Jitter Does Matter: Adapting Gaze Estimation to New Domains

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Abstract

Deep neural networks have demonstrated superior performance on appearance-based gaze estimation tasks. However, due to variations in person, illuminations, and background, performance degrades dramatically when applying the model to a new domain. In this paper, we discover an interesting gaze jitter phenomenon in cross-domain gaze estimation, i.e., the gaze predictions of two similar images can be severely deviated in target domain. This is closely related to cross-domain gaze estimation tasks, but surprisingly, it has not been noticed yet previously. Therefore, we innovatively propose to utilize the gaze jitter to analyze and optimize the gaze domain adaptation task. We find that the high-frequency component (HFC) is an important factor that leads to jitter. Based on this discovery, we add high-frequency components to input images using the adversarial attack and employ contrastive learning to encourage the model to obtain similar representations between original and perturbed data, which reduces the impacts of HFC. We evaluate the proposed method on four cross-domain gaze estimation tasks, and experimental results demonstrate that it significantly reduces the gaze jitter and improves the gaze estimation performance in target domains.

1 Introduction

Gaze indicates the direction along which a person is looking. It has been adopted in various applications, such as semi-autonomous driving (Demiris 2007; Majaranta and Bulling 2014; Park, Jain, and Sheikh 2013) and human-robot interaction (Admoni and Scassellati 2017; Terzioğlu, Mutlu, and Şahin 2020; Wang et al. 2015). With an increasing demand for predicting user intent implicitly, appearance-based gaze estimation has attracted more attention recently. To train the gaze estimator using deep learning neural networks, a number of large-scale datasets have been proposed (Zhang et al. 2020; 2017; Funes Mora, Monay, and Odobez 2014; Kellnhofer et al. 2019).

However, due to variations in subjects, backgrounds, and illuminations, the performance of deep learning-based gaze estimation algorithms deteriorate significantly when applying the model trained in one dataset to new datasets. Recently, several techniques have been applied to address this cross-domain problem, such as adversarial learning (Tseng et al. 2017; Cui et al. 2020), few-shot learning (Park et al. 2019; Yu, Liu, and Odobez 2019), and self-training (Cai, Lu, and Sato 2020). Among them, unsupervised domain adaptation (UDA) method (Wang et al. 2019; Kellnhofer et al. 2019; Liu et al. 2021) is one of the promising approaches that attracts much attention. While requiring no labels makes it more applicable to real-world scenarios, it also makes the task more challenging.

Existing approaches usually optimize the gaze accuracy during adaptation directly. Instead, we design an approach that starts with the analysis of a phenomena we observed that occurs in crossing domain tests. Where we can look for the factors that cause the problems, and the factors can then be used as guidance for us to find a more explainable solution for domain adaptation.

In this paper, we observe the gaze jitter phenomena: two very similar images could be predicted with gazes severely deviated (shown in Fig. 1), particularly when crossing domains. As shown in Fig. 1 on the test set in the source domain, the model gives similar predictions when the input images are similar. In contrary, in the target domain, even if the input images are very similar, the model may still give predictions that are severely deviated. In this paper, we name this phenomenon as gaze jitter, and in addition, we consider gaze jitter as a manifestation of gaze error across domains, and use this phenomenon as a starting point to find a solution for domain adaptation.

Based on the above observation, we start to analyze why the gaze jitter phenomenon occurs and discover an important factor, i.e., the high-frequency component (HFC), which introduces gaze jitter problem and lowers the gaze estimation accuracy. Inspired by this, we propose our gaze adaptation framework. At first, our framework adds additive HFC to the input data, then it employs contrastive learning to keep the consistency between the original data and the perturbed data, thus making the model learn features with less impact of high-frequency component. Our method leads to significant jitter reduction and performance improvement on various cross-domain gaze estimation tasks. The primary contributions of this paper are summarized as follows:

• For the first time, we discover the gaze jitter problem on cross-domain gaze estimation tasks. We find that high-frequency component is an important factor introducing jitters.
• We propose a framework for cross-domain gaze estima-
2.2 Unsupervised domain adaption

