# DKC: Differentiated Knowledge Consolidation for Cloth-Hybrid Lifelong Person Re-identification

## Supplementary Material

In this supplementary material, we detail additional experimental results on training *Order-2*, *Order-3*, and *Order-4*. Besides, more t-SNE results of the cloth-consistent dataset (Market-1501 [11]) on training *Order-1* are further provided for comprehensive verification. Finally, we visualize the re-identification results on training *Order-1* of each dataset to intuitively show the effectiveness of our method compared to the state-of-the-art method DKP.

## 1. More Detailed Experimental Results

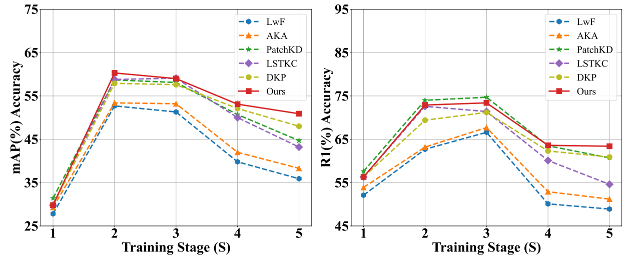
In this section, we present more detailed experimental results to further verify the generalizability and anti-forgetting performance of our proposed DKC on multiple training orders. To this end, several existing state-of-the-art methods are employed for verification, including: LwF [1], AKA [2], PatchKD [5], USP [9], SPD [6], CRL [10], MEGE [3], LSTKC [8], and DKP [7].

### 1.1. Comparison at Each Training Stage

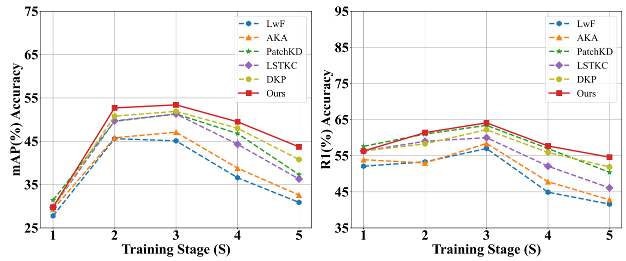
Firstly, we present the performance tendency of our proposed DKC with existing LReID methods at each stage on training *Order-2* in Fig. 1. It can be seen that our method achieves consistent performance priority in both cloth-consistent and cloth-hybrid scenarios. The above results further illustrate that our method achieves a better balance between cloth-relevant and cloth-irrelevant information through dynamically modelling differentiated new knowledge while preserving old knowledge by reconstructing old latent space, thus verifying the robustness of our method.

### 1.2. Comparison of Average Forgetting Score

To further verify the anti-forgetting performance of our proposed DKC, we further report the performance comparison on the Average Forgetting (AF) score on training *Order-2* in Tab. 1. The experimental results demonstrate that our method reaches the minimal AF score in both cloth-consistent and cloth-changing scenarios and achieves **5.5%/6.8%** on average mAP/R1 accuracy. This is because our DKC improves the compatibility of differentiated cloth-relevant and cloth-irrelevant knowledge by aligning them at different feature distribution levels, thereby achieving the best anti-forgetting performance while eliminating the derived catastrophic knowledge conflicts.




(a) Performance in cloth-consistent scenario




(b) Performance in cloth-hybrid scenario

Figure 1. Performance tendency at different training stages on training *Order-2*.

| Method | Cloth-Consistent | Cloth-Changing | Average |
|---|---|---|---|
| | AF(mAP/R1)↓ | AF(mAP/R1)↓ | AF(mAP/R1)↓ |
| USP [9] | 37.0/35.8 | 2.2/3.0 | 25.4/24.9 |
| LSTKC [8] | 19.6/20.7 | 5.0/5.9 | 14.7/15.8 |
| LwF [1] | 14.8/17.7 | 3.8/5.2 | 11.1/13.5 |
| AKA [2] | 15.0/16.8 | 2.4/2.5 | 10.8/12.0 |
| DKP [7] | 11.0/12.4 | 2.5/3.1 | 8.2/9.3 |
| PatchKD [5] | 11.2/10.9 | 1.7/3.8 | 8.0/8.5 |
| **Ours** | **7.5/9.2** | **1.6/2.1** | **5.5/6.8** |

Table 1. AF performance on training *Order-2*.

