Abstract

Unsupervised domain adaptation (UDA) aims to learn a well-performed model in an unlabeled target domain by leveraging labeled data from one or multiple related source domains. It remains a great challenge due to 1) the lack of annotations in the target domain and 2) the rich discrepancy between the distributions of source and target data. We propose Spectral UDA (SUDA), an efficient yet effective UDA technique that works in the spectral space and is generic across different visual recognition tasks in detection, classification and segmentation. SUDA addresses UDA challenges from two perspectives. First, it mitigates inter-domain discrepancies by a spectrum transformer (ST) that maps source and target images into spectral space and learns to enhance domain-invariant spectra while suppressing domain-variant spectra simultaneously. To this end, we design novel adversarial multi-head spectrum attention that leverages contextual information to identify domain-variant and domain-invariant spectra effectively. Second, it mitigates the lack of annotations in target domain by introducing multi-view spectral learning which aims to learn comprehensive yet confident target representations by maximizing the mutual information among multiple ST augmentations capturing different spectral views of each target sample. Extensive experiments over different visual tasks (e.g., detection, classification and segmentation) show that SUDA achieves superior accuracy and it is also complementary with state-of-the-art UDA methods with consistent performance boosts but little extra computation.

1 Introduction

Deep learning methods \cite{39, 67, 66, 28} have achieved great success in various visual recognition tasks in image classification \cite{39, 66, 28}, image segmentation \cite{45, 57, 2, 11} and object detection \cite{23, 22, 55, 54, 44, 12, 8, 88}. Their great success is at the price of large quantities of well-annotated training data which are often prohibitively expensive and time-consuming to collect \cite{43, 15, 12, 14}. One potential alternative that could mitigate this constraint is to leverage the off-the-shelf labeled data from one or multiple related source domains. However, the models trained with source-domain data often experience clear performance drops when applied to a target domain where the data usually have discrepant distributions as compared with source-domain data \cite{62, 68, 63, 13, 61, 34, 32}.
Unsupervised domain adaptation (UDA) has been explored to mitigate the discrepancy across source and target domains. One typical approach is to align source and target data in the input space, mostly by image-to-image translation with generative adversarial networks (GANs) which modify source data to have target styles \cite{1,38,35,42}. However, GANs-based image translation is inefficient requiring non-negligible parameters, and it makes UDA not end-to-end trainable as it needs to train GANs firstly before applying them. In addition, it could impair UDA by modifying domain-invariant image structures which are closely entangled with domain-variant image styles in spatial space.

In this work, we propose an innovative Spectral UDA (SUDA) technique that addresses UDA challenges by learning domain-invariant spectral features efficiently and effectively. SUDA mitigates UDA challenges from two perspectives. First, it introduces a spectrum transformer (ST) that learns to reduce inter-domain discrepancies by weighting up domain-invariant frequency components and weighting down domain-variant frequency components adaptively as illustrated in Fig. 1. To this end, we design novel adversarial multi-head spectrum attention (AMSA) that learns to identify domain-variant and domain-invariant frequency components accurately. ST thus works like an online image preprocessor which preserves domain-invariant features, keeps the whole UDA network end-to-end trainable, and is learnable on the fly. Second, we design multi-view spectral learning (MSL) that learns comprehensive yet confident target representations by maximizing the mutual information among multiple ST augmentations of each target sample. MSL introduces certain self-supervision which mitigates the lack of annotations in the target domain effectively.

The proposed SUDA has three desirable characteristics: 1) It is a generic technique that performs consistently well across different visual recognition tasks such as object detection, image classification and image segmentation; 2) It is an online and learnable technique whereas GANs-based image translation is offline and traditional image preprocessing methods are mostly non-learnable; 3) It is complementary with existing UDA methods and can be incorporated with consistent performance boosts but little extra computation. We verify these features experimentally in Section 4.6.

The contributions of this work can be summarized in three aspects. First, we designed SUDA that effectively addresses UDA challenges by learning domain-invariant spectral features. To the best of our knowledge, this is the first work that explores spectral learning for the UDA problem. Second, we design an online learnable spectrum transformer that mitigates inter-domain discrepancy by weighting up domain-invariant frequency components and weighting down domain-variant frequency components elegantly. To this end, we design AMSA that leverages contextual information to identify domain-variant and domain-invariant frequency components accurately. Third, we design an MSL technique that aims to learn comprehensive yet confident target representations from multiple spectral views of each target sample. MSL greatly mitigates the lack of annotations in the target domain by maximizing the mutual information among multiple ST augmentations of each target sample.