Unsupervised domain adaption (UDA) is a transfer learning task that requires no target labels. Previous UDA approaches can be divided into three categories: discrepancy, reconstruction, and adversarial methods. Discrepancy methods aim to minimize the domain gap using some distance metrics, such as Maximum Mean Discrepancy (MMD) (Ghifary, Kleijn, and Zhang 2014) and Local Maximum Mean Discrepancy (LMMMD) (Zhu et al. 2020). Reconstruction methods (Glorot, Bordes, and Bengio 2011; Bousmalis et al. 2016) use a reconstruction strategy that allows a model to learn features from both domains (Wang and Deng 2018). Adversarial methods are inspired by the generative adversarial network (GAN) (Goodfellow et al. 2014). In UDA tasks, contrastive learning is usually used to help the model learn better representations. It encourages augmentations of the same input to have more similar representations compared to augmentations of different inputs. Common contrastive learning frameworks achieve this aim by constructing two kinds of pairs: positive pairs containing similar instances and negative pairs containing different instances. Then it maximizes the consistency over the positive pairs and pushes apart samples from the negative pairs. Recent contrastive learning studies, e.g., Memory Bank (Wu et al. 2018), MoCo (He et al. 2020), SimCLR (Chen et al. 2020), and PCL (Li et al. 2020) have reached considerable improvement on some downstream tasks.

Contrastive learning has been used for UDA in some tasks, such as action recognition (Kang et al. 2020) and semantic segmentation (Liu et al. 2021b). The significant effect shows the capability of contrastive learning to learn useful representations.

3 Motivation

In this section, we observe that gaze jitter is a significant phenomenon in cross-domain gaze estimation. Then, we discover one important factor introducing jitter: high-frequency
component. Finally, we design a framework to adapt the gaze estimation to new domains with the guidance of this discovery.

3.1 Gaze Jitter: an Observation in Cross-Domain Gaze Estimation

As we know, the performance of pre-trained gaze estimation model usually degrades in unseen target domains. Most previous works study this problem only focusing the rise of gaze estimation error in target domains. However, along with the rise in error, we observe the gaze jitter phenomenon, i.e., images with similar appearances and labels can be predicted with severely deviated gaze directions. In our further analysis, we find the jitter is significantly larger in the target domain than in the source domain (Fig. 1). To numerically measure the magnitude of jitter, we define a new metric mean-angular-deviation (mav) as follow.

**Definition.** We denote the test dataset as \( \mathcal{D} = \{ (x_i, y_i)_i\}_{i=1}^N \), where \( x_i \) and \( y_i \) denote the i-th image and the corresponding gaze direction, \( N_D \) is the number of images. \( \{ \hat{y}_i \}_{i=1}^{N_D} \) is the prediction from an estimation model. We design \( \text{mav} \) to measure the magnitude of jitter:

\[
\text{mav}(\mathcal{D}) = \frac{1}{N} \sum_{x_i, x_j \in \mathcal{D}} |\langle \hat{y}_i, \hat{y}_j \rangle - \langle y_i, y_j \rangle|,
\]

s.t. \( \text{SSIM}(x_i, x_j) > \alpha \), \( \langle y_i, y_j \rangle < \beta \).

where \( \langle y_i, y_j \rangle \) indicates the angle between \( y_i \) and \( y_j \), \( N \) is the number of image pairs that satisfy the constraint, and \( \text{SSIM} \) measures the similarity between images [Wang et al. 2004]. The \( \text{mav} \) calculates the deviation between the angles of the predictions and labels from image pairs with similar appearance and labels. Empirically, we set \( \alpha = 0.75 \) and \( \beta = 1^\circ \).

To briefly verify the correctness of \( \text{mav} \), we add random noise (Gaussian) with gradually increasing level to the test data, the change of \( \text{mav} \) is illustrated in Fig. 2(a). The \( \text{mav} \) reflects the trend of magnitude correctly, i.e., stronger noise results in stronger jitter.

