

Person re-identification in video surveillance systems by feature replacement of occluded parts of human figures

- [Original Article](#)
- Published: 13 May 2025
- Volume 28, article number 102, (2025)
- [Cite this article](#)

- [Shiping Ye,](#)
- [R. Bohush,](#)
- [S. Ihnatsyeva &](#)
- [S. Ablameyko](#)

Abstract

The algorithm for re-identifying people in intelligent video surveillance systems is proposed. It is based on the construction of a compound neural network descriptor and replacing features of occluded parts of a human figure. Composite descriptors are generated for all images in a gallery and recorded in a table. They characterize the global and local features of each person, considering his individual parts' visibility. Detection and selection of areas of interest for the formation of local descriptors is carried out based on detecting key points of the human body. If a person is partially occluded by other people or objects, then the corresponding region is classified as invisible, and the compound descriptor of respective component will be invalid and equal to zero. For images whose feature vector has zero components, the feature table is ranked according to the cosine similarity metric for each visible local fragment. Based on the feature table rankings, the k -nearest neighbors are determined and the k_1 -best are selected from them. The corresponding k_1 -nearest neighbors' component average value of the feature vector is used to replace the zero descriptor components. The feature table is then

updated for the generated vectors and ranking is performed according to the query using the cosine similarity metric. ResNet-50 and DenseNet-121 were used as backbone CNNs for feature extraction, and testing was performed using Market-1501, DukeMTMC-ReID, Occluded-Duke, MSMT17, and PolReID1077 datasets.

Data availability

No datasets were generated or analysed during the current study.

References

1. Chen H, Ihnatsyeva SA, Bohush RP, Ablameyko SV (2023) Person re-identification in video surveillance systems using deep learning: analysis of the existing methods. *Autom Remote Control* 5:497–5282. <https://doi.org/10.1134/S0005117923050041>

Article Google Scholar

2. Zhong Z, Zheng L, Kang G et al (2020) Random erasing data augmentation. *AAAI Conf Artif Intell.* 34(07): 13001–13008. <https://doi.org/10.1609/aaai.v34i07.7000>
3. Wang G, Yang S, Liu H et al (2020) High-order information matters: learning relation and topology for occluded person re-identification. In: 2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), pp 6448–6457. <https://doi.org/10.1109/CVPR42600.2020.00648>
4. Yang J, Zhang J, Yu F et al (2021) Learning to know where to see: a visibility-aware approach for occluded person re-identification. In: 2021 IEEE/CVF International Conference on Computer Vision (ICCV), pp 11865–11874. <https://doi.org/10.1109/ICCV48922.2021.01167>
5. Fang H, Xie S, Tai Y, Lu C (2017) RMPE: regional Multi-person Pose Estimation. In: 2017 IEEE International Conference on Computer Vision (ICCV), pp 2353–2362. <https://doi.org/10.1109/ICCV.2017.256>

6. Chen LC, Papandreou G, Schroff F, Adam H (2017) Rethinking atrous Convolution for semantic image segmentation. ArXiv Abs. /1706.05587<https://doi.org/10.48550/arXiv.1706.05587>

Article Google Scholar

7. Yang Q, Wang P, Fang Z, Lu Q (2020) Focus on the visible regions: semantic-guided alignment model for occluded person re-identification. Sensors 20(16):4431. <https://doi.org/10.3390/s20164431>

Article Google Scholar

8. Yao Z, Wu X, Xiong Z, Ma Y (2019) A dynamic part-attention model for person re-identification. Sensors 19(9): 2080. <https://doi.org/10.3390/s19092080>
9. Sun Y, Zheng L, Yang Y et al (2018) Beyond part models: person retrieval with refined part pooling (and A strong convolutional Baseline). Comput Vis – ECCV 2018 Lecture Notes Comput Sci 11208:501–518

Google Scholar

10. Miao J, Wu Y, Liu P et al (2019) Pose-guided feature alignment for occluded person re-identification. In: 2019 IEEE/CVF International Conference on Computer Vision (ICCV), pp 542–551. <https://doi.org/10.1109/ICCV.2019.00063>
11. Miao J, Wu Y, Yang Y (2022) Identifying visible parts via pose Estimation for occluded person re-Identification. IEEE Trans Neural Netw Learn Syst 33(9):4624–4634. <https://doi.org/10.1109/TNNLS.2021.3059515>

