GaitGCI: Generative Counterfactual Intervention for Gait Recognition –Supplementary Materials–

A. Implementation Details

A.1. Low-rank Backbone

To improve the efficiency and alleviate the learning difficulty, we adopt the backbone with four layers of low-rank 3D convolution, where each layer is implemented by sequential $1 \times 1 \times 3$, $1 \times 3 \times 1$, and $3 \times 1 \times 1$ convolutions as shown in Fig. 1. Low-rank convolution could efficiently save 2/3 parameters while reducing the redundancy of 3D convolution. One temporal downsampling layer with kernel size of 3 and one spatial downsampling layer with kernel size of 2 are performed after the first layer and the second layer, respectively.

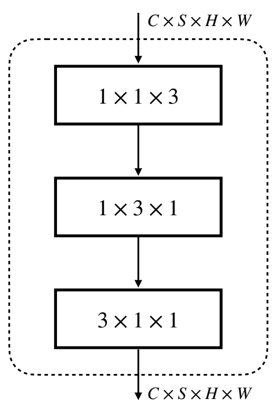


Figure 1. Illustration of low-rank 3D convolution, which aims to improve the efficiency and reduce the redundancy of 3D convolution.

A.2. More Details

The data pre-processing method is from [1]. The input resolution of all datasets is 64×44, and we report extra results under the resolution of 128×88 on Gait3D. The margin of triplet loss is set to 0.2. The frame is set to 30 at the training stage, while it is unfixed at the inference stage. All experiments are implemented by Pytorch with Nvidia 3090 GPUs.

B. Details of DCDC

B.1. Derivative of Schatten 1-norm.

Schatten 1-norm $||\mathbf{W}||_{S_1}$ is the convex approximation to rank function $Rank(\mathbf{W})$ and is differentiable. First, we decompose $\mathbf{W}$ as $\mathbf{U\Sigma V}^T$ based on singular value decomposition (SVD) assumption. Then, $\partial\mathbf{W}$ could be obtained as follows:

$$\partial\mathbf{W} = (\partial\mathbf{U})\mathbf{\Sigma}\mathbf{V}^T + \mathbf{U}(\partial\mathbf{\Sigma})\mathbf{V}^T + \mathbf{U}\mathbf{\Sigma}(\partial\mathbf{V}^T). \tag{1}$$

Next, $\partial\mathbf{\Sigma}$ should be figured out, and it could be represented as:

$$\partial\mathbf{\Sigma} = \mathbf{U}^T\partial(\mathbf{W})\mathbf{V} - \mathbf{U}^T(\partial\mathbf{U})\mathbf{\Sigma} - \mathbf{\Sigma}(\partial\mathbf{V}^T)\mathbf{V} = \mathbf{U}^T(\partial\mathbf{W})\mathbf{V}, \tag{2}$$

where $(-\mathbf{U}^T(\partial\mathbf{U})\mathbf{\Sigma} - \mathbf{\Sigma}(\partial\mathbf{V^T})\mathbf{V}) = 0$ .Thus, the process of the derivative on $||\cdot||_{S_1}$ could be accomplished as follows:

$$\frac{\partial||\mathbf{W}||_{S_1}}{\partial\mathbf{W}} = \frac{tr(\partial\mathbf{\Sigma})}{\partial\mathbf{W}} = \frac{tr(\mathbf{U}^T(\partial\mathbf{W})\mathbf{V})}{\partial\mathbf{W}} = \frac{tr(\mathbf{V}\mathbf{U}^T(\partial\mathbf{W}))}{\partial\mathbf{W}} = (\mathbf{V}\mathbf{U}^T)^T = \mathbf{U}\mathbf{V}^T. \tag{3}$$

B.2. Complexity Analysis of DCDC

We omit the kernel size for simplicity. For parameter complexity, static convolution and dynamic convolution require C^2 and $KC^2(K \geq 4)$, respectively. By contrast, DCDC requires sample-agnostic kernel $\mathbf{W}_0$ and sample-adaptive kernel $\mathbf{P\Phi}(\mathbf{X})\mathbf{Q}^T$ with C^2 and $(2CL + (C + L^2)\frac{C}{r})$ parameters, respectively. $\mathbf{P}/\mathbf{Q}$ is implemented by convolutions and $\mathbf{\Phi}(\mathbf{X})$ is implemented by MLP. The parameters of DCDC is summarized as:

$$Parameter_{DCDC} = C^2 + 2CL + (C + L^2)\frac{C}{r} < (1 + \frac{2}{r})C^2 + 2C\sqrt{C}(L^2 < C). \tag{4}$$

Therefore, DCDC is more parameter-efficient than dynamic convolution while using similar computation costs.

