Appendix A: Matrix Identities

(a) Woodbury’s Matrix Identity

\[
(A + uv^T)^{-1} = A^{-1} - \frac{[A^{-1}u][v^T A^{-1}]}{1 + v^T A^{-1}u}
\]  
(A.1)

(b) Matrix Inverse Identity

\[(A + BCD)^{-1} = A^{-1} - A^{-1}B(DA^{-1}B + C^{-1})^{-1}DA^{-1}
\]  
(A.2)

(c) Matrix-Vector Inverse Identity

\[
\begin{bmatrix}
U^T U & U^Td \\
d^T U & d^Td
\end{bmatrix}^{-1} = \begin{bmatrix}
(U^T U)^{-1} + \beta U^# dd^T(U^#)^T & -\beta U^# d \\
-\beta d^T(U^#)^T & \beta
\end{bmatrix},
\]  
(A.3)

where

\[U^# = (U^T U)^{-1}U\]

and

\[\beta = \left\{d^T \left[I - U(U^T U)^{-1}U^T\right]d\right\}^{-1} = \left\{d^T [P^u] d\right\}^{-1}.
\]

(d) Matrix-Inverse Identity

\[\beta = \left\{d^T \left[I - U(U^T U)^{-1}U^T\right]d\right\}^{-1} = \left\{d^T [P^u] d\right\}^{-1},
\]  
(A.4)

where \(I = [C - B^T A^{-1}B]^{-1}\).
Glossary

A
AD  Anomaly detection, Chap. 6
ALMM  Adaptive linear mixing model, Chap. 9
ALSMA  Adaptive linear spectral mixture analysis, Chap. 9
ANC  Abundance nonnegativity constraint, Chap. 9
ARHBP  Adaptive recursive hyperspectral band processing, Chap. 9
ASC  Abundance sum-to-one constraint, Chap. 9
ATGP  Automatic target generation process, Chap. 4
AVIRIS  Airborne visible/infrared imaging spectrometer, Chap. 1

C
CBR-AD  Causal band K-RXD, Chap. 14
CBR-AD  Causal band R-RXD, Chap. 14
CBRCM  Causal band correlation matrix, Chaps. 13 and 14
CEM  Constrained energy minimization, Chap. 5
CK-AD  Causal K-AD, Chap. 14
CLCRM  Causal line correlation matrix, Chap. 5
CR-AD  Causal R-AD, Chap. 6
CSCRM  Causal sample correlation matrix, Chap. 5
CSCVM  Causal sample covariance matrix, Chaps. 5 and 6

D
DSV  Determinant-based simplex volume, Chap. 2
Dist-SGA  Distance-based simple growing algorithm
DSGA  Determinant-based SGA, Chaps. 2, 11, and 12
DR  Dimensionality reduction

E
EFA  Endmember finding algorithm
EIDA  Endmember identification algorithm
F
FCLS  Fully constrained least-squares method, Chap. 9
FPGA  Field Programmable Gate Array

G
GSGA  Geometric simplex growing algorithm, Chaps. 12 and 18
GSVA  Growing simplex volume analysis, Chaps. 12 and 18
GSV  Geometric simplex volume, Chap. 2
GSV-OP  Geometric simplex volume by orthogonal projection, Chaps. 11 and 12
GSV-SH  Geometric simplex volume by simplex height, Chap. 12
GSV-PD  Geometric simplex volume by perpendicular distance, Chaps. 11 and 12

H
HFC  Harsanyi–Farrand–Chang, Chap. 4
HOS  High-order statistics
HSI  Hyperspectral imaging
HYDICE  HYperspectral Digital Imagery Collection Experiment, Chap. 1

I
IBSI  Interband spectral information, Chap. 4
IPPI  Iterative pure pixel index, Chap. 18

K
KF-OSP-GSGA  Kalman filter–based orthogonal subspace projection geometric simplex growing algorithm, Chap. 12
KF-OVP-GSGA  Kalman filter–based orthogonal vector projection geometric simplex growing algorithm, Chap. 12
K-AD  Anomaly detection using autocovariance matrix K, Chap. 5

L
LCMV  Linearly constrained minimum variance, Chap. 5
LCVF  Lunar Crater Volcanic Field, Chap. 1
LSE  Least-squares error
LSU  Linear spectral unmixing
LSMA  Linear spectral mixture analysis, Chap. 9