Using the \( \text{mav} \), we measure the magnitude of jitter on both source and target domains. Results are shown in Fig. 2(b), and the gaze jitter is indeed more significant on the target domain. Therefore, we treat gaze jitter as a good indicator to help analyze and optimize cross-domain gaze estimation.

3.2 Why Does Gaze Jitter Occur?

The question that arises is: Why does gaze jitter occur? According to [Wang et al. 2020], CNNs may capture high-frequency component (HFC) that are misaligned with human visual preference. This conclusion is coincide with the observed gaze jitter: images which are similar to human (similar appearance) could be very different to CNN (severely deviated gaze predictions). Therefore, we speculate HFC could also be a factor introducing jitter.

To verify this idea, we filter out information of target domain images from high to low-frequency by Fourier transform during testing and see the influence. Particularly, the proportion of information filtered out gradually increases (from 0 to 100%). As shown in Fig. 3(a), filtering out HFC reduces both the gaze jitter and error, which proves the conjecture that HFC is one of the factors introducing gaze jitter. In addition, the results in Fig. 2(a) also support this conjecture, since HFC is also added when adding random noise. Based on this discovery, reducing the impact of HFC can be an effective direction to improve cross-domain accuracy and reduce gaze jitter.

3.3 Domain Adaptation by Contrastive Learning

To reduce the impact of HFC, we propose to utilize contrastive learning. In contrastive learning, positive pairs are generated from a given sample by data augmentations. Then, contrastive loss pulls the features of positive pairs closer. As a result, the model extracts better feature and learns better generalization ability [Kang et al. 2020]. The model extracts similar feature from positive pairs and learns to neglect irrelevant differences between positive pairs caused by data augmentation.

Accordingly, we propose to generate such positive pairs from target domain images by adding HFC. Under the con-

![Figure 2](image-url)

Figure 2: (a) The magnitude of jitter measured by \( \text{mav} \) when adding random noise (Gaussian) with gradually increasing scale to the test data. (b) The magnitude of jitter on the source and target domains. The ETH-XGaze and Gaze360 datasets are employed as source domains, and the MPIIGaze and EyeDiap datasets are used as target domains.

![Figure 3](image-url)

Figure 3: (a) and (b) illustrate the level of gaze jitter and angular gaze error on the target domain (MPIIGaze) using low-pass images, respectively. X axis indicates the percentage of high-frequency information filtered out, and the dotted lines illustrate the results when giving original images as input.
strain of contrastive loss, gaze estimation model extracts similar features for positive pairs i.e. original image and image with additive HFC. In this way, the impact of HFC are reduced. Consequently, gaze jitter in target domain is reduced and the generalization ability to target domain is improved.

The final question is what type of HFC should be used. In this paper, we show that using adversarial noise to generate positive pairs is effective. First, adversarial noise is a form of HFC [Zhou et al. 2021][Olivier, Raj, and Shah 2021]. Second, previous work [Wang et al. 2020] proves that adversarial vulnerability is a indicator when CNN captures HFC. Our experiments show that adversarial noise outperforms other data augmentation methods in Sec. 5.2.

4 Method

4.1 Overview

First in the data augmentation phase (Sec. 4.2), we use adversarial attacks to add high frequency information to the data and generate positive pairs. Then, the contrastive learning module will reduce the impact of HFC by optimizing the contrastive loss (Sec. 4.3). Finally, we follow the idea of commonly-used adversarial learning to adapt the model to the target domain (Sec. 4.4). An overview of the architecture is described in Fig. 4.

4.2 Data Augmentation for Contrastive Learning

Adversarial Attack According to Sec. 3.3, adversarial attack is a good choice for data augmentation. Therefore, we use adversarial attacks to add adversarial noise and generate positive pairs. Existing adversarial attacks mainly follow two different ideas, the first one is fast gradient sign method (FGSM) [Goodfellow, Shlens, and Szegedy 2014]:

\[
    x' = x + \epsilon \cdot \text{sign}(\nabla_x \mathcal{L}(f(x), y)),
\]

where \( \epsilon \) is the magnitude of the perturbation. This attack is a simple one-step scheme. By contrast, another idea is to use the multi-step variant, which is essentially projected gradient descent (PGD) [Madry et al. 2017a]:

\[
    x^{t+1} = \Pi_{x+S}(x^t + \epsilon \cdot \text{sign}(\nabla_x \mathcal{L}(f(x), y))),
\]

where \( \Pi \) is the projection function. In this paper, we simultaneously use FGSM and PGD to generate adversarial noise. Although the noise usually cannot affect human cognition, it can easily fool deep neural networks.

