Index

A1-IN-FINDR algorithm, 232, 233, 234, 235, 238, 239. See also Alternative N-FINDR (AN-FINDR); N-finder (N-FINDR) algorithm

Absolute value distance (AVD), 746

Absolute value distance (AVD)-SDFC, 747, 748, 749, 750, 751, 753, 754, 764, 766. See also Spectral derivative feature coding (SDFC) performance of, 764, 766

RSDPW values for, 752, 766

Abundance, estimating, 39–40

Abundance-constrained FLSMA (AC-FLSMA), 391, 392, 409–410, 412. See also Fisher’s LSMA (FLSMA); Linear spectral mixture analysis (LSMA)

Abundance-constrained fully constrained least-squares (AC-FCLS) method, 392. See also Fully abundance-constrained least-squares (FCLS) method

Abundance-constrained least-squares FLDA (ACLS-FLDA), types of, 416–417. See also Fisher’s ratio-based linear discriminant analysis (FLDA)

Abundance-constrained least-squares FLDA (ACLS-FLDA) approach, 392, 397–398

Abundance-constrained least-squares LSMA, 409–410. See also Linear spectral mixture analysis (LSMA)

Abundance-constrained LSMA (AC-LSMA), 392, 411, 412, 413, 927. See also AC-LSMA entries; Linear spectral mixture analysis (LSMA)

LSE problems derived from, 413
using LSE as a criterion, 432–433

Abundance constraints, 225, 435, 505, 418, 968–969

Abundance estimator, 40

Abundance-FCLS method, 924. See also Fully abundance-constrained least-squares (FCLS) method

Abundance fraction(s), 33, 38, 39, 54, 55, 78, 106, 351–352, 362, 363, 364, 367, 368, 563, 564, 791, 809–810

detected, 92, 93
detected by $\delta_{\text{OSPA}}$ and $\delta_{\text{RXD}}$, 387–388, 389–390

