Dual Domain-Adversarial Learning for Audio-Visual Saliency Prediction

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ABSTRACT
Both visual and auditory information are valuable to determine the salient regions in videos. Deep convolution neural networks (CNN) showcase strong capacity in coping with the audio-visual saliency prediction task. Due to various factors such as shooting scenes and weather, there often exists moderate distribution discrepancy between source training data and target testing data. The domain discrepancy induces to performance degradation on target testing data for CNN models. This paper makes an early attempt to tackle the unsupervised domain adaptation problem for audio-visual saliency prediction. We propose a dual domain-adversarial learning algorithm to mitigate the domain discrepancy between source and target data. First, a specific domain discrimination branch is built up for aligning the auditory feature distributions. Then, those auditory features are fused into the visual features through a cross-modal self-attention module. The other domain discrimination branch is devised to reduce the domain discrepancy of visual features and audio-visual correlations implied by the fused audio-visual features. Experiments on public benchmarks demonstrate that our method can relieve the performance degradation caused by domain discrepancy.

CCS CONCEPTS
• Computing methodologies → Interest point and salient region detections.

KEYWORDS
Audio-visual saliency prediction, Cross-modal self-attention, Unsupervised domain adaptation.

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1 INTRODUCTION
Visual saliency prediction (VSP) aims to extract important regions from input images, which is inspired by the selective attention mechanism of humans. It has a very wide range of application in computer vision tasks, such as video summarization [1], stream compression [2], video monitoring [3], etc. In real world, visual signals are usually accompanied by audio signals, which can also provide valuable clues for locating salient regions. Recently, the audio-visual saliency prediction (AVSP) task has attracted extensive research interest. Benefiting from their strong representation capacity, deep convolutional neural networks (CNN) bring huge development to this field [4, 5]. However, CNN models trained with source data usually do not perform well on target data due to the data distribution shift. This paper focuses on studying the unsupervised domain adaptation problem for AVSP.

Existing AVSP methods [4–6] mainly concentrate on modeling the feature representations of auditory and visual inputs and the interactions between the two kinds of inputs. They all employ a two-branch framework to encode the audio and video inputs. A 3D convolution branch is leveraged to extract visual features from video inputs. [4] utilizes a 3D convolution branch to extract auditory feature representations from the log mel-spectrogram frames of the audio inputs, while [5–7] implement the audio representation modeling with SoundNet [8]. Fusing the visual and auditory features is the other critical point in AVSP. [5] simply uses the concatenation operation to fuse the two kinds of features. [6] devises attention mechanisms to explore the spatial and temporal dependencies between the two features. These methods achieve excellent performance under the circumstance that testing data obeys the same distribution with training data. However, the unsupervised adaptation of them to unseen testing data is still under research.

The exploration of visual contrast information and audio-visual interaction is critical to settle the AVSP task. However, these factors...
can be easily influenced by the shooting conditions. Objects having relatively higher contrast to background stuffs are more prone to attract attention of humans. The identities of such objects are flexible and vary as the change of shooting scenes. Visual data differences induced by such factors can degrade the performance of AVSP methods learned with stationary source data. It is likely to contain crucial cues for recognizing salient regions in the audio information accompanying video data. However, the intrinsic attributes of sound data such as pitch, loudness, and timbre are diversified among videos. On the other hand, the relevance between audio and salient regions is variant according to different types of videos. For example, the sound resource locations are usually consistent with salient regions in speaking videos as indicated by the ’news’ example of Fig. 1; salient regions can not be thoroughly identified out according to sounds in more general social videos like the ’soccer’ example of Fig. 1; in natural scene videos (’scenery’ and ’kids playing in leaves’ of Fig. 1), the audio data is generated by multiple sound resources, and the connection between audio and salient regions is sometimes ambiguous. Due to the above factors, the performance of AVSP methods can be hampered by the domain discrepancy caused by variances of the audio data and the video data.

