Silhouette based View embeddings for Gait Recognition under Multiple Views



Introduction: \succ Gait is a biometric presenting the walking style of people and has an edge over other biometrics because it can be recognized at a distance with much less cooperation. > Viewpoint differences is a very tricky problem, because it may bring greater visual differences than the identity.

- > Many methods have been proposed based on silhouette image sequences, for example, GaitSet, GaitGL, GaitPart.
- \succ However, all of these methods mainly focus on how to extract features through spatial-temporel modeling. None of them take view itself into consideration.



> In this paper, we proposed a general framework for multi-view gait recognition by explicit view angle embedding, based on which, two state-of-the-art gait recognition backbones, i.e.Gaitset and GaitGL are enhanced. Compared with the original ones, the enhanced ones, improve the performance. The effectiveness is well demonstrated by the experiments on CASIA-B and OUMVLP datasets.

Tianrui Chai, Xinyu Mei, Annan Li, Yunhong Wang State Key Laboratory of Virtual Reality Technology and Systems, School of Computer Science and Engineering, Beihang University, Beijing 100191, China. {trchai,xymei,liannan,yhwang}@buaa.edu.cn



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Method:

 \succ The feature map X_f is calculated form the input X_{in} using the backbone E as well as the view feature f_{ν} :

 $X_f = E(X_{in})$ and $f_v = F(P_{Global} Av_q(X_f))$

- > Especially for Gaitset, there is another feature map X_a , then the view feature is defined as:
- $f_v = F(P_{Global_Avg}([X_f; X_g]))$ \succ Where F denotes a fc layer. Then the predicted view can be expressed as:

 $\hat{p} = W_{view} f_v + B_{view}$ and

- \triangleright Where $\hat{y} \in \{0, 1, 2, \dots, M\}$ and M is the number of views (10 for CASIA-B and 14 for OU-MVLP). The corresponding set of projection matrixes is: $Z_{\hat{y}} = \{W_i | i = 1, 2, ..., n\}$
- > Assuming the feature obtained after HPP module are: $f_{HPM} \in \mathbb{R}^{n \times D}$
- > Then the final Identity feature is:

$$f_{final,i} = W_i f_{HPM,i}$$

$$f_{final} = [f_{final,1}, f_{final,2}, \dots, f_{final,n}]_{i}$$

> The joint loss is

$$\mathcal{L}_{CE} = -\sum_{i=1}^{N} \sum_{i=1}^{M} y_j \log(p_{ji}) \quad w.r.t. \quad p_{ji} = \sum_{i=1}^{N} \mathcal{L}_{trip} = \frac{1}{K} \sum_{i=1}^{K} \sum_{j=1}^{n} \max(m - d_{ij}^- + d_{ij}^-)$$

$$\mathcal{L} = \lambda_{CE} \mathcal{L}_{CE} + \lambda_{i}$$

$$\hat{y} = \arg\max_{i} \hat{p_i}$$

 $\sum_{i=1}^{M} e^{\hat{p}_{ji}}$ $d_{ij}^+, 0)$ $trip \mathcal{L} trip$

Experiments:



Table 2. Rank-1 accuracy (%) on OU-MVLP under 14 probe views excluding identical-view cases.

Probe angle	Gallery All 14 views					
	GEINet	Gaitset	Vi-Gaitset	GaitPart	GaitGL	Vi-GaitGL
0°	11.4	79.5	81.8	82.6	84.3	85.6
15°	29.1	87.9	89.2	88.9	89.8	90.2
30°	41.5	89.9	90.5	90.8	90.8	91.2
45°	45.5	90.2	90.5	91.0	91.0	91.5
60°	39.5	88.1	89.2	89.7	90.5	91.1
75°	41.8	88.7	89.5	89.7	90.5	90.9
90°	38.9	87.8	89.0	89.9	90.3	90.4
180°	14.9	81.7	83.9	85.2	88.1	88.3
195°	33.1	86.7	88.1	88.1	87.9	88.7
210°	43.2	89.0	89.7	90.0	89.6	90.6
225°	45.6	89.3	89.8	90.1	89.8	90.6
240°	39.4	87.2	88.6	89.0	88.9	90.1
255°	40.5	87.8	88.5	89.1	88.9	89.9
270°	36.3	86.2	87.6	88.2	88.2	89.4
mean	35.8	87.1	88.3	88.7	89.1	89.9

(More experiments of dataset CASIA-B can be find in the paper)

Conclusion

- Combined the task of view prediction and gait recognition.
- Proposed a general view embedding framework for improving multi-view gait recognition.
- The proposed framework with GaitSet and GaitGL as the backbone meets the state-of-the-art on two large-scale public gait datasets.