estimated by KFSSQ, 839–840, 857

estimated/estimating, 250, 380, 412, 420, 924


of FCLS unmixed pixels, 608

in hyperspectral target detection, 79

for implanted panels, 565

Kalman filters and estimating, 821

KFSSQ-estimated, 840–841, 842, 849–850

LSOSP-unmixed, 114

of mixed pixel panels, 570

NCLS-estimated, 111

of panel pixels, 423, 425, 426, 427, 428, 429, 514, 515

of panel pixel vectors, 886–887, 890

of panels, 888–889

quantification results of, 514, 524

quantified by KFSSQ, 851–852

quantifying, 432

of R pixel vectors, 891

of signature vectors, 850

simulated for panel pixels, 529

for subpixel/mixed pixel panels, 566

of target signatures, 894

of the target signature vector, 789

© 2013 John Wiley & Sons, Inc. Published 2013 by John Wiley & Sons, Inc.
Abundance fraction(s) (Continued)
  UFCLS-unmixed, 569
  unmixed, 420, 445, 512–517, 520, 679–681, 703–706
  of Y pixel vectors, 891
Abundance fractional maps, 516, 517
Abundance fraction estimation, 828–829, 895–896
  KFLU-performed, 824
  UFCLS-performed, 579
Abundance fraction estimates, of R pixel vectors, 889–890
Abundance fraction maps, 81, 86, 254, 521–523, 603
  FCLS-estimated, 890
Abundance fraction quantification, 674
Abundance fraction results, 421
  of AC-LSMA methods, 428, 430
  of R panel pixels, 427–429, 431, 432
Abundance fully constrained least-squares FLSMA
  (AFCLS-FLSMA) approach, 392, 398, 409–410, 413. See also Fisher’s LSMA
  (FLSMA); Linear spectral mixture analysis (LSMA)
  FCLS vs., 401–402, 403–405, 406, 407
  quantitative results produced by, 402, 409
Abundance NCLS, 438. See also Non-negativity abundance-constrained least-squares (NCLS)
  method
Abundance non-negativity–constrained least-squares FLSMA (ANCLS-FLSMA) approach, 392, 398, 409–410, 413. See also Fisher’s LSMA (FLSMA); Linear spectral mixture analysis (LSMA); Non-negativity abundance-constrained least-squares (NCLS) method
Abundance non-negativity constraint (ANC), 319, 323, 349, 392, 411, 412, 435, 438, 880, 927, 965, 966, 968, 969. See also ANC-LSMA
Abundance percentage, 92
Abundance percentage mixed-to-pure pixel converter (APMPCV), 92
Abundance purity, 516
Abundance quantification, 254
  by UFCLS, 576
Abundance sum-to-one constraint (ASC), 101, 106, 223, 225, 323, 349, 392, 411, 412, 501, 880, 927, 965, 967, 968, 969. See also ASC-LSMA
  implementing, 439
Abundance sum-to-one constrained least-squares FLSMA (ASCLS-FLSMA) approach, 392, 398, 409–410, 413. See also Fisher’s LSMA (FLSMA); Linear spectral mixture analysis (LSMA); Sum-to-one constrained least-squares (SCLS) entries
Abundance-unconstrained LSMA, 967. See also Linear spectral mixture analysis (LSMA)
Abundance-unconstrained LSOSP method, 924. See also Least-squares-based orthogonal subspace projection (LSOSP)
Abundance-unconstrained methods, 436
Abundance vector estimation, 824
Abundance vectors, 29, 823, 826, 849
  estimated, 822
AC-based spectral feature probabilistic coding, 756. See also Arithmetic coding (AC)
Acceptance region, 36
Accurate signature knowledge, 973–974
ACE–matched filter distance (MFDACE), 476. See also Matched filter distance (MFD)
AC-encoded words, 757. See also Arithmetic coding (AC)
AC-LSMA classifier, 426. See also Abundance-constrained LSMA (AC-LSMA)
AC-LSMA methods, abundance fraction results of, 428, 430
AC-LSMA performance, 429
ACORN software, 22
Adaptive anomaly detectors, 975
Adaptive beamforming approach, 197–198
  LCMV-based, 43–44
Adaptive CEM (ACEM), 904. See also Constrained energy minimization (CEM)
Adaptive Coherence Estimator (ACE), 476
Adaptive matched detector (AMD), 39–41, 44, 61
Adaptive matched filter, 40
Adaptive RXDs (ARXDs), 904. See also RX detector (RXD, \( \delta^{\text{RXD}} \))
Adaptive subspace detector (ASD, \( \delta^{\text{ASD}} \)), 41–43, 44, 55, 61
  extensions of, 43
Additive Gaussian noise, 334
Additive Gaussian noise–corrupted scenario, 303–305
AFC-LSMA, 418. See also Linear spectral mixture analysis (LSMA)
Agent signatures, discrimination among, 817
AHSD/normalized AHSD values, 726–729, 734–736. See also Average Hamming spectra distance (AHSD)
AHSD per band, 721
A-ID-PIPP algorithms, 588. See also Initialization-driven PIPP (ID-PIPP); Projection index (PI)-based projection pursuit (PIPP)
Airborne visible infrared imaging spectrometer (AVIRIS) data, 19, 20–26, 436, 764.  
See also AVIRIS entries

CB data vs., 818

computer simulations using, 831–842

Airborne visible infrared imaging spectrometer (AVIRIS) data sets, 156, 330–331, 760

Algorithm design, 10

Algorithm evaluation process, 102

Algorithm-generated endmembers, 202–203

Algorithm initiation, 266

 initial endmembers required for, 313

Algorithm performance, 102

issues determining, 266–267

Algorithms

compendium of, 997–1051

efficacy of, 526–527, 539–540

dendmember pixels extracted by, 261

to extract pixel information, 528

for finding endmembers, 201–202

performance of, 540

for pixel information analysis, 539

pixel information extracted by, 536, 538

quantification, 828

results produced by, 532–534

RX-anomaly detection, 539

two-dimensional image compression, 541

Algorithm termination, 267

Alternative hypothesis, 66

Alternative N-FINDR (AN-FINDR), 201, 230.  
See also N-finder (N-FINDR) algorithm

