Análise da remoção de background no processo de Person Re-Identification

Diógenes Wallis

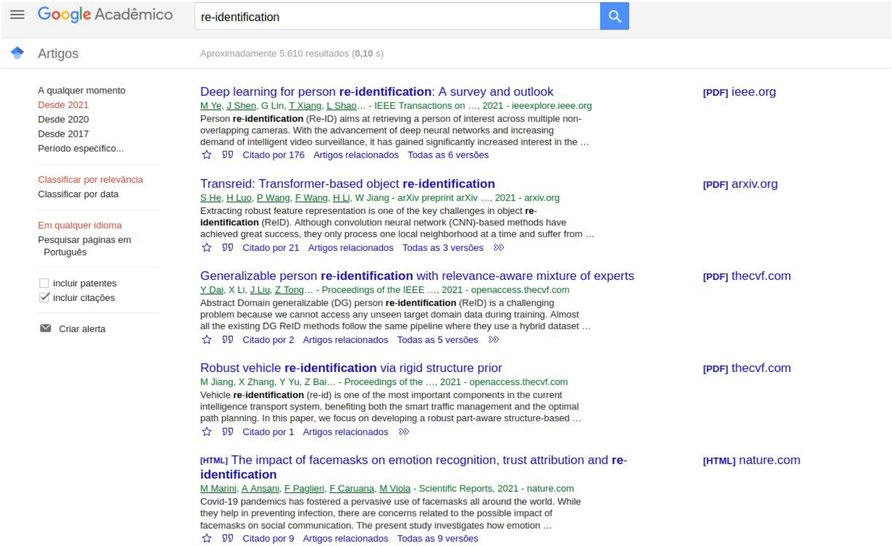
Re-Identification

- Relevância no mercado de sistemas de vigilância.
- Forma inteligente de localizar pedestres por imagens capturadas em posições diferentes.

[1] Marco Cristani, Vittorio Murino, Chapter 10 - Person re-identification, Editor(s): Rama Chellappa, Sergios Theodoridis, Academic Press Library in Signal Processing, Volume 6, Academic Press, 2018, Pages 365-394, ISBN 9780128118894, https://doi.org/10.1016/B978-0-12-811889-4.00010-5.

Re-Identification

- Destaque acadêmico


Google Acadêmico re-identification

Artigos Aproximadamente 5.610 resultados (0,10 s)

A qualquer momento
Desde 2021
Desde 2020
Desde 2017
Período específico...

Classificar por relevância
Classificar por data

Em qualquer idioma
Pesquisar páginas em Português

incluir patentes
incluir citações

Criar alerta

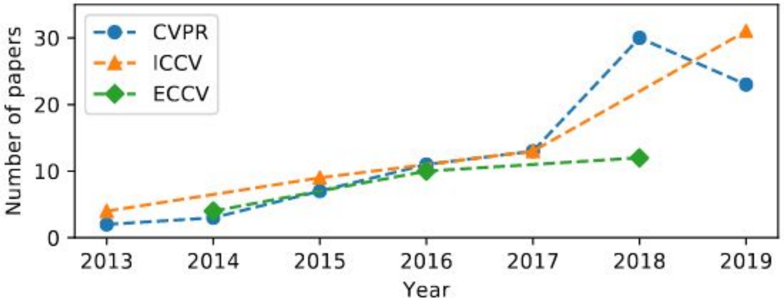
Deep learning for person **re-identification**: A survey and outlook [PDF] ieee.org
M Ye, J Shen, G Lin, T Xiang, L Shao... - IEEE Transactions on ..., 2021 - ieeexplore.ieee.org
Person **re-identification** (Re-ID) aims at retrieving a person of interest across multiple non-overlapping cameras. With the advancement of deep neural networks and increasing demand of intelligent video surveillance, it has gained significantly increased interest in the ...
Citado por 176 Artigos relacionados Todas as 6 versões

Transreid: Transformer-based object **re-identification** [PDF] arxiv.org
S He, H Luo, P Wang, F Wang, H Li, W Jiang - arXiv preprint arXiv ..., 2021 - arxiv.org
Extracting robust feature representation is one of the key challenges in object **re-identification** (ReID). Although convolution neural network (CNN)-based methods have achieved great success, they only process one local neighborhood at a time and suffer from ...
Citado por 21 Artigos relacionados Todas as 3 versões