## 2 Related Work

**Unsupervised Domain Adaptation.** UDA has been investigated extensively in recent years, largely for alleviating data annotation constraint in deep network training in various detection, segmentation and classification tasks \cite{20,62,13,29,61,76,85,6,40,78,89,72,42}. Besides the widely studied adversarial learning \cite{13,29,40,85,61,82,78,89,72,42} and self-training \cite{81,37,89,26}, image-to-image translation \cite{42,38,35,1} which modifies source images to have target-alike styles has been studied for reducing inter-domain discrepancy in the input space. To this end, a number of GANs \cite{24,86} have been specifically designed for translating image styles yet with minimal modification of semantic image structures. However, GAN training is usually tedious and time-consuming, and it also makes the whole UDA framework not end-to-end trainable as it needs to train GANs firstly before applying them to UDA tasks. In addition, GAN-based translation works in spatial space where image styles and image structures are closely entangled which inevitably modifies semantic image structures undesirably. Some work \cite{80} attempts to perform image translation in frequency space by swapping certain pre-defined frequency components of source and target images, but it is non-learnable and cannot accommodate individual images that usually have different spectral characteristics.

We design a spectrum transformer that learns to identify domain-variant and domain-invariant frequency components that are specific to each individual image. It mitigates the inter-domain
Figure 1: Illustration of the proposed spectrum transformer (ST): For the real-world source image and clipart-style target image in col. 1, cols. 2-4 show their decomposition into low-frequency, middle-frequency and high-frequency components, respectively. ST identifies and weights up domain-invariant middle and high frequency components and weights down domain-variant low-frequency components which mitigates inter-domain discrepancy in the restored spatial-space images.

discrepancy by adaptively weighting up domain-invariant frequency components and weighting down domain-variant ones across source and target images.

Learning in Frequency Space. Image preprocessing in spectral space has been widely studied with various spectral filters in the traditional image processing and computer vision tasks [5,10]. However, most traditional spectral preprocessing techniques are deterministic which handle each individual image in the same manner. Spectrum learning has attracted increasing attention recently with the advance of deep learning, and it has been studied for different computer vision tasks such as image translation [18,77,17], image compression [77] and network generalization [33].

We investigate spectrum learning for the challenge of UDA. Besides the spectrum transformer that learns to mitigate the inter-domain discrepancy, we design multi-view spectral learning that generates different spectral views for each target image and maximizes their mutual information to learn comprehensive yet confident target representations without any labels or annotations.

Attention Mechanism. Visual attention has been adopted in various image recognition tasks. It can be broadly categorized into channel attention and spatial attention, where channel attention [30,53] aims to identify useful information across feature channels while spatial attention [73] aims to capture spatial dependencies within a single channel. Certain hybrid attention [75,7,41] that integrates channel attention and spatial attention has also been developed for better focus on informative regions. Recently, self-attention [71] has attracted increasing interest by mapping a query and a set of key-value pairs to an output. Multi-head self-attention, which aggregates information from different positions with multiple self-attention, has been explored in different visual tasks [8,88,16,84].

We propose adversarial multi-head spectrum attention for UDA. The proposed AMSA introduces adversarial learning to help identify domain-variant and domain-invariant frequency components. In addition, it works in spectral space with multiple disentangled frequency components which allow to model multi-head attention more effectively.

3 Method

3.1 Task Definition

This work focuses on UDA in different visual recognition tasks such as object detection, image classification and image segmentation. It involves a source domain \( D_s = \{ (x_i^s, y_i^s) \}_{i=1}^{N_s} \), where \( y_i^s \) is the label of the sample \( x_i^s \), and an unlabeled target domain \( D_t = \{ (x_i^t) \}_{i=1}^{N_t} \). The goal is to train a
We propose SUDA, an innovative spectral-space UDA technique that addresses UDA challenges which allows to learn more comprehensive and robust target representations.

