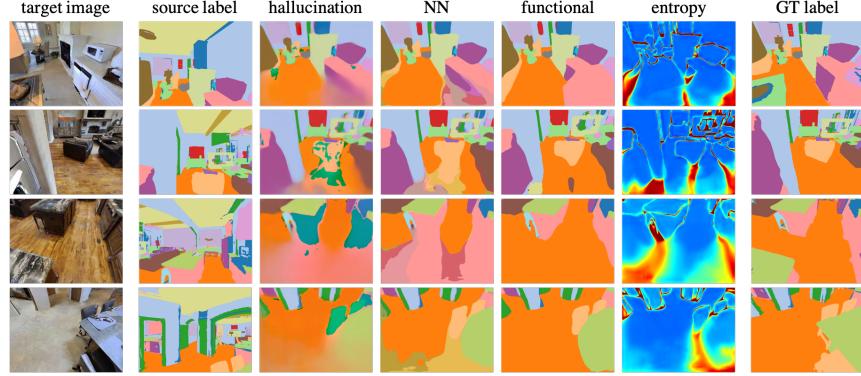
Figure 6: Effectiveness of the proposed functional transportation strategy. The target semantic images (3rd) are hallucinated from the source counterparts (2nd), which are decoded into semantic labels using nearest neighbor search (4th) or the proposed functional strategy (5th) with uncertainties (6th).

(horizontal and vertical). These lifted features are followed by L layers described below:

$$Q^l = \text{FFN}^l_Q(Q^{l-1}) \tag{1}$$

$$K^l = \text{FFN}^l_K(K^{l-1}) \tag{2}$$

$$\hat{V}^l = \text{ATTN}(Q^{l-1}, K^{l-1}, V^{l-1}W^l) \tag{3}$$

$$\bar{V}^l = \text{FFN}^l_{V1}(\hat{V}^l) + V^{l-1} \tag{4}$$

$$V^l = \text{FFN}^l_{V2}(\bar{V}^l) + \bar{V}^l \tag{5}$$

$$x^l_Q = \xi_D(V^l) \tag{6}$$

where $\text{FFN}^l_Q, \text{FFN}^l_K$ are two feed-forward networks of downsampling and upsampling convolutional layers with layernorm to maintain the size of the updated keys and queries. And the feed-forward networks $\text{FFN}^l_{V1}, \text{FFN}^l_{V2}$ are simply convolutional layers whose stride is equal to one. Note, for each V^l, we apply the shared decoder ξ_D to map it to the image space, and x^L_Q will be the final output of the proposed view transformation network ψ.

Training loss and data augmentation. For training the network $\psi(x_V; x_K, x_Q)$ in Fig. 5, we apply color jittering to the input images. Specifically, the hue of x^s_i, x^τ_i are perturbed by a random factor to get x_Q and x_K, and by a different factor to get $\bar{x}_Q$ and x_V, where $\bar{x}_Q$ is the expected output of $\psi(x_V; x_K, x_Q)$. Different hue perturbations can help prevent information leakage, since now x_Q (input) and $\bar{x}_Q$ (expected output) are not identical, yet the consistency between x_V and $\bar{x}_Q$ is preserved to enable meaningful hallucination. In addition, we apply the same color permutation to x_V and $\bar{x}_Q$, *e.g.*, red to green and yellow to blue, to further prevent information leakage from x_Q to the output. More details can be found in the appendix. The training loss for ψ is:

$$\mathcal{L}^\psi = \sum_{x_Q \in \{\mathcal{D}^\tau\}} \sum_{l=1}^{L} \lambda_l \|x^l_Q - \bar{x}_Q\|_1 \tag{7}$$

with λ_l the weighting coefficient for the l-th layer's output x^l_Q, which is decoded from V^l, and we set $\lambda_l = 2^{-(L-l)}$ so that early predictions are weighted less. Note, x_K, x_V can be indexed by x_Q.

