Deep Disguised Faces Recognition

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1. Experiment

1.1. Training Details

In this paper, authors merge several public web-collected face recognition datasets including CASIA-WebFace, CelebA [3], MS1M [2], UMDFaces [1] and VGGFace2 as the generic face recognition training dataset. They have removed the images or identities overlap between training and testing based on provided identity names. For disguised face recognition adaptation, they select the first 250 transformation vectors to form the subspace projection W_{select}.

1.2. Testing Details

They use L_2 distance to compute the identity distance in their two-stage training. In the one-stage training, they compute the cosine similarity as identity similarity. In the Disguised Faces in the Wild (DFW) training, for a given subject, positive pairs are constructed from normal, validation and disguised face images. In contrast, negative pairs are constructed from normal and impostor face images as well as cross subject face images.

1.3. One-stage Training

As shown in Figure 1, authors use two DCNNs for unaligned and aligned faces respectively. In one-stage training, they evaluate the effectiveness of using multiple DCNNs. The results of the experiment is shown in Figure 2 and Table 1, it can be seen that combining different DCNNs can improve the performance.

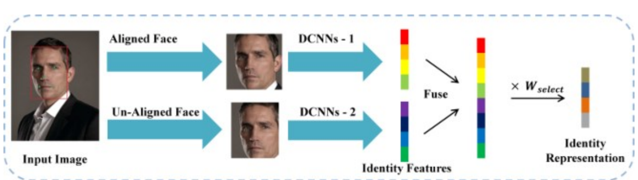

Figure 1. Illustration of overall identity representation extraction pipeline.

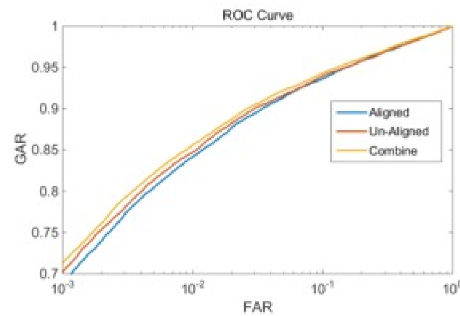

Figure 2. Evaluation of different DCNNs. These DCNNs are trained using one-stage training.

Table 1. Evaluation of different DCNNs. These DCNNs are trained using one-stage training.

Methods	GAR@FAR=1%	GAR@FAR=0.1%
Aligned	0.8421	0.6912
Un-Aligned	0.8474	0.7038
Combined	0.8571	0.7131

1.4. Two-stage Training

In two-stage training, they utilize the small-scale DFW training set. As shown in Figure 3 and Table 2, it can be seen that two-stage training can improve the performance compared with one-stage training.

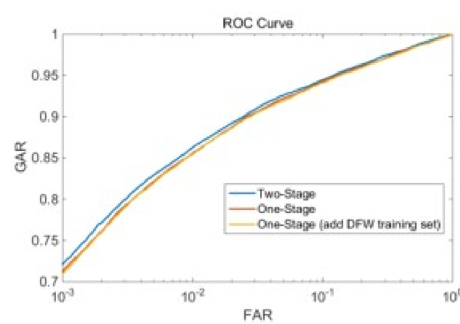

Figure 3. Evaluation of different training approaches.

Table 2. Evaluation of different DCNNs. These DCNNs are trained using one-stage training.

Methods	GAR@FAR=1%	GAR@FAR=0.1%
One-stage	0.8421	0.6912
Two-stage	0.8474	0.7038

References

[1] A. Bansal, A. Nanduri, C. D. Castillo, R. Ranjan, and R. Chellappa. UMDFaces: An annotated face dataset for training deep networks. In *IJCB*, pages 464–473, 2017. 1

[2] Y. D. Guo, L. Zhang, Y. X. Hu, X. D. He, and J. F. Gao. MS-Celeb-1M: A dataset and benchmark for large-scale face recognition. In *ECCV*, pages 87–102, 2016. 1

[3] Z. W. Liu, P. Luo, X. G. Wang, and X. O. Tang. Deep learning face attributes in the wild. In *ICCV*, pages 3730–3738, 2015. 1