### 1.3. Comparison on Traditional LReID task

In addition to the above experimental results on the CH-LReID task, Tab. 2 and Tab. 3 further report the detailed performance of our proposed DKC on the traditional LReID task. Benefiting from the capacity of adaptively capturing new knowledge, our DKC achieves comparable results by an average performance of **51.6%/64.1%** and **51.6%/63.5%** on mAP/R1 accuracy on training *Order-3* and training *Order-4*, respectively. The above results strongly support that our method can incrementally improve the performance of lifelong learning in the cloth-hybrid scenario without sacrificing the performance in the cloth-consistent scenario, thus enabling strong versatility in realistic environments.

## 2. More Visualization Results

In this section, we present more visualization results to intuitively demonstrate the effectiveness of our DKC.

### 2.1. T-SNE Visualization Results

In addition to the feature distribution changes of the cloth-changing dataset LTCC [4] at each training stage in training *Order-1* shown in the main manuscript, we further visualize more feature distribution sampled from the cloth-consistent dataset Market-1501 [11]. As shown in Fig. 2, as the alternation of cloth-changing and cloth-consistent data continues, the existing DKP method fails to achieve stable intra-class consistency due to the inevitable conflict between the cloth-relevant and cloth-irrelevant knowledge. However, our DKC can always capture cloth-relevant discriminative information under the interference of cloth-irrelevant information during each training stage. Overall, the above results strongly verify the capacity of our DKC to model differentiated knowledge and balance the conflicting new and old knowledge.

### 2.2. ReID Visualization Results

Finally, we compare the re-identification results of our proposed DKC to the existing SOTA method DKP [7] on each dataset on training *Order-1* in Fig. 3, Fig. 4, Fig. 5, Fig. 6, where the query image is framed by the black box and the correct/incorrect re-identification results are framed by the green/red box. Obviously, our method can retrieve more correct gallery samples than DKP in cases of moderate and drastic clothing changes. This is because our DKC captures more discriminative information by balancing differentiated knowledge, including clothing style, body shape, face information, etc. The above results further verify the effectiveness and generalization of our proposed DKC.

## References


[1] Dangwei Li, Xiaotang Chen, Zhang Zhang, and Kaiqi Huang. Learning deep context-aware features over body and latent parts for person re-identification. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 384–393, 2017. 1, 3

[2] Nan Pu, Wei Chen, Yu Liu, Erwin M Bakker, and Michael S Lew. Lifelong person re-identification via adaptive knowledge accumulation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 7901–7910, 2021. 1, 3

[3] Nan Pu, Zhun Zhong, Nicu Sebe, and Michael S Lew. A memorizing and generalizing framework for lifelong person re-identification. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 2023. 1, 3

[4] Xuelin Qian, Wenxuan Wang, Li Zhang, Fangrui Zhu, Yanwei Fu, Tao Xiang, Yu-Gang Jiang, and Xiangyang Xue. Long-term cloth-changing person re-identification. In *Proceedings of the Asian Conference on Computer Vision*, 2020. 2

[5] Zhicheng Sun and Yadong Mu. Patch-based knowledge distillation for lifelong person re-identification. In *Proceedings of the 30th ACM International Conference on Multimedia*, pages 696–707, 2022. 1, 3

[6] Frederick Tung and Greg Mori. Similarity-preserving knowledge distillation. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 1365–1374, 2019. 1, 3

[7] Kunlun Xu, Xu Zou, Yuxin Peng, and Jiahuan Zhou. Distribution-aware knowledge prototyping for non-exemplar lifelong person re-identification. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 16604–16613, 2024. 1, 2, 3

[8] Kunlun Xu, Xu Zou, and Jiahuan Zhou. Lstkc: Long short-term knowledge consolidation for lifelong person re-identification. In *Proceedings of the AAAI Conference on Artificial Intelligence*, pages 16202–16210, 2024. 1, 3

[9] Yuming Yan, Huimin Yu, Yubin Wang, Shuyi Song, Weihu Huang, and Juncan Jin. Unified stability and plasticity for lifelong person re-identification in cloth-changing and cloth-consistent scenarios. *IEEE Transactions on Circuits and Systems for Video Technology*, 2024. 1

[10] Bo Zhao, Shixiang Tang, Dapeng Chen, Hakan Bilen, and Rui Zhao. Continual representation learning for biometric identification. In *Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision*, pages 1198–1208, 2021. 1, 3

[11] Liang Zheng, Liyue Shen, Lu Tian, Shengjin Wang, Jingdong Wang, and Qi Tian. Scalable person re-identification: A benchmark. In *Proceedings of the IEEE International Conference on Computer Vision*, pages 1116–1124, 2015. 1, 2

| Method | Market | | CUHK-SYSU | | DukeMTMC | | MSMT17 | | CUHK03 | | Average | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | mAP | R1 | mAP | R1 | mAP | R1 | mAP | R1 | mAP | R1 | mAP | R1 |
| Joint | 68.1 | 85.2 | 81.4 | 83.8 | 60.4 | 75.7 | 24.6 | 48.9 | 42.7 | 43.6 | 55.4 | 67.5 |
| SPD [6] | 35.6 | 61.2 | 61.7 | 64.0 | 27.5 | 47.1 | 5.2 | 15.5 | 42.2 | 44.3 | 34.4 | 46.4 |
| LwF [1] | 56.3 | 77.1 | 72.9 | 75.1 | 29.6 | 46.5 | 6.0 | 16.6 | 36.1 | 37.5 | 40.2 | 50.6 |
| CRL [10] | 58.0 | 78.2 | 72.5 | 75.1 | 28.3 | 45.2 | 6.0 | 15.8 | 37.4 | 39.8 | 40.5 | 50.8 |
| AKA [2] | 58.1 | 77.4 | 72.5 | 74.8 | 28.7 | 45.2 | 6.1 | 16.2 | 38.7 | 40.4 | 40.8 | 50.8 |
| MEGE [3] | 39.0 | 61.6 | 73.3 | 76.6 | 16.9 | 30.3 | 4.6 | 13.4 | 36.4 | 37.1 | 34.0 | 43.8 |
| PatchKD [5] | **68.5** | **85.7** | 75.6 | 78.6 | 33.8 | 50.4 | 6.5 | 17.0 | 34.1 | 36.8 | 43.7 | 53.7 |
| LSTKC [8] | 54.7 | 76.0 | 81.1 | 83.4 | 49.4 | 66.2 | **20.0** | **43.2** | **44.7** | **46.5** | 50.0 | 63.1 |
| DKP [7] | 60.3 | 80.6 | 83.6 | 85.4 | **51.6** | **68.4** | 19.7 | 41.8 | 43.6 | 44.2 | **51.8** | **64.1** |
| **Ours** | 59.9 | 81.0 | **83.9** | **85.6** | 51.5 | 67.4 | 19.6 | 41.5 | 43.2 | 44.9 | 51.6 | **64.1** |

Table 2. Performance on training *Order-3*: Market-1501→CUHK-SYSU→DukeMTMC-ReID→MSMT17-V2→CUHK03.

| Method | DukeMTMC | | MSMT17 | | Market | | CUHK-SYSU | | CUHK03 | | Average | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | mAP | R1 | mAP | R1 | mAP | R1 | mAP | R1 | mAP | R1 | mAP | R1 |
| Joint | 60.4 | 75.7 | 24.6 | 48.9 | 68.1 | 85.2 | 81.4 | 83.8 | 42.7 | 43.6 | 55.4 | 67.5 |
| SPD [6] | 28.5 | 48.5 | 3.7 | 11.5 | 32.3 | 57.4 | 62.1 | 65.0 | 43.0 | 45.2 | 33.9 | 45.5 |
| LwF [1] | 42.7 | 61.7 | 5.1 | 14.3 | 34.4 | 58.6 | 69.9 | 73.0 | 34.1 | 34.1 | 37.2 | 48.4 |
| CRL [10] | 43.5 | 63.1 | 4.8 | 13.7 | 35.0 | 59.8 | 70.0 | 72.8 | 34.5 | 36.8 | 37.6 | 49.2 |
| AKA [2] | 42.2 | 60.1 | 5.4 | 15.1 | 37.2 | 59.8 | 71.2 | 73.9 | 36.9 | 37.9 | 38.6 | 49.4 |
| MEGE [3] | 21.6 | 35.5 | 3.0 | 9.3 | 25.0 | 49.8 | 69.9 | 73.1 | 34.7 | 35.1 | 30.8 | 40.6 |
| PatchKD [5] | **58.3** | **74.1** | 6.4 | 17.4 | 43.2 | 67.4 | 74.5 | 76.9 | 33.7 | 34.8 | 43.2 | 54.1 |
| LSTKC [8] | 49.9 | 67.6 | 14.6 | 34.0 | 55.1 | 76.7 | 82.3 | 83.8 | **46.3** | **48.1** | 49.6 | 62.1 |
| DKP [7] | 53.4 | 70.5 | 14.5 | 33.3 | **60.6** | 81.0 | 83.0 | **84.9** | 45.0 | 46.1 | 51.3 | 63.2 |
| **Ours** | 53.7 | 70.6 | **15.0** | **34.3** | 60.5 | **81.1** | **83.4** | **84.9** | 45.3 | 46.6 | **51.6** | **63.5** |

Table 3. Performance on training *Order-4*: DukeMTMC-ReID→MSMT17-V2→Market-1501→CUHK-SYSU→CUHK03.

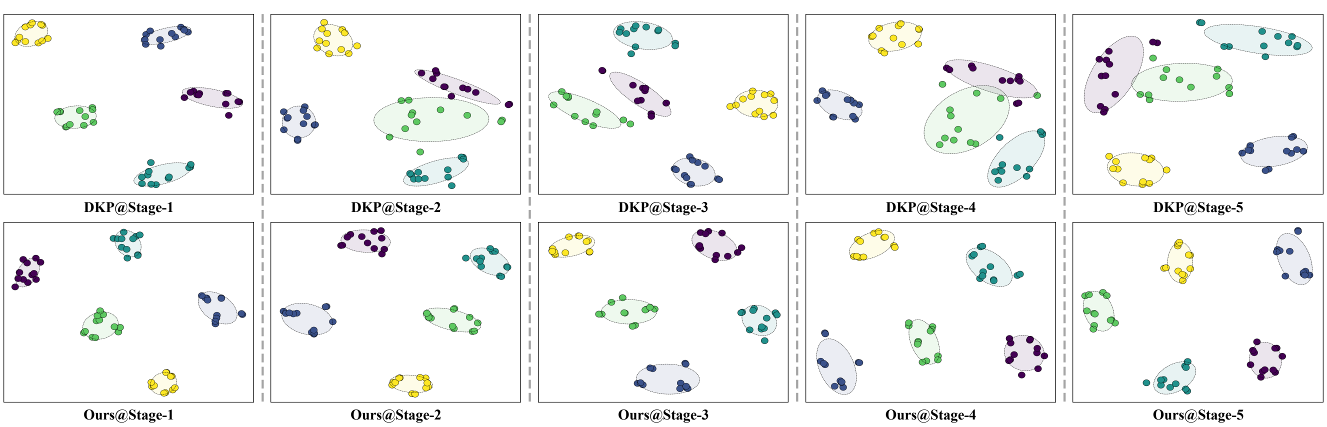



Figure 2. The t-SNE visualization of the Market-1501 dataset at each training stage, where different colours represent different identities.


Figure 3. Re-identification results on the Market-1501 dataset.



Figure 4. Re-identification results on the LTCC and the PRCC datasets.

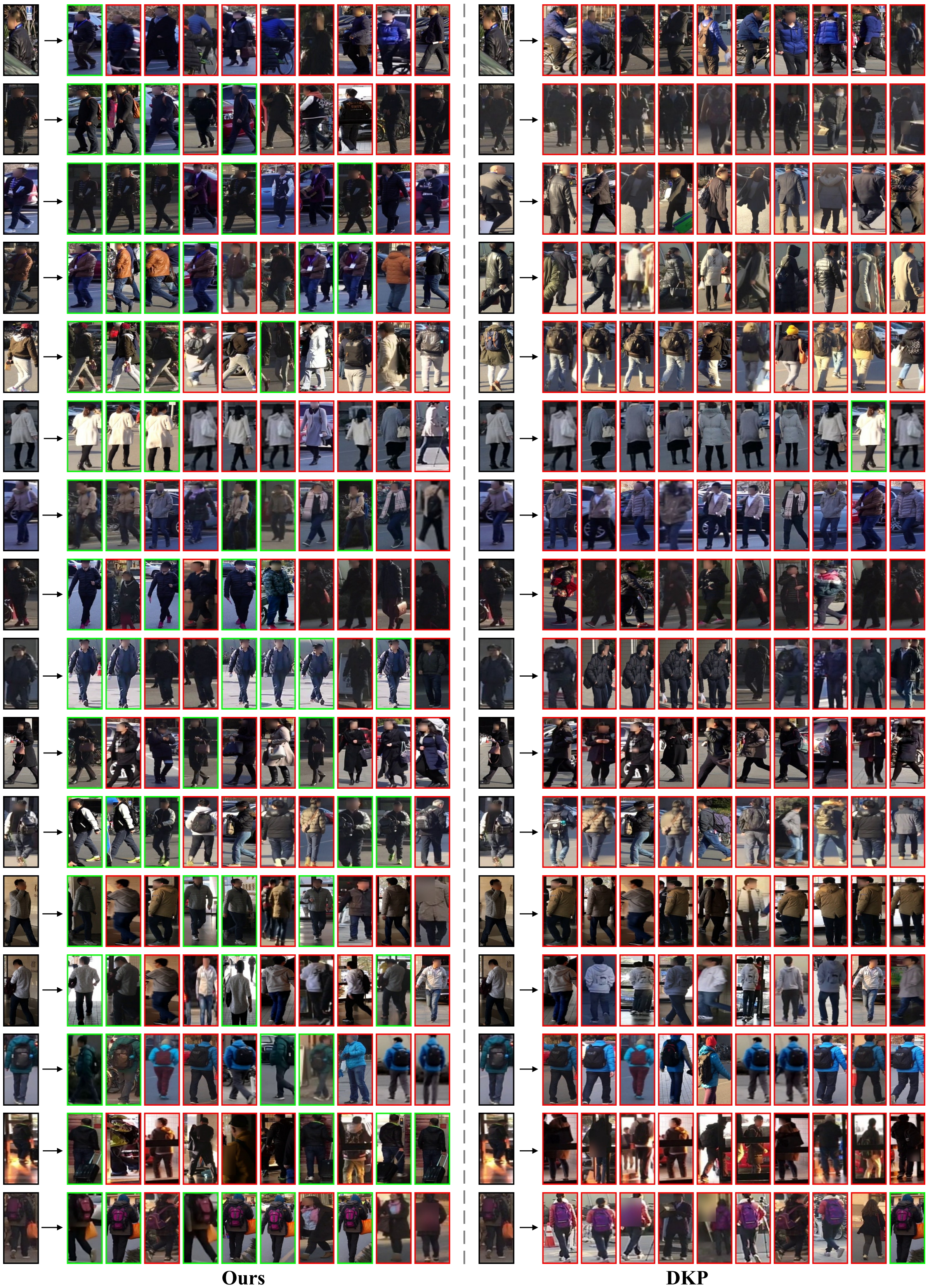



Figure 5. Re-identification results on the MSMT17-V2 dataset.

Figure 6. Re-identification results on the CUHK03 dataset.