3.3 Functional label hallucination

Given the trained ψ, we can hallucinate the target semantic images for x^τ_i's, *i.e.*, $\hat{y}^\tau_i = \psi(x_V; x_K, x_Q)$, by setting $x_Q = x^\tau_i, x_K = x^s_i$ and $x_V = y^s_i$. We can then convert the hallucinated semantic images into semantic labels (integers) via nearest neighbor search in the color space to adapt a semantic segmentation network to the target domains. However, the converted labels sometimes could be wrong due to noise in the predicted color (see Fig. 6).

To resolve the ambiguities, we propose the following functional label hallucination by treating $\psi(\cdot; x^s_i, x^\tau_i)$ as the functional representation of an unknown mapping $T(x^s_i, x^\tau_i) : \Omega_s \to \Omega_\tau$ conditioned on the color images x^s_i, x^τ_i. Here Ω_s, Ω_τ represent the source and target image domains/grids.
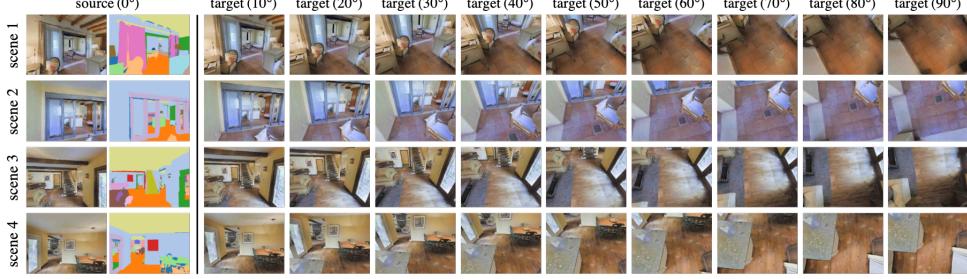
Figure 7: Samples from the proposed dataset (one source and nine target domains) for benchmarking unsupervised domain adaptation methods on viewpoint change in semantic segmentation.

According to [31], if T is a bijective mapping between Ω_s and Ω_τ, the actual mapping T can then be recovered from $\psi(\cdot; x_i^s, x_i^\tau)$ by checking its output of indicator functions of the elements in Ω_s. However, recovering the underlying unknown mapping T is unnecessary in our scenario, and, indeed, we do not have any constraints that T is bijective. Instead, we utilize the functional representation $\psi(\cdot; x_i^s, x_i^\tau)$ to find regions in Ω_τ that share the same label with those in Ω_s. Let $\mathbf{1}_{y_i^s=c}$ be the indicator function of the regions that are classified as class c, then $\hat{y}_{ic}^\tau = \psi(\mathbf{1}_{y_i^s=c}; x_i^s, x_i^\tau)$ indicates the regions of class c in Ω_τ. And the hallucinated labels can be written as:

$$\hat{y}_i^\tau = softmax(\psi(\mathbf{1}_{y_i^s=1}; x_i^s, x_i^\tau), ..., \psi(\mathbf{1}_{y_i^s=C}; x_i^s, x_i^\tau)) \tag{8}$$

with C the number of semantic classes within the datasets, and now the hallucinated target view labels $\hat{y}_i^\tau$ represent the probabilistic distributions over the C classes for each pixel.

Adapting to target domains. With the functional transportation strategy, we can avoid performing a nearest neighbor search in the color space, which improves the accuracy of the generated labels even when the hallucinated color is noisy (see Fig. 6). Moreover, the soft probabilistic labels are more suitable for adapting the semantic segmentation network ϕ to the target domains, avoiding errors of hard labels when the hallucination is of low confidence. We simply finetune ϕ for each target domain using the target dataset $\mathcal{D}^\tau = \{(x_i^\tau, \hat{y}_i^\tau)\}$ augmented with the soft labels:

$$\mathcal{L}^\phi = \sum_i \mathbb{H}(\hat{y}_i^\tau, \phi(x_i^\tau)) \tag{9}$$

where $\mathbb{H}$ is the cross-entropy. Next, we introduce the evaluation benchmark and the experiments.