To deal with the issue of domain discrepancy, we propose a dual domain-adversarial learning framework on the basis of the unsupervised domain adaptation paradigm (Fig. 2 (a)). Following existing methods [5, 6], we set up independent branches for extracting features from audio and video inputs respectively. First, an auditory feature domain discriminator is set up to eliminate the impacts of audio data variance. It guides the optimization of the audio feature extraction branch via adversarial training and helps to produce domain-invariant audio features. Then, a cross-modal self-attention module as shown in Fig. 2 (b) is devised to fuse auditory features into visual features extracted by a 3D convolution backbone. The other domain discriminator is adopted to learn fused audio-visual features having a uniform distribution across source and target domains. This is helpful for mitigating the domain discrepancy caused by the variance of visual features and the relation between auditory and visual features. To synthesize the effect of domain discrepancy, we set up two experimental settings: 1) videos captured under different types of scenes are regarded as samples of source and target domains; 2) datasets collected from different sites are regarded as source and target domains. Extensive experiments on two settings demonstrate that our proposed method is effective in making up the performance reduction caused by domain discrepancy.

In summary, the main contributions of this paper are as follows.

1) We make an early attempt to tackle the unsupervised domain adaptation problem for audio-visual saliency prediction.
2) A dual domain adversarial learning framework is proposed for aligning the audio-visual feature distributions between source and target domains.
3) We conduct extensive experiments on cross-scene and cross-dataset adaptation settings, validating the efficacy of our proposed method.

2 RELATED WORK
2.1 Video Saliency

With the development of deep convolutional neural networks, a vast number of saliency prediction methods are proposed, and they achieve excellent performance on the image saliency prediction [9–12] and video saliency prediction [13–16] task. In video saliency prediction, many recent methods utilize an LSTM to extract spatial and temporal visual features. Wang et al. [15] propose a CNN-LSTM network architecture with an attention mechanism. Linardos et al. [17] add a ConvLSTM to an existing neural network and wrap a convolutional layer by using a temporal exponential moving average(EMA) operation. Some existing models have explored 3D-CNN architecture to learn visual features. TASED-Net [16] is a 3D fully-convolutional network, including an encoding network to extract spatiotemporal features and a prediction network to produce a single saliency map. STSConvNet [13] extract the temporal and spatial information by using a two-stream network architecture, then fusing them to get a saliency map. Fang et al. [18] proposed a densely nested top-down flows (DNTDF)-based framework to predict pixel-wise salient object regions. [19] designed an ICON to integrate the features from the micro level and macro level. In [20], a relational reasoning network is proposed for SOD in optical RSIs.
[21] review some visual saliency detection algorithms with comprehensive information. Liu et al. [22] incorporated multi-modal information to learn attention by integrating self-attention and each other’s attention. [23] is the first work to employ uncertainty for RGB-D saliency detection, which generates multiple saliency maps by modeling human annotation uncertainty. A survey of RGB-D salient object detection is provided by Zhou et al. [24].

2.2 Audio-Video Saliency

Some early audio-visual saliency prediction methods have been explored for application-specific [25–28]. They employ traditional signal processing techniques for visual saliency and audio localization. Coutrot et al. [29] extract static and dynamic video features by using Gabor filters, then weighing the face regions appropriately and combining the visual saliency map to generate the final audio-visual saliency map. Also, Min et al. [30] propose an audio-visual model to predict the salient region in the scenes containing moving and sound-generating objects. They generate the saliency map by fusing the audio, spatial, and temporal attention maps.

However, only a few works have explored the end-to-end network for audio-visual saliency fixation prediction based on deep learning. Tavakoli et al. [4] adopt two 3D-ResNet as the backbone of the two modalities respectively, and their outputs are catenated for encoding. Tsiami et al. [5] propose STAViS, which employs a multi-modal network that combines visual and auditory information at multiple stages. Furthermore, they investigate the fusion approaches such as computing the cosine similarity, taking the weighted inner product, and bilinear transformation to fuse the audio modality. Jain et al. [7] propose a hierarchical structure for audio-video saliency prediction. They analyze three fusion mechanisms, including simple concatenation, bilinear fusion, and transformer-based fusion, to fuse video and audio cues. Zhu et al. [31] propose a lightweight audio-visual saliency model for the audio-visual saliency fixation prediction task. Although these methods show excellent performance, they do not involve the study of unsupervised domain adaptation when the distribution of unlabeled testing data differs from training data.