Adding High-Frequency Component Here we use adversarial attack described before for data augmentation, where HFC is added to the data. As shown in Fig. 4, our method takes source-target pairs \((x^s, x^t)\) as inputs. The gaze estimation network \( G(\theta_G) \) contains a feature extractor \( F(\theta_G) \), which follows a multi-layer perceptron. Note that the parameters \( \theta_G \) loaded by \( G \) before adaptation are pre-trained with the source domain data \( D_s \).

Before adaptation, with the target domain data \( D_t \) as input, the network \( G(\theta_G) \) would generate pseudo labels \( \{y_{iN}^{t}\}_{i=1}^{N} \) by simply forward propagation. At each training iteration, a batch of \( B \) source-target pairs are randomly sampled from \( D_s \) and \( D_t \), resulting in pairs: \( \{ (x_{i}^{s}, x_{i}^{t})_{i=1}^{B} \} \).

Their augmented samples \( \{ (x_{i}^{s}, x_{i}^{t})_{i=1}^{B} \} \) are generated as follow:

\[
    x_{i}^{s,t} = \begin{cases} \text{FGSM}(x_{i}^{s,t}, y_{i}^{s,t}, \mathcal{L}_{gaze}), & 0.5, \\ \text{PGD}(x_{i}^{s,t}, y_{i}^{s,t}, \mathcal{L}_{gaze}), & 0.5. \end{cases}
\]

where FGSM and PGD are defined as Eq. 2 and Eq. 3. During adaptation, each image is augmented with 50-50 probability using one of both methods. \( \mathcal{L}_{gaze} \) is usually defined as L1 loss:

\[
    \mathcal{L}_{gaze}(x, y; \theta_G) = \|G(x; \theta_G) - y\|_1.
\]

4.3 Contrastive Optimization

As described in Sec. 3.3, we use contrastive learning to reduce the impact of HFC. By encouraging the original and augmented samples to have similar representations, the network learns the ability to learn features with less impact of HFC.

After the data augmentation, we have in total \( 4B \) samples \( \{x_{i}^{s}, x_{i}^{t}, x_{i}^{s}, x_{i}^{t}\}_{i=1}^{B} \). Taking a target sample \( x_{i}^{t} \) for example, only \( (x_{i}^{u}, x_{i}^{u}) \) is treated as a positive pair for contrastive learning, the other \( 4B - 2 \) samples are considered negative ones. Therefore, following the definition from (Chen et al. 2020), we define the contrastive loss \( \ell_{con}(x_{u}, x_{v}) \) for a positive pair \( (x_{u}, x_{v}) \) as:

\[
\begin{align*}
\ell_{con}(x_{u}, x_{v}; \theta_G) &= -\log \frac{\exp(sim(F(x_{u}; \theta_G), F(x_{v}; \theta_G))/\tau)}{\sum_{i\neq u} \exp(sim(F(x_{u}; \theta_G), F(x_{i}; \theta_G))/\tau)}, \\
\text{where } \tau &= \text{a temperature hyper-parameter (Wu et al. 2018),}
\end{align*}
\]

we empirically set \( \tau = 0.5 \). The similarity measure \( sim(f_{u}, f_{v}) \) is defined with dot product as:

\[
    \text{sim}(f_{u}, f_{v}) = \frac{f_{u} \cdot f_{v}}{||f_{u}|| \cdot ||f_{v}||},
\]

In our method, the total contrastive loss \( \mathcal{L}_{con}(x^s, x^t, x^s, x^t) \) is computed over all positive pairs in a batch.