4 Experiments

4.1 Data generation

Due to the lack of benchmarks for evaluating UDA methods on viewpoint change, we propose a new dataset whose source and target domains are generated by varying camera elevation and viewing angles. Moreover, we explicitly control the viewpoint changes, such that we can quantitatively assess the adaptation performance with respect to the degree of domain gaps. We resort to simulation for data collection since 1) it is much easier to obtain semantic segmentation ground-truth in simulation; 2) the degree of the domain gap caused by viewpoint change is more controllable; and 3) it is more friendly to the personnel who is in charge of the data collection given the pandemic.

Furthermore, we maximize the realism of the generated data by employing the Matterport3D dataset [3], which contains 90 building-scale real-world scenes with pixel-wise semantic annotations[4]. The scenes from Matterport3D are then imported into the Habitat simulation platform [41] for our data generation. Specifically, we first randomly sample two states in the scene, with one state (the position and yaw angle[5] of a virtual camera) representing the starting state, and the other the end state. We then perform collision-free path planning between these two states. The resulted path is accepted if it has a length larger than 15 path points, and images at each point along the path are collected. To synthesize the domain gaps, we set the pitch angle of the virtual camera to $0°$ for collecting the source

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[4]we completed the Terms of Use agreement form and obtained consent from the creators, and the data does not contain any personally identifiable information

[5]orientation within a horizontal plane, similarly, the pitch angle is the orientation within a vertical plane

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Table 1: Ablation study on different inductive biases for zero-shot semantic image hallucination. Numbers are the mIoUs of the hallucinated semantic labels on the training set of each target domain.

Method	Target Domains								
	10°	20°	30°	40°	50°	60°	70°	80°	90°
UNet	49.76	28.19	13.69	9.26	6.56	4.71	2.59	1.63	1.28
Flow	33.04	27.59	22.72	19.36	17.02	14.21	11.55	9.67	8.34
RAFT [47]	70.62	61.25	53.92	42.54	18.17	9.36	7.57	6.24	5.58
3D	28.16	22.12	18.35	15.80	13.14	11.22	9.20	6.61	2.86
ADeLA (single)	54.85	46.29	42.66	37.75	27.71	21.33	14.18	8.69	4.17
ADeLA (multiple)	48.42	41.87	35.73	30.39	24.11	17.40	11.79	8.82	7.34
UNet+F	73.62	49.07	27.12	20.08	16.48	13.68	11.61	9.79	8.53
ADeLA (single)+F	70.07	**67.63**	**58.62**	**54.33**	**47.45**	**37.81**	**28.39**	**19.78**	**15.17**
ADeLA (multiple)+F	**75.75**	66.29	57.45	49.57	40.38	30.00	20.96	15.44	12.60

domain videos (annotations), which resembles the working viewpoint for semantic segmentation networks trained on existing scene parsing datasets [44, 46, 68]. Moreover, we increase the pitch angle of the virtual camera by 10° (up to 90°) for collecting target domain videos (no annotations), which results in 9 different target domains. For each domain, we collect 13,500 training images and 2,700 test images with resolution 384×512. Please see Fig. 7 for samples from the collected datasets.

4.2 Implementation details.

We adapt the UNet structure [37] with reduced capacity and layernorm activation to construct the feed-forward networks FFN_Q and FFN_K. Similar to [62], W is a convolutional layer with kernel size 1×1, $\text{FFN}_{V1}, \text{FFN}_{V2}$ consist of one and two convolutional layers respectively. Both FFN_{V1} and FFN_{V2} use leakyrelu as the activation function. Our view transformation network contains $L = 8$ attention modules. Training of the view transformation network ψ is carried out on eight Nvidia V100 GPUs, with batch size 16. We use the Adam optimizer with an initial learning rate of 1e-4 and momentums of 0.9 and 0.999. The training converges after 10 epochs. We use the DeepLabv2 [5] with the ResNet101 backbone as the semantic segmentation network ϕ, which is initialized with the pre-trained weights on ImageNet [29, 65, 59, 24, 52]. Soft labels for each target view τ are hallucinated using Eq. (8). Moreover, the semantic segmentation networks ϕ^τ for each target domain are trained using Eq. (9) with the Adam optimizer, with a batch size of 6 and an initial learning rate of 7.5e-5. The learning rate is then halved after 10 and 15 epochs. The training converges at 25 epochs. To have a fair comparison with the state-of-the-art domain adaptation methods that adapt from a single source domain to a single target domain, we also train the segmentation network for each target domain separately. We use mean intersection-over-union (mIoU) as the metric.

