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Parameter optimization for low-rank matrix recovery in hyperspectral imaging

Abstract: An approach to parameter optimization for the low-rank matrix recovery method (LRMR) in hyperspectral imaging is discussed. We formulate an optimization problem with respect to the parameters of LRMR. The performance for different parameter settings is compared in terms of computational times and memory. The results are evaluated by computing the peak signal-to-noise ratio as quantitative measure. The optimization method is tested on standard and openly available hyperspectral data sets including Indian Pines.

Keywords: noise reduction, optimization, low-rank modeling, hyperspectral imaging, signal-to-noise ratio improvement

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1 Background

In hyperspectral imaging (HSI), spectral signatures of objects are recorded for each image pixel. HSI precision and reliability are essential for many applications including digitalization and robotization. This work is part of *coADDVA - ADDing VAlue by Computing in Manufacturing* project funded by the Regional Council of Central Finland/Council of Tampere Region and European Regional Development Fund. It supports the project's goals to improve the efficiency of robotics by developing optimal control methods leading to flexible imaging and automation in image processing.

HSI combines spatial and spectral information in a hyperspectral data cube. Its application in Earth and space exploration is important. Naturally, the amount of generated data is huge, and an efficient and reliable approach to noise reduction takes advantage of the internal dependencies between the wavebands. The LRMR is a low-rank modeling approach [1] and has been discussed among other advanced image processing methods in more detail in [3] and [4]. We use here the LRMR together with the GoDec algorithm as presented in [2] in the inner iteration steps of the approach. Parameter optimization in advanced image processing can provide important indirect information for control and real-time decision-making.

2 Methods

The first LRMR model was proposed in [5]. Given the real matrix D of size $m \times n$ containing the observed data and assuming corruption by the sparse error matrix S and a random Gaussian noise modelled by the matrix N, the goal is to recover the low-rank matrix L with $D = L + S + N$, all real number matrices of the same size. The minimization problem

$$\min_{L,S} \|D - L - S\|_F^2 \text{ s.t. } \operatorname{rank}(L) \leq r, \operatorname{card}(S) \leq p$$

is solved with r denoting the upper bound for the rank of L and p for the cardinality of S which is related to the estimation of noise corruption. Redundancies between the wavebands yield the low-rank property. LRMR modelling is then applied together with the GoDec algorithm [2] in order to solve the subproblems.

The main focus of this work is the detailed investigation of the LRMR method with respect to its main variable parameters including rank r and blocksize of the subcubes b, estimation parameter for the percentage of noise corruption p and stepsize s in the iteration. We apply nonlinear optimization in order to determine the best parameter values for the method with respect to the peak signal-to-noise ratio (PSNR). The PSNR is computed by

$$PSNR = 10 * \log_{10} \frac{\max(c)^2 * M * N * W}{\|c - \tilde{c}\|^2},$$

where c and $\tilde{c}$ denote the original and denoised data cube, respectively. The sizes of the spatial and spectral dimensions are denoted by M, N and W.

In addition, LRMR is analyzed in terms of computational efficiency and memory with regard to different parameter choices. The performance of LRMR and differences in the implementation between Matlab and Python are investigated.

3 Results

It is shown that different parameter values and their combination have an effect on the PSNR and computational times of the LRMR method. The optimization algorithms depend on the starting value and reach local minima. The resulting parameter choices are studied in terms of computational times in addition to their performance with respect to PSNR.

Applying nonlinear optimization with respect to the noise estimation parameter p, a real number, has resulted in an improvement in PSNR. The integer parameters have been analyzed on series of test sets. The optimized values are chosen according to their best PSNR performance. We have tested the method on openly available data sets. Figure 1 shows the performance of the method for a noise-corrupted waveband of the Indian Pines data set [6]. In Figure 2, the negative PSNR values of the iteration steps of the nonlinear minimization method *fminsearch* in Matlab are presented computed with respect to p. The results in Figure 2 show a convergence towards a local minimum. The value yields an improvement in PSNR. Figure 3 shows the PSNR for different rank r and stepsize s values, whereas other parameter values b and p are set constant.