Our network can effectively work with a single ST without multi-view spectral learning, more details to be discussed in the experiment section.

model $G$ that well performs in $D_t$. The baseline model is trained with source data $x_s \in D_s$ only:

$$L_{sup} = l(G(x_s), y_s),$$

where $l(\cdot)$ denotes a task-related loss, e.g., the standard cross-entropy loss for image classification.

### 3.2 Spectral Unsupervised Domain Adaptation

We propose SUDA, an innovative spectral-space UDA technique that addresses UDA challenges by learning domain-invariant spectral features. SUDA has two key designs including a spectrum transformer for inter-domain adaptation and multi-view spectral learning for intra-domain adaptation.

**Overview.** Fig. 2 shows the framework of the proposed spectral unsupervised domain adaptation (on the top), and the design of the proposed spectrum transformer (at the bottom). Given a source-domain image $x_s \in D_s$ and a target-domain image $x_t \in D_t$, two complementary spectrum transformers $ST_1$ and $ST_2$ first transform the two images into spectral space and decompose them into multiple spectral components. The proposed AMSA within ST identifies and enhances domain-invariant spectra while suppressing domain-variant spectra via the adversarial loss $L_{adv}$ with the discriminator $C_d$. AMSA thus achieves inter-domain adaptation by mitigating inter-domain discrepancies.

Here $\hat{x}_s^1$ and $\hat{x}_s^2$ capture two different spectral views of $x_t$ after the preprocessing by $ST_1$ and $ST_2$ which have different parameters with a discrepancy loss $L_{dis}$. They are fed to a visual task model $G$ for intra-domain adaptation, where the proposed MSL strives to maximize the mutual information among the two augmentations of $x_t$. Note we employ two spectrum transformers for producing multiple views of $x_t$ which allows to learn more comprehensive and robust target representations. Our network can effectively work with a single ST without multi-view spectral learning, more details to be discussed in the experiment section.
Spectrum Transformer for Inter-domain Adaptation. Given an input image \( x \in \mathbb{R}^{3 \times H \times W} \), ST employs Fast Fourier Transform (FFT) to transform it into spectral representation and decomposes the spectral representation into \( N \) spectral components \( x^N = \{ x^n \}_{n=1}^N \) evenly by using a band pass filter.

The decomposed \( x^N \) is further flattened into a vector with dimension of \( d = 3N \) (i.e., \( x^N_\ast \in \mathbb{R}^{3N \times HW} \)) and fed into the proposed AMSA to weight up domain-invariant spectra and weight down domain-invariant spectra adaptively. The visual description of AMSA is shown at the bottom of Fig. 2 and its definition is presented below.

**Definition 1** The proposed Adversarial Multi-head Spectrum Attention is defined by:

\[
AMSA(x^N_\ast) = \text{Concat}(A_1(x^N_\ast), A_2(x^N_\ast), ..., A_h(x^N_\ast), ..., A_H(x^N_\ast))P_H,
\]

where AMSA consists of \( H \) single attention heads (i.e., \( A_h(\cdot) \), where \( h = 1, ..., H \)) and \( \text{Concat}(\cdot) \) denotes the concatenation of the \( H \) outputs from \( A_h(\cdot) \). The projection of the concatenation is performed by \( P_H \in \mathbb{R}^{Hd_h \times d} \), where \( d = 3N \) and \( d_h = d/H \). Each single attention head \( A_h(\cdot) \) is defined as a standard scaled dot-product attention, which maps a query (\( Q \)) and a set of key-value (\( K, V \)) pairs into an output:

\[
(K, V, Q) = x^N_\ast P_{kvq}, \tag{3}
\]

\[
A_h(x^N_\ast) = \text{Softmax}(QK^T / \sqrt{d_h})V, \tag{4}
\]

where the value of \( K, V \) and \( Q \) for each head is projected from input \( x^N_\ast \) by \( P_{kvq} \in \mathbb{R}^{d \times 3d_h} \).

Finally, the output of the AMSA is reshaped back into the size of \( (3 \times N \times H \times W) \) and then restored back to a full-spectrum spatial image \( \hat{x} \in \mathbb{R}^{3 \times H \times W} \) by concatenation. The proposed ST thus mitigates the inter-domain discrepancy by weighting up the domain-invariant spectra and weighting down the domain-variant spectra in the input space.