2.3 Domain Adaptation

Unsupervised domain adaptation (UDA) is targeted at aligning the data distribution of labeled source domain and unlabeled target domain. Thus, the model trained in the source domain can be directly migrated to the target domain without significant performance degradation. The core issue in UDA is how to align the distributions of source and target data. A large number of UDA algorithms have been proposed for classical computer vision tasks such as image classification and semantic segmentation, based on image translation [32, 33], maximum mean discrepancy minimization [34], or domain adversarial learning [35, 36]. In this paper, we concentrate on the unsupervised domain adaptation for audio-visual saliency prediction which has not been studied in previous literature.

3 METHOD

This paper aims to tackle the unsupervised domain adaptation for AVSP. Assume the source domain data be $\{(A_s^i, V_s^i)\}_{i=1}^{N_s}$, where $A_s^i$ and $V_s^i$ denotes the video and audio of the $i$-th sample respectively. $N_s$ represents the number of source samples. The ground-truth saliency map for the $i$-th sample in the source dataset is denoted as $G_s^i$. For the target data, only a subset of unlabeled samples $\{(A_t^j, V_t^j)\}_{j=1}^{N_t}$, $N_t$ represents the number of target samples. The
The goal of this paper is to learn a CNN model capable of achieving high AVSP performance on the target domain data. A dual domain adversarial training pipeline is proposed for addressing the above problem. Technical details are introduced in following subsections.

### 3.1 Architecture Overview

Fig. 3 illustrates the proposed architecture for cross-modal audio-visual saliency prediction. The proposed architecture consists of a visual branch to extract visual features, an audio branch to extract audio features, a cross-modal self-attention module to obtain correlated meaningful audio-visual features for saliency prediction, and a decoder module to decode the audio-visual features and get the final saliency map. Domain adaptation modules are added to make the model learn generalizable features. We input consecutive video frames $V$ and the corresponding sampled audio sequences $A$ into the visual and audio branches, respectively, and the final output is a saliency prediction map $P$. Each domain classifier outputs a binary result to indicate whether the input video comes from the target domain or the source domain.

For visual branch, we use S3D [37] as the backbone to extract visual features. The size of input video frames $V$ is $C_0 \times F_0 \times H_0 \times W_0$, where $F_0 = 32$ is the number of frames and $C_0 = 3$ is the number of frame channels. $H_0$ and $W_0$ represents the height and width of each frame, respectively. The output of the visual branch is $O_V$. The size of $O_V$ is $C \times F \times H \times W$, where $C = 1024$, $F = \frac{F_0}{8}$, $H = \frac{H_0}{32}$, and $W = \frac{W_0}{32}$.

For the audio branch, we adopt SoundNet [8] to encode the representation of the audio sequence, which is a 1-D fully convolutional network and is initially proposed for audio classification. The size of pre-processed audio sequence $A$ is $1 \times T_A \times 1$, and the size of the output features $O_A$ is $1024 \times 3 \times 1$.

For audio-visual fusion, inspired by [38], we use the cross-modal self-attention mechanism to fuse two modalities. $O_A$ and $O_V$ through dimensional changes are input to the cross-modal self-attention fusion module. For the details, see Section 3.2. Then the fusion information goes through a fully-connected layer and is added with $X_V$ to obtain the salient audio-visual features $O_{AV}$.

Afterwards, $O_{AV}$ are fed into a decoder consisting of six decoding layers. The first decoding layer contains a 3D convolution and a trilinear interpolation layer. Each of the next three decoding layers contains a concatenation, a 3D convolutional, and a trilinear upsampling layer. The concatenation operation combines the output of the visual block and the output of the last decoder layer along the temporal dimension. The fourth decoding layer is similar to the first layer. The last decoding layer is composed of two 3D convolutional layers, which project the channel and temporal dimension to 1. Finally, the single map goes through a sigmoid activation function to obtain a saliency map $P$.

Domain adaptation modules are applied to make the knowledge acquired in the labeled source domain to be better generalized in the unlabeled target domain. Specifically, the branch consisting of a gradient reversal layer and a domain classifier is added after the audio output and the output of the fusion module, respectively.