4.3 Ablation study

Effectiveness of the proposed inductive bias. Qualitative comparisons in Fig. 4 show that the proposed inductive bias and the architecture facilitate zero-shot semantic image hallucination. In Tab. 1 we quantitatively confirm its effectiveness and check how it extends across different levels of view-dependent domain gaps. Besides the color transformation bias (UNet), we also test the inductive biases introduced by explicitly modeling the dense 2D correspondence ("Flow") and by explicitly modeling the image formation process in 3D ("3D"). For "Flow," we adapt the architecture of RAFT [47] and train it to estimate the flow that reconstructs the target color image from the source, and use the flow for warping the semantic labels. For "3D", we adapt the state-of-the-art single view synthesis framework [56], and supply it with ground-truth camera poses for semantic image synthesis. We report the performance of our method under two settings. One is the single source to single target setting (ADeLA (single)), the other is the single source to multiple targets setting (ADeLA (multiple)). The labels for ADeLA (single) and ADeLA (multiple) are generated using nearest neighbor search. We also report the score of the warped labels using the fully supervised RAFT model for reference.

We can make the following observations: 1) UNet (color transformation) does not work at large viewpoint change. 2) the 2D dense correspondence inductive bias ("Flow") works better for large viewpoint change, which verifies our proposal for biasing towards transportation. However, the comparison between "Flow" and "RAFT" shows that the spatial correspondence learned from color images can be erroneous, so "Flow" is much worse than "RAFT" at small viewpoint changes.
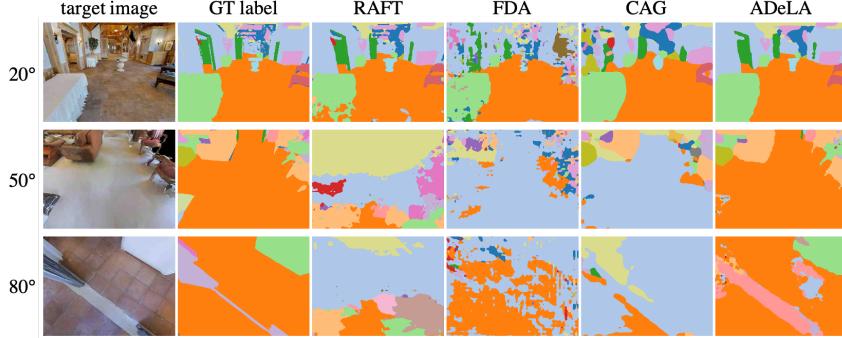
Figure 8: Qualitative comparison to competing methods on different target domains.

Table 2: Quantitative comparison to state-of-the-art methods on the proposed benchmark. Numbers are mIoU scores of the adapted semantic segmentation networks on the test set of each target domain.

