# A Robust Local Linear Data Decomposition

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Principal Component Analysis (PCA) is one of the most fundamental tools for general data analysis, but suffers from severe sensitivity to outliers such as impulse noise or (in the context of image and video analysis) small occlusions. A recent development in matrix completion (a branch of compressed sensing) is Principal Component Pursuit [1], a robust form of PCA that decomposes a data matrix into low rank and sparse components, the former representing a low-dimensional linear model of the data, and the latter representing sparse deviations from the low-dimensional subspace. This decomposition has been applied, with promising results, to a variety of data analysis problems, including in image and video analysis.

A significant limitation, however, is that the underlying model assumes the data lie in a single global low-dimensional subspace. We have generalized this model to a union of low-dimensional subspaces, which can describe data lying within a nonlinear manifold. Our approach is motivated by the observation that it should be possible to represent a point in a low-dimensional subspace as a sparse linear combination of its neighbors in the same subspace. The decomposition represents the data matrix as the sum of a sparse additive component and a structured sparse representation using itself as a dictionary. An efficient Alternating Direction Method of Multipliers [2] based algorithm has been developed for this decomposition.

We demonstrate the performance of this new decomposition on a video background modeling problem. Principal Component Pursuit achieves very good results for video from a stationary camera, but the single low dimensional subspace model of the background is violated when the camera is slowly panning. In this case, our more general model shows significantly better performance.

## References

[1] E. J. Candès, X. Li, Y. Ma, and J. Wright, "Robust principal component analysis?," *J. ACM*, vol. 58, pp. 11:1–11:37, June 2011.

[2] S. Boyd, N. Parikh, E. Chu, B. Peleato, and J. Eckstein, "Distributed optimization and statistical learning via the alternating direction method of multipliers," *Foundations and Trends in Machine Learning*, vol. 3, no. 1, pp. 1–122, 2010.

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