In the following, we mainly describe the cross-modal self-attention mechanism of the fusion module (see Section 3.2) and domain adaptation (see Section 3.3).

### 3.2 Cross-modal Self-attention

For the fusion of two modalities, previous methods such as computing the cosine similarity between two modalities, simple concatenation, bilinear fusion and so on, can not fully explore the correlation between two modalities. In order to obtain meaningful audio-visual correlation information, we adopt a cross-modal self-attention mechanism, which enables visual modality to receive information from audio modality selectively. The source audio
modality is used to reconstruct the information of visual modality and the cross-modal interaction between vision and audio is realized. Details about the cross-modal self-attention are as follows.

The output features of the visual branch $\mathbf{O}_V$ are first processed with a max pooling layer and are flattened to $\mathbf{x}_V \in \mathbb{R}^{C \times (HW)}$. Then the $\mathbf{x}_V$ passes through a 1-D convolution and then are collapsed as a vector $\mathbf{X}_V \in \mathbb{R}^{T_x \times d_v}$, and the audio features $\mathbf{O}_A$ are passed through a 1-D convolution and then are collapsed as a vector $\mathbf{X}_A \in \mathbb{R}^{T_x \times d_a}$. Where $T_x = H \times W = 42$, $T_A = 3$, and $d_V = d_A = 512$. $T_{i,j}$ is the length of the sequence and $d_{i,j}$ is the feature dimension. The cross-modal attention from $\mathbf{X}_A$ to $\mathbf{X}_V$ is defined as $Y_{A\rightarrow V}$. The calculation process is as below:

$$Y_{A\rightarrow V} = \text{softmax}\left(\frac{\mathbf{Q}_V^T \mathbf{K}_A}{\sqrt{d_k}}\right) \mathbf{V}_A$$

where $\mathbf{Q}_V = \mathbf{X}_V \mathbf{W}_{QV}$, $\mathbf{K}_A = \mathbf{X}_A \mathbf{W}_{K_A}$ and $\mathbf{V}_A = \mathbf{X}_A \mathbf{W}_{V_A}$ represent query, key and value in the cross-modal self-attention module. $\mathbf{W}_{QV} \in \mathbb{R}^{d_V \times d_k}$, $\mathbf{W}_{K_A} \in \mathbb{R}^{d_A \times d_k}$ and $\mathbf{W}_{V_A} \in \mathbb{R}^{d_A \times d_k}$ are weights.

In this way, we get the correlation between the audio sequence and the corresponding video, which plays a great role in determining the saliency region of the video. Then, $Y_{A\rightarrow V}$ is added back into $\mathbf{X}_V$, and a residual multi-layer perceptron is attached for further feature enhancement. The complete calculation process is illustrated in Fig. 2 (b).

### 3.3 Domain Adaptation

Our unsupervised domain adaptation module is constituted by a gradient inversion layer and a domain classifier. The gradient inversion layer is located between the feature extraction module and the domain classifier. During the error backpropagation process, this layer reverses the gradient direction, namely making the feature extraction module confuse the domain classifier. Such a manner avoids the two-stage training process of adversarial training. For the domain classifier, three $1 \times 1$ spatial convolution layers are adopted to compress the feature dimension. Afterwards, three fully-connected layers are attached, producing the domain classification score.

We setup two separate domain classifiers for audio features and fused audio-visual features respectively. The domain classifier of audio features is denoted as $D_A$, and that of audio-visual features is denoted as $D_{AV}$. Suppose the audio feature and the audio-visual feature extracted from a source domain sample $(A^s, V^s)$ be $O_A^s$ and $O_{AV}^s$, respectively. $O_A^s$ and $O_{AV}^s$ denotes the audio feature and the audio-visual feature of a target domain sample $(A^t, V^t)$, respectively. $O_A^t$ and $O_{AV}^t$ are fed into the audio classifier $D_A$, resulting in prediction scores $d_A^s$ and $d_A^t$, respectively. On the other hand, $D_{AV}$ predicts domain classification scores $d_{AV}^s$ and $d_{AV}^t$ from $O_{AV}^s$ and $O_{AV}^t$, respectively. The domain classification loss for $D_A$ is defined as $L_A$ and the loss for $D_{AV}$ is $L_{AV}$:

$$L_A(d_A^s, d_A^t) = -\log(d_A^s) - \log(1 - d_A^t),$$

$$L_{AV}(d_{AV}^s, d_{AV}^t) = -\log(d_{AV}^s) - \log(1 - d_{AV}^t).$$

### 3.4 Loss Function

The source domain images are employed for training the saliency prediction model with the Kullback-Leibler (KL) divergence. The training loss $L_s$ on source domain images is as below:

$$L_s(P^s, G^s) = \sum_{i=1}^{p_s} G^s(i) \log(\epsilon + \frac{G^s(i)}{P^s(i) + \epsilon}),$$

where $P^s$ is the saliency map predicted from $A^s$ and $V^s$, $G$ is the corresponding ground-truth map, and $\epsilon$ is a regularization parameter. $G^s(i)$ and $P^s(i)$ represents the $i$-th pixel of $G^s$ and $P^s$, respectively. $|P^s|$ denotes the number of pixels in $P^s$. The final loss function is formed by summing up (2), (3), and (4):

$$L = L_A + L_{AV}.$$
Figure 4: Sample frames from Coutrot1 dataset, and the corresponding ground truth, and saliency maps without adding DA, and adding DA after the audio branch and fusion module.

Table 2: Performance of our proposed method under various domain adaptation settings.

| Source data | Approach       | CC   | NSS  | sAUC  | AUC-J  | SIM   |
|-------------|----------------|------|------|-------|--------|-------|
| Faces       | w/o DA         | 0.4099 | 1.670 | 0.5981 | 0.8442 | 0.3587 |
|             | DA(audio)      | 0.4352 | 1.785 | 0.6021 | 0.8591 | 0.3574 |
|             | DA(audio + fusion) | **0.4488** | **1.843** | 0.5988 | **0.8625** | **0.3608** |
| Social      | w/o DA         | 0.477 | 1.9711 | 0.6019 | 0.8717 | 0.3742 |
|             | DA(audio)      | 0.4951 | 2.064 | 0.6016 | 0.8721 | 0.3964 |
|             | DA(audio + fusion) | **0.4985** | **2.084** | **0.6083** | **0.8727** | **0.3833** |

| Source data | Approach       | CC   | NSS  | sAUC  | AUC-J  | SIM   |
|-------------|----------------|------|------|-------|--------|-------|
| Coutrot1    | w/o DA         | 0.4685 | 2.274 | 0.5881 | 0.8673 | 0.3962 |
|             | DA(audio)      | 0.4749 | 2.298 | 0.5926 | 0.8716 | 0.3962 |
|             | DA(audio + fusion) | **0.4891** | **2.364** | **0.5927** | **0.8723** | **0.4057** |
| DIEM        | w/o DA         | 0.5640 | 2.281 | 0.6744 | 0.8857 | 0.4710 |
|             | DA(audio)      | 0.5692 | 2.300 | 0.6782 | 0.8898 | 0.4712 |
|             | DA(audio + fusion) | **0.5758** | **2.315** | **0.6797** | **0.8911** | **0.4714** |

4.2 Experimental Setup

In our experiment, for the visual branch, we use the weights pre-trained on DHF1K [15] to initialize the model. For the audio feature extraction network, we initialize the weights from the SoundNet pre-trained in the sound localization task [8]. The learning rate is set to be $10^{-4}$, and the batch size is 8 when training the model without domain adaptation. When adding the domain adaptation, the learning rate is set to be $10^{-5}$, and the batch size is set to 6. In all experiments, we adopt the Adam optimizer to update network parameters.

4.3 Results

We conduct domain adaptation experiments on several different combinations of datasets. Specifically, we take Faces/Social datasets as the source domain, and Nature dataset as the target domain, forming domain adaptation settings: Faces→Nature and Social→Nature. The result of not adding the domain adaptation (DA) is tested, denoted by w/o DA, which means the model is trained on the source domain and is tested directly on the target domain. DA(audio) and DA(audio + fusion) represent adding DA after the audio branch and adding DA after the audio branch and fusion module. The results
Figure 5: Sample frames from Coutrot2 and Coutrot1 datasets, and the corresponding ground truth, and saliency maps generated by our cross-model self-attention fusion and bilinear fusion for comparisons.

