

第三方评价整理流程

1. 打开谷歌学术，搜索论文题目

The screenshot shows the Google Scholar search results for the paper "The devil is in the channels: Mutual-channel loss for fine-grained image classification". The search bar at the top contains the title. On the left, there are filters for "Any time" (Since 2022, Since 2021, Since 2018, Custom range...), "Sort by relevance" (Sort by date), "Any type" (Review articles), and checkboxes for "include patents" and "include citations". The main result shows the title, authors (D. Chang, Y. Ding, J. Xie, A.K. Bhunia, X. Li...), the journal (Image Processing, 2020 - ieeexplore.ieee.org), and a brief abstract. The citation count "Cited by 150" is highlighted with a red box. The right side of the result shows a PDF link from IEEE.org and access information for the University of Surrey.

2. 查看某篇文章的引用情况

This screenshot is identical to the one above, showing the Google Scholar search results for the same paper. The citation count "Cited by 150" is highlighted with a red box.

Google Scholar

Articles About 150 results (0.10 sec)

Any time
Since 2022
Since 2021
Since 2018
Custom range...

Sort by relevance
Sort by date

Create alert

The devil is in the channels: Mutual-channel loss for fine-grained image classification
Search within citing articles

Fine-grained visual classification via progressive multi-granularity training of jigsaw patches
R Du, D Chang, AK Bhunia, J Xie, Z Ma... - ... on Computer Vision, 2020 - Springer
Fine-grained visual classification (FGVC) is much more challenging than traditional classification tasks due to the inherently subtle intra-class object variations. Recent works ...
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Deep audio-visual learning: A survey
H Zhu, MD Luo, R Wang, AH Zheng, R He - International Journal of ..., 2021 - Springer
Audio-visual learning, aimed at exploiting the relationship between audio and visual modalities, has drawn considerable attention since deep learning started to be used ...
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AP-CNN: Weakly supervised attention pyramid convolutional neural network for fine-grained visual classification
Y Ding, Z Ma, S Wen, J Xie, D Chang... - ... on Image Processing, 2021 - ieeexplore.ieee.org
Classifying the sub-categories of an object from the same super-category (eg, bird species and cars) in fine-grained visual classification (FGVC) highly relies on discriminative feature ...
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Lifelong Zero-Shot Learning.
K Wei, C Deng, X Yang - IJCAI, 2020 - ijcai.org
Abstract Zero-Shot Learning (ZSL) handles the problem that some testing classes never appear in training set. Existing ZSL methods are designed for learning from a fixed training ...
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[PDF] arxiv.org

[HTML] springer.com
Access @ Univ of Surrey

[PDF] ieee.org
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[PDF] ijcai.org

3. 查看文章对该工作的评价

打开文章，找到引用的部分。

ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=9521886

Unsupervised and Self-Adaptive Techniques for Cross-Domain Person Re-Identification

target domain for adaptation. However, they do not perform cross-camera mining, cluster filtering, nor ensembling. These elements of our solution allow it to outperform SSG in all adaptation scenarios.

ECN [32], ECN-GPP [33], MMCL [34], and Dual-Refinement [35] use a memory bank to store features, which is updated along the training to avoid the direct use of features generated by the model in further iterations. The authors aim to avoid propagating noisy labels to future training steps, contributing to keeping and increasing the discrimination of features during training.

PAST [10] applies HDBSCAN [36] as the clustering method, which is similar to OPTICS [37] — the algorithm of choice in our work. However, the memory complexity of OPTICS is $O(n)$, while for HDBSCAN is $O(n \log n)$, making our model more memory efficient in the clustering stage.

MMT [12], MEB-Net [13], ACT [38], SSKD [39], and ABMT [16] are ensemble-based methods. They consider two or more networks and leverage mutual teaching by sharing one network's outputs with the others, making the whole system more discriminative on the target domain. However, training models in a mutual-teaching regime brings complexity in memory and to the general training process. Besides that, noisy labels can be propagated to other ensemble models, hindering the training process. Nonetheless, ensemble-based learning provides the best performance among state-of-art methods. We propose using ensembles only during inference to simultaneously eliminate the complexity added to the training, still taking advantage of knowledge complementary between the models.

Our work is also based on Curriculum Learning with Diversity [40], a schema whereby the model starts learning with easier examples, i.e., samples that are correctly classified

Number of images in the source domain
Number of images in the target domain
Number of anchors per camera in a cluster
Margin parameter of the Triplet Loss
Batch of triplets in an iteration

alignment of low and mid-level features. Third, methods in both categories need images from source and target domains during adaptation. Finally, the last Label Proposing methods consider mutual-learning or co-teaching, which brings complexity to the training stage.

Similarly, we assume to have only camera-related information, i.e., we know from which camera (viewpoint) an image was taken. In all steps, we use pseudo-identity information exclusively given by the clustering algorithm without relying on any ground-truth information. We differ from the prior art by using a new diversity learning scheme and generating triplets based on each cluster's diversity of points of view. As we train the whole model, the method also learns high-level features on the target domain. We simplify the training process by considering one backbone at a time, without mutual information exchange during adaptation. Finally, we apply model ensembling for inference after the training process.

III. PROPOSED METHOD

Our approach to Person ReID comprises two phases: training and inference. Figure 1 depicts the training process, while Table I shows the variables used in this work.

During training, we independently optimize n_b different backbones to adapt the model to the target domain. This phase is divided into five main stages that are performed iteratively: feature extraction from all data; clustering; cluster selection;

评价最好能体现方法比较好，比如：直接对文章进行正向评价，或者以该文章作为 baseline 等。

4. 查看团队情况

Unsupervised and Self-Adaptative Techniques for Cross-Domain Person Re-Identification

Gabriel C. Bertocco¹, Fernanda Andalo², *Member, IEEE*, and Anderson Rocha³, *Senior Member, IEEE*

Abstract—Person Re-Identification (ReID) across non-overlapping cameras is a challenging task, and most works in prior art rely on supervised feature learning from a labeled dataset to match the same person in different views. However, it demands the time-consuming task of labeling the acquired data, prohibiting its fast deployment in forensic scenarios. Unsupervised Domain Adaptation (UDA) emerges as a promising alternative, as it performs feature adaptation

and to, ultimately, propose candidate suspects for further investigation [1].

Person ReID aims to match the same person in different non-overlapping views in a camera system. Thanks to the considerable discrimination power given by deep learning, recent works [2]–[6] consider supervised feature learning on a labeled dataset, which yields high values of mean Average

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注意事项：重点收集 IEEE/AAAI/ACM 等 **国外非华人知名学者** 的评价

整理格式：

1. 论文 1 题目

[1] IEEE Fellow XXX 评价本文提出的基于元学习机制的域泛化模型优化方法首次将以 MAML 为代表的元学习方法引入到域泛化问题中。 [论文链接] [相关评价截图]

[2] 与马尔奖得主、牛津大学 Philip Torr 教授团队所提出的模型比较，主流数据集上的 5-way 1-shot 分类准确率平均提升约 4% [论文链接] [相关评价截图]

2. 论文 2 题目

[1] 与 ACM SIGGRAPH 成就奖得主、麻省理工学院 Ramesh Raskar 教授团队所提出的模型比较，主流数据集上的分类识别精度平均提升 10%左右 [论文链接] [相关评价截图]

[2] AAAI Fellow XXX 认为 XXX [论文链接] [相关评价截图]