4.4 Adversarial Domain Adaptation

For better adaptation, we follow the idea of commonly-used adversarial learning to adapt the model to new domains. A domain discriminator \( \mathcal{D}(\cdot; \theta_D) \) is introduced, and the loss functions are defined as follows to encourage it to play a min-max game with the feature extractor \( F \).

\[
\begin{align*}
\arg\min_{\theta_D} \mathcal{L}_{dis}(x^s, x^t; \theta_D) &= -\log(1 - D(F(x^s, x^t); \theta_D)) - \log D(F(x^t, x^t); \theta_D), \\
\arg\min_{\theta_G} \mathcal{L}_{adv}(x^t; \theta_G) &= -\log(1 - D(F(x^t; \theta_G))).
\end{align*}
\]
The adversarial learning follows the classical procedure that are proved to be effective on domain adaptation tasks (Tzeng et al. 2017; Cui et al. 2020). In summary, our goal of optimization on the gaze estimation network is defined as:

\[
\mathcal{L} = \mathcal{L}_{\text{gaze}}(x^s, y^s; \theta_G) + \mathcal{L}_{\text{gaze}}(x'^s, y^s; \theta_G) + \\
\lambda_1 \mathcal{L}_{\text{con}}(x^s, x'^s, y^s; \theta_G) + \\
\lambda_2 (\mathcal{L}_{\text{adv}}(x^s; \theta_G) + \mathcal{L}_{\text{adv}}(x'^s; \theta_G)),
\]

where \(\lambda_1\) and \(\lambda_2\) are tunable parameters. We empirically set \(\lambda_1 = 1.0\) and \(\lambda_2 = 0.1\) in our experiments.

### 4.5 Adaptation Procedure

The adaptation procedure is summarized in Algorithm 1. A small amount of data (i.e., 100 images) with ground-truth labels from the source domain \(D_s\) and a small amount of data (i.e., 100 images) from the target domain \(D_t\) are used for unsupervised adaptation. During adaptation, the network \(G(\cdot; \theta_G)\) is trained by minimizing the loss function Eq. (9), and the domain discriminator \(D(\cdot; \theta_D)\) is trained by minimizing the loss function Eq. (8).

#### 5 Experiments

### 5.1 Data preparation

Due to the variation in different datasets, data preparation is necessary. In our domain adaptation task, we utilize the ETH-XGaze (E) and Gaze360 (G) dataset as source domains, and MPIIGaze (M) and EyeDiap (D) dataset as target domains.

The ETH-XGaze dataset (Zhang et al. 2020) provides 80 subjects (i.e., 756,540 images), and we use them all as a source domain. For the Gaze360 dataset (Kellnhofer et al. 2019), we remove the images without subjects’ faces and employ the remaining 112,251 images. For the MPIIGaze dataset (Zhang et al. 2017), we adopt the provided evaluation protocol to generate the evaluation set, which contains 3,000 images.

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**Algorithm 1: Our gaze adaptation framework**

**Input:** \(G(\cdot; \theta_G^{(0)})\) pre-trained on source domain, small \(D_s\), and small \(D_t\).

**Output:** \(G(\cdot; \theta_G^{(T)})\)

1. Initialize: \(y^t \sim G(x^t; \theta_G^{(0)}); D(\cdot; \theta_D^{(0)})\) \(\triangleright \theta_D\) randomly initialized.
2. for \(t = 1\) to \(T\) do
3. \(x^s, y^s \sim D_s, D_t\)
4. \(x'^s, x'^t \sim x^s, y^s, x^t, y^t, G, D\) with Eq. (4)
5. \(\mathcal{L}_{\text{gaze}} \leftarrow y^t, G(x^s; \theta_G^{(t-1)}), G(x'^s; \theta_G^{(t-1)})\) with Eq. (5)
6. \(\mathcal{L}_{\text{adv}} \leftarrow x^t_i, x'^t_i, G, D\) with Eq. (6)
7. \(\mathcal{L}_{\text{con}} \leftarrow \frac{1}{B} \sum_{i=1}^B [\mathcal{L}_{\text{con}}(x^s_i, x'^s_i) + \mathcal{L}_{\text{con}}(x'^t_i, x'^t_i)]\) with Eq. (7)
8. Update \(G(\cdot; \theta_G^{(t)})\) with Eq. (8)
9. \(\mathcal{L}_{\text{dis}} \leftarrow x^s, x'^t, x'^s, x'^t, G, D\) with Eq. (8)
10. Update \(D(\cdot; \theta_D^{(t)})\) with \(\mathcal{L}_{\text{dis}}\)
11. end for
images for each subject (i.e., 45,000 images). For the Eye-Diap dataset (Funes Mora, Monay, and Odobez 2014), we employ 16,674 images from 14 subjects under screen target sessions as the evaluation set.

