PureGaze: Purifying Gaze Feature for Generalizable Gaze Estimation

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Abstract

Gaze estimation methods learn eye gaze from facial features. However, among rich information in the facial image, real gaze-relevant features only correspond to subtle changes in eye region, while other gaze-irrelevant features like illumination, personal appearance and even facial expression may affect the learning in an unexpected way. This is a major reason why existing methods show significant performance degradation in cross-domain/dataset evaluation. In this paper, we tackle the cross-domain problem in gaze estimation. Different from common domain adaptation methods, we propose a domain generalization method to improve the cross-domain performance without touching target samples. The domain generalization is realized by gaze feature purification. We eliminate gaze-irrelevant factors such as illumination and identity to improve the cross-domain performance. We design a plug-and-play self-adversarial framework for the gaze feature purification. The framework enhances not only our baseline but also existing gaze estimation methods directly and significantly. To the best of our knowledge, we are the first to propose domain generalization methods in gaze estimation. Our method achieves not only state-of-the-art performance among typical gaze estimation methods but also competitive results among domain adaption methods. The code is released in https://github.com/yihuacheng/PureGaze.

Introduction

Human gaze implicates important cues for understanding human cognition (Rahal and Fiedler 2019) and behavior (Dias et al. 2020). It enables researchers to gain insights into many areas such as saliency detection (Wang et al. 2019b) (Wang and Shen 2018), virtual reality (Xu et al. 2018) and first-person video analysis (Yu et al. 2020). Recently, appearance-based gaze estimation with deep learning becomes a hot topic. They leverage convolutional neural networks (CNNs) to estimate gaze from human appearance (Park, Spurr, and Hilliges 2018; Xiong, Kim, and Singh 2019), and achieve accurate performance.

CNN-based gaze estimation requires a large number of samples for training. But collecting gaze sample is difficult and time-consuming. This challenge can be ignored in a fixed environment, but becomes a bottleneck when gaze estimation is required in a new environment. The changed environment brings many unexpected factors such as different illumination, thus degrades the performance of pre-trained model. Recent methods usually handle the cross-environment problem as a domain adaption problem. Researchers aim to adapt the model trained in source domains to target domains (Zhang et al. 2018; Kellnhofer et al. 2019). However, these methods usually require target samples and time-consuming setup. These requirements greatly harm the flexibility of methods.

In this paper, we innovate a new direction to solve the problem. We propose a domain generalization method for improving the cross-domain performance. Our method does not require any images or labels in target domains, but aims to learn a generalized model in the source domain for any “unseen” target domains. We notice the intrinsic gaze pattern is similar in all domains, but there are domain differences in gaze-irrelevant factors such as illumination and identity. These factors are usually domain-specific, and directly blend in captured images. The in-depth fusion makes these factors difficult to be eliminated during feature extraction. As a result, the trained model usually learns a joint distribution of gaze and these factors, i.e., overfit in source do-

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We refer it as cross-domain/dataset problem in the rest.
As shown in Fig. 1, the key idea of our method is to purify gaze feature, i.e., we eliminate gaze-irrelevant factors such as illumination and identity. The purified feature is more generalized than original feature, and naturally brings improvement in cross-domain performance. To be specific, we propose a plug-and-play self-adversarial framework. As shown in Fig. 2 the framework contains two tasks, which are to preserve gaze information and to remove general facial image information. Simultaneously optimizing the two tasks, we implicitly purify the gaze feature without defining gaze-irrelevant feature. In fact, it is also non-trivial to define all gaze-irrelevant features. We also realize the framework with a practical neural network. As shown in Fig. 3 the two tasks are respectively approximated as a gaze estimation task and an adversarial reconstruction task. We propose the final PureGaze to simultaneously perform the two tasks to purified the gaze feature. The PureGaze contains a plug-and-play SA-Module, which can be used to enhance existing gaze estimation methods directly and significantly.

The contributions of this work are threefold:

- We propose a plug-and-play domain-generalization framework for gaze estimation methods. It improves the cross-dataset performance without knowing the target dataset or touching any new samples. To the best of our knowledge, it is the first domain-generalization framework in gaze estimation.
- The domain-generalizability comes from our proposed gaze feature purification. We design a self-adversarial framework to purify gaze features, which eliminates the gaze-irrelevant factors such as illumination and identity. The purification is easily explainable via visualization as shown in the experiment.
- Our method achieves state-of-the-art performance in many benchmarks. Our plug-and-play module also enhances existing gaze estimation methods significantly.

### Related Works

#### Typical Gaze Estimation

Recently, many gaze estimation methods are proposed. Cheng et al. explore the two-eye asymmetry (Cheng, Lu, and Zhang 2018; Cheng et al. 2020b), Park et al. generate pictorial gaze representation to handle subject variance (Park, Spurr, and Hilliges 2018), Fisher et al. leverage two VGG networks to process two eye images (Fischer, Jin Chang, and Demiris 2018). Zhang et al. utilize attention mechanism to weight facial feature (Zhang et al. 2017), Chen et al. leverage dilated convolution to estimate gaze (Chen and Shi 2019). Bao et al. leverage face and eye images to estimate point of gaze (Bao et al. 2020), Zheng et al. propose a gaze/head redirection network and use generated images for data augmentation (Zheng et al. 2020). Cheng et al. estimate gaze from facial images and refine the gaze with eye images (Cheng et al. 2020a).

#### Cross-domain Gaze Estimation

Cheng et al. (Cheng et al. 2018) fine tune the pre-trained model in target domain. Wang et al. (Wang et al. 2019a) and Kellnhofer et al. (Kellnhofer et al. 2019) propose to use adversarial learning to align the features in the source and target domain. Liu et al. (Liu et al. 2021) propose an ensemble of networks that learn collaboratively with the guidance of outliers. These methods utilize data from target domain, which is not always user-friendly.

### Overview

#### Definition of the Purification

We first formulate the proposed self-adversarial framework in this section. Without loss of generality, we formulate the gaze estimation problem as

$$g = F_\phi(E_\theta(I)), \quad (1)$$

where $E_\theta$ is a feature extraction function (e.g., neural networks), $F_\phi$ is a regression function, $I$ is a face/eye appear-
In the previous section, we propose two key tasks, i.e., Eq. (14) and Eq. (15). The two tasks compose a self-adversarial framework to purify feature. In this section, we propose PureGaze based on the framework. We realize the two tasks with two practical tasks, gaze estimation and adversarial reconstruction. 3We also propose two loss function for the framework.

Gaze estimation: We use gaze estimation tasks to preserve gaze information in the extracted feature, i.e., Eq. (15). In fact, the task can be realized with any gaze

Learning to Purify in the Framework

We simultaneously solve Eq. (14) and Eq. (15). In other words, the extracted feature needs to contain more gaze information (Eq. (15)) and less image information (Eq. (14)). The two optimization tasks compose a self-adversarial framework on the extracted feature. During the optimization, gaze-irrelevant feature is eliminated to satisfy Eq. (14) and gaze-relevant feature is preserved to satisfy Eq. (15). In the other word, we purify extracted feature with the self-adversarial framework.

In addition, Eq. (14) and Eq. (15) implicate the minimax problem of $H(G,Z)$. It is intuitive that the extracted feature will gradually discard some gaze-relevant information to decrease image information, i.e., to satisfy Eq. (14). Meanwhile, to satisfy Eq. (15), the feature having weak relations with gaze will be discarded first.

PureGaze

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Self-Adversarial Framework

As shown in Fig. 2, we design two tasks for feature purification. The first task is to minimize the mutual information (MI) between image feature and the extracted feature, i.e.,

$$\theta^* = \arg \min_\theta H(I, Z)$$

(3)

The function $H(X, Y)$ computes the MI between $X$ and $Y$. It indicates the relation between $X$ and $Y$, e.g., $H(X, Y) = 0$ if $X$ is independent with $Y$. This task also means the extracted feature should contain less image information.

The other task is to maximize the MI between gaze-relevant feature and extracted feature, i.e.,

$$\theta^* = \arg \max_\theta H(G, Z)$$

(4)

This constraint means the extracted feature should contain more gaze-relevant information.

\[ \text{Figure 3: The architecture of PureGaze. It is consist of two share-weight backbones (ResNet-18) for feature extraction, one two-layer MLP (Muti-layer Perception) for gaze estimation, and one SA-Module (N=5) for recovering images. The backbone and MLP are cooperative to preserve gaze information, i.e., perform gaze estimation, while the backbone and SA-Module are adversarial to remove general image information, i.e., perform adversarial reconstruction. The backbone simultaneously performs the two tasks while the two tasks are not cooperative but adversarial. The backbone performs adversarial learning with itself to purify extracted feature.} \]
estimation network. We simply divide gaze estimation networks into two subnets, backbone for extracting feature and MLP for regressing gaze from the feature (Fig. 3(a)). We use a gaze loss function $L_{\text{gaze}}$, such as L1 loss to optimize the two subnets. The two subnets cooperate to preserve gaze information.

**Adversarial reconstruction:** We propose an adversarial reconstruction task to remove general image information from extracted feature, i.e., Equ. (14). Our assumption is that if the reconstruction network cannot recover input images from extracted feature, it means the extracted feature contains no image information.

Therefore, we first propose a SA-Module for reconstruction as shown in Fig. 3(c). It contains a block for up-sampling and a $1 \times 1$ convolution layer to align channels. Further, the network architecture for adversarial reconstruction is shown in Fig. 3(b). We use a backbone for feature extraction and SA-Module for recovering images. We assign adversarial losses to the backbone and SA-Module. The SA-Module tries to reconstruct images and is optimized with an reconstruction loss $L_{\text{rec}}$ such as pixel-wise MSE Loss. The backbone tries to prevent the reconstruction. We use an adversarial loss $L_{\text{adv}}$ to optimize it, where

$$L_{\text{adv}} = 1 - L_{\text{rec}}. \quad (5)$$

It is obvious that the backbone and the SA-Module are adversarial in reconstruction, i.e., the backbone finally removes general image information from extracted feature.

**Architecture of PureGaze**

The architecture of PureGaze is shown in the left part of Fig. 3. We respectively build two networks for gaze estimation and adversarial reconstruction with the same backbone, and share the weight of two backbones.

In general, PureGaze contains three networks, which are a backbone for feature extraction, a MLP for gaze estimation and a SA-Module for image reconstruction. The loss functions of the three parts are

$$L_{\text{SA}} = L_{\text{rec}}. \quad (6)$$

$$L_{\text{MLP}} = L_{\text{gaze}}. \quad (7)$$

$$L_{\text{backbone}} = \alpha L_{\text{adv}} + \beta L_{\text{gaze}}, \quad (8)$$

where $\alpha$ and $\beta$ are hyper-parameters. In this paper, we use L1 Loss for gaze estimation and pixel-wise MSE for reconstruction:

$$L_{\text{gaze}} = \|g - \hat{g}\|_1. \quad (9)$$

$$L_{\text{rec}} = \|I - \hat{I}\|_2. \quad (10)$$

**Purifying Feature in Training:** PureGaze uses one backbone to extract feature. The backbone has two goals, minimizing $L_{\text{gaze}}$ and minimizing $L_{\text{adv}}$. Minimizing $L_{\text{gaze}}$ means the backbone should extract gaze-irrelevant feature, while minimizing $L_{\text{adv}}$ means the backbone should not extract any image feature. The two goals are not cooperative but adversarial, and compose an adversarial learning to purify the extract feature. In addition, $L_{\text{adv}}$ is easily satisfied with learning a local optimal solution to cheat the SA-Module. We design another task $L_{\text{rec}}$ to against $L_{\text{adv}}$ to avoid the local optimal solution. The two novel adversarial tasks both are important parts in PureGaze.

**Local Purification Loss**

It is intuitive that eye region is more important than other facial regions for gaze estimation. Therefore, we want PureGaze to pay more attention to purify the feature of eye region. One simple solution is to directly use eye images as input. However, we believe it is unreasonable since other facial regions also provide useful information.

As a result, we propose the local purification loss (LP-Loss). We use an attention map to focus the purification on a local region. Note that, the attention map is only applied to $L_{\text{adv}}$, i.e., the loss function of the backbone is modified as

$$L_{\text{backbone}} = \alpha \mathbb{E}[M * (1 - (I_i - \hat{I}_i)^2)] + \beta L_{\text{gaze}}. \quad (11)$$

where $M$ is the attention map, and $*$ means element-wise multiplication. In this paper, we use mixed gaussian distribution to generate the attention map. We use the coordinates of two eye centers as mean values, and the variance $\Sigma = \text{diag}(\sigma^2, \sigma^2)$ of the distribution can be customized.

The loss function can be understood as following. On the one hand, LP-Loss focuses the purification on eye region. On the other hand, LP-Loss does not change the loss function of gaze estimation, i.e., $L_{\text{gaze}}$. Human gaze is estimated from whole face images rather than weighted face images.

**Truncated Adversarial Loss**

The adversarial reconstruction task plays an important role in the PureGaze. It ensures the extracted feature contains less image feature. In PureGaze, we minimize $L_{\text{adv}}$ to prevent the reconstruction. A smaller value of $L_{\text{adv}}$ indicates a larger pixel difference between the generated and original images. However, we think it is redundant to produce a very large pixel difference. The reason is that $L_{\text{adv}}$ is designed to prevent the reconstruction rather than recover an “inverse” version of the original image.

Therefore, we further propose the truncated adversarial loss (TA-Loss). We use a threshold $k$ to truncate the adversarial loss $L_{\text{adv}}$. In one word, $L_{\text{adv}}$ will be zero if the pixel difference is larger than $k$. The final loss function of the backbone is:

$$L_{\text{backbone}} = \alpha \mathbb{E}[M * \mathbb{1}_{1-\|I_i - \hat{I}_i\|_2 > k} * \mathbb{1}_{1-((I_i - \hat{I}_i)^2)}>k] + \beta L_{\text{gaze}}. \quad (12)$$

where $\mathbb{1}$ is the indicator function and $k$ is the threshold.

**Experiments**

**Data-preprocessing**

**Task definitions:** We use Gaze360 (Kellhofer et al. 2019) and ETH-XGaze (Zhang et al. 2020) as training set, since they have a large number of subjects, various gaze range and head pose. We test our model in two popular datasets, which are MPIIGaze (Zhang et al. 2017) and EyeDiap (Funes Mora, Monay, and Odobez 2014). We totally conduct four cross-dataset tasks, and denote them as E (ETH-XGaze)→M (MPIIGaze), E→D (EyeDiap), G (Gaze360)→M, G→D.

**Data Preparing.** We follow Cheng et al. 2021 to prepare datasets. Gaze360 (Kellhofer et al. 2019) dataset contains a total of 172K images from 238 subjects. Note that some
of the images in Gaze360 only captured the back side of the subject. These images is not suitable for appearance-based methods. Therefore, we first clean the dataset with a simple rule. We remove the images without face detection results based on the provided face detection annotation. ETH-XGaze (Zhang et al. 2020) contains a total of 1.1M images from 110 subjects. It provides a training set containing 80 images from 15 subjects. EyeDiap (Funes Mora, Monay, and Odobez 2014) provides a total of 94 video clips from 16 subjects. We split 5 subjects for validation and others are used for training. MPIIGaze (Zhang et al. 2017) is prepared based on the standard protocol. We collect a total of 45K images from 15 subjects. EyeDiap (Funes Mora, Monay, and Odobez 2014) provides a total of 94 video clips from 16 subjects. We follow the common steps to prepare the data as in (Zhang et al. 2017; Cheng et al. 2020a). Concretely, we select the VGA videos of screen targets session and sample one image every fifteen frames. We also truncate the data to ensure the number of images from each subject is the same.

Data rectification. Data rectification is performed to simplify the gaze estimation task. We follow (Sugano, Matsushita, and Sato 2014) to preprocess MPIIGaze and (Zhang, Sugano, and Bulling 2018) to process EyeDiap. ETH-XGaze is already rectified before publication. Gaze360 rectifies their gaze directions to cancel the effect caused by camera pose. We directly use their provided data.

Comparison Methods

Baseline: We remove the SA-Module in PureGaze. The new network is denoted as Baseline. It is obvious the performance difference between PureGaze and Baseline is caused by SA-Module. We also denote the feature extracted by Baseline as original feature, and the feature extracted by PureGaze as purified feature.

Gaze estimation methods: We compare our method with four methods, which are Full-Face (Zhang et al. 2017), RT-Gene (Fischer, Jin Chang, and Demiris 2018), Dilated-Net (Chen and Shi 2019) and CA-Net (Cheng et al. 2020a). These methods all perform well within-dataset evaluation. We implement Full-Face and Dilated-Net using Pytorch, and use the official code of the other two methods.

Domain adaption methods: We also compare our method with domain adaption methods for reference. In fact, it is unfair to compare our method with domain adaption methods since these methods require target samples. Adversarial learning (ADL) (Kellnhofer et al. 2019) is proved useful in gaze estimation, and has a similar feature with our method. We implement ADL for main comparison. We also modify the method as ADL*, where we only use a discriminator to distinguish personal feature in source domains. ADL* does not require target samples as our methods. In addition, we directly report the performance of other domain adaption methods from (Liu et al. 2021) for reference.

Performance Comparison with SOTA Methods

We first conduct experiments in four cross-dataset tasks. The result is shown in Tab. 3. Note that, Dilated-Net, CA-Net and RT-Gene are not applicable in ETH-XGaze, since ETH-XGaze cannot always provide reliable eye images. In addition, ETH-XGaze dataset uses an off-the-shelf ResNet50 as
Table 2: We apply the self-adversarial framework into other advanced gaze estimation methods. Our framework directly enhances existing gaze estimation methods. The experiment also provides a more fair comparison with these methods.

| Methods                  | G→M | G→D | E→M | E→D |
|--------------------------|-----|-----|-----|-----|
| Full-Face                | 11.13° | 14.42° | 12.35° | 30.15° |
| Full-Face+SA (ours)      | 9.16° | 14.20° | 11.50° | 21.01° |
| CA-Net                  | 27.13° | 31.41° | - | - |
| CA-Net+SA (ours)        | 9.03° | 9.71° | - | - |
| Baseline (ours)         | 9.89° | 11.42° | 8.13° | 7.74° |
| PureGaze (ours)         | 9.28° | 9.32° | 7.08° | 7.48° |

baseline. We follow the protocol and replace the backbone in our method and ADL with ResNet50 in ETH-XGaze.

Comparison with typical gaze estimation methods: The second row of Tab. 3 shows the comparison between our method and gaze estimation methods. Our method and compared methods are all trained on source domains and evaluated on target domains. It is obvious that gaze estimation methods usually have bad performance in cross-dataset evaluation. This is because these methods are easily over-fitted in source domains. In contrast, our Baseline has good performance in all tasks due to simple architecture. PureGaze further improves the performance of Baseline and achieves the state-of-the-art performance in all tasks.

Comparison with domain adaption methods: The third row of Table 1 shows the performance of domain adaption methods. ADL has the same backbone as PureGaze. It improves the performance in three tasks and fails in E→D. It also has the best performance among compared methods in E→M. Compared with ADL, PureGaze surpasses the performance of ADL in three tasks without target samples. This proves the effectiveness of our method.

On the other hand, we evaluate the performance of ADL+ and show the result in the second row of Table 1. Without target samples, ADL+ cannot always bring performance improvement. This is because it is hard to improve performance in all unknown domains, and also demonstrate the value of our method. PureGaze surpasses ADL+ in all tasks.

Table 1 also shows the performance of other domain adaption methods. PureGaze shows competitive result among these domain adaption methods without domain adaption. In addition, we also provide a simple application of PureGaze, where we sample 5 images per person from target domains to fine tune PureGaze. Fine-tuned PureGaze further improves the performance with a fast calibration/adaption. More valuable, we observe fine-tuned PureGaze also has better performance than fine-tuned Baseline. This proves PureGaze learns a better feature representation.

Plug Existing Gaze Estimation Methods

We also apply our self-adversarial framework into Full-Face (Zhang et al. 2017) and CA-Net (Cheng et al. 2020a). We input their final facial feature maps into SA-Module, and simply add two loss functions, $L_{rec}$ and $L_{adv}$.

Figure 4: We evaluate the hyper-parameters of the two loss function. The first row shows the result about LP-Loss, where w/o means we ablate the loss. The second row shows the result about TA-Loss, where $k=0$ means we ablate TA-Loss. Our method is the best when $\sigma^2$ is 20 and $k=0.75$.

The result is shown in Tab. 2. It is surprising that CA-Net has the worst performance in G→M, while CA-Net+SA has the best performance in G→M. Besides, it also improved by nearly 70% in G→D. Full-Face+SA also shows better performance than Full-Face in all tasks. The experiment provides a more fair comparison with typical gaze estimation methods, and proves the plug-and-play attribute of our self-adversarial framework. Note that, our framework does not require additional inference parameters and training images. This is a key advantage of our method.

Ablation Study of Two Loss Function

Self-adversarial framework provides a primary architecture of PureGaze while it is rough. We also propose two loss functions (LP-Loss and TA-Loss) to enhance PureGaze. The two loss functions both have hyper-parameters, i.e., variance $\sigma^2$ in LP-Loss and threshold $k$ in TA-Loss. We conduct experiments about different hyper-parameters in this section.

As shown in Fig. 4(a) and Fig. 4(b), we set four values for $\sigma^2$, which are 10, 20, 30 and 40, and also evaluate the performance without the loss. We illustrate the generated attention maps in the top of the two figures. As for TA-Loss, we set four values for $k$, which are 0, 0.25, 0.5 and 0.75. $k=0$ also means we ablate TA-Loss. The results are shown in Fig. 4(c) and Fig. 4(d). It is obvious that the two loss functions both brings performance improvement. When $k=0.75$ and $\sigma^2 = 20$, PureGaze has best performance.

Visualize Extracted Feature via Reconstruction

To verify the key idea of gaze feature purification, we visualize purified features for further understanding. We provide
reconstruction results of purified features and original features for comparison. We directly show the output of SA-Module to visualize the purified feature. We freeze the parameters of the pre-trained model and simply train a SA-Module to reconstruct images from the original feature.

According to the visualization result shown in Fig. 5, we could easily draw following conclusions:

- The purified feature contains less identity information than original feature. The reconstructed face appearances are approximately the same for each subject.
- The purified feature contains less illumination factors. Besides, it is interesting that our method also recover a bright gaze region accurately from low-light images. This means our method is able to effectively extract gaze information under the dash area.
- Except illumination and identity factors, our method also eliminates other gaze-irrelevant features like the head rest in Fig. 5(a).

Note that our method does not specify eliminated factors. PureGaze automatically purifies the learned feature. This is an advantage of our method since it is non-trivial to manually list all gaze-irrelevant feature.

**Discussion**

1) **Domain generalization.** Gaze estimation methods usually have large performance drop when tested in new environment. This feature limits the application of gaze estimation. In this paper, we innovate a new direction to solve the cross-domain problem. Compared with domain adaption (DA) methods, domain generalization (DG) methods are more flexible, e.g., the setup of DA methods usually is time-consuming while DG methods can be directly applied to new domains. But as a trade-off, DG methods usually perform worse than DA methods due to the lack of target domains information. The trade-off between flexibility and accuracy should be considered by researchers.

2) **Self-adversarial framework.** We propose a self-adversarial framework to learn purified feature. The purified feature improves the cross-domain performance without touching target samples. In fact, our framework can also be considered as a zero-shot cross-domain method since we require no samples in target domains. The zero-shot mechanism is designed based on the observation, gaze pattern is similar in all domains, while some gaze-irrelevant factors are usually domain-specific and bring performance drop. Our method eliminates some gaze-irrelevant feature and naturally improves the cross-domain performance. However, the same as DA methods, our method is unstable in source domains. Our method slightly changes the performance in source domain (±0.2°). This is because an over-fitting model can achieve better performance in source domain compared with PureGaze. Learning more generalized model is a future direction of our framework.

**Conclusion**

In this paper, we innovate a new direction to solve the cross-dataset problem in gaze estimation. We propose a plug-and-play domain-generalization framework. The framework purifies gaze feature to improve the performance in unknown target domains without touching the domain. Experiments show our method achieves state-of-the-art performance among typical gaze estimation methods and also has competitive result compared with domain adaption methods.
Appendix

In the supplementary document, we first provide a background of gaze estimation. Then, we provide the deduction from self-adversarial framework to PureGaze and describe the implementation details of PureGaze. Finally, we provide additional experiments. We give an apple-to-apple comparison between different types of gaze estimation methods. This comparison will provide a deep understanding about the advantage and disadvantage of domain generalization methods. We also provide the experiments about illumination factors. In the visualization, PureGaze eliminates illumination factors from extracted feature in very dark environments. We further provide the quantitative improvement on each illumination intensity. The quantitative result also matches the visualization result.

Background

Appearance-based gaze estimation methods aim to infer human gaze $g$ from appearance $I \in \mathbb{R}^{H \times W \times C}$. They usually learn a mapping function $g = f(I)$ to directly map appearance to gaze. Recently, Many methods leverage CNNs to model the mapping function and achieve outstanding performance (Wang, Su, and Ji 2019; Wang et al. 2019a). They first use an auto-encoder to learn feature representation and then use meta-learning to learn an person-specific gaze mapping from feature representation to gaze. Recently, Many methods leverage CNNs to model the mapping function and achieve outstanding performance. They use redirected eye images to improve specific gaze mapping from feature representation to gaze. Recently, Many methods leverage CNNs to model the mapping function and achieve outstanding performance (Wang, Su, and Ji 2019; Wang et al. 2019a).

Cross-person and cross-dataset problems are two key challenges in gaze estimation. Conventional gaze estimation methods usually have large error in cross-person problem (Sugano, Matsushita, and Sato 2014). Recently, with the development of deep learning, appearance-based methods have good and saturated performance in cross-person problem. To further improve the cross-person performance, researchers also aim to learn person-specific models with few-shot additional calibration samples. For example, Park et al. propose a few-shot gaze estimation methods (Park et al. 2019). They first use an auto-encoder to learn feature representation and then use meta-learning to learn an person-specific gaze mapping from feature representation to gaze. Yu et al. propose a gaze redirection network (Yu, Liu, and Odobez 2019). They use re-directed eye images to improve the performance in a specific user.

Cross-dataset problem is more challenging than cross-person problem. Besides the personal difference, there are many known and unknown environment factors which have large impacts on cross-dataset performance. Overview, we believe personal difference, environment difference and data distribution difference are three mainly problems in cross-dataset problem. Our work provides an framework to handle the first two problems, which is a contribution of our work.

Evaluation metric: We use angular error as the evaluation metric like most of methods (Cheng et al. 2020a; Park et al. 2019; Zhang et al. 2019). Assuming the actual gaze direction is $g \in \mathbb{R}^3$ and the estimated gaze direction is $\hat{g} \in \mathbb{R}^3$, the angular error can be computed as:

$$
\mathcal{L}_{\text{angular}} = \frac{g \cdot \hat{g}}{||g|| \cdot ||\hat{g}||}
$$

(13)

A smaller error represents a better model.

Methodology

Deduction from the Framework to PureGaze

In the main manuscript, we propose a self-adversarial framework containing two adversarial tasks:

$$
\theta^* = \arg \min_{\theta} H(I, Z)
$$

(14)

and

$$
\theta^* = \arg \max_{\theta} H(G, Z).
$$

(15)

Here, we introduce how to deduct the PureGaze from the two formulations.

To realize the framework, we first simplify Eq. (14) and Eq. (15). The mutual information $H(X, Y)$ can be further deduced as:

$$
H(X, Y) = \mathbb{E}_{x \sim p(x), y \sim p(y)}[\log p(y|x)] - \mathbb{E}_{x \sim p(x)}[\log p(x)]
\times \mathbb{E}_{x \sim p(x), y \sim p(y)}[\log p(x|y)]
$$

(16)

Substituting Eq. (16) into Eq. (14) and Eq. (15), we get:

$$
\theta^* = \arg \min_{\theta} \mathbb{E}_{i \sim p(I), z \sim p(Z)}[\log p(i|z)],
$$

(17)

and

$$
\theta^* = \arg \max_{\theta} \mathbb{E}_{g \sim p(G), z \sim p(Z)}[\log p(g|z)].
$$

(18)

Eq. (17) means we should minimize the probability $p(i|z)$. We approximate this probability with a reconstruction network $R : Z \rightarrow I$. To minimize $p(i|z)$, we want $R$ to fail reconstructing images from the extracted feature. In other words, the feature extraction network $E$ should extract the feature which is independent with images. Certainly, it is easy for feature extraction network $E$ to fool a pre-trained reconstruction network. And it is time-consuming to train a special reconstruction network for each iteration. Thus, $E$ and $R$ are designed to perform an adversarial reconstruction task. $R$ tries to reconstruct images from the feature, while $E$ tries to prevent the reconstruction. With the adversarial reconstruction, $E$ will discard all image information so that $R$ cannot reconstruct images, i.e., minimize $H(I, Z)$.

Eq. (18) means we should maximize the probability of $p(g|z)$, i.e., given image feature $z$, we should accurately recover gaze information from $z$. We approximate $p(g|z)$ as a gaze regression network $F : Z \rightarrow G$. $F$ aims to accurately estimate gaze from the extracted feature.

Implementation Detail

In this paper, we use the convolutional part of ResNet-18 as the backbone. We use a two-layer MLP for gaze estimation, where the output numbers of the two layers are 1000 and 2. As for SA-Module, we use a five-layers SA-Module (N=5). The numbers of feature maps are 256, 128, 64, 32, 16 for each block (from bottom to top) and 3 for last 1 × 1 convolutional layer. We use Adam for optimization and the learning rate is 0.0001 for all three networks. We empirically set $\alpha$ and $\beta$ as 1 and $k$ as 0.75. The $\sigma^2$ of attention map is 20 pixel. Indeed, the backbone, MLP and SA-Module are arbitrary where we only need to ensure the SA-Module can output a image having the same sizes with input image.
Table 3: We provide an apple-to-apple comparison between different types of methods. We select three methods with the same backbone for fair comparison. PureGaze (domain generalization methods) achieves better performance than Baseline (typical gaze estimation methods) under the same condition. This is an advantage of our method. ADL (domain adaption methods) also has better performance than Baseline while it requires time for setup and target samples for adaption.

| Methods | Types                      | Accuracy | Params | Setup   | Target Samples | Model   |
|---------|----------------------------|----------|--------|---------|----------------|---------|
| Baseline | Typical gaze estimation    | 9.89°    | 11.2M  | Not required | Not required | Unique  |
| PureGaze | Domain generalization      | 9.28°    | 11.2M  | Not required | Not required | Unique  |
| ADL     | Domain adaption            | 9.70°    | 11.2M  | > 1h    | > 50 images    | Specific |

**Additional Experiments**

**Comparison between Different Types of Methods**

Our method is a domain generalization method. We further provide an apple-to-apple comparison among our method, typical gaze estimation methods and domain adaption methods in this section. We choose the Baseline as the representation of typical gaze estimation methods and ADL [Kellnhofer et al. 2019] as the representation of domain adaption methods. The three methods have the same backbone and provide a fair comparison.

The result is shown in Tab. 3 PureGaze, Baseline and ADL have the same number in parameters. This is because PureGaze and ADL both are plug-and-play. The two methods learn more generalized feature representation rather than changes the network architecture to improve cross-domain performance. Compared with Baseline, PureGaze achieves better performance under the same condition. This is an advantage of our method.

ADL also achieves better performance than Baseline while it decreases the flexibility. ADL requires a time-consuming setup and some target samples for domain adaption. Although recent domain adaption methods require less samples, these user-unfriendly requirement limits the application of gaze estimation methods. On the other hand, ADL learns specific models for each domain. In contrast, PureGaze learns one unique model for all domains. PureGaze cannot improve the performance in a specific domain with a large margin, for example, use a known domain-specific information to calibrate a specific model. This is a limitation of our method.

**Visualization on Very Dark Environment.**

The visualization result of reconstruction shows our method eliminates the illumination factor. In this section, we provide more strict cases to prove the ability of our method.

The original images are shown in the first row of Fig. 6. Subjects in these images are invisible due to extremely dark environment. Therefore, we manually augment these images and show them in the second row. The reconstruction result of PureGaze is shown in the third row. Even in very dark environment, our method still eliminates the illumination factor and captures gaze-relevant information. In addition, compare the reconstructed images with the augmented images, it is obvious our method accurately captures the eye movement.

**Quantitative Evaluation in Illumination**

The feature reconstruction experiments show our method has the ability to remove the illumination factor from the extracted features. In this section, we provide the performance improvement distribution across different illumination intensities for quantitatively analysis. We train the model in ETH-XGaze and test it in MPIIGaze for their rich illumination variance. We first cluster the images into 51 clusters according to their mean intensity. Then we remove clusters less than 7 images and compute the average accuracy.

We illustrate the performance improvement of the PureGaze compared with the baseline in Fig. 6. It is interesting that our method improves the performance in extreme illumination conditions. It is because our method tries to remove the gaze-irrelevant illumination information from the extracted feature, therefore becomes more robust than the baseline especially in extreme illumination conditions. These results prove the advantage of the purified feature.
Figure 7: Quantitative evaluation in illumination. We show the performance improvement of PureGaze compared with Baseline in different illumination intensity. PureGaze largely improves the performance in the extreme illumination condition. This conclusion also matches the feature visualization result.

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