Generalizable person **re-identification** with relevance-aware mixture of experts [PDF] thecvf.com
Y Dai, X Li, J Liu, Z Tong... - Proceedings of the IEEE ..., 2021 - openaccess.thecvf.com
Abstract Domain generalizable (DG) person **re-identification** (ReID) is a challenging problem because we cannot access any unseen target domain data during training. Almost all the existing DG ReID methods follow the same pipeline where they use a hybrid dataset ...
Citado por 2 Artigos relacionados Todas as 5 versões

Robust vehicle **re-identification** via rigid structure prior [PDF] thecvf.com
M Jiang, X Zhang, Y Yu, Z Bai... - Proceedings of the ..., 2021 - openaccess.thecvf.com
Vehicle **re-identification** (re-id) is one of the most important components in the current intelligence transport system, benefiting both the smart traffic management and the optimal path planning. In this paper, we focus on developing a robust part-aware structure-based ...
Citado por 1 Artigos relacionados

[HTML] The impact of facemasks on emotion recognition, trust attribution and **re-identification** [HTML] nature.com
M Marini, A Ansani, F Paglieri, F Caruana, M Viola - Scientific Reports, 2021 - nature.com
Covid-19 pandemics has fostered a pervasive use of facemasks all around the world. While they help in preventing infection, there are concerns related to the possible impact of facemasks on social communication. The present study investigates how emotion ...
Citado por 9 Artigos relacionados Todas as 9 versões



[2] ZHOU, Kaiyang; XIANG, Tao. Torchreid: A library for deep learning person re-identification in pytorch. arXiv preprint arXiv:1910.10093, 2019.

Re-Identification

- Problemas

Method	Publication	Backbone	Market1501		CUHK03		Duke		MSMT17	
			R1	mAP	R1	mAP	R1	mAP	R1	mAP
ShuffleNet†‡ [78]	CVPR'18	ShuffleNet	84.8	65.0	38.4	37.2	71.6	49.9	41.5	19.9
MobileNetV2†‡ [43]	CVPR'18	MobileNetV2	87.0	69.5	46.5	46.0	75.2	55.8	50.9	27.0
BraidNet† [63]	CVPR'18	BraidNet	83.7	69.5	-	-	76.4	59.5	-	-
HAN† [29]	CVPR'18	Inception	91.2	75.7	41.7	38.6	80.5	63.8	-	-
OSNet† (ours)	ICCV'19	OSNet	93.6	81.0	57.1	54.2	84.7	68.6	71.0	43.3
DaRe [64]	CVPR'18	DenseNet	89.0	76.0	63.3	59.0	80.2	64.5	-	-
PNGAN [39]	ECCV'18	ResNet	89.4	72.6	-	-	73.6	53.2	-	-
KPM [46]	CVPR'18	ResNet	90.1	75.3	-	-	80.3	63.2	-	-
MLFN [2]	CVPR'18	ResNeXt	90.0	74.3	52.8	47.8	81.0	62.8	-	-
FDGAN [11]	NeurIPS'18	ResNet	90.5	77.7	-	-	80.0	64.5	-	-
DuATM [47]	CVPR'18	DenseNet	91.4	76.6	-	-	81.8	64.6	-	-
Bilinear [52]	ECCV'18	Inception	91.7	79.6	-	-	84.4	69.3	-	-
G2G [44]	CVPR'18	ResNet	92.7	82.5	-	-	80.7	66.4	-	-
DeepCRF [3]	CVPR'18	ResNet	93.5	81.6	-	-	84.9	69.5	-	-
PCB [53]	ECCV'18	ResNet	93.8	81.6	63.7	57.5	83.3	69.2	68.2	40.4
SGGNN [45]	ECCV'18	ResNet	92.3	82.8	-	-	81.1	68.2	-	-
Mancs [60]	ECCV'18	ResNet	93.1	82.3	65.5	60.5	84.9	71.8	-	-
AANet [56]	CVPR'19	ResNet	93.9	83.4	-	-	87.7	74.3	-	-
CAMA [71]	CVPR'19	ResNet	94.7	84.5	66.6	64.2	85.8	72.9	-	-
IANet [17]	CVPR'19	ResNet	94.4	83.1	-	-	87.1	73.4	75.5	46.8
DGNet [84]	CVPR'19	ResNet	94.8	86.0	-	-	86.6	74.8	77.2	52.3
OSNet (ours)	ICCV'19	OSNet	94.8	84.9	72.3	67.8	88.6	73.5	78.7	52.9