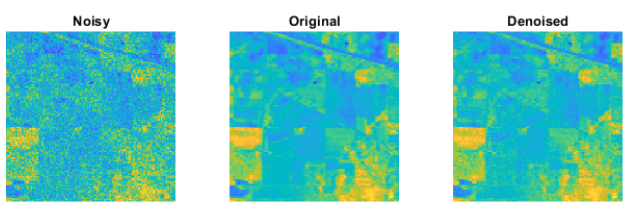

Fig. 1. The noise removal performance of LRMR on a noise-corrupted waveband for the Indian Pines data set. The image is restored efficiently.

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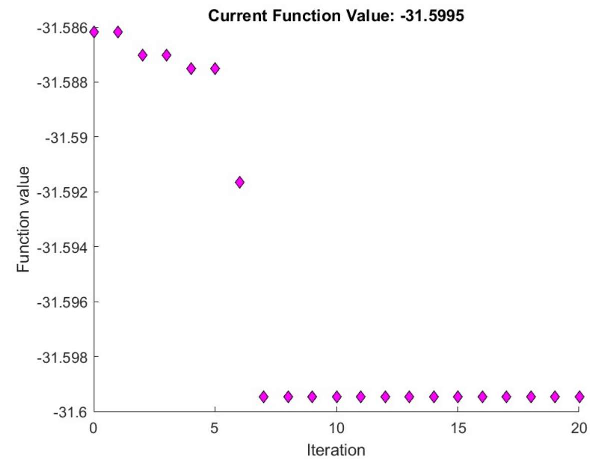

Fig. 2. The function values of the iteration steps of the nonlinear optimization method with respect to p.

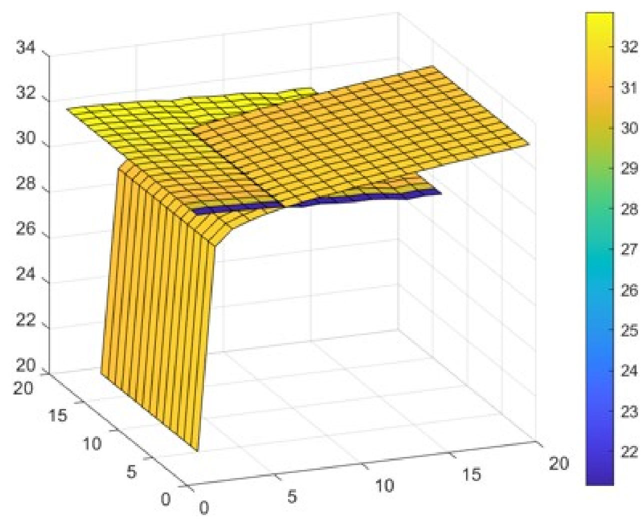

Fig. 3. PSNR surface plots for different r and s intersect.

References

[1] Zhang, H., He, W., Zhang, L., Shen, H., and Yuan, Q., "Hyperspectral image restoration using low-rank matrix recovery," *IEEE transactions on geoscience and remote sensing*, 52(8), 4729-4743 (2013).

[2] Zhou, T., and Tao, D., "Godec: Randomized low-rank & sparse matrix decomposition in noisy case," *Proceedings of the 28th International Conference on Machine Learning*, ICML (2011).

[3] Ghamisi, P., Yokoya, N., Li, J., Liao, W., Liu, S., Plaza, J., Rasti, B., and Plaza, A., "Advances in hyperspectral image and signal processing: A comprehensive overview of the state of the art," *IEEE Geoscience and Remote Sensing Magazine* 5(4), 37–78 (2017).

[4] Rasti, B., Scheunders, P., Ghamisi, P., Licciardi, G., and Chanussot, J., "Noise reduction in hyperspectral imagery: Overview and application," *Remote Sensing* 10(3), 482 (2018).

[5] Wright, J., Ganesh, A., Rao, S., Peng, Y., and Ma, Y., "Robust principal component analysis: Exact recovery of corrupted low-rank matrices via convex optimization," in Proc. NIPS, 2009, pp. 2080–2088.

[6] Indian Pines data set, Purdue University Research Repository (doi: 10.4231/R7RX991C).