Changes in head poses can significantly affect the appearance of face images. Therefore, we normalized the images following the method in [Zhang et al. 2017], which ensures that the influence of head poses is eliminated.

5.2 Ablation Study

Data Augmentation. In Sec. 4.2, we combine two adversarial attacks (FGSM and PGD) to add additive HFC to the input images. To prove the optimality, we conduct experiments to compare with other methods to add high-frequency noise. We employ random noises (Gaussian and Poisson) and adversarial noises (FGSM and PGD) to add high-frequency noise respectively. The results are shown in Table 1. We can see that FGSM and PGD each achieve the best results on some tasks, so the final strategy is to use both as augmentation while adaptation (50% probability of each being used), and the results are shown in the ”Both” row.

Besides, in Sec. 3.2, directly removing high-frequency can also improve the performance. Therefore, it is also considered one possible data augmentation method in our experiment. So we directly use low-pass data instead of adding HFC during the data augmentation phase, and the results are shown in the ”low-pass” row in Table 1. The performance is not as good as adding additive HFC.

Contrastive Learning. In this section, we conduct experiments to explore how contrastive loss affects our method’s performance. Recall that in Sec. 4.3, we adopt the loss setting from SimCLR (Chen et al. 2020) for implementation. To find the suitable contrastive loss, we further replace this part with the loss settings from the other two commonly-used frameworks MoCo (He et al. 2020) and PCL (Li et al. 2020), respectively.

To this end, we rebuild our method with different contrastive modules, then adapt these modified versions under the same condition. Specifically, for the contrastive loss from MoCo, we utilize a temporal average model to generate the contrastive loss, then we term this version as Ours-MoCo. When it comes to PCL, we follow the settings from its original paper and introduce clustering to generate the contrastive loss. This version is named Ours-PCL. For a fair comparison, each of these models uses 100 target samples for UDA, and tests on the whole target domain.

One important indicator of the contrastive learning module is the ability to reduce the impact of HFC. To compare this ability, we use triplet loss [Schroff, Kalenichenko, and Philbin 2015] as an evaluation metric to measure the feature difference between the original and adversarial data. Fig. 5 shows the triplet loss, which reflects the capability of different modules for keeping the consistency before and after being added HFC. In this figure, we find our method gets the consistently lowest triplet loss, even with the variation of margins, which means it better reduces the impact of HFC.

Furthermore, we compare the cross-domain gaze estimation performances with these different contrastive learning modules. Quantitative results are shown in Table 2. Statistical results consistently show that our method also achieves the highest stability and accuracy on these four tasks.

Ablation. An ablation study is conducted to demonstrate the effectiveness of each component from our method. The components are shown below.

- CNN: A CNN gaze estimation network using ResNet18 (He et al. 2016). The network is pre-trained on the source domain.
- adv: Adversarial domain adaptation module, which is used to minimize the distance between the source and target domains.
- con: Contrastive learning module, which reduces the impact of HFC by keeping the consistency between original and adversarial samples.

For all the experiments, we load the model trained on the
In this section, we conduct experiments to verify the performance of the model on the source domain after adaptation to the target domain.

We take the pre-trained model and adapted models and compare their \( \text{mav} \) and gaze accuracy on the “perturbed” target data. As announced in Sec. 4.3, the contrastive learning module reduces the impact of HFC. After adding the proposed contrastive learning module, our method achieves the best results on all these 4 tasks, which confirms the effectiveness of reducing the impact of HFC.

