Information and Abbreviations of DLSM Algorithms

	Group	Abbreviation	Algorithm name	Authors
1	RPCA	RPCA	Robust Principal Component Analysis	De la Torre and Black [1]
2	RPCA	PCP	Principal Component Pursuit	Candes et al. [2]
3	RPCA	FPCP	Fast PCP	Rodriguez and Wohlberg [3]
4	RPCA	R2PCP	Riemannian Robust Principal Component Pursuit	Hintermüller and Wu [4]
5	RPCA	AS-RPCA	Active Subspace: Towards Scalable Low-Rank Learning	Liu and Yan [5]
6	RPCA	ALM	Augmented Lagrange Multiplier	Tang and Nehorai [6]
7	RPCA	EALM	Exact ALM	Lin et al. [7]
8	RPCA	IALM	Inexact ALM	Lin et al. [7]
9	RPCA	IALM-LMSVDS	IALM with LMSVDS	Liu et al. [8]
10	RPCA	IALM-BLWS	IALM with BLWS	Lin and Wei [9]
11	RPCA	APG-PARTIAL	Partial Accelerated Proximal Gradient	Lin et al. [7]
12	RPCA	APG	Accelerated Proximal Gradient	Lin et al. [7]
13	RPCA	DUAL	Dual RPCA	Lin et al. [7]
14	RPCA	SVT	Singular Value Thresholding	Cai et al. [10]
15	RPCA	ADM	Alternating Direction Method	Yuan and Yang [11]
16	RPCA	LSADM	LSADM	Goldfarb et al. [12]
17	RPCA	L1F	L1 Filtering	Liu et al. [13]
18	RPCA	DECOLOR	Contiguous Outliers in the Low-Rank Representation	Zhou et al. [14]
19	RPCA	RegL1-ALM	Low-Rank Matrix Approximation under Robust L1-Norm	Zheng et al. [15]
20	RPCA	GA	Grassmann Average	Hauberg et al. [16]
21	RPCA	GM	Grassmann Median	Hauberg et al. [16]
22	RPCA	TGA	Trimmed Grassmann Average	Hauberg et al. [16]
23	RPCA	STOC-RPCA	Online Robust PCA via Stochastic Optimization	Feng et al. [17]
24	RPCA	MoG-RPCA	Mixture of Gaussians RPCA	Zhao et al. [18]
25	RPCA	noncvxRPCA	Robust PCA via Nonconvex Rank Approximation	Kang et al. [19]
26	RPCA	NSA1	Non-Smooth Augmented Lagrangian v1	Aybat et al. [20]
27	RPCA	NSA2	Non-Smooth Augmented Lagrangian v2	Aybat et al. [20]
28	RPCA	PSPG	Partially Smooth Proximal Gradient	Aybat et al. [21]
29	RPCA	flip-SPCP-sum-SPG	Flip-Flop version of Stable PCP-sum solved by Spectral Projected Gradient	Aravkin et al. [22]
30	RPCA	flip-SPCP-max-QN	Flip-Flop version of Stable PCP-max solved by Quasi-Newton	Aravkin et al. [22]
31	RPCA	Lag-SPCP-SPG	Lagrangian SPCP solved by Spectral Projected Gradient	Aravkin et al. [22]
32	RPCA	Lag-SPCP-QN	Lagrangian SPCP solved by Quasi-Newton	Aravkin et al. [22]
33	RPCA	FW-T	SPCP solved by Frank-Wolfe method	Mu et al. [23]
34	RPCA	BRPCA-MD	Bayesian Robust PCA with Markov Dependency	Ding et al. [24]
35	RPCA	BRPCA-MD-NSS	BRPCA-MD with Non-Stationary Noise	Ding et al. [24]
36	RPCA	VBRPCA	Variational Bayesian RPCA	Babacan et al. [25]
37	RPCA	PRMF	Probabilistic Robust Matrix Factorization	Wang et al. [26]
38	RPCA	OPRMF	Online PRMF	Wang et al. [26]
39	RPCA	MBRMF	Markov BRMF	Wang and Yeung [27]
40	RPCA	TFOCS-EC	TFOCS with equality constraints	Becker et al. [28]
41	RPCA	TFOCS-IC	TFOCS with inequality constraints	Becker et al. [28]
42	RPCA	GoDec	Go Decomposition	Zhou and Tao [29]
43	RPCA	SSGoDec	Semi-Soft GoDec	Zhou and Tao [29]
44	RPCA	GreGoDec	Greedy Semi-Soft GoDec Algorithm	Zhou and Tao [30]
45	ST	GRASTA	Grassmannian Robust Adaptive Subspace Tracking Algorithm	He et al. [31]
46	ST	GOSUS	Grassmannian Online Subspace Updates with Structured-sparsity	Xu et al. [32]
47	ST	pROST	Robust PCA and subspace tracking from incomplete observations using L0-surrogates	Hage and Kleinsteuber [33]
48	ST	ReProCS	Provable Dynamic Robust PCA or Robust Subspace Tracking	Narayanamurthy and Vaswani [34]