C. Detailed Results

C.1. Results of Each View on CASIA-B.

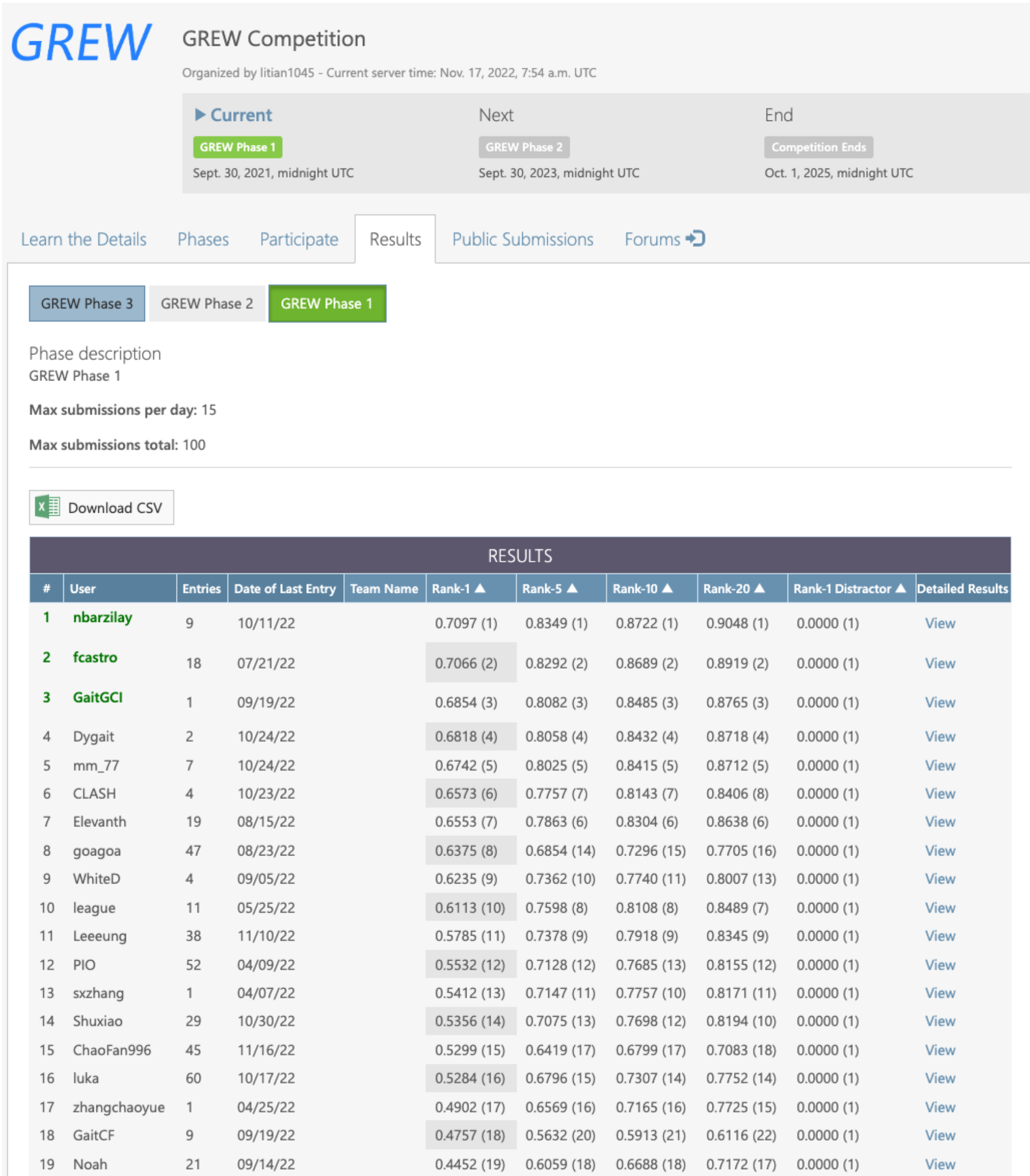
The performance under NM, BG, CL, and Mean condition is shown in the main manuscript. Further, the detailed cross-view performance is shown in Tab. 1. GaitGCI efficiently outperforms state-of-the-art performance at almost all viewpoints, which indicates the superior cross-view retrieval ability of GaitGCI.

