Supplementary Material for BioNet: A Biologically-inspired Network for Face Recognition

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This supplementary material includes:

1. The influence of the attribute number (K) when ResNet-101 employs the Visual Cortex Network.
2. The Top-K accuracy on IJB-B [13] and IJB-C [10] datasets.
3. The performance on LFW [4], CFP-FP [11], CALFW [16], CPLFW [15], SLLFW [1], and YTF [14].
4. We list the performance of previous attribute-enhanced FR models [3, 8, 12]. Their theoretical limitations are introduced in the Related Work of the submitted paper.
5. The experiments with ResNet-101 also support the conclusion that the vanilla deep FR models and their straightforward improvement with borrowed mechanisms do not capture the human biological characteristics and can not boost FR performance as significantly as our BioNet.
6. The detailed illustration of the Straightforward Improvement with borrowed mechanisms in the submitted Tab.3 and our BioNet.

1. Influence of the Attribute Number (K) when ResNet-101 employs the VCN.

We employ the ResNet-101 and conduct the same experiments of the submitted Tab.6. The results in the following Tab.1 support the conclusion in the submitted paper, *i.e.* increasing the number of attributes is an effective method to improve the performance of BioNet.

2. Top-K Accuracy on IJB datasets

The top-K accuracies on IJB-B [13] and IJB-C [10] datasets are presented in Tab.2.

	#attr	IJB-A	IJB-B		IJB-C		MegaFace
		@1e-4	@1e-4	@1e-5	@1e-4	@1e-5	rank1
Baseline: ResNet-101	0	96.83	95.93	85.45	97.18	91.98	98.65
BioNet: Observed	4	97.51	**96.13**	92.18	97.32	94.57	99.19
BioNet: Latent	4	97.27	**96.13**	90.66	97.19	93.89	99.03
	10	97.35	96.10	91.36	96.95	93.41	98.83
	16	**97.69**	95.97	**92.96**	**97.91**	**94.58**	**99.21**

Table 1. Influence of attribute number (K).

	IJB-B			IJB-C		
	rank1	rank5	rank10	rank1	rank5	rank10
Baseline: CASIA-Net	88.03	92.47	94.21	89.05	93.35	94.51
BioNet: Latent	89.25	94.06	**95.89**	90.19	94.02	95.47
BioNet: Observed	**89.32**	**94.11**	95.68	**90.28**	**94.09**	**95.51**
Baseline: ResNet-101	93.54	95.51	96.93	94.51	95.49	97.09
BioNet: Latent	94.62	97.35	97.99	95.52	97.46	98.09
BioNet: Observed	**94.86**	**97.52**	**98.08**	**96.77**	**97.62**	**98.19**

Table 2. Top-K accuracy on IJB-B and IJB-C.

3. Performance on LFW, CFP-FP, CALFW, CPLFW, SLLFW, and YTF datasets

The performance on the evaluation datasets are presented in the following Tab.3. We observed our BioNet boost the GroupFace [6] with a marginal. We hypothesize it is because these small-scale evaluation datasets are not as challenging as the large-scale ones, which leads our improvement is not as significant as on the IJB-A/B/C and MegaFace.

	LFW	CFP-FP	CALFW	CPLFW	SLLFW	YTF
Baseline: CASIA-Net	99.30	94.00	91.60	80.44	97.28	95.12
BioNet: Latent	99.47	94.59	92.33	81.18	**98.03**	**95.44**
BioNet: Observed	**99.48**	**94.71**	**92.48**	**81.21**	97.87	95.42
Baseline: ResNet-101	99.82	98.14	95.28	92.01	99.33	97.76
BioNet: Latent	99.80	98.41	95.47	93.18	99.35	97.62
BioNet: Observed	**99.83**	**98.60**	**96.23**	**93.23**	**99.38**	**97.78**

Table 3. Performance on LFW, CFP, CALFW, CPLFW, SLLFW, and YTF

4. Performance of previous attribute-enhanced FR models

All the previous attribute-enhanced FR models have not evaluated their FR performance seriously. Besides, their performance is much inferior to the current status. This is the reason why we did not report their performance in the main paper. Their evaluation results are listed in the following:

1. Taherkhani *et al*. [12] proposed the PM method and evaluated it only on MegaFace [5]. Its performance is 78.82%.

2. Hu *et al*. [3] proposed GTNN and evaluated it on LFW [4], NIR-VIS 2.0 [9], and Multi-PIE [2]. We list its performance on LFW which is 99.65% and on NIR- VIS 2.0 which is 99.94%. For the performance on Multi-PIE, we refer to their paper because the evaluation protocol of Multi-PIE is complex.