49	ST	MEDRoP	Memory Efficient Dynamic Robust PCA	Narayanamurthy and Vaswani [35]
50	MC	PG-RMC	Nearly Optimal Robust matrix Completion	Cherapanamjeri et al. [36]
51	MC	FPC	Fixed point and Bregman iterative methods for matrix rank minimization	Ma et al. [37]
52	MC	GROUSE	Grassmannian Rank-One Update Subspace Estimation	Balzano et al. [38]
53	MC	IALM-MC	Inexact ALM for Matrix Completion	Lin et al. [7]
54	MC	LMaFit	Low-Rank Matrix Fitting	Wen et al. [39]
55	MC	LRGeomCG	Low-rank matrix completion by Riemannian optimization	Bart Vandereycken, 2013 [40]
56	MC	MC-logdet	Top-N Recommender System via Matrix Completion	Kang et al. [41]
57	MC	MC-NMF	Nonnegative Matrix Completion	Xu et al. [42]
58	MC	OP-RPCA	Robust PCA via Outlier Pursuit	Xu et al. [43]
59	MC	OptSpace	Matrix Completion from Noisy Entries	Keshavan et al. [44]
60	MC	OR1MP	Orthogonal rank-one matrix pursuit for low rank matrix completion	Wang et al. [45]
61	MC	RPCA-GD	Robust PCA via Gradient Descent	Yi et al. [46]
62	MC	ScGrassMC	Scaled Gradients on Grassmann Manifolds for Matrix Completion	Ngo and Saad [47]
63	MC	SVP	Guaranteed Rank Minimization via Singular Value Projection	Meka et al. [48]
64	MC	SVT	A singular value thresholding algorithm for matrix completion	Cai et al. [49]
65	LRR	EALM	Exact ALM	Lin et al. [7]
66	LRR	IALM	Inexact ALM	Lin et al. [7]
67	LRR	ADM	Alternating Direction Method	Lin et al. [50]
68	LRR	LADMAP	Linearized ADM with Adaptive Penalty	Lin et al. [50]
69	LRR	FastLADMAP	Fast LADMAP	Lin et al. [50]
70	LRR	ROSL	Robust Orthonormal Subspace Learning	Shu et al. [51]
71	TTD	3WD	3-Way-Decomposition	Oreifej et al. [52]
72	TTD	MAMR	Motion-Assisted Matrix Restoration	Ye et al. [53]
73	TTD	RMAMR	Robust Motion-Assisted Matrix Restoration	Ye et al. [53]
74	TTD	ADMM	Alternating Direction Method of Multipliers	Parikh and Boyd [54]
75	NMF	NMF-MU	NMF solved by Multiplicative Updates	unknown
76	NMF	NMF-PG	NMF solved by Projected Gradient	unknown

77	NMF	NMF-ALS	NMF solved by Alternating Least Squares	unknown
78	NMF	NMF-ALS-OBS	NMF solved by Alternating Least Squares with Optimal Brain Surgeon	unknown
79	NMF	PNMF	Probabilistic Non-negative Matrix Factorization	unknown
80	NMF	ManhNMF	Manhattan NMF	Guan et al. [55]
81	NMF	NeNMF	NMF via Nesterov's Optimal Gradient Method	Guan et al. [55]
82	NMF	LNMF	Spatially Localized NMF	Li et al. [56]
83	NMF	ENMF	Exact NMF	Gillis and Glineur [57]
84	NMF	nmfLS2	Non-negative Matrix Factorization with sparse matrix	Ji and Eisenstein [58]
85	NMF	Semi-NMF	Semi Non-negative Matrix Factorization	unknown
86	NMF	Deep-Semi-NMF	Deep Semi Non-negative Matrix Factorization	Trigeorgis et al. [59]
87	NMF	iNMF	Incremental Subspace Learning via NMF	Bucak and Gunsel [60]
88	NMF	DRMF	Direct Robust Matrix Factorization	Xiong et al. [61]
89	NTF	betaNTF	Simple beta-NTF implementation	Antoine Liutkus [62]
90	NTF	bcuNTD	Non-negative Tucker Decomposition by block-coordinate update	Xu and Yin [63]
91	NTF	bcuNCP	Non-negative CP Decomposition by block-coordinate update	Xu and Yin [63]
92	NTF	NTD-MU	Non-negative Tucker Decomposition solved by Multiplicative Updates	Zhou et al. [64]
93	NTF	NTD-APG	Non-negative Tucker Decomposition solved by Accelerated Proximal Gradient	Zhou et al. [64]
94	NTF	NTD-HALS	Non-negative Tucker Decomposition solved by Hierarchical ALS	Zhou et al. [64]