The ST-preprocessed image \( \hat{x} \) and its corresponding domain label (0 or 1) are then forwarded to a discriminator \( C_d \) to reduce inter-domain discrepancies in the input space. \( C_d \) performs adversarial learning with an adversarial loss \( L_\text{adv} \):

\[
L_\text{adv} = E[\log C_d(ST(x_\ast))] + E[\log(1 - C_d(ST(x_\ast)))] \tag{5}
\]

**Remark 1** Note ST performs inter-domain adaptation by employing attention mechanisms which are essentially simple matrix multiplication operations. Compared with GANs that perform image translation, ST is much more efficient as it can be trained with visual task model \( G \) in an end-to-end manner. Specifically, ST only involves 1 multi-head attention layer with about 37,000 parameters whereas a typical image translation GAN involves 9 convolutional layers with about 11,000,000 parameters which are computation-intensive [50]. In addition, GANs need to be pre-trained before UDA and they also tend to modify image semantic structures which is undesirable for UDA.

Multi-view Spectral Learning for Intra-domain Adaptation. For each target image \( x_\ast \), SUDA creates two complementary spectral views \( \hat{x}_1^\ast \) and \( \hat{x}_2^\ast \) by employing two spectrum transformers \( ST_1 \) and \( ST_2 \). We enforce \( ST_1 \) and \( ST_2 \) to have different parameters by a discrepancy weight loss \( L_\text{dis} \) so that \( ST_1 \) and \( ST_2 \) can learn complementary domain-invariant spectra of \( x_\ast \):

\[
L_\text{dis} = \frac{\tilde{\theta}_1 \cdot \tilde{\theta}_2}{\|\tilde{\theta}_1\| \|\tilde{\theta}_2\|}, \tag{6}
\]

where \( \tilde{\theta}_1 \) and \( \tilde{\theta}_2 \) denote the parameters in \( ST_1 \) and \( ST_2 \).

The two complementary views of the target image are then forwarded to a visual task model \( G \) which produces \( p_1 = G(\hat{x}_1^\ast) \) and \( p_2 = G(\hat{x}_2^\ast) \). To achieve intra-domain alignment, we maximize the mutual information of these two spectral views by minimizing a similarity loss \( L_\text{sim} \) between their predictions as follows:

\[
L_\text{sim} = \|p_1 - p_2\| \tag{7}
\]
Algorithm 1 The proposed Spectral Unsupervised Domain Adaptation (SUDA).

**Require:** Source domain \( D_s \); Target domain \( D_t \); Visual task model \( G \); Spectrum transformers \( ST_1 \) and \( ST_2 \)

**Ensure:** Learnt networks \( ST_1 \), \( ST_2 \) and \( G \)

1: for \( iter = 1 \) to \( Max\_Iter \) do
2: Sample a source data \( \{x_s, y_s\} \in D_s \) and a target data \( x_t \in D_t \)
3: \textbf{Inter-domain Adaptation:}
4: Calculate \( ST_1(x_s), ST_2(x_s), ST_1(x_t) \) and \( ST_2(x_t) \) via Eq. 2
5: Calculate \( L_{adv} \) by Eq. 5
6: \textbf{Intra-domain Adaptation:}
7: Calculate \( L_{dis} \) by Eq. 6
8: Calculate \( L_{sim} \) by Eq. 7
9: \textbf{Supervised Learning:}
10: Calculate \( L_{sup} \) by Eq. 1
11: Optimize \( ST_1, ST_2 \) and visual task model \( G \) by Eq. 8
12: end for
13: return \( ST_1, ST_2 \) and \( G \)

**Remark 2** Note SUDA employs a discrepancy loss \( L_{dis} \) as defined in Eq. 6 to learn two complementary ST modules, and this helps identify more comprehensive and discriminative domain-invariant spectra during the training process. Assume that a source image and a target image share 50% domain-invariant spectra in total, and a single ST could identify the most domain-invariant parts (e.g., the top 25% of them) only while striving to deceive the discriminator. With \( L_{dis} \), each of the two STs can identify different domain-invariant spectra and they together will identify much more than the top 25% most domain-invariant spectra.

