GPGait: Generalized Pose-based Gait Recognition
Supplemental Material

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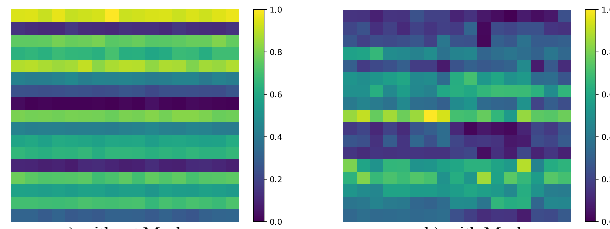
7. Human-Oriented Descriptor of Angle

Human-Oriented Descriptor of angle generates two types of skeleton angles to describe the gait movements, known as inner and peripheral. As shown in Fig.3, inner angle is the angle between two adjacent bones of a joint, which describes angular changes of the skeleton inside human body. While peripheral ones are formed between vertical lines and adjacent bones of joints on the outside, which reflect movements at the edge of skeletons. This calculation method does not rely on the absolute coordinate and is entirely human-oriented, which makes it more generalizable across different cameras and environments.



a) without Mask b) with Mask

Figure 6. The visualization of the keypoint heatmaps. a) points to the network without Part-Aware mechanism, and b) points to the network with Part-Aware mechanism. The x-axis represents the keypoints (17) of human body, and the y-axis represents the channels (17) taken from the final embedding.

8. Analysis of Over-Smooth

Over-smooth is a common problem in Graph Convolutional Networks [2–4] , *i.e.*, with the increase of non-linearity layers in GCN, the representation of each node in a connected component tends to converge to the same value. For the graph of human skeletons, each node contains its own semantic information and over-smooth is expected not to be so severe. Our proposed Part-Aware method can restrict the interaction of keypoint information within parts, which helps alleviate over-smooth to a large extent. By visualizing the heatmap of keypoints in the network, as shown in Fig.6, we can see that the value of each keypoint feature becomes more discriminative. This demonstrates the effectiveness of Part-Aware GCN blocks in reducing the over-smooth.

9. More Discussion on Comparison

First, as stated in Sec.5, GPGait does not achieve the highest performance (but comparable to state-of-the-art) on the source domain for some of the datasets. The main reason is the adoption of Human-Oriented Transformation, aimed at achieving a unified representation that can be compared across various cameras and scenes. During this transformation, certain attributes present exclusively in a single domain (*e.g*. the relative height of the human body) are lost. However, as far as we can see, a unified representation is essential to improve the generalization ability and achieve practical recognition, which is verified by a thorough cross-domain study.

Second, it can be observed from Tab.1 that our method is the most stable one across different datasets. For example, GaitTR achieves remarkable results on CASIA-B, while its performance on OUMVLP-Pose and Gait3D is instead much inferior to GaitGraph2 (*e.g*. GaitTR: 39.77% *v.s.* GaitGraph2: 70.68% on OUMVLP-Pose). In comparison, GPGait achieves the highest or close to the highest accuracy on the source domain of each dataset, and more importantly, the cross-domain performance is improved by a large margin (*e.g*. +34.69% for GREW→ CASIA-B).

In summary, our work makes one of the pioneering attempts to improve the generalization ability of pose-based gait recognition, which is worthy of continuous attention due to its robustness to carrying and clothing. We have built a project[1] to release GPGait as well as the re-implementations of improved baselines (GaitGraph [6], GaitGraph2 [5], GaitTR [7]), and we hope these efforts will promote pose-based research for gait recognition.

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[1] https://github.com/BNU-IVC/FastPoseGait

10. Ethical Statements

Our work is guided by a strong commitment to upholding ethical and security standards [1] when handling biometric data, with the aim of promoting the development of gait recognition for the betterment of society and the improvement of human well-being.

References

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