95	TD	HoSVD	Higher-order Singular Value Decomposition (Tucker Decomposition)	unknown
96	TD	HoRPCA-IALM	HoRPCA solved by IALM	Goldfarb and Qin [65]
97	TD	HoRPCA-S	HoRPCA with Singleton model solved by ADAL	Goldfarb and Qin [65]
98	TD	HoRPCA-S-NCX	HoRPCA with Singleton model solved by ADAL (non-convex)	Goldfarb and Qin [65]
99	TD	Tucker-ADAL	Tucker Decomposition solved by ADAL	Goldfarb and Qin [65]
100	TD	Tucker-ALS	Tucker Decomposition solved by ALS	unknown
101	TD	CP-ALS	PARAFAC/CP decomposition solved by ALS	unknown
102	TD	CP-APR	PARAFAC/CP decomposition solved by Alternating Poisson Regression	Chi et al. [66]
103	TD	CP2	PARAFAC2 decomposition solved by ALS	Bro et al. [67]
104	TD	RSTD	Rank Sparsity Tensor Decomposition	Yin Li [68]
105	TD	t-SVD	Tensor SVD in Fourrier Domain	Zhang et al. 2013 [69]
106	TD	OSTD	Online Stochastic Tensor Decomposition	Sobral et al. [70]

Author details

References

1. De la Torre, F., Black, M.J.: Robust principal component analysis for computer vision. In: Proceedings Eighth IEEE International Conference on Computer Vision. ICCV 2001, vol. 1, pp. 362–369 (2001). IEEE
2. Candès, E.J., Li, X., Ma, Y., Wright, J.: Robust principal component analysis? Journal of the ACM (JACM) **58**(3), 11 (2011)
3. Rodriguez, P., Wohlberg, B.: Fast principal component pursuit via alternating minimization. In: 2013 IEEE International Conference on Image Processing, pp. 69–73 (2013). IEEE
4. Hintermüller, M., Wu, T.: Robust principal component pursuit via inexact alternating minimization on matrix manifolds. Journal of Mathematical Imaging and Vision **51**(3), 361–377 (2015)
5. Liu, G., Yan, S.: Active subspace: Toward scalable low-rank learning. Neural computation **24**(12), 3371–3394 (2012)
6. Tang, G., Nehorai, A.: Robust principal component analysis based on low-rank and block-sparse matrix decomposition. In: 2011 45th Annual Conference on Information Sciences and Systems, pp. 1–5 (2011). IEEE
7. Lin, Z., Chen, M., Ma, Y.: The augmented lagrange multiplier method for exact recovery of corrupted low-rank matrices. arXiv preprint arXiv:1009.5055 (2010)
8. Liu, X., Wen, Z., Zhang, Y.: Limited memory block krylov subspace optimization for computing dominant singular value decompositions. SIAM Journal on Scientific Computing **35**(3), 1641–1668 (2013)
9. Lin, Z., Wei, S.: A block lanczos with warm start technique for accelerating nuclear norm minimization algorithms. arXiv preprint arXiv:1012.0365 (2010)
10. Cai, J., Candes, E., Shen, Z.: A singular value thresholding algorithm for matrix completion. arxiv, math. OC **810**, 1 (2008)
11. Yuan, X., Yang, J.: Sparse and low-rank matrix decomposition via alternating direction methods. preprint **12**, 2 (2009)
12. Goldfarb, D., Ma, S., Scheinberg, K.: Fast alternating linearization methods for minimizing the sum of two convex functions. Mathematical Programming **141**(1-2), 349–382 (2013)
13. Liu, R., Lin, Z., Wei, S., Su, Z.: Solving principal component pursuit in linear time via l_1 filtering. arXiv preprint arXiv:1108.5359 (2011)
14. Zhou, X., Yang, C., Yu, W.: Moving object detection by detecting contiguous outliers in the low-rank representation. IEEE transactions on pattern analysis and machine intelligence **35**(3), 597–610 (2012)