**Overall Training Objective.** The objective of the proposed SUDA consists of three losses as shown in Algorithm 1. It includes a supervised task loss \( L_{sup} \) as defined in Eq. 1, an inter-domain adaptation loss \( L_{adv} \) as defined in Eq. 5, and an intra-domain adaptation loss \( L_{intra} \) which is the combination of the discrepancy loss \( L_{dis} \) in Eq. 6 and a similarity loss \( L_{sim} \) in Eq. 7. The overall training objective of the proposed SUDA can thus be formulated by

\[
\max_{C_d} \min_{G, ST} L_{sup} - \lambda_c L_{adv} + \lambda_i L_{intra},
\]

where \( \lambda_c \) and \( \lambda_i \) denote the balance weights for the inter-domain adaptation loss and the intra-domain adaptation loss, respectively.

### 3.3 Theoretical Insights

The proposed SUDA is inherently connected with some existing deep learning theories. Specifically, the inter-domain adaptation (by spectrum transformer) can be modeled as an example of cross-domain divergence minimization [3]. The intra-domain adaptation (by multi-view spectral learning) can be modeled as an example of Classification Expectation Maximization (CEM):

**Proposition 1** The inter-domain alignment (by ST) can be modelled as a cross-domain divergence minimization problem optimized via adversarial learning.

**Proposition 2** The intra-domain alignment (by MSL) can be modelled as a classification maximum likelihood (CML) problem optimized via Classification Expectation Maximization (CEM).

The proofs of Proposition 1 and 2 are provided in Section A.1 and A.2 of the Appendix, respectively.

### 4 Experiments

This section presents experiments including datasets and implementation details, domain adaptation evaluations for object detection, image classification, and semantic segmentation tasks, and discussion. More details are to be described in the ensuing subsections.
Table 1: Ablation study of the proposed Spectrum Transformer and Multi-view Spectral Learning over object detection task Cityscapes → Foggy Cityscapes.

| ST | MSL | person | rider | car | truck | bus | train | bicycle | mAP |
|----|-----|--------|-------|-----|-------|-----|-------|---------|-----|
| Single ST | | 49.3 | 38.0 | 57.2 | 15.2 | 34.7 | 14.4 | 28.1 | 42.4 | 34.0 |
| Two STs | ✓ | 50.4 | 49.3 | 62.8 | 21.1 | 44.4 | 16.6 | 33.1 | 47.4 | 40.6 |
| ✓ | | 50.9 | 52.1 | 67.7 | 20.1 | 42.7 | 17.7 | 33.9 | 49.3 | 41.8 |
| ✓ ✓ | | 50.5 | 51.7 | 64.1 | 26.7 | 48.5 | 13.1 | 38.1 | 49.5 | 42.8 |

Table 2: Experiments on UDA-based object detection task Cityscapes → Foggy Cityscapes.

| Method | DAF [13] | SWDA [61] | CRDA [76] | SCDA [87] | SAP [40] | CF [85] |
|--------|-----------|-----------|-----------|-----------|---------|--------|
| Faster R-CNN [35] (Baseline) | | | | | | |
| ResNet-50 | 49.3 | 49.0 | 49.1 | 51.2 | 50.5 | 49.4 |
| ResNet-50+ | 50.4 | 49.7 | 51.1 | 51.6 | 51.7 | 49.7 |
| ResNet-50+ | 50.9 | 50.3 | 51.7 | 51.6 | 51.6 | 49.7 |
| ResNet-50+ | 50.6 | 49.6 | 50.8 | 50.7 | 50.5 | 49.8 |
| ResNet-50+ | 50.2 | 51.7 | 50.9 | 49.8 | 49.8 | 49.8 |
| ResNet-50+ | 49.4 | 49.3 | 49.1 | 49.5 | 49.3 | 49.1 |