3. Kumar *et al*., [8] evaluated their proposals only on LFW [4] which is 85.29%

In the view of attribute-enhanced FR, we carefully evaluate the performance of our proposals on all mainstream evaluation datasets, e.g., IJB-A/B/C [7, 10, 13], MegaFace [5], LFW [4], CFP-FP [11], CALFW [16], CPLFW [15], SLLFW [1], and YTF [14]. What's more, our BioNet significantly boosts the latest state-of-the-arts.

5. Studies about the Vanilla ResNet-101 Model and Its Straightforward Improvement

We employ the ResNet-101 and conduct the same experiments in the submitted Tab.3. The results in the following Tab.4 support the conclusion in the submitted paper.

		IJB-A @1e-4	IJB-B @1e-5	IJB-C @1e-5	MegaFace rank1	Feat From	Attr4 acc
Baseline: ResNet-101	FA	-	-	-	-		95.22
	FR	96.83	85.45	91.98	98.65	feat_id layer4	72.44 84.18
Straight-forward	Multitask I	94.99	74.04	87.75	98.41	feat_id	94.03
	Multitask II	95.12	86.64	92.09	98.60	feat_attrs	95.55
Improve-ment	Self-Attention	96.69	87.76	92.16	98.76	feat_id layer4	64.56 69.69
	Supervised-Attention	96.88	87.99	92.06	98.63	feat_attrs	95.53
ment	Avg-Ensemble	97.10	86.64	91.83	98.83	feat_attrs	95.46
ment	Adaptive-Ensemble	97.35	89.78	93.14	98.89	feat_attrs	95.48
Ours: BioNet		**97.51**	**92.18**	**94.57**	**99.19**	feat_attrs	**95.56**

Table 4. Studies about the vanilla FR model and its straightforward improvement.

6. Detailed Illustration of the *Straightforwad Improvement* of Previous CNNs

The submitted Tab.3 provides six straightforward improvement settings of the vanilla CNNs. They borrowed lessons from the attention mechanism, multi-task learning mechanism, and ensemble mechanism. The detailed illustrations of the settings are shown in the following Fig.1(A-F)

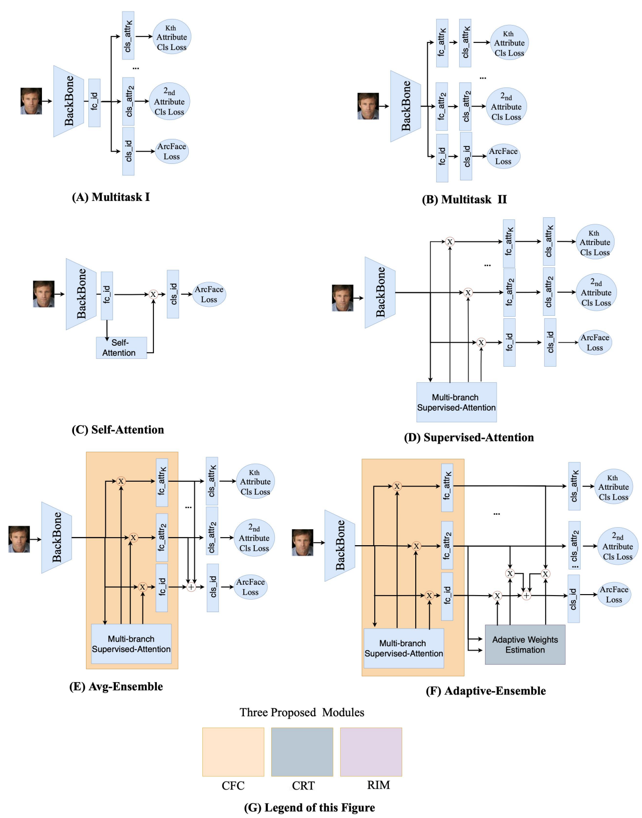

Figure 1. Straightforward improvement with borrowed mechanisms(A-F). (G) is the legend.