M
MEAC  Minimum estimated abundance covariance, Chap. 10
MLE  Maximum likelihood estimation, Chap. 10
MVT  Minimum volume transform

N
NCLS  Nonnegativity constrained least-squares method, Chaps. 4 and 9
N-FINDR  N-Finder algorithm
NPD  Neyman–Pearson detection/detector
NWHFC  Noise-whitened Harsanyi–Farrand–Chang, Chap. 4
O
OP  Orthogonal projection
OPSGA  Orthogonal projection–based simple growing algorithm, Chap. 11
OSP  Orthogonal subspace projection

P
P-AD  Progressive anomaly detection, Chap. 6
PHBP  Progressive hyperspectral band processing, Chaps. 14–20
P-CEM  Progressive constrained energy minimization, Chap. 5
PKP  Progressive skewer set processing, Chaps. 19 and 20
PPI  Pixel purity index
PSP  Progressive sample processing, Chap. 1

R
R-AD  RXD using autocorrelation matrix R, Chap. 5
RHBP  Recursive hyperspectral band processing, Chap. 1
RHBP-AD  Recursive hyperspectral band processing of anomaly detection, Chap. 14
RHBP-ATGP  Recursive hyperspectral band processing of the automatic target generation process, Chap. 15
RHBP-CEM  Recursive hyperspectral band processing of constrained energy minimization, Chap. 13
RHBP-C-IPPI  Recursive hyperspectral band processing of causal iterative pixel purity index, Chap. 19
RHBP-FIPPI  Recursive hyperspectral band processing of fast iterative pixel purity index, Chap. 20
RHBP-GSGA  Recursive hyperspectral band processing of geometric simplex growing algorithm, Chap. 18
RHBP-GSVA  Recursive hyperspectral band processing of growing simplex volume analysis, Chap. 18
RHBP-LSMA  Recursive hyperspectral band processing of linear spectral mixture analysis, Chap. 17
RHBP-OSP  Recursive hyperspectral band processing of orthogonal subspace projection, Chap. 16
RHBP-PS-IPPI  Recursive hyperspectral band processing of progressive-skewer iterative pixel purity index, Chap. 19
RHBP-SGA  Recursive hyperspectral band processing of simplex growing algorithm, Chap. 18
RHSP  Recursive hyperspectral sample processing, Chap. 1
RHSP-ATGP  Recursive hyperspectral sample processing of the automatic target generation process, Chap. 7
RHSP-GSGA  Recursive hyperspectral sample processing of geometric simplex growing algorithm, Chap. 12
RHSP-LSMA  Recursive hyperspectral sample processing of linear spectral mixture analysis, Chap. 9
**RHSP-MLE** Recursive hyperspectral sample processing of maximum likelihood estimation, Chap. 10

**RHSP-OPSGA** Recursive hyperspectral sample processing of orthogonal projection–based simple growing algorithm, Chap. 11

**RHSP-OSP** Recursive hyperspectral sample processing of orthogonal subspace projection, Chap. 8

**ROC** Receive operating characteristic

**RSP** Recursive skewer processing, Chap. 20

**RXD** RX detector, Chap. 5

**RT** Real time

**S**

**SAM** Spectral angle mapper

**SC N-FINDR** SuCcessive N-FINDR

**SGA** Simplex growing algorithm, Chap. 2

**SID** Spectral information divergence

**SNR** Signal-to-noise ratio

**SQ N-FINDR** SeQuential N-FINDR

**SV** Simplex volume

**SVGA** Simplex volume growing analysis, Chaps. 11 and 12

**T**

**TE** Target embeddedness

**TI** Target implantation

**TSVD** Target-specified virtual dimensionality, Chap. 4

**U**

**UFCLS** Unsupervised fully constrained least-squares, Chap. 4

**UNCLS** Unsupervised nonnegativity constrained least-squares, Chap. 4

**UROSP** Unsupervised recursive orthogonal subspace projection, Chap. 8

**V**

**VCA** Vertex component analysis, Chap. 11

**VD** Virtual dimensionality, Chap. 4

**VS** Virtual signature, Chaps. 9 and 10
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