15. Zheng, Y., Liu, G., Sugimoto, S., Yan, S., Okutomi, M.: Practical low-rank matrix approximation under robust l 1-norm. In: 2012 IEEE Conference on Computer Vision and Pattern Recognition, pp. 1410–1417 (2012). IEEE
16. Hauberg, S., Feragen, A., Black, M.J.: Grassmann averages for scalable robust pca. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 3810–3817 (2014)
17. Feng, J., Xu, H., Yan, S.: Online robust pca via stochastic optimization. In: Advances in Neural Information Processing Systems, pp. 404–412 (2013)
18. Zhao, Q., Meng, D., Xu, Z., Zuo, W., Zhang, L.: Robust principal component analysis with complex noise. In: International Conference on Machine Learning, pp. 55–63 (2014)
19. Kang, Z., Peng, C., Cheng, Q.: Robust pca via nonconvex rank approximation. In: 2015 IEEE International Conference on Data Mining, pp. 211–220 (2015). IEEE
20. Aybat, N.S., Goldfarb, D., Iyengar, G.: Fast first-order methods for stable principal component pursuit. arXiv preprint arXiv:1105.2126 (2011)
21. Aybat, N.S., Goldfarb, D., Ma, S.: Efficient algorithms for robust and stable principal component pursuit problems. Computational Optimization and Applications **58**(1), 1–29 (2014)
22. Aravkin, A., Becker, S., Cevher, V., Olsen, P.: A variational approach to stable principal component pursuit. arXiv preprint arXiv:1406.1089 (2014)
23. Mu, C., Zhang, Y., Wright, J., Goldfarb, D.: Scalable robust matrix recovery: Frank–wolfe meets proximal methods. SIAM Journal on Scientific Computing **38**(5), 3291–3317 (2016)
24. Ding, X., He, L., Carin, L.: Bayesian robust principal component analysis. IEEE Transactions on Image Processing **20**(12), 3419–3430 (2011)
25. Babacan, S.D., Luessi, M., Molina, R., Katsaggelos, A.K.: Sparse bayesian methods for low-rank matrix estimation. IEEE Transactions on Signal Processing **60**(8), 3964–3977 (2012)
26. Wang, N., Yao, T., Wang, J., Yeung, D.-Y.: A probabilistic approach to robust matrix factorization. In: European Conference on Computer Vision, pp. 126–139 (2012). Springer
27. Wang, N., Yeung, D.-Y.: Bayesian robust matrix factorization for image and video processing. In: Proceedings of the IEEE International Conference on Computer Vision, pp. 1785–1792 (2013)
28. Becker, S.R., Candès, E.J., Grant, M.C.: Templates for convex cone problems with applications to sparse signal recovery. Mathematical programming computation **3**(3), 165 (2011)
29. Zhou, T., Tao, D.: Godec: Randomized low-rank & sparse matrix decomposition in noisy case. In: Proceedings of the 28th International Conference on Machine Learning, ICML 2011 (2011)
30. Zhou, T., Tao, D.: Greedy bilateral sketch, completion & smoothing. Journal of Machine Learning Research (2013)
31. He, J., Balzano, L., Lui, J.: Online robust subspace tracking from partial information. arXiv preprint arXiv:1109.3827 (2011)

32. Xu, J., Ithapu, V.K., Mukherjee, L., Rehg, J.M., Singh, V.: Gosus: Grassmannian online subspace updates with structured-sparsity. In: Proceedings of the IEEE International Conference on Computer Vision, pp. 3376–3383 (2013)
33. Hage, C., Kleinsteuber, M.: Robust pca and subspace tracking from incomplete observations using ℓ_0-surrogates. Computational Statistics **29**(3-4), 467–487 (2014)