Table 3: Experimental results of using different auditory and visual feature fusion methods. Evaluation metrics are calculated by averaging results on ETMD, SumMe, Coutrot1, Coutrot2, DIEM and AVAD.

| Methods | CC   | NSS  | sAUC | AUC-J | SIM  |
|---------|------|------|------|-------|------|
| C       | 0.6167 | 3.367 | 0.6993 | 0.9155 | 0.4422 |
| B       | 0.6090 | 3.412 | 0.6965 | 0.9152 | 0.4427 |
| CM      | 0.6138 | 3.428 | 0.6757 | 0.9191 | 0.4735 |

Table 4: Comparision results. Evaluation metrics are calculated by averaging results on ETMD, SumMe, Coutrot1, Coutrot2, DIEM and AVAD.

|       | CC   | NSS  | sAUC | AUC-J | SIM  |
|-------|------|------|------|-------|------|
| STAViS | 0.5644 | 2.9683 | 0.6584 | 0.854 | 0.4345 |
| AViNet | 0.6118 | 3.3683 | 0.6998 | 0.9178 | 0.4445 |
| Ours  | 0.6138 | 3.428 | 0.6757 | 0.9191 | 0.4735 |

are shown in Table2. Among DIEM, Coutrot1 and AVAD datasets, we take AVAD dataset as the source domain, and DIEM/Coutrot1 datasets as the target domain, forming another two domain adaptation settings: AVAD→DIEM and AVAD→Coutrot1. The experimental results are shown in Table 2.

The experimental results show that the performance of the model on the unlabeled target domain datasets is improved by adding DA module. This indicates that the model with DA has learned the domain-invariant characteristics, and the discrepancy between source and target domain is mitigated. We also visualize the results in Fig.4, where the model with DA module performs better.

4.4 Ablation Study

**Efficacy of Dual Domain-Adversarial Learning.** We analyze the improvement of the model’s performance by adding DA (domain adaptation) in different parts of the model so as to determine the most appropriate position for adding DA. We perform ablation experiments in the following two cases: (1) adding DA after the audio branch (DA(audio)); (2) adding DA after the audio branch and fusion module (DA(audio + fusion)). Table 2 shows the test results of the model in the above two cases. The results show that adding DA after the audio branch and fusion module performs better.

**Efficacy of Cross-Modal Self-Attention.** We verify the effectiveness of our proposed fusion strategy on six audio-visual datasets by comparing it with existing fusion methods. One is concatenating
visual and auditory features, and the other is bilinear fusion. Table 3 shows the averaged evaluation metrics. ‘C’ represents simple concatenation, ‘B’ represents bilinear fusion, and ‘CM’ represents our proposed fusion strategy based on cross-modal self-attention mechanism. It can be seen from Table 3 that the proposed fusion method is superior to other methods on NSS, AUC-J, and SIM, demonstrating the effectiveness of our proposed fusion method. Furthermore, we compare the fusion methods qualitatively. In Fig.5, the first row depicts the sample frames from Coutrot2 and Coutrot1. The ground-truth saliency maps are presented in the second row. The final two rows include the saliency maps generated by bilinear fusion and our cross-modal self-attention fusion. As shown in the Figure 5, our results are closer to the ground truth. What’s more, to prove our model’s efficacy without DA for AVSP task, we compare our model with other AVSP methods. Table 4 shows the averaged evaluation metrics on six audio-visual datasets. As is shown, our method obtains better performance on several metrics.

5 CONCLUSION
In this work, we propose a dual domain-adversarial learning algorithm to solve the problem of unsupervised domain adaptation in audio-visual saliency detection. Specifically, we establish two domain discrimination branches to align the distribution of auditory audio-visual saliency detection. Experimental results show that our method can relieve the performance degradation caused by domain discrepancy on the audio-visual saliency prediction task.

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