### 5.4 Performance in Source Domains

In this section, we conduct experiments to verify the performance of the model on the source domain after adaptation to the target domain.

We directly test the model, which has been adapted to the target domain, in the source domain, and the experimental results are shown in Table 5. It can be seen that the \( \text{mav} \) and gaze error of the adapted model increase only slightly, and the \( \text{mav} \) even decreases on the Gaze360 dataset. This indicates that our method can also continue to maintain its performance in source domains after adaptation.

### 5.5 Comparison with SOTA UDA Methods

We also compare the UDA performances between our method and other state-of-the-art UDA methods.

Table 5: Performance of our method in the source domains after adaptation to the target domains.

| Noise | Model       | \( \text{E} \rightarrow \text{M} \) \( \text{mav} \) | \( \text{E} \rightarrow \text{D} \) \( \text{mav} \) | \( \text{G} \rightarrow \text{M} \) \( \text{mav} \) | \( \text{G} \rightarrow \text{D} \) \( \text{mav} \) |
|--------|-------------|-----------------|-----------------|-----------------|-----------------|
| G~0.01 | Baseline    | 4.10 8.79       | 4.47 9.60       |                  |                  |
|        | Our         | 2.25 5.36       | 3.53 7.14       |                  |                  |
| G~0.05 | Baseline    | 6.44 10.61      | 5.96 10.77      |                  |                  |
|        | Our         | 4.21 6.37       | 4.48 6.99       |                  |                  |
| P~10   | Baseline    | 5.76 10.12      | 5.58 10.50      |                  |                  |
|        | Our         | 3.56 6.09       | 4.26 6.99       |                  |                  |
| P~15   | Baseline    | 7.24 11.31      | 6.47 11.26      |                  |                  |
|        | Our         | 4.73 6.92       | 5.04 7.06       |                  |                  |

Table 5: Performance of our method in the source domains after adaptation to the target domains.

| Noise | Model       | \( \text{E} \rightarrow \text{M} \) \( \text{mav} \) | \( \text{E} \rightarrow \text{D} \) \( \text{mav} \) | \( \text{G} \rightarrow \text{M} \) \( \text{mav} \) | \( \text{G} \rightarrow \text{D} \) \( \text{mav} \) |
|--------|-------------|-----------------|-----------------|-----------------|-----------------|
| Baseline | 3.99 8.56 | 6.65 8.60 | 4.38 9.52 | 6.00 10.05 |
| Fine-tune | 2.73 4.37 | 5.35 5.64 | 3.20 5.63 | 4.38 5.74 |
| ADDA* | 2.99 5.53 | 3.83 5.87 | 2.76 6.18 | 5.31 7.92 |
| Dagen* | 3.91 8.56 | 4.38 4.56 | 4.23 7.02 | 5.10 11.38 |
| GazeAdv | 3.28 5.87 | 6.31 7.38 | 3.98 7.42 | 4.89 9.28 |
| GazeAdv | 3.66 7.61 | 6.50 8.27 | 4.46 8.21 | 5.63 10.68 |
| GVBG* | 3.00 6.68 | 5.66 7.27 | 4.67 8.39 | 5.23 12.44 |
| PureGaze | 3.88 7.08 | 5.97 7.48 | 6.16 9.28 | 5.50 9.32 |
| Ours | 2.21 5.35 | 4.52 6.62 | 3.51 7.18 | 4.81 8.61 |

Table 6: Comparison with state-of-the-art unsupervised domain adaptation approaches. * indicates that target gaze labels are used. † indicates that experimental settings are different. ‡ indicates that more than 100 target samples are used during adaptation.
6 Conclusion

In this paper, we present a novel framework for adapting gaze estimation to new domains. We start by analyzing the gaze jitter phenomenon that occurs when crossing domains, and discover that HFC is one important factor leading to gaze jitter. This factor guides us to design the proposed method. Extensive experiments demonstrate the superior performance of our method for cross-domain gaze estimation tasks. Our method has the potential to be used in real-world gaze estimation applications.

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