Article Google Scholar

12. Kalayeh MM, Basaran E, Gokmen M et al (2018) Human semantic parsing for person re-identification. In: 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition, pp 1062–1071. <https://doi.org/10.1109/CVPR.2018.00117>
13. Chen Y, Zhu X, Gong S et al (2017) Person re-identification by deep learning multi-scale representations. In: 2017 IEEE International Conference on Computer Vision Workshops (ICCVW), pp 2590–2600. <https://doi.org/10.1109/ICCVW.2017.304>

14. Lin Y, Zheng L, Zheng Z, et al (2019) Improving person re-identification by attribute and identity learning. ArXiv abs/170307220. <https://doi.org/10.1016/j.patcog.2019.06.006>
15. Liao S, Shao L (2022) Graph sampling based deep metric learning for generalizable person re-identification. arXiv:2104.01546. <https://doi.org/10.48550/arXiv.2104.01546>
16. Tan H, Liu X, Yin B, Li X (2023) MHSA-Net: multihead self-attention network for occluded person re-identification. IEEE Trans Neural Networks Learn Syst 34(11):8210–8224. <https://doi.org/10.1109/TNNLS.2022.3144163>

Article Google Scholar

17. Mamedov T, Konushin A, Konushin V (2024) ReMix: Training generalized person re-identification on a mixture of data. arXiv:2410.21938. <https://doi.org/2410.21938>
18. Li W, Zhao R, Xiao T, Wang X (2014) DeepReID: Deep Filter Pairing Neural Network for Person Re-identification. In: 2014 IEEE Conference on Computer Vision and Pattern Recognition, pp 152–159. <https://doi.org/10.1109/CVPR.2014.27>
19. Zheng L, Shen L, Tian L (2015) Scalable Person Reidentification: A Benchmark. In: 2015 IEEE International Conference on Computer Vision (ICCV), pp 1116–1124. <https://doi.org/10.1109/ICCV.2015.133>
20. Ristani E, Solera F, Zou RS et al (2016) Multi-camera Track ArXiv abs. Performance Measures and a Data Set for Multi-target/1609.01775. <https://doi.org/10.48550/arXiv.1609.01775>
21. Wei L, Zhang S, Gao W, Tian Q (2018) Person transfer GAN to bridge domain gap for person re-identification. In: 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition, pp 79–88. <https://doi.org/10.1109/CVPR.2018.00016>
22. Fu D, Chen D, Bao J et al (2021) Unsupervised pre-training for person re-identification. In: 2021 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), pp 14745–14754. <https://doi.org/10.1109/CVPR46437.2021.01451>

23. Zheng Z (2017) Person_reID_baseline_pytorch. https://github.com/layumi/Person_reID_baseline_pytorch. Accessed 23 Dec 2024
24. Huang Y, Wu Q, Zhong Y, Zhang Z (2021) Clothing status awareness for long-term person re-identification. In: 2021 IEEE/CVF International Conference on Computer Vision, pp 11895–11904. <https://doi.org/10.1109/ICCV48922.2021.01168>
25. Wang G, Lai J, Huang P, Xie X (2019) Spatial-temporal person re-identification. Proc AAAI Conf Artif Intell 33(01):8933–8940. <https://doi.org/10.1609/aaai.v33i01.33018933>

Article Google Scholar

26. Choi S, Kim T, Jeong M et al (2021) Meta batch-instance normalization for generalizable person re-identification. In: 2021 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), pp 3424–3434. <https://doi.org/10.1109/CVPR46437.2021.00343>
27. Chen P, Dai P, Liu J et al (2021) Dual distribution alignment network for generalizable person re-identification. Proc AAAI Conf Artif Intell 35(2):1054–1062. <https://doi.org/10.1609/AAAI.V35I2.16190>
28. Zhao C, Chen K, Wei Z et al (2019) Multilevel triplet deep learning model for person re-identification. Pattern Recognit Lett 117:161–168. <https://doi.org/10.1016/j.patrec.2018.04.029>

Article Google Scholar

29. Yao Y, Jiang X, Fujita H, Fang Z (2022) A sparse graph wavelet convolution neural network for video-based person re-identification. Pattern Recogn 129(16):108708. <https://doi.org/10.1016/j.patcog.2022.108708>

Article Google Scholar

30. Ye S, Bohush R, Chen H et al (2023) Data augmentation and fine tuning of Convolution neural network during training for person Re-identification in video surveillance system. Opt Memory Neural Netw 4(32):233–246. <https://doi.org/10.3103/S1060992X23040124>

