

GPGait: Generalized Pose-based Gait Recognition

Paper Review 05/02

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- Title: GPGait: Generalized Pose-based Gait Recognition
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- Year: 2023

Motivation

- Poor generalization ability of pose-based methods
- Performance degradation from unseen environments
- Cross-domain factors
 - Scale variation (distance from camera)
 - Tilt view (deployment of camera)

Proposed Method

- Human-Oriented Transformation (HOT)
 - Obtain unified representation
- Human-Oriented Descriptors (HOD)
 - Generate invariant features of bone and angle
 - Capture body structure and gait motion
- Part-Aware Graph Convolutional Network (PAGCN)
 - Graph partitioning based on body structure
 - Capture local and global information with different masks

Proposed Method

Human-Oriented Transformation (HOT)

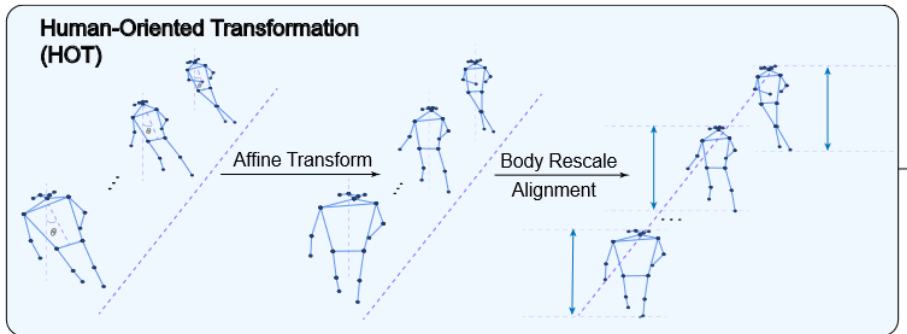


Figure 1: HOT Overview

Proposed Method

Human-Oriented Transformation (HOT)

- Affine transformation
 - Take spine angle as reference
 - neck position & hip joint
 - Applied if angle θ is larger than threshold
- Rescale
 - Height normalization
- Alignment
 - Subtract neck joint coordinate
 - Remove offsets from camera positioning

Proposed Method

Human-Oriented Descriptors (HOD)

- Bone features
 - Calculated by adjacent joints
- Angle features
 - Inner angle
 - Angular changes inside body
 - Peripheral angle
 - Movement of skeleton edge

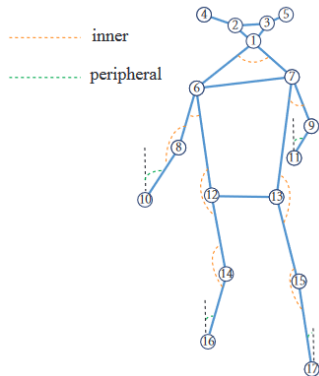


Figure 2: HOD Overview

Proposed Method

Part-Aware Graph Convolutional Network (PAGCN)

- Three parameter branches
 - joint
 - Bone
 - Angle
- Local PAGCN
 - Partition mask
 - Capture fine-grained body information
- Global PAGCN
 - Capture global spatial keypoint relationship

Proposed Method

Part-Aware Graph Convolutional Network (PAGCN)

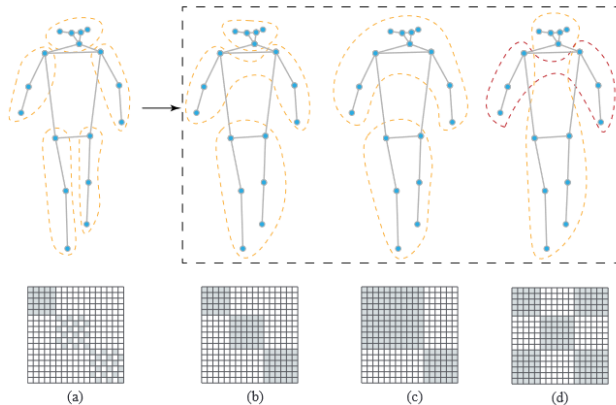


Figure 3: Mask Partition

Experiments

Result

Source Dataset	Method	Target Dataset						
		CASIA-B				OUMVLP-Pose	GREW	Gait3D
		NM	BG	CL	Mean			
CASIA-B	GaitGraph [36]	86.37	76.5	65.24	76.04	0.07	0.45	0.90
	GaitGraph2 [35]	80.29	71.40	63.80	71.83	0.07	0.48	1.10
	GaitTR [42]	94.72	89.29	86.65	90.22	0.07	0.62	1.10
	GPGait(ours)	93.60	80.15	69.29	81.01	2.84	9.97	8.90
OUMVLP-Pose	GaitGraph [36]	4.85	4.84	3.90	4.53	4.24	0.67	1.50
	GaitGraph2 [35]	8.83	7.62	5.13	7.19	70.68	0.85	1.40
	GaitTR [42]	10.10	8.26	5.17	7.84	39.77	1.06	2.60
	GPGait(ours)	44.36	31.97	22.35	32.90	59.11	11.13	9.00
GREW	GaitGraph [36]	10.54	7.73	5.73	8.00	0.17	10.18	4.40
	GaitGraph2 [35]	8.85	7.18	5.13	7.05	0.22	34.78	8.30
	GaitTR [42]	7.60	6.36	6.40	6.79	0.06	48.58	7.30
	GPGait(ours)	57.87	45.98	24.23	42.69	4.25	57.04	18.50
Gait3D	GaitGraph [36]	16.47	12.18	8.29	12.31	0.27	3.14	8.60
	GaitGraph2 [35]	12.32	9.93	5.43	9.23	0.09	2.39	11.20
	GaitTR [42]	4.50	3.90	3.96	4.12	0.06	4.38	7.20
	GPGait(ours)	48.83	40.26	19.43	36.17	2.79	11.02	22.40

Experiments

Ablation Study

Method	CASIA-B→Gait3D		Gait3D→CASIA-B	
	Source	Target	Source	Target
HOT(ours)	81.01	8.90	22.40	36.17
Spine-Unit [2,23]	74.53	5.50	14.50	15.74
Dataset-Independent [29]	87.03	1.50	9.90	11.54

Experiments

Ablation Study

Method(w/wo)	CASIA-B→Gait3D		Gait3D→CASIA-B	
	Source	Target	Source	Target
GaitGraph	40.91	1.96	11.00	29.24
GaitGraph2	45.66	3.20	12.20	24.49
GaitTR	64.37	2.40	8.10	21.74
GPGait	81.01	8.90	22.40	36.17
GaitGraph	76.04	0.90	8.60	12.31
GaitGraph2	71.83	1.10	11.20	9.23
GaitTR	90.22	1.10	7.20	4.12
GPGait	86.15	2.70	16.00	20.30

Experiments

Ablation Study

- Multi-Branch vs. Single-Branch
 - Focus on different type of features
- With mask partition vs. Without mask partition
 - Able to capture fine-grained features

Conclusion

- Performance on source-domain
- vs. silhouette-based methods
 - Keypoint vs. Body shape
 - Robustness to wearing and carrying, etc
- Compared to last reviewed paper
 - temporal information
 - computational cost

Thanks for Listening

Q & A