4.1 Datasets

**Adaptation for Object Detection:** We consider two adaptation tasks Cityscapes [14] → Foggy Cityscapes [64] and PASCAL VOC [19] → Clipart1k [35]. Cityscapes has 2975 training images and 500 validation images, where the bounding boxes are generated from pixel-wise annotations as in [15] [61]. Foggy Cityscapes is derived from Cityscapes by adding simulated fog. We adopt the training images of Cityscapes and Foggy cityscapes as source domain and target domain, and evaluate on the 500 validation images of Foggy Cityscapes. PASCAL VOC [19] is collected from real world, while Clipart1k [35] is an artistic dataset from CMPlaces [9] and two image search engines. We adopt PASCAL VOC 2007 (with 2, 501 training images and 2, 510 validation images) and PASCAL VOC 2012 (with 5, 717 training images and 5, 823 validation images) as source domain, 1, 000 images in Clipart1k as target domain and half of Clipart1k as validation dataset as in [35] [38] [61].

**Adaptation for Image Classification:** We evaluate two adaptation tasks VisDA17 [51] and Office-31 [59]. VisDA17 has 152, 409 synthetic image and 55, 400 real images with 12 categories in common. We consider the synthetic→real here. Office-31 has images of 31 classes from Amazon (A), Webcam (W) and DSLR (D) which have 2817, 795 and 498 images, respectively. Following [90] [59] [65], we study six adaptation tasks: A→W, D→W, W→D, A→D, D→A, and W→A.

**Adaptation for Semantic Segmentation:** We consider two synthetic-to-real tasks including GTA5 [59] → Cityscapes [14] and SYNTHIA [58] → Cityscapes. Cityscapes here has 30 categories with pixel-wise annotations. GTA5 has 24, 966 synthetic images and shares 19 categories with Cityscapes. For SYNTHIA, we use ‘SYNTHIA-RAND-CITYSCAPES’ which contains 9, 400 synthetic images and shares 16 categories with Cityscapes. For the two tasks, we adopt the 2975 training images in Cityscapes as target domain and evaluate on the 500 validation images in Cityscapes.
Table 4: Experiments on UDA-based image classification task over Office-31.

| Method     | A→W | D→W | W→D | A→D | D→A | W→A | Mean  |
|------------|-----|-----|-----|-----|-----|-----|-------|
| ResNet-50  | 81.9 | 8.5 | 3.8 | 85.9 | 0.1 | 3.8 | 85.9  |
| DAN [56]   | 80.5 | 97.3 | 99.6 | 78.6 | 63.6 | 62.8 | 80.4  |
| RGT [77]   | 84.5 | 96.8 | 99.4 | 77.5 | 66.2 | 64.8 | 81.4  |
| DANN [88]  | 82.0 | 96.9 | 99.1 | 79.7 | 68.2 | 67.4 | 82.2  |
| ADDA [50]  | 86.2 | 96.2 | 98.4 | 77.8 | 69.5 | 68.9 | 82.9  |
| JAN [53]   | 85.4 | 97.4 | 99.8 | 84.7 | 68.5 | 70.4 | 84.1  |
| GTA [67]   | 89.5 | 97.9 | 99.8 | 87.7 | 72.8 | 71.4 | 86.5  |
| CBST [90]  | 87.8 | 98.5 | 100 | 86.5 | 71.2 | 70.9 | 85.8  |
| +SUDA      | 91.2 | 99.2 | 100 | 93.4 | 75.2 | 73.6 | 88.8  |
| CRST [50]  | 89.4 | 98.9 | 100 | 88.9 | 72.5 | 70.9 | 86.5  |
| +SUDA      | 91.6 | 98.6 | 100 | 94.3 | 76.2 | 75.9 | 89.4  |
| SUDA       | 90.1 | 98.0 | 99.8 | 93.0 | 73.7 | 73.5 | 88.0  |

Table 5: Experiments on UDA-based image classification task VisDA17.