Method	Source	Target: Duke				Source	Target: Market1501			
		R1	R5	R10	mAP		R1	R5	R10	mAP
MMFA [31]	Market1501 + Duke (U)	45.3	59.8	66.3	24.7	Duke + Market1501 (U)	56.7	75.0	81.8	27.4
SPGAN [8]	Market1501 + Duke (U)	46.4	62.3	68.0	26.2	Duke + Market1501 (U)	57.7	75.8	82.4	26.7
TJ-AIDL [62]	Market1501 + Duke (U)	44.3	59.6	65.0	23.0	Duke + Market1501 (U)	58.2	74.8	81.1	26.5
ATNet [32]	Market1501 + Duke (U)	45.1	59.5	64.2	24.9	Duke + Market1501 (U)	55.7	73.2	79.4	25.6
CamStyle [90]	Market1501 + Duke (U)	48.4	62.5	68.9	25.1	Duke + Market1501 (U)	58.8	78.2	84.3	27.4
HHL [88]	Market1501 + Duke (U)	46.9	61.0	66.7	27.2	Duke + Market1501 (U)	62.2	78.8	84.0	31.4
ECN [89]	Market1501 + Duke (U)	63.3	75.8	80.4	40.4	Duke + Market1501 (U)	75.1	87.6	91.6	43.0
OSNet-IBN (ours)	Market1501	48.5	62.3	67.4	26.7	Duke	57.7	73.7	80.0	26.1
MAR [72]	MSMT17+Duke (U)	67.1	79.8	-	48.0	MSMT17+Market1501 (U)	67.7	81.9	-	40.0
PAUL [70]	MSMT17+Duke (U)	72.0	82.7	86.0	53.2	MSMT17+Market1501 (U)	68.5	82.4	87.4	40.1
OSNet-IBN (ours)	MSMT17	67.4	80.0	83.3	45.6	MSMT17	66.5	81.5	86.8	37.2

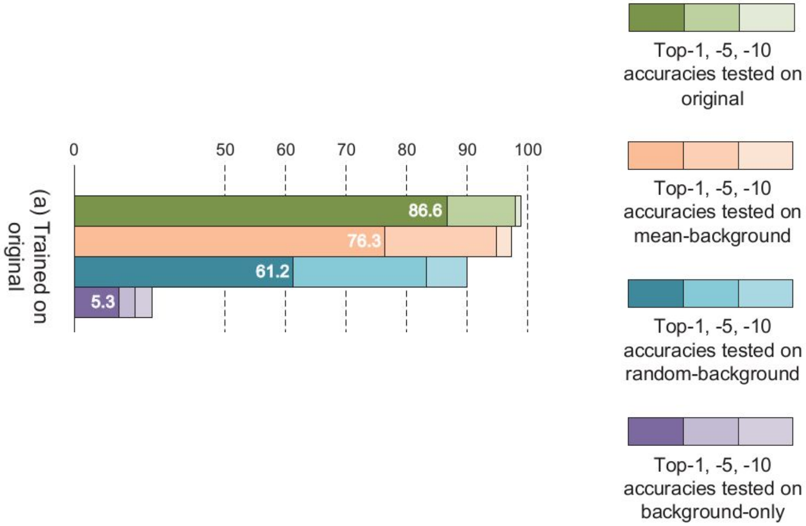
[4] ZHOU, Kaiyang et al. Learning generalisable omni-scale representations for person re-identification. IEEE Transactions on Pattern Analysis and Machine Intelligence, 2021.

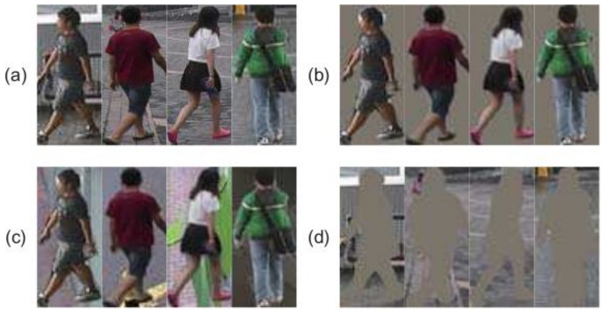
Re-Identification

- Datasets

[7] Zheng, L., Shen, L., Tian, L., Wang, S., Wang, J., and Tian, Q. (2015).
Scalable person re-identification: A benchmark. In ICCV.