Alternative SM N-FINDR (ASM N-FINDR), 223–225, 240.  See also Simultaneous N-FINDR (SM-NFINDR)

Alunite/kaolinite mixed pixel, 534

Alunite signature, 312

AMD-based subsample target detection, 41.  
See also Adaptive matched detector (AMD)

AMEE-extracted panel pixels, 531.  See also Automated morphological endmember extraction (AMEE) entries

AMEE-extracted pixels, 535, 536, 537, 539

Analysis. See also Components analysis entries;

Convex cone analysis (CCA); Data analysis;

Eigen-analysis; Fisher’s ratio-based linear discriminant analysis (FLDA); Image analysis;

Independent component analysis (ICA) entries;

Kernel-based Fisher’s linear discriminant analysis; Linear spectral mixture analysis (LSMA); Minimum misclassification canonical analysis (MMCA); Mixed PCA/ICA component analysis; Mixed sample analyses; Principal components analysis (PCA); Progressive high-order statistics component analysis; Progressive independent component analysis; Progressive principal components analysis; Receiver operating characteristics (ROC) analysis; Spatial domain analysis; Subsample analysis; Subpixel analyses; Three-dimensional receiver operating characteristics (3D ROC) analysis; Two-dimensional receiver operating characteristics (2D ROC) analysis; Vertex component analysis (VCA); Wavelet analysis canonical, 195

discriminant, 195–196

literal, 1

mixed sample, 10

nonliteral, 1, 6–7

real-to-complex, 4–5

ROC, 10, 41, 63

spatial domain–based literal, 7

subsample, 10

ANC-LSMA, 418.  See also Abundance non-negativity constraint (ANC); Linear spectral mixture analysis (LSMA)

An information criterion (AIC), 6, 127, 130–131, 138, 165

Anomalies, defining, 975–976

Anomalous pixels, 467, 526, 527, 530, 534, 537–538

Anomalous pixel vectors, 14

Anomaly classification, 975

Anomaly detection, 383, 386–390, 467, 474, 527, 559, 560–561

multiple-window, 977

performance of, 387–388

by RXD detection algorithm, 122–123

signal-to-noise ratio and, 387

Anomaly detection algorithms, 527–528, 975

Anomaly detectors, 384–385, 972, 974–977

global, 977

APDP/AHSD identification of a mixed signature, 730–733.  See also A posteriori discrimination probability (APDP);

APDP/AHSD identifications, 737–739

APDP/HSD identification of a mixed signature, 730–733.  See also .  See also Hamming spectral distance (HSD)