| Method     | Aero | Bike | Bus | Car | Horse | Knife | Motor | Person | Plant | Skateboard | Train | Track |
|------------|------|------|-----|-----|-------|-------|-------|--------|-------|------------|-------|-------|
| ResNet-101 | 85.1 | 53.5 | 61.9 | 59.1 | 80.6 | 17.9 | 97.7 | 31.2 | 81.0 | 26.3 | 75.3 | 8.5 | 52.4 |
| MMD [46]   | 87.1 | 63.0 | 76.5 | 42.0 | 90.3 | 42.9 | 85.9 | 53.1 | 49.7 | 36.3 | 85.8 | 20.7 | 61.1 |
| DANN [46]  | 81.9 | 77.7 | 82.8 | 44.3 | 81.2 | 29.5 | 65.1 | 28.6 | 51.9 | 45.6 | 82.8 | 7.8 | 57.4 |
| ENM [46]   | 80.3 | 75.5 | 75.8 | 48.3 | 77.9 | 27.3 | 69.7 | 40.2 | 46.5 | 46.6 | 79.3 | 16.0 | 57.0 |
| MCD [62]   | 87.0 | 60.9 | 83.7 | 64.0 | 88.9 | 79.6 | 84.7 | 76.9 | 88.6 | 40.3 | 83.0 | 25.8 | 71.9 |
| ADR [62]   | 87.8 | 79.5 | 83.7 | 65.3 | 92.3 | 61.8 | 88.9 | 73.2 | 87.8 | 60.0 | 85.5 | 32.3 | 74.8 |
| SimNet-Res5 [49] | 93.1 | 82.3 | 73.5 | 47.2 | 87.9 | 49.2 | 75.1 | 79.7 | 85.3 | 68.5 | 81.1 | 50.3 | 72.9 |
| GTA-Res152 | 89.8 | - | - | - | - | - | - | - | - | - | - | - | 77.1 |
| CBST [89]  | 87.2 | 78.8 | 96.5 | 55.4 | 83.1 | 79.2 | 83.8 | 71.7 | 82.8 | 88.8 | 69.0 | 72.0 | 66.4 |
| +SUDA      | 91.5 | 79.7 | 71.9 | 66.5 | 88.5 | 81.1 | 85.6 | 79.5 | 86.2 | 86.5 | 79.9 | 74.3 | 80.9 |
| SUDA       | 88.3 | 79.3 | 66.2 | 64.7 | 87.4 | 80.1 | 85.9 | 78.3 | 86.3 | 87.5 | 78.8 | 74.5 | 79.8 |

4.2 Implementation Details

**Object Detection:** For Cityscapes→ Foggy Cityscapes, we adopt deformable-DETR [88] and Faster R-CNN [55] as detection networks and ResNet-50 [28] as backbone as in [6, 78, 88]. For deformable-DETR, we adopt SGD optimizer [4] with a momentum 0.9 and a weight decay $1e^{-4}$. The initial learning rate is $2e^{-4}$. For Faster R-CNN, we use SGD optimizer [4] with a momentum 0.9 and a weight decay $5e^{-4}$. The initial learning rate is 0.001. For PASCAL VOC → Clipart1k, we adopt Faster R-CNN with ResNet-101 [28] as the detection network as in [35, 61]. We use SGD optimizer [4] with a momentum 0.9, a weight decay 0.0001, and an initial learning rate 0.001.

**Image Classification:** Following [90, 59, 61], we use ResNet-101 and ResNet-50 [28] as backbones for the tasks VisDAA17 and Office-31, respectively. We adopt SGD optimizer [4] with a momentum 0.9 and a weight decay $5e^{-4}$. The initial learning rate is $1e^{-3}$.

**Semantic Segmentation:** We use DeepLab-V2 [11] with ResNet-101 [28] as the segmentation network as in [68, 89]. We use SGD optimizer [4] with a momentum 0.9 and a weight decay $1e^{-4}$. The initial learning rate is $2.5e^{-4}$ and decayed by a polynomial policy of power 0.9 [11].

For all visual recognition tasks, we set the number of frequency components $N$ at 32. For AMSA, we set the number of heads $H$ at 8. The weight factors $\lambda_c$ and $\lambda_t$ in Eq. [8] are fixed at 0.1. All experiments are conducted in Pytorch with a single Tesla V100 GPU, except for the experiments using deformable-DETR [55] as the detection network, which uses 4 Tesla V100 GPUs.

4.3 Domain Adaptive Object Detection

We perform ablation studies on the task Cityscapes→ Foggy Cityscapes. Table 1 shows experimental results, where Single ST and Two STs denote a single ST and two STs (ST1 and ST2) of different parameters, respectively. It can be seen that both Single ST and Two STs outperform the baseline (deformable-DETR) by large margins, while Two STs performs clearly better than Single ST as two complementary STs encourage to learn more comprehensive and discriminative domain-invariant spectra. In addition, SUDA with Two STs and MSL performs clearly the best, demonstrating the effectiveness of the proposed multi-view spectral learning.