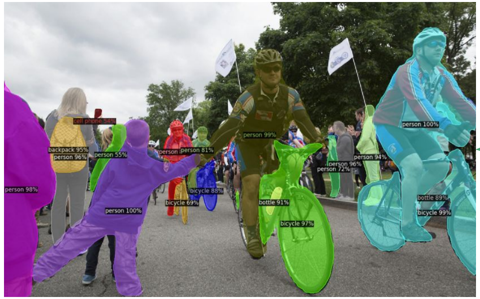
Impacto do background





[10] TIAN, Maoqing et al. Eliminating background-bias for robust person re-identification. In: Proceedings of the IEEE conference on computer vision and pattern recognition. 2018. p. 5794-5803.

Metodologia

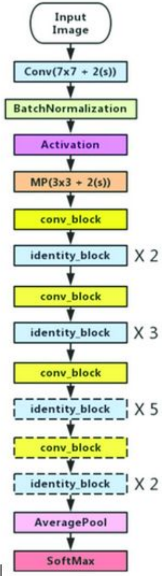


Market-1501

Segmentação

ResNet50

Análise dos resultados



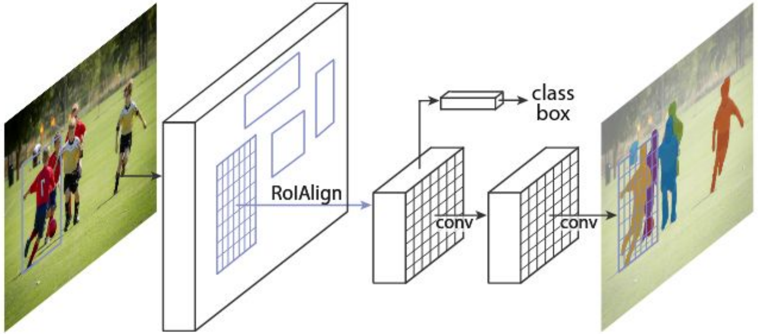
Metodologia

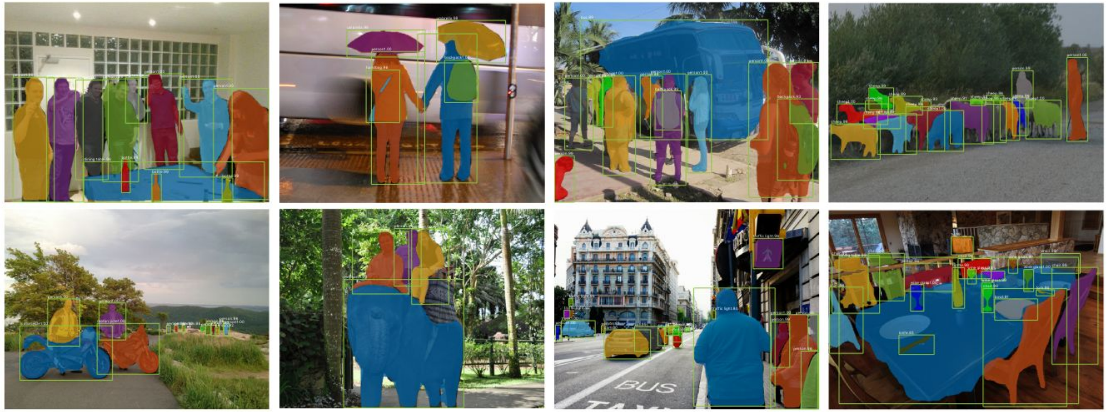
- Dataset Market-1501
- Imagens capturadas por 6 câmeras diferentes
- 1501 pessoas (751 para treino e 750 para teste)
- 19372 imagens para teste, 12936 para treino e 3368 para consulta.

[7] Zheng, L., Shen, L., Tian, L., Wang, S., Wang, J., and Tian, Q. (2015). Scalable person re-identification: A benchmark. In ICCV.

