Person Re-identification by Null Space Marginal Fisher Analysis

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Abstract:

For better describing pedestrian's appearance, the feature representations used in person re-identification are usually of high dimension - typically amounting to thousands or even higher. However, this incurs the typical Small Sample Size (SSS) problem, i.e., the number of training samples in most re-identification datasets is much smaller than the feature dimension. Although some dimension reduction techniques or metric regularization could be applied to alleviate this problem, they may result in the loss of discriminative power.

In this work, we propose to overcome SSS problem by embedding training samples into a discriminative null space based on Marginal Fisher Analysis (MFA). In such a null space, the within-class distribution of the images of the same pedestrian will shrink to a single point, resulting the extreme fisher analysis criterion. We theoretically analyze the subspace where the discriminant vectors lie on and derive a closed-form solution. Furthermore, we also extend the proposed method to nonlinear domain via the kernel trick. Experiments on VIPeR, PRID450S and 3DPes benchmark datasets show that our method achieves 56.30%, 76.80% and 66.88% rank-1 matching rates respectively, outperforming the state-of-the-art results by 2.74%, 15.38% and 9.59%.

Our contributions including:

1. We develop a novel null space learning method called Null Space Marginal Fisher Analysis (NSMFA) to overcome the Small Sample Size (SSS) problem in person re-identification.
2. To deal with the highly nonlinear patterns of pedestrian appearance, the proposed method is further extended to nonlinear case via the kernel trick, Kernel Null Space Marginal Fisher Analysis (KNSMFA).
3. Experiments on three challenging datasets including VIPeR, PRID450S, and 3DPes, demonstrate that our method improves the state-of-the-art results significantly.

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Acknowledgements
This work was partially supported by National Natural Science Foundation of China (NSFC Grant No. 61272258, 61170124, 6130129, 61272005), Provincial Natural Science Foundation of Jiangsu (Grant No. BK20151254, BK20151260), Key Laboratory of Symbolic Computation and Knowledge Engineering of Ministry of Education, Jilin University (Grant No. 93K172016K08), and Collaborative Innovation Center of Novel Software Technology and Industrialization.