Supplementary Material: Learning Continual Compatible Representation for Re-indexing Free Lifelong Person Re-identification

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1. More Experimental Results

In this section, we present more experimental results to verify the overall performance and anti-forgetting performance of the proposed C^2R on *Order-2* compared with existing state-of-the-art methods, including LwF [1], AKA [2], PatchKD [3], and CVS [4].

1.1. Comparison on AF Performance

As shown in Tab. 1, the compared methods suffer from larger forgetting on old tasks (AF(mAP) $\geq$ 15.2% and AF(R@1) $\geq$ 18.6%) than our C^2R (AF(mAP) = **13.5**% and AF(R@1) = **16.5**%). The lowest AF performance of our C^2R illustrates that our method achieves better anti-forgetting performance of old knowledge by balancing the capturing of both new and old knowledge with continuously transferring old gallery features to the new feature space.

1.2. Performance Comparison in Each Training Stage

We show more detailed results at each learning stage on *Order-2* in Fig. 1. It can be seen that our C^2R consistently achieves the highest mAP and R@1 performance at each training stage. After five stages of training, the final performance of our method reaches **39.7**% and **48.4**% on average mAP and R@1 performance. This demonstrates that the proposed BCD module and BAD module keep the compatibility of the transferred features, while balancing the old and the new knowledge in the transferred feature space, thereby achieving the highest RFL-ReID performance.

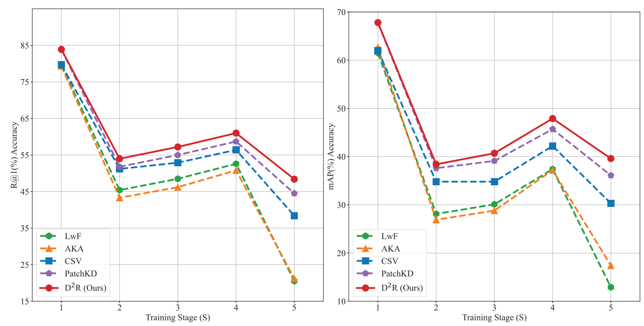

Figure 1. Lifelong learning performance comparison in RFL-ReID task on *Order-2*.

Method	LwF	AKA	CVS	PatchKD	**Ours**
AF(mAP)	30.8	32.8	17.9	15.2	**13.5**
AF(R@1)	42.7	43.8	23.7	18.6	**16.5**

Table 1. AF performance of C^2R compared with existing methods on *Order-2*. (The lower the AF is, the less the model forgets.)

2. More Visualization Results

In this section, we present more visualization results to intuitively compare our C^2R with the existing SOTA methods.

2.1. T-SNE Visualization Results

We present the t-SNE results of each compared method in Tab. 1 and our C^2R in Fig. 2, where all samples are randomly selected from all datasets. It can be seen that all the compared methods fail to cluster the sample belonging to the same person well. However, precisely due to the balanced modelling and distillation of the old and the new knowledge, our method achieves better intra-class consistency through continuous compatible transferring.

2.2. Comparison on Re-identification Results

To intuitively verify the effectiveness of our C^2R, we visualize and analyse the R@1 ReID results in Fig. 3. As shown above, the ReID results of the compared methods are usually interfered by similar people's appearances, body shapes, clothing colors and scenarios. In contrast, our method balances the old and new knowledge in the L-ReID process, so that the discriminative information of the same person can be extracted and identified based on more comprehensive knowledge. Finally, our C^2R significantly outperforms existing methods in various practical scenarios.

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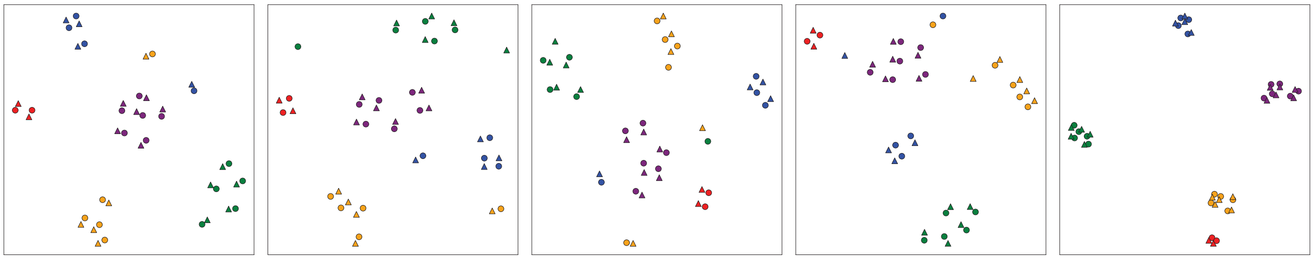

(a) LwF (b) AKA (c) CVS (d) PatchKD(Base) (e) our C^{2}R

Figure 2. TSNE results of our C^{2}R compared with existing method. Different colours represent different identities, while the circles and the triangles represent gallery features and query features, respectively.

Figure 3. Visualization of our C^{2}R (Ours) and the compared methods on *Order-1*. The Rank-1 results are presented, where green and red boxes indicate correct and incorrect ReID results, respectively.

References

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