Method	Target Domains								
	10°	20°	30°	40°	50°	60°	70°	80°	90°
Baseline	27.90	20.24	12.22	7.63	4.41	2.53	1.80	1.53	1.53
RAFT [47]	29.46	_26.74_	_24.15_	16.92	_8.66_	4.54	3.35	2.82	2.41
MFNet [67]	29.20	24.53	13.16	6.65	4.76	3.95	3.00	2.81	2.48
DICL [53]	29.62	26.45	22.01	_17.75_	6.25	4.44	3.40	2.75	2.49
ProDA [64]	25.26	19.35	12.03	7.46	4.39	1.74	1.12	0.83	0.77
CLAN [29]	28.22	21.21	13.17	7.53	4.37	2.66	2.02	1.74	1.73
CAG [65]	27.17	22.22	15.05	8.57	5.24	2.43	1.83	1.50	1.54
FDA [59]	**37.80**	23.34	12.33	6.69	3.58	2.15	1.56	1.67	1.32
LTIR [22]	26.22	20.50	13.43	6.16	3.90	2.09	1.82	1.65	1.66
CCM [24]	28.26	19.48	10.56	4.92	2.78	1.50	1.14	0.95	0.90
Advent [52]	11.38	7.93	4.98	3.28	2.54	2.16	1.60	1.52	1.49
Intrada [32]	10.16	7.84	6.13	4.08	2.67	1.98	1.58	1.67	0.93
AppFlow [70]	14.73	12.91	10.46	8.43	7.30	_5.68_	4.66	_3.87_	_3.39_
Synsin [56]	14.43	11.44	9.15	8.29	6.24	5.43	_4.67_	3.36	1.88
UNet	30.51	22.36	12.26	8.44	6.58	4.80	3.81	2.98	2.22
ADeLA	_31.19_	**27.66**	**24.31**	**20.71**	**15.88**	**12.28**	**8.27**	**7.16**	**5.03**

Moreover, "RAFT" is worse than "Flow" at large viewpoint changes, which indicates that the exact dense correspondence may not be suitable for semantic label hallucination. 3) The 3D inductive bias ("3D") does not perform well since the learned 3D representation from color images does not generalize to semantic images. 4) Our model performs well across all target domains, due to the proposed spatial transportation bias, and the capability to hallucinate beyond exact correspondence.

Moreover, we show the quality of the semantic labels hallucinated using the proposed functional label hallucination strategy ("UNet+F," "ADeLA(single)+F," "ADeLA(multiple)+F"). As seen in Tab. 1 (bottom), functional hallucination significantly improves the performance of UNet and our models, demonstrating its effectiveness in resolving the ambiguities in the hallucinated semantic images. Note, "Flow" and RAFT warp labels with explicit dense correspondence, thus they are unable to take advantage of the functional strategy. The same observation holds for "3D", whose 3D representation learned with color images does not generalize even if supplied with ground-truth camera poses.

4.4 Benchmarking

We carry out an extensive study of state-of-the-art methods on unsupervised domain adaptation for viewpoint changes in semantic segmentation [64, 29, 65, 59, 22, 24, 52, 32]. Among those methods, [64, 24] focus on self-training, [29, 65, 32] perform class-wise and curriculum domain alignment, and [59, 52, 22] align domains in the image/output space. We also experiment with three best performing dense correspondence estimation methods [47, 67, 53], and two single view synthesis methods [70, 56] to generate target view labels to help adapt the semantic segmentation networks. All methods are re-trained on the training sets of the proposed benchmark, and tested on the test sets of the nine target domains. Our method consistently achieves positive adaptation gain and performs much better than the other methods at large viewpoint changes. Note FDA [59] performs better on

the target domain of $10°$ (small gap) due to its strong style randomization mechanism. However, our method outperforms FDA by a significant margin on the remaining target domains even without any data augmentation in adapting the semantic segmentation network. See Fig. 8 for visual comparisons.

5 Discussion

We tackle UDA for viewpoint change in the semantic segmentation task. Extensive experiments on the new benchmark collected with controlled domain gaps caused by changing views demonstrate the effectiveness of the proposed inductive bias for zero-shot view hallucination, strengthened by the proposed functional transportation strategy, in reducing the domain gaps. Our experiments also verify that aligning statistics of domains in a shared space could be counter-productive due to the content shift across viewing angles. Our method achieves higher adaptation gains, especially in the regime of large viewpoint changes. However, the adaptation gain of our method also decreases toward the extreme case where the viewing angles are perpendicular. Like many visual perception methods, there is a potential ethical and societal concern when applied to downstream applications. In our code release, we will explicitly specify allowable uses of our system with appropriate licenses. In the future, we would like to explore how the temporal information can be utilized to reduce further the domain gaps caused by extreme views.

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