Generalizable Face Landmarking Guided by Conditional Face Warping

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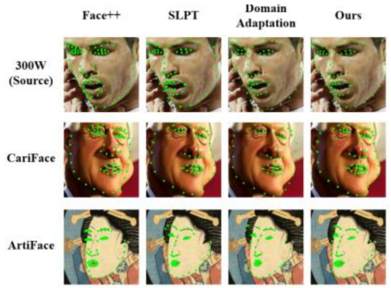
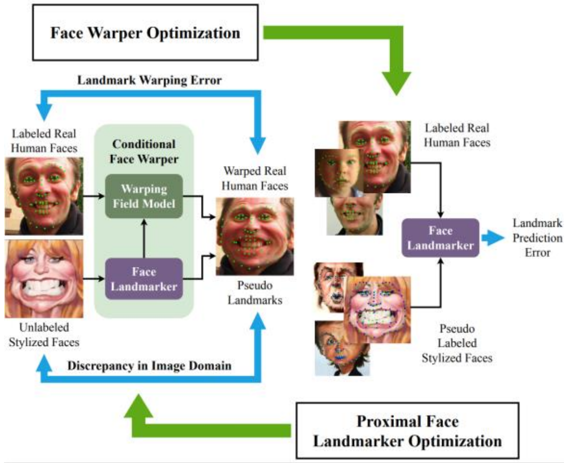
What Happened when SOTA Face Landmarkers generalize to unseen domains?



Even if applying SOTA domain adaptation strategies, the generalizability of the learned landmarkers in the stylized facial image domain is still unsatisfactory.

A Simple but Effective Learning Paradigm



$$\min_{\theta,\gamma} \underbrace{\sum_{j=1}^{N_L} \|f_\theta(\boldsymbol{X}_j^{(L)}) - \boldsymbol{Y}_j^{(L)}\|_F^2}_{\text{Landmarking error in the source domain}} + \underbrace{\sum_{i=1}^{N_U}\sum_{j=1}^{N_L} \|\nabla \widehat{\boldsymbol{X}}_{j|i}^{(L)} - \nabla \boldsymbol{X}_i^{(U)}\|_F^2}_{\text{Discrepancy of image gradient}} + \underbrace{\sum_{i=1}^{N_U}\sum_{j=1}^{N_L}\|w_{i,\gamma}(\widehat{\boldsymbol{Y}}_i^{(U)}) - \boldsymbol{Y}_j^{(L)}\|_F^2}_{\text{Landmark warping error}},$$

We learn a face landmarker embedded in a conditional face warper.

Key Idea: In each step, the face landmarker is updated to

i) minimize the discrepancy between the stylized faces and the corresponding warped real human faces;

ii) minimize the prediction errors of both real and pseudo landmarks.

Models and code are publicly available:

[generalized-face-landmarker]

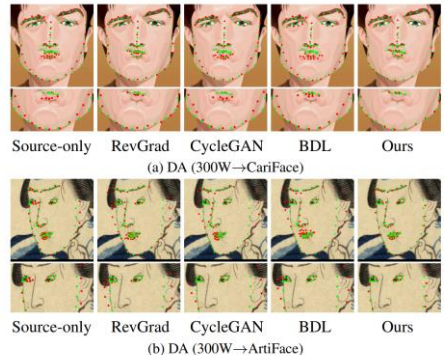
Experiments

Comparisons for various domain adaptation methods on their NMEs.

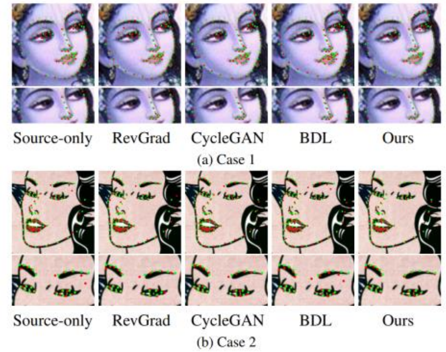
Model	300W-Full	CariFace	ArtiFace	Average NME
SL+RevGrad	3.38	12.19	5.16	7.83
SL+CycleGAN	3.27	12.11	4.70	7.70
SL+BDL	3.84	13.63	5.65	8.77
SL+ASN	3.38	12.21	4.75	7.80
SL+FDA	3.34	12.66	4.60	8.07
Ours	**3.20**	**7.70**	**3.95**	**5.46**

Experiments are conducted under DA(300W -> CariFace) and GZSL(Unseen ArtiFace).

Visualization Results

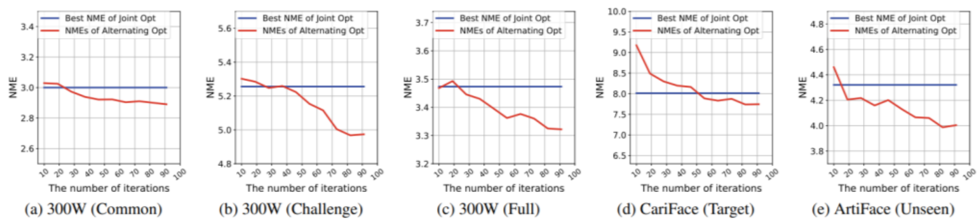


Comparison in two DA settings



Comparison in GZSL (Unseen ArtiFace)

Importance of Alternating Optimization



Comparisons for different optimization strategies in the GZSL (Unseen ArtiFace) setting.