34. Narayanamurthy, P., Vaswani, N.: Provable dynamic robust pca or robust subspace tracking. IEEE Transactions on Information Theory **65**(3), 1547–1577 (2018)
35. Narayanamurthy, P., Vaswani, N.: Nearly optimal robust subspace tracking. arXiv preprint arXiv:1712.06061 (2017)
36. Cherapanamjeri, Y., Gupta, K., Jain, P.: Nearly optimal robust matrix completion. In: Proceedings of the 34th International Conference on Machine Learning-Volume 70, pp. 797–805 (2017). JMLR. org
37. Ma, S., Goldfarb, D., Chen, L.: Fixed point and bregman iterative methods for matrix rank minimization. Mathematical Programming **128**(1-2), 321–353 (2011)
38. Balzano, L., Nowak, R., Recht, B.: Online identification and tracking of subspaces from highly incomplete information. In: 2010 48th Annual Allerton Conference on Communication, Control, and Computing (Allerton), pp. 704–711 (2010). IEEE
39. Wen, Z., Yin, W., Zhang, Y.: Solving a low-rank factorization model for matrix completion by a nonlinear successive over-relaxation algorithm. Mathematical Programming Computation **4**(4), 333–361 (2012)
40. Vandereycken, B.: Low-rank matrix completion by riemannian optimization. SIAM Journal on Optimization **23**(2), 1214–1236 (2013)
41. Kang, Z., Peng, C., Cheng, Q.: Top-n recommender system via matrix completion. In: Thirtieth AAAI Conference on Artificial Intelligence (2016)
42. Xu, Y., Yin, W., Wen, Z., Zhang, Y.: An alternating direction algorithm for matrix completion with nonnegative factors. Frontiers of Mathematics in China **7**(2), 365–384 (2012)
43. Xu, H., Caramanis, C., Sanghavi, S.: Robust pca via outlier pursuit. In: Advances in Neural Information Processing Systems, pp. 2496–2504 (2010)
44. Keshavan, R.H., Montanari, A., Oh, S.: Matrix completion from noisy entries. Journal of Machine Learning Research **11**(Jul), 2057–2078 (2010)
45. Wang, Z., Lai, M.-J., Lu, Z., Fan, W., Davulcu, H., Ye, J.: Orthogonal rank-one matrix pursuit for low rank matrix completion. SIAM Journal on Scientific Computing **37**(1), 488–514 (2015)
46. Yi, X., Park, D., Chen, Y., Caramanis, C.: Fast algorithms for robust pca via gradient descent. In: Advances in Neural Information Processing Systems, pp. 4152–4160 (2016)
47. Ngo, T., Saad, Y.: Scaled gradients on grassmann manifolds for matrix completion. In: Advances in Neural Information Processing Systems, pp. 1412–1420 (2012)
48. Jain, P., Meka, R., Dhillon, I.S.: Guaranteed rank minimization via singular value projection. In: Advances in Neural Information Processing Systems, pp. 937–945 (2010)
49. Cai, J.-F., Candès, E.J., Shen, Z.: A singular value thresholding algorithm for matrix completion. SIAM Journal on Optimization **20**(4), 1956–1982 (2010)
50. Lin, Z., Liu, R., Su, Z.: Linearized alternating direction method with adaptive penalty for low-rank representation. In: Advances in Neural Information Processing Systems, pp. 612–620 (2011)
51. Shu, X., Porikli, F., Ahuja, N.: Robust orthonormal subspace learning: Efficient recovery of corrupted low-rank matrices. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 3874–3881 (2014)
52. Oreifej, O., Li, X., Shah, M.: Simultaneous video stabilization and moving object detection in turbulence. IEEE transactions on pattern analysis and machine intelligence **35**(2), 450–462 (2012)