Article Google Scholar

31. Dataset
PolReID1077 <https://github.com/SvetlanaIgn/PolReID1077>.
Accessed 23 Dec 2024
32. Wong KY (2022)
Yolo7. <https://github.com/WongKinYiu/yolov7/tree/pose>.
Accessed 23 Dec 2024
33. Li W, Wang X (2013) Locally aligned feature transforms across views. IEEE Conference on Computer Vision and Pattern Recognition, Portland, OR, USA. pp 3594–3601. <https://doi.org/10.1109/CVPR.2013.461>
34. Song G, Leng B, Liu Y et al (2018) Region-based quality estimation network for large-scale person re-identification. Thirty-Second AAAI Conf Artif Intell (AAAI-18) 32(1):7347–7354. <https://doi.org/10.1609/aaai.v32i1.12305>

Article Google Scholar

35. Zheng L, Bie Z, Sun Y et al (2016) MARS: a video benchmark for large-scale person re-identification. ECCV 2016. Lecture Notes in Computer Science. 9910:863–884. https://doi.org/10.1007/978-3-319-46466-4_52
36. Ye M, Shen J, Lin G et al (2021) Deep learning for person re-identification: a survey and outlook. IEEE Trans Pattern Anal Mach Intell 44(6):2872–2893. <https://doi.org/10.1109/TPAMI.2021.3054775>

Article Google Scholar

37. Bohush R, Ihnatsyeva S, Ablameyko S (2022) Person re-identification accuracy improvement by training a CNN with the new large joint dataset and re-rank. Mach Graphics Vis 31(1/4):93–109. <https://doi.org/10.22630/MGV.2022.31.1.5>

Article Google Scholar

38. Chen M, Wang Z, Zheng F (2021) Benchmarks for corruption invariant person reidentification. ArXiv abs/2111.00880. <https://doi.org/10.48550/arXiv.2111.00880>
39. Luo H, Gu YZ, Liao XY et al (2019) Bag of tricks and a strong baseline for deep person re-identification. In: IEEE/CVF Conference on Computer Vision and Pattern Recognition

Workshops (CVPRW). pp 1487–
1495. <https://doi.org/10.1109/CVPRW.2019.00190>

40. Li Y, Yang Z, Chen Y et al (2022) Occluded person Re-Identification method based on multiscale features and human feature reconstruction. IEEE Access 10:98584–98592. <https://doi.org/10.1109/ACCESS.2022.3203706>

Article Google Scholar

41. Kim M, Cho M, Lee H et al (2022) Occluded person re-identification via relational adaptive feature correction learning. ICASSP 2022–2022 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pp 2719–2723. <https://doi.org/10.1109/ICASSP43922.2022.9746734>
42. Wang P, Ding C, Shao Z et al (2022) Quality-Aware part models for occluded person re-Identification. IEEE Trans Multimedia 25:3154–3165. <https://doi.org/10.1109/TMM.2022.3156282>

Article Google Scholar

Download references

Author information

Authors and Affiliations

1. **Zhejiang Shuren University, Shuren Str., 8, Hangzhou, China**
Shiping Ye
2. **Polotsk State University, Blokhina str.29, Novopolotsk, Belarus**
R. Bohush & S. Ihnatsyeva
3. **Belarusian State University, Nezavisimosti Avenue 4, Minsk, Belarus**
S. Ablameyko
4. **United Institute of Informatics Problems, Surganova str. 6, Minsk, Belarus**
S. Ablameyko

Contributions

All authors contribute equally to this paper.

Corresponding author

Correspondence to [R. Bohush](#).

Ethics declarations

Conflict of interest

The authors declare no competing interests.

Additional information

Publisher's note

Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Rights and permissions

Springer Nature or its licensor (e.g. a society or other partner) holds exclusive rights to this article under a publishing agreement with the author(s) or other rightsholder(s); author self-archiving of the accepted manuscript version of this article is solely governed by the terms of such publishing agreement and applicable law.

Reprints and permissions

About this article

Cite this article

Ye, S., Bohush, R., Ihnatsyeva, S. *et al.* Person re-identification in video surveillance systems by feature replacement of occluded parts of human figures. *Pattern Anal Applic* **28**, 102 (2025). <https://doi.org/10.1007/s10044-025-01482-1>

Download citation

- Received 30 January 2025
- Accepted 28 April 2025
- Published 13 May 2025
- Version of record 13 May 2025
- DOI <https://doi.org/10.1007/s10044-025-01482-1>

Keywords

- **Convolution neural networks**
- **Database for re-identification**
- **Compound descriptor**
- **Image augmentation**