Table 1. Averaged rank-1 accuracy on CASIA-B without identical views cases, including GaitSet [1], GaitPart [2], MT3D [5], CSTL [3], 3DLocal [4], and GaitGL [6].

Gallery NM #1-4		0°-180°											Mean
Probe	Method	0°	18°	36°	54°	72°	90°	108°	126°	144°	162°	180°	
NM	GaitSet	90.8	97.9	99.4	96.9	93.6	91.7	95.0	97.8	98.9	96.8	85.8	95.0
	GaitPart	94.1	98.6	99.3	98.5	94.0	92.3	95.9	98.4	99.2	97.8	90.4	96.2
	MT3D	95.7	98.2	99.0	97.5	95.1	93.9	96.1	98.6	99.2	98.2	92.0	96.7
	CSTL	97.2	99.0	99.1	98.0	96.3	95.6	97.1	98.7	99.2	98.9	96.7	97.9
	3DLocal	96.0	**99.0**	**99.5**	**98.9**	97.1	94.2	96.3	99.0	98.8	98.5	95.2	97.5
	GaitGL	96.0	98.3	99.0	97.9	96.9	95.4	97.0	98.9	**99.3**	98.8	94.0	97.4
	Ours	**97.3**	98.6	99.2	98.2	**97.3**	**95.7**	**97.1**	**99.2**	99.0	**99.1**	**96.8**	**97.9**
BG	GaitSet	83.8	91.2	91.8	88.8	83.3	81.0	84.1	90.0	92.2	94.4	79.0	87.2
	GaitPart	89.1	94.8	96.7	95.1	88.3	84.9	89.0	93.5	96.1	93.8	85.8	91.5
	MT3D	91.0	95.4	97.5	94.2	92.3	86.9	91.2	95.6	97.3	96.4	86.6	93.0
	CSTL	91.7	96.5	97.0	95.4	90.9	88.0	91.5	95.8	97.0	95.5	90.3	93.6
	3DLocal	92.9	95.9	97.8	96.2	93.0	87.8	92.7	96.3	97.9	98.0	88.5	94.3
	GaitGL	92.6	96.6	96.8	95.5	93.5	89.3	92.2	96.5	98.2	96.9	91.5	94.5
	Ours	**93.2**	**96.8**	**97.6**	**96.2**	**93.9**	**90.5**	**93.7**	**96.8**	**98.3**	**97.2**	**91.7**	**95.0**
CL	GaitSet	61.4	75.4	80.7	77.3	72.1	70.1	71.5	73.5	73.5	68.4	50.0	70.4
	GaitPart	70.7	85.5	86.9	83.3	77.1	72.5	76.9	82.2	83.8	80.2	66.5	78.7
	MT3D	76.0	87.6	89.8	85.0	81.2	75.7	81.0	84.5	85.4	82.2	68.1	81.5
	CSTL	78.1	89.4	91.6	86.6	82.1	79.9	81.8	86.3	88.7	86.6	75.3	84.2
	3DLocal	78.2	90.2	92.0	87.1	83.0	76.8	83.1	86.6	86.8	84.1	70.9	83.7
	GaitGL	76.6	90.0	90.3	87.1	84.5	79.0	84.1	87.0	87.3	84.4	69.5	83.6
	Ours	**81.1**	**91.3**	**93.2**	**90.4**	**85.7**	**80.6**	**87.1**	**88.3**	**89.3**	**87.3**	**75.5**	**86.4**

C.2. Results on GREW Competition.

The screenshot of the results on GREW competition is shown in Fig. 2. GaitGCI efficiently achieves 3^{th} in GREW competition only using silhouette, which indicates the necessity and effectiveness of alleviating the confounders for practical application.