Metodologia

- Segmentação
- Utilização do detectron2

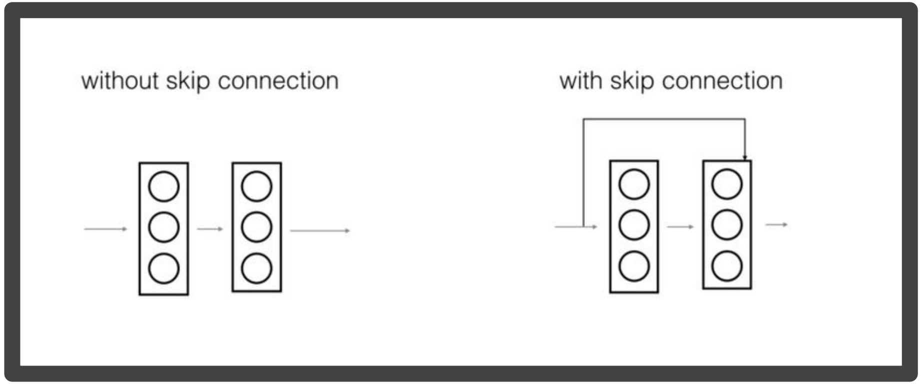


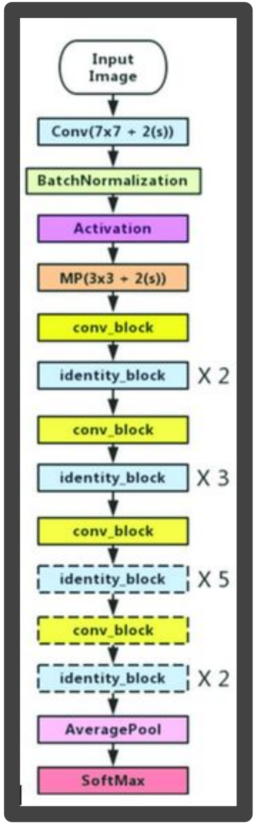


[15] Yuxin Wu and Alexander Kirillov and Francisco Massa and Wan-Yen Lo and Ross Girshick , Detectron2 (2019), https://github.com/facebookresearch/detectron2.

Metodologia

- ResNet50





[11] He, K., Zhang, X., Ren, S., and Sun, J. (2016). Deep residual learning for image recognition. In CVPR.

Experimentos

- Problemas na segmentação
- Imagens de baixa resolução
- Necessidade de ajustar o segmentador e redimensionar a imagem
- 2 datasets criados (com e sem resize)

Imagem original

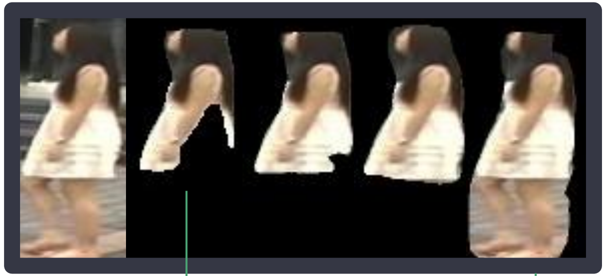


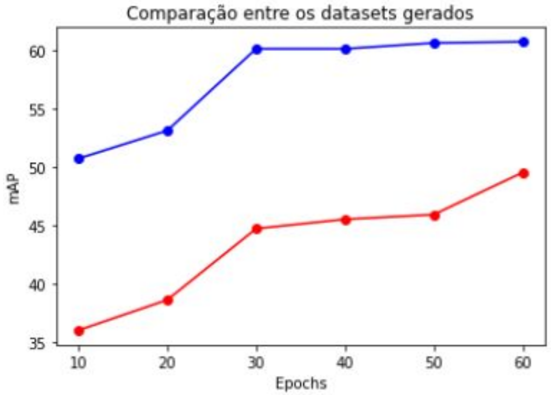
Imagem segmentada sem resize

Imagem segmentada após processamentos e ajustes

Resultados

- Métricas utilizadas: mAP e Rank
- Resultados com os 2 datasets gerados

Metodo	Backbone	Dataset	mAP	Rank-1	Rank-5	Rank-10
Torchreid	ResNet50	Market1501	66.8	84.5	93.8	96.1
Torchreid	ResNet50	Nosso (sem resize)	49.5	70.5	85.7	89.9
Torchreid	ResNet50	Nosso (com resize)	60.7	79.8	91.3	94.4



Azul (com resize) e vermelho (sem resize)

Conclusão

- Remover o background resultou em piora no re-ID em ambos os datasets gerados
- O dataset com pior segmentação apresentou o pior resultado
- A segmentação contendo o pedestre mais algumas partes do background ainda foi ligeiramente inferior aos testes com o dataset original
- O background em preto pode ter influenciado nos resultados

Trabalhos futuros

- Desenvolver um segmentador especificamente para problemas de re-ID
- Usar outros backbones ou criar uma rede própria
- Realizar os testes em mais Datasets