Continuous Adaptation of Multi-Camera Person Identification Models through Sparse Non-redundant Representative Selection - Supplementary Material

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This appendix/supplementary material accompanies the manuscript "Continuous Adaptation of Multi-Camera Person Identification Models through Sparse Non-redundant Representative Selection". In this supplementary material we are providing the time complexity analysis of the FISTA (Beck and Teboulle, 2009) steps involved in finding the redundancy restricted representatives and the sparse representations of the test set.

1. Time Complexity Analysis

The rate of convergence of FISTA algorithm in terms of the number of iterations is provided in (Beck and Teboulle, 2009). Here, we are providing the following time complexity per FISTA step. FISTA being an iterative method, it is important to note the time complexity of the FISTA steps for each iteration. The major contributor to the time complexity for the representative selection phase are the matrix multiplications in computing the gradient and Lipschitz constants $\nabla g(X)$ and L_g respectively (ref. eqn. (12) in the main paper). Considering the sizes of the 3 matrices $Z, \hat{Z}_0$ and X as provided in Table 1 of the main paper, we can see that the time complexity of computing the gradient $\nabla g(X)$ is $O(n^2d)+O(n^2d+n^3)+O(ndn_0+n^2n_0+n^3)$ while the same for computing the Lipschitz constant L_g is $O(n^2d+n^2)+O(ndn_0+n^2n_0+n^2)$. Since d is

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a constant, we can further reduce the above complexities to $O(n^3)$ and $O(n^2)$ respectively. Similarly, the SRC classifier also employs FISTA algorithm for the optimization. While other algorithms specifically tuned for sparse optimization (e.g., LASSO, LARS etc.) could have been used (which may have provided better time complexity depending on the dictionary element dimension and the number of dictionary elements), we opted for FISTA as we used the same algorithm for representative selection and thus makes the whole framework more general. The major contributor to the time complexity for the SRC classification are the matrix multiplications in computing the gradient and Lipschitz constants $\nabla p(C)$ and L_p respectively (ref. eqn. (13) of the main paper). Assuming the number of test images to be N (i.e., the sizes of the matrices $\hat{Y}_0, Y, C$ and L to be $d_1 \times n_0$, $d_1 \times N$, $n_0 \times N$ and $N \times N$- in our case d_1 extracted feature dimension and N is the number of test images), we can see that the time complexity of computing the gradient $\nabla p(C)$ is $O(n_0 d_1 n) + O(n_0^2 d_1 + n_0^2 N) + O(n_0 N^2)$ while the same for computing the Lipschitz constant L_p is $O(n_0^2 d_1 + n_0^2) + O(N^2)$. It should be noted that the computation of the proximal operators (ref. eqn. (14) and (15) of the main paper) also contributes to the complexity per FISTA iteration. However, these are second order only ($O(n^2)$ and $O(n_0 N)$ respectively) and thus the major contributor to the computational complexity are as given earlier.