GREW

GREW Competition

Organized by litian1045 - Current server time: Nov. 17, 2022, 7:54 a.m. UTC

Current	Next	End
GREW Phase 1	GREW Phase 2	Competition Ends
Sept. 30, 2021, midnight UTC	Sept. 30, 2023, midnight UTC	Oct. 1, 2025, midnight UTC

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GREW Phase 3 GREW Phase 2 GREW Phase 1

Phase description

GREW Phase 1

Max submissions per day: 15

Max submissions total: 100

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RESULTS

#	User	Entries	Date of Last Entry	Team Name	Rank-1	Rank-5	Rank-10	Rank-20	Rank-1 Distractor	Detailed Results
1	nbarzilay	9	10/11/22		0.7097 (1)	0.8349 (1)	0.8722 (1)	0.9048 (1)	0.0000 (1)	View
2	fcastro	18	07/21/22		0.7066 (2)	0.8292 (2)	0.8689 (2)	0.8919 (2)	0.0000 (1)	View
3	GaitGCI	1	09/19/22		0.6854 (3)	0.8082 (3)	0.8485 (3)	0.8765 (3)	0.0000 (1)	View
4	Dygait	2	10/24/22		0.6818 (4)	0.8058 (4)	0.8432 (4)	0.8718 (4)	0.0000 (1)	View
5	mm_77	7	10/24/22		0.6742 (5)	0.8025 (5)	0.8415 (5)	0.8712 (5)	0.0000 (1)	View
6	CLASH	4	10/23/22		0.6573 (6)	0.7757 (7)	0.8143 (7)	0.8406 (8)	0.0000 (1)	View
7	Elevanth	19	08/15/22		0.6553 (7)	0.7863 (6)	0.8304 (6)	0.8638 (6)	0.0000 (1)	View
8	goagoa	47	08/23/22		0.6375 (8)	0.6854 (14)	0.7296 (15)	0.7705 (16)	0.0000 (1)	View
9	WhiteD	4	09/05/22		0.6235 (9)	0.7362 (10)	0.7740 (11)	0.8007 (13)	0.0000 (1)	View
10	league	11	05/25/22		0.6113 (10)	0.7598 (8)	0.8108 (8)	0.8489 (7)	0.0000 (1)	View
11	Leeeung	38	11/10/22		0.5785 (11)	0.7378 (9)	0.7918 (9)	0.8345 (9)	0.0000 (1)	View
12	PIO	52	04/09/22		0.5532 (12)	0.7128 (12)	0.7685 (13)	0.8155 (12)	0.0000 (1)	View
13	sxzhang	1	04/07/22		0.5412 (13)	0.7147 (11)	0.7757 (10)	0.8171 (11)	0.0000 (1)	View
14	Shuxiao	29	10/30/22		0.5356 (14)	0.7075 (13)	0.7698 (12)	0.8194 (10)	0.0000 (1)	View
15	ChaoFan996	45	11/16/22		0.5299 (15)	0.6419 (17)	0.6799 (17)	0.7083 (18)	0.0000 (1)	View
16	luka	60	10/17/22		0.5284 (16)	0.6796 (15)	0.7307 (14)	0.7752 (14)	0.0000 (1)	View
17	zhangchaoyue	1	04/25/22		0.4902 (17)	0.6569 (16)	0.7165 (16)	0.7725 (15)	0.0000 (1)	View
18	GaitCF	9	09/19/22		0.4757 (18)	0.5632 (20)	0.5913 (21)	0.6116 (22)	0.0000 (1)	View
19	Noah	21	09/14/22		0.4452 (19)	0.6059 (18)	0.6688 (18)	0.7172 (17)	0.0000 (1)	View

Figure 2. The screenshots of the results on GREW competition, where proposed GaitGCI achieves 3^{th} among these methods.

D. Ethical Statements

In our research, we pay great attention to bio-information security and ethics. We should use gait recognition technology to affect social development and human happiness positively.

References

[1] Hanqing Chao, Yiwei He, Junping Zhang, and Jianfeng Feng. GaitSet: Regarding gait as a set for cross-view gait recognition. In *AAAI*, 2019. 1, 2

[2] Chao Fan, Yunjie Peng, Chunshui Cao, Xu Liu, Saihui Hou, Jiannan Chi, Yongzhen Huang, Qing Li, and Zhiqiang He. Gaitpart: Temporal part-based model for gait recognition. In *IEEE Conf. Comput. Vis. Pattern Recog.*, 2020. 2

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[6] Beibei Lin, Shunli Zhang, and Xin Yu. Gait recognition via effective global-local feature representation and local temporal aggregation. In *Int. Conf. Comput. Vis.*, pages 14648–14656, October 2021. 2