Tables 2 and 3 show experiments on the UDA tasks Cityscapes→ Foggy Cityscapes and PASCAL VOC → Clipart1k, respectively. It can be observed that SUDA achieves very competitive object detection performance as compared with all state-of-the-art methods with different network archi-
Table 6: Experiments on UDA-based semantic segmentation task GTA5 → Cityscapes.

| Method   | Cityscapes | SynthIA | GTA5 |
|----------|------------|---------|------|
| Baseline | 9.8        | 14.1    | 6.8  |
| PatAlign | 14.9       | 19.1    | 11.2 |
| AdaptSeg | 16.1       | 20.1    | 12.3 |
| AdaSeg   | 17.7       | 21.7    | 13.4 |
| AdvEnt   | 18.9       | 22.9    | 14.5 |
| IFPSM     | 19.6       | 23.6    | 15.1 |
| IDA       | 20.1       | 24.1    | 15.6 |
| CRST      | 20.5       | 24.5    | 16.1 |
| BDL       | 21.0       | 25.0    | 16.6 |
| CoCoDA    | 21.5       | 25.5    | 17.1 |
| SIM       | 21.7       | 25.7    | 17.3 |
| +SUDA     | 22.3       | 26.3    | 17.9 |

Table 7: Experiments on UDA-based semantic segmentation task SYNTHIA → Cityscapes.

| Method   | Cityscapes | SynthIA | GTA5 |
|----------|------------|---------|------|
| Baseline | 9.8        | 14.1    | 6.8  |
| PatAlign | 14.9       | 19.1    | 11.2 |
| AdaptSeg | 16.1       | 20.1    | 12.3 |
| AdaSeg   | 17.7       | 21.7    | 13.4 |
| AdvEnt   | 18.9       | 22.9    | 14.5 |
| IFPSM     | 19.6       | 23.6    | 15.1 |
| IDA       | 20.1       | 24.1    | 15.6 |
| CRST      | 20.5       | 24.5    | 16.1 |
| BDL       | 21.0       | 25.0    | 16.6 |
| CoCoDA    | 21.5       | 25.5    | 17.1 |
| SIM       | 21.7       | 25.7    | 17.3 |
| +SUDA     | 22.3       | 26.3    | 17.9 |

4.4 Domain Adaptive Image Classification

4.5 Domain Adaptive Semantic Segmentation

4.6 Discussion

Generalization across Computer Vision Tasks: We demonstrate that SUDA is a generic UDA technique across various visual recognition tasks in object detection, image classification and semantic segmentation. For different tasks, the implementation of SUDA is simple as described in Section 4.2 without little fine-tuning. Experiments in Table 6 show that SUDA performs consistently well.

Complementarity Study: We demonstrate that SUDA is complementary to existing state-of-the-art methods consistently across different visual recognition tasks in Tables 6, 7. The synergistic effect is largely attributed to the spectral transformer that mitigates domain gaps and the multi-view spectral learning that captures more comprehensive and confident representations of target-domain data.

Due to the parameter limit, we provide the parameter studies of parameter $N$ and balance weights ($\lambda_c$, $\lambda_s$) in the supplementary material.
5 Conclusion

In this work, we present SUDA, an innovative spectral-space UDA technique that addresses UDA challenges by learning domain-invariant spectral features. SUDA consists of two key designs. The first is a spectrum transformer that mitigates inter-domain alignment by highlighting domain-invariant spectra and suppressing domain-variant spectra in the input space. The other is multi-view spectral learning that performs intra-domain alignment by learning multiple spectral representations of each target sample. The proposed SUDA has three unique features. First, it is generic to various visual recognition tasks with consistently superior performance. Second, It is learnable and can be end-to-end trained with down-stream tasks. Third, it complements with existing UDA methods with consistent performance boosts. Extensive experiments show its superior performance across various visual recognition tasks. Moving forwards, we will continue to investigate novel techniques and strategies for unsupervised domain adaptation in the spectral space.

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