References

[1] Weihong Deng, Jiani Hu, Nanhai Zhang, Binghui Chen, and Jun Guo. Fine-grained face verification: Fglfw database, baselines, and human-dcmn partnership. *Pattern Recognition*, 66:63–73, 2017. 1, 2

[2] Ralph Gross, Iain Matthews, Jeffrey Cohn, Takeo Kanade, and Simon Baker. Multi-pie. *Image and vision computing*, 28(5):807–813, 2010. 2

[3] Guosheng Hu, Yang Hua, Yang Yuan, Zhihong Zhang, Zheng Lu, Sankha S Mukherjee, Timothy M Hospedales, Neil M Robertson, and Yongxin Yang. Attribute-enhanced face recognition with neural tensor fusion networks. In *Proceedings of the IEEE International Conference on Computer Vision*, pages 3744–3753, 2017. 1, 2

[4] Gary B Huang, Marwan Mattar, Tamara Berg, and Eric Learned-Miller. Labeled faces in the wild: A database forstudying face recognition in unconstrained environments. 2008. 1, 2

[5] Ira Kemelmacher-Shlizerman, Steven M Seitz, Daniel Miller, and Evan Brossard. The megaface benchmark: 1 million faces for recognition at scale. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 4873–4882, 2016. 2

[6] Yonghyun Kim, Wonpyo Park, Myung-Cheol Roh, and Jongju Shin. Groupface: Learning latent groups and constructing group-based representations for face recognition. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 5621–5630, 2020. 1

[7] Brendan F Klare, Ben Klein, Emma Taborsky, Austin Blanton, Jordan Cheney, Kristen Allen, Patrick Grother, Alan Mah, and Anil K Jain. Pushing the frontiers of unconstrained face detection and recognition: Iarpa janus benchmark a. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 1931–1939, 2015. 2

[8] Neeraj Kumar, Alexander C Berg, Peter N Belhumeur, and Shree K Nayar. Attribute and simile classifiers for face verification. In *2009 IEEE 12th international conference on computer vision*, pages 365–372. IEEE, 2009. 1, 2

[9] Stan Li, Dong Yi, Zhen Lei, and Shengcai Liao. The casia nir-vis 2.0 face database. In *Proceedings of the IEEE conference on computer vision and pattern recognition workshops*, pages 348–353, 2013. 2

[10] Brianna Maze, Jocelyn Adams, James A Duncan, Nathan Kalka, Tim Miller, Charles Otto, Anil K Jain, W Tyler Niggel, Janet Anderson, Jordan Cheney, et al. Iarpa janus benchmark-c: Face dataset and protocol. In *2018 International Conference on Biometrics (ICB)*, pages 158–165. IEEE, 2018. 1, 2

[11] Soumyadip Sengupta, Jun-Cheng Chen, Carlos Castillo, Vishal M Patel, Rama Chellappa, and David W Jacobs. Frontal to profile face verification in the wild. In *Applications of Computer Vision (WACV), 2016 IEEE Winter Conference on*, pages 1–9. IEEE, 2016. 1, 2

[12] Fariborz Taherkhani, Nasser M Nasrabadi, and Jeremy Dawson. A deep face identification network enhanced by facial attributes prediction. In *Proceedings of the IEEE conference on computer vision and pattern recognition workshops*, pages 553–560, 2018. 1, 2

[13] Cameron Whitelam, Emma Taborsky, Austin Blanton, Brianna Maze, Jocelyn Adams, Tim Miller, Nathan Kalka, Anil K Jain, James A Duncan, Kristen Allen, et al. Iarpa janus benchmark-b face dataset. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops*, pages 90–98, 2017. 1, 2

[14] Lior Wolf, Tal Hassner, and Itay Maoz. Face recognition in unconstrained videos with matched background similarity. In *CVPR 2011*, pages 529–534. IEEE, 2011. 1, 2

[15] Tianyue Zheng and Weihong Deng. Cross-pose lfw: A database for studying cross-pose face recognition in unconstrained environments. *Beijing University of Posts and Telecommunications, Tech. Rep*, 5, 2018. 1, 2

[16] Tianyue Zheng, Weihong Deng, and Jiani Hu. Cross-age lfw: A database for studying cross-age face recognition in unconstrained environments. *arXiv preprint arXiv:1708.08197*, 2017. 1, 2