APDP/HSD identifications, 736–737, 737–738

APDP values, 730

A posteriori correlation, hyperspectral measures weighted by, 474–477

A posteriori correlation–based hyperspectral measures, 476
A posteriori discrimination probability (APDP), 719, 720, 729, 740. See also APDP entries
A posteriori information, 357, 375, 482
A posteriori knowledge, 972, 973
trial-and-error approach to, 841
A posteriori probability distributions, 366, 962
A posteriori target information, 886
A posteriori-weighted hyperspectral measures, identification errors resulting from, 478
Approximation error, 776
Approximation signatures, 860, 863, 864
corruption of, 865–866, 866–867
signatures self-tuned by, 869–870
Approximation spaces, 862
A priori correlations, hyperspectral measures weighted by, 473–474
A priori information, 357, 358, 375, 383, 482
A priori knowledge, 972, 973, 974, 975
Arbitrary-bit encoders, 771
Area under curve (AUC), 64, 68, 90, 93, 612, 706, 713–714
Area under curve (AUC) values, 946, 950
Arithmetic coding (AC), 718, 741, 755–756
as a memory coding method, 757
with SFPC, 756–758
in spectral signature coding, 742–743
Array processing, 131
ASC-LSMA, 418. See also Abundance sum-to-one constraint (ASC); Linear spectral mixture analysis (LSMA)
Asymptotic equipartition property theorem, 288
ATGP-based ICA, 555. See also ATGP-ICA-EEA; Automatic target generation process (ATGP); Independent component analysis (ICA) entries
ATGP–Bayes detector, 961
ATGP-extracted pixels, 536
ATGP-FastICA algorithm, 604. See also FastICA entries
ATGP-FastICA cube, FCLS quantification for, 608
ATGP-FCLS algorithm, 880, 888–889. See also Fully constrained least-squares (FCLS) method in subpixel target size estimation, 881
ATGP-generated BKG/target VSs, 504. See also Background entries; Background (BKG) virtual signatures (VSs); Virtual signatures (VSs)
ATGP-generated pixels, 326
ATGP-generated simplexes, 329
ATGP-generated target pixels, 319, 407, 422, 431, 506
ATGP-generated targets, 190, 317
ATGP-generated target sample vectors, 325
ATGP-generated vectors, 189
ATGP-HFC methods, 961, 962. See also Harsanyi–Farraud–Chang (HFC) method
ATGP-HOS-EEA, 277. See also Endmember extraction algorithms (EEAs); High-order statistics (HOS)
ATGP-ICA-EEA, 277, 278, 279, 280, 282, 283, 284, 285. See also Independent component analysis (ICA) entries
ATGP-ID-PIPP algorithm, 589. See also Initialization-driven PIPP (ID-PIPP);
Projection index (PI)-based projection pursuit (PIPP)
ATGP-IN-FINDR, 314, 315. See also Iterative N-finder algorithm (IN-FINDR)
ATGP-kurtosis-EEA, 278, 279, 280, 282, 283, 284, 285
ATGP–Neyman–Pearson detector, 961
ATGP-N-FINDR, 276, 278, 279, 280, 281, 282, 283, 284, 285, 315. See also N-finder algorithm (N-FINDR)
ATGP-OSP algorithm, 928. See also Orthogonal subspace projection (OSP)
ATGP/PCA relationship, 321–322. See also Principal components analysis (PCA)
ATGP-PPI, 276, 278, 280, 281, 282, 283, 284, 285, 322, 323. See also Pixel purity index (PPI) entries
endmember extraction by, 323, 324, 325, 326, 327, 328
ATGP/PPI relationship, 319–320
ATGP-prioritized PICA (ATGP-PICA) algorithm, 931, 932. See also Prioritized ICA (PICA)
ATGP-SC N-FINDR, 275–276, 314, 315
ATGP-skewness-EEA, 278, 279, 280, 282, 283, 284, 285. See also Endmember extraction algorithms (EEAs)
ATGP-SQ-N-FINDR, 314, 315. See also SeQuential N-FINDR (SQ N-FINDR)
ATGP-UVSFA, 512, 513. See also Unsupervised virtual signature finding algorithms (UVSFAs)
target VSs extracted by, 491, 492, 493, 495
ATGP-VCA, 275, 322, 323. See also Vertex component analysis (VCA) endmember extraction by, 323, 324, 325, 326, 327, 328
Atmospherically corrected data, 534
Autocorrelated bands, 910, 938, 942, 943
Autocorrelated spectral band images, 902
Autocorrelation matrix, 135, 972
Autocovariance matrix, 135
Automated morphological endmember extraction (AMEE), 230–231, 240, 538, 539
Automated morphological endmember extraction (AMEE) algorithm (AMEE A), 201, 204, 207, 209, 527
pixel extraction using, 533, 534
Automatic EEA (AEEA), 204. See also Endmember extraction algorithms (EEAs)
Automatic PPI (APP1), 289. See also Pixel purity index (PPI) entries
Automatic target detection, 18
Automatic target detection and classification program (ATDCA), 272, 405
applications of, 964
for CADCA, