Source-free Adaptive Gaze Estimation with Uncertainty Reduction Supplementary Materials

Xin Cai[1,2], Jiabei Zeng[1], Shiguang Shan[1,2,3], Xilin Chen [1,2]
[1]Institute of Computing Technology, Chinese Academy of Sciences, Beijing, 100090, China
[2]University of Chinese Academy of Sciences, Beijing, 100090, China
[3]Peng Cheng Laboratory, Shenzhen, 518055, China
{caixin20s,jiabei.zeng,sgshan,xlchen}@ict.ac.cn

Appendix

This supplementary material provides further experiments, analysis and illustrations. We investigate the sensitivity of hyperparameters of the proposed methods (Appendix A) and qualitative results of face enhancement and performance improvement of gaze adaptation (Appendix B).

A. Ablation Study on Hyperparameters

A.1. Loss Weight Parameter γ

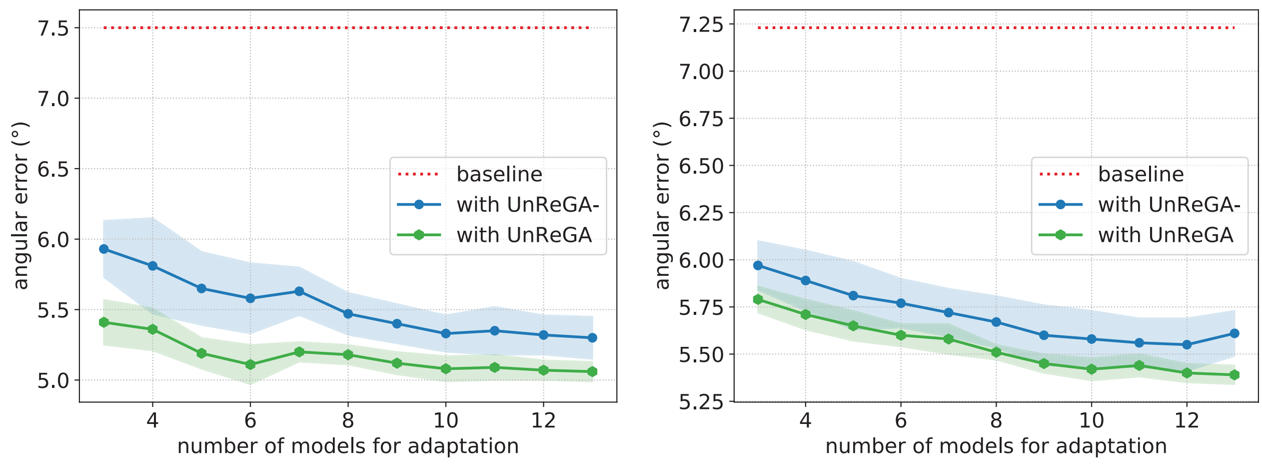
we evaluate how the UnReGA^{-} and UnReGA performance varies with loss weight parameter γ in Eq.(9) of the main paper. We conduct experiments with $\gamma = \{0.001, 0.01, 0.1\}$. The results are shown in Table 1, where we find that the most proper system performance occurs at the value $\gamma = 0.01$. Therefore, we set $\gamma = 0.01$ for the remaining experiments.

Table 1. Mean angular gaze error ($^{\circ}$) and stand deviation of source-free adaptation with different hyperparameters γ.

Method	$\mathcal{D}_E \rightarrow \mathcal{D}_M$	$\mathcal{D}_E \rightarrow \mathcal{D}_D$	$\mathcal{D}_E \rightarrow \mathcal{D}_C$	$\mathcal{D}_G \rightarrow \mathcal{D}_M$	$\mathcal{D}_G \rightarrow \mathcal{D}_D$	$\mathcal{D}_G \rightarrow \mathcal{D}_C$
UnReGA^{-}						
$\gamma = 0.001$	$\mathbf{5.33} \pm 0.14$	6.20 ± 0.16	5.96 ± 0.13	5.60 ± 0.12	6.18 ± 0.18	6.82 ± 0.15
$\gamma = 0.01$	5.35 ± 0.20	6.06 ± 0.17	$\mathbf{5.91} \pm 0.14$	$\mathbf{5.58} \pm 0.15$	$\mathbf{5.84} \pm 0.16$	$\mathbf{6.80} \pm 0.18$
$\gamma = 0.1$	5.78 ± 0.15	$\mathbf{6.01} \pm 0.12$	6.04 ± 0.16	5.72 ± 0.13	5.95 ± 0.19	6.95 ± 0.14
UnReGA						
$\gamma = 0.001$	5.15 ± 0.08	6.00 ± 0.12	5.83 ± 0.11	5.48 ± 0.06	6.02 ± 0.12	6.57 ± 0.11
$\gamma = 0.01$	$\mathbf{5.11} \pm 0.09$	$\mathbf{5.70} \pm 0.16$	$\mathbf{5.75} \pm 0.09$	$\mathbf{5.42} \pm 0.06$	$\mathbf{5.80} \pm 0.13$	$\mathbf{6.52} \pm 0.11$
$\gamma = 0.1$	5.19 ± 0.10	5.80 ± 0.10	5.99 ± 0.08	5.61 ± 0.07	5.82 ± 0.12	6.65 ± 0.12

A.2. Number of models for Adaptation

In order to explore the influence of different number of models (K in Eq(5) of the main paper) in the proposed method , we evaluate the performance of UnReGA^{-} and UnReGA with different numbers of models on tasks $\mathcal{D}_E \rightarrow \mathcal{D}_M$ and $\mathcal{D}_G \rightarrow \mathcal{D}_M$. The results are illustrated in Fig 1. It indicates that the adaptation with a small number (like $K = 3$) of models provide considerable performance improvement over baseline and gaze errors of adaptation basically decrease as the number of models increases. We choose $K = 10$ due to the balance between adaptation performance and computational cost.



(a) $\mathcal{D}_E \rightarrow \mathcal{D}_M$ (b) $\mathcal{D}_G \rightarrow \mathcal{D}_M$

Figure 1. The trend of angular errors (°) over iterations with gradually increasing the number of models for adaptation. The light colors denote the standard deviation of 20 times experiments.

Table 2. Angular gaze errors (°) ± stand deviations of adaptation with different number of target samples.

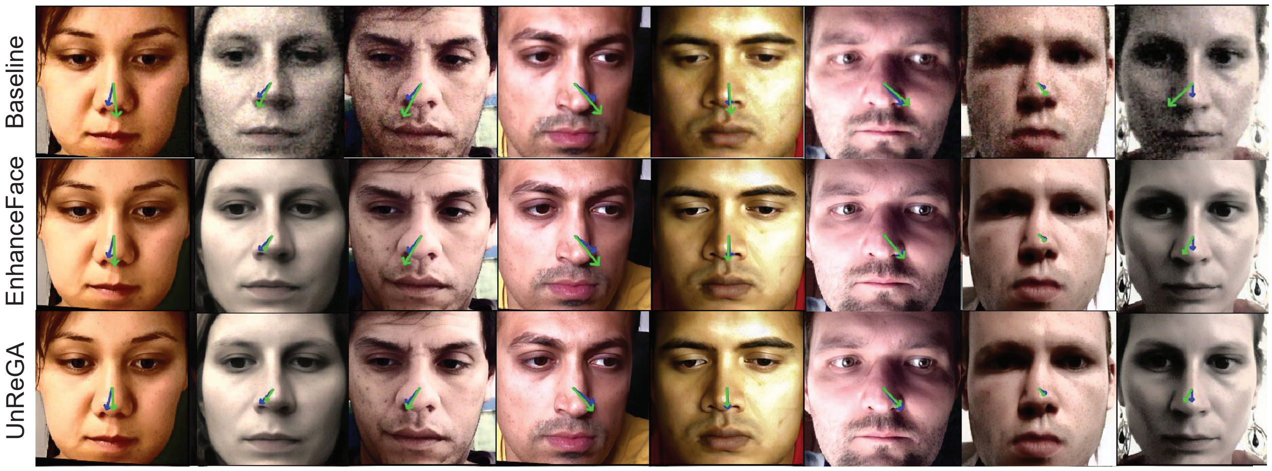
Number of Samples	20	50	100	200	500	1000	2000
UnReGA$^-$	5.30 ± 0.24	5.33 ± 0.21	5.35 ± 0.20	5.37 ± 0.17	5.39 ± 0.11	5.40 ± 0.10	5.42 ± 0.07
UnReGA	5.14 ± 0.12	5.12 ± 0.10	5.11 ± 0.09	5.16 ± 0.07	5.21 ± 0.07	5.23 ± 0.06	5.27 ± 0.05

A.3. Number of samples for adaptation

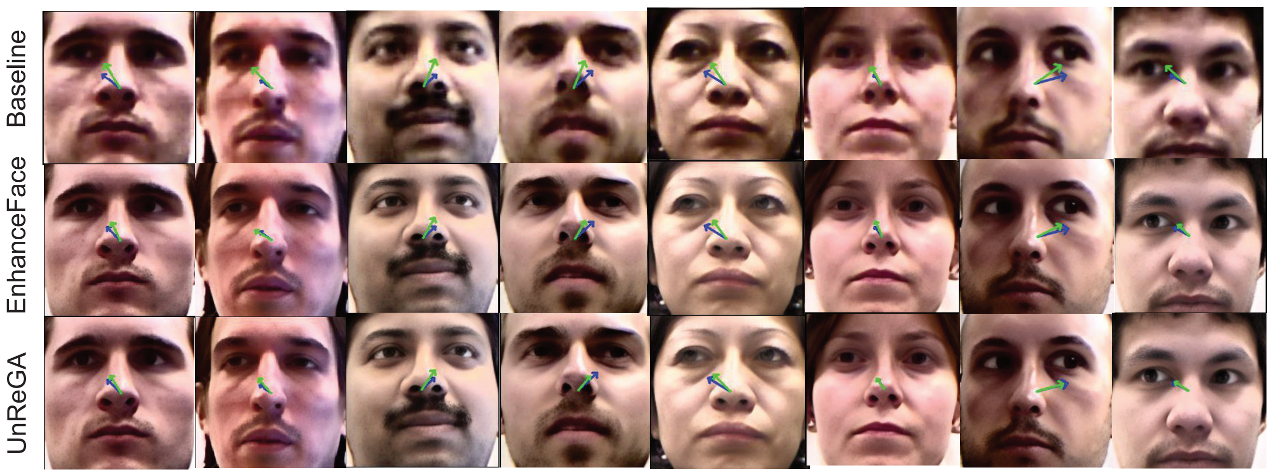
We conduct cross-domain experiments on $\mathcal{D}_E \rightarrow \mathcal{D}_M$ with different numbers of samples for source-free adaptation with UnReGA$^-$ and UnReGA. Table 2 shows the results that adaptation with 20 or 100 samples achieves better performance than adaptation with 500 or 2000 samples. It is indicated that a small number of samples is enough for the adaptation.

B. Illustrations of Face Enhancement and Gaze Adaptation

To understand the effectiveness of the proposed UnReGA intuitively, we visualize the enhancement results and gaze prediction before and after adaptation on cross-domain tasks $\mathcal{D}_E \rightarrow \mathcal{D}_M$ and $\mathcal{D}_E \rightarrow \mathcal{D}_D$ in Fig.2. The gaze ground truth and gaze prediction are denote by blue and green arrows respectively. We compare EnhanceFace and UnReGA with baseline and the results imply the superiority of the proposed methods.



(a) $\mathcal{D}_E \rightarrow \mathcal{D}_M$



(b) $\mathcal{D}_E \rightarrow \mathcal{D}_D$

Figure 2. Visualization examples of EnhanceFace and UnReGA on different cross-domain tasks. The blue and green arrows denote the gaze labels and the predictions respectively.