53. Ye, X., Yang, J., Sun, X., Li, K., Hou, C., Wang, Y.: Foreground–background separation from video clips via motion-assisted matrix restoration. IEEE Transactions on Circuits and Systems for Video Technology **25**(11), 1721–1734 (2015)
54. Parikh, N., Boyd, S., *et al.*: Proximal algorithms. Foundations and Trends® in Optimization **1**(3), 127–239 (2014)
55. Guan, N., Tao, D., Luo, Z., Shawe-Taylor, J.: Mahnmf: Manhattan non-negative matrix factorization. arXiv preprint arXiv:1207.3438 (2012)
56. Li, S.Z., Hou, X., Zhang, H., Cheng, Q.: Learning spatially localized, parts-based representation. CVPR (1) **207**, 212 (2001)
57. Gillis, N., Glineur, F.: On the geometric interpretation of the nonnegative rank. Linear Algebra and its Applications **437**(11), 2685–2712 (2012)
58. Ji, Y., Eisenstein, J.: Discriminative improvements to distributional sentence similarity. In: Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing, pp. 891–896 (2013)
59. Trigeorgis, G., Bousmalis, K., Zafeiriou, S., Schuller, B.: A deep semi-nmf model for learning hidden representations. In: International Conference on Machine Learning, pp. 1692–1700 (2014)
60. Bucak, S.S., Gunsel, B., Gursoy, O.: Incremental nonnegative matrix factorization for background modeling in surveillance video. In: 2007 IEEE 15th Signal Processing and Communications Applications, pp. 1–4 (2007). IEEE
61. Xiong, L., Chen, X., Schneider, J.: Direct robust matrix factorizatoin for anomaly detection. In: 2011 IEEE 11th International Conference on Data Mining, pp. 844–853 (2011). IEEE
62. Liutkus, A.: Simple to Use NMF/NTF with Beta Divergence. https://www.mathworks.com/matlabcentral/fileexchange/38109-simple-to-use-nmf-ntf-with-beta-divergence
63. Xu, Y., Yin, W.: A block coordinate descent method for regularized multiconvex optimization with applications to nonnegative tensor factorization and completion. SIAM Journal on imaging sciences **6**(3), 1758–1789 (2013)
64. Zhou, G., Cichocki, A., Xie, S.: Fast nonnegative matrix/tensor factorization based on low-rank approximation. IEEE Transactions on Signal Processing **60**(6), 2928–2940 (2012)
65. Goldfarb, D., Qin, Z.: Robust low-rank tensor recovery: Models and algorithms. SIAM Journal on Matrix Analysis and Applications **35**(1), 225–253 (2014)
66. Chi, E.C., Kolda, T.G.: On tensors, sparsity, and nonnegative factorizations. SIAM Journal on Matrix Analysis and Applications **33**(4), 1272–1299 (2012)
67. Kiers, H.A., Ten Berge, J.M., Bro, R.: Parafac2—part i. a direct fitting algorithm for the parafac2 model. Journal of Chemometrics: A Journal of the Chemometrics Society **13**(3-4), 275–294 (1999)
68. Li, Y., Yan, J., Zhou, Y., Yang, J.: Optimum subspace learning and error correction for tensors. In: European Conference on Computer Vision, pp. 790–803 (2010). Springer
69. Zhang, Z., Ely, G., Aeron, S., Hao, N., Kilmer, M.: Novel factorization strategies for higher order tensors: Implications for compression and recovery of multi-linear data. arXiv preprint arXiv:1307.0805 (2013)
70. Sobral, A., Javed, S., Ki Jung, S., Bouwmans, T., Zahzah, E.-h.: Online stochastic tensor decomposition for background subtraction in multispectral video sequences. In: Proceedings of the IEEE International Conference on Computer Vision Workshops, pp. 106–113 (2015)