Sparse Representation for 3D Shape Estimation: A Convex Relaxation Approach

Supplementary Material

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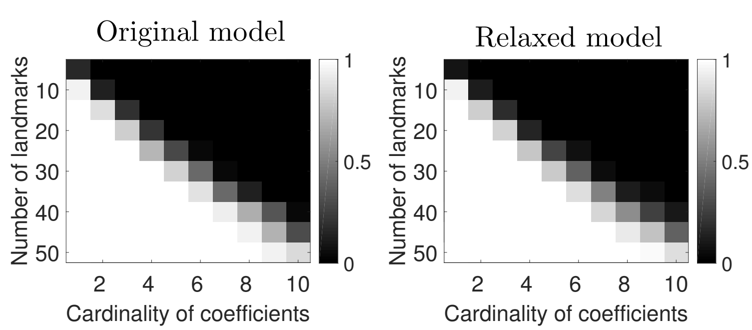
Video

The video (MPEG-4 files with H.264 encoding) in the supplementary material shows several 3D pose sequences reconstructed by the proposed method and the alternating minimization on the CMU Mocap dataset. The reconstructions by the convex method are much smoother over time compared to the ones by the nonconvex method which suffer from abrupt changes due to the inherent instability of nonconvex optimization.

Additional simulation results

As a supplement to the simulation in Section 5.1 in the manuscript, additional results for various problem settings are presented.

In Section 5.1, the relaxed model (31) was used to synthesize the data. In the additional experiment, the original model in Eq. (6) was used to synthesize the data and the evaluation was carried out again. The frequency of exact recovery is shown in the figure below (left panel), which is very similar to the result in Section 5.1 with the relaxed model (also shown in the right panel below).



In Section 5.1, the entries of basis shapes were sampled independently from i.i.d. Gaussian. In the additional experiment, a correlation coefficient was introduced to control the correlation between entries of basis shapes and the evaluation was performed with various degrees of correlation. The estimation error vs. the degree of correlation between bases for both noiseless and noisy ($\sigma = 0.1$) cases is shown in the figure below. e_M and e_S denote the estimation errors of M_is and reconstructed shape S, respectively. In the noiseless case, e_M is not affected by the correlation between the bases except for the extreme case where the correlation equals to 1. In such an extreme case, the observation is reduced to $W = (\sum_i M_i)B$. Therefore, it is impossible to recover separate M_is, as an infinite number of solutions exist. But e_S is still zero because in this case any linear combination of bases yields the same shape (up to a scale) and $\sum_i M_i$ as a whole can be correctly estimated. In the noisy case, e_M increases as the correlation gets larger. But e_S doesn't increase and even decrease as there is less shape variability when basis shapes become correlated with each other. In summary, the correlation between bases influences the recovery of M_is (analogous to what happens in Lasso where the reliable feature selection requires the irrepresentable condition). But for the recovery of shape S, the high correlation between bases results in less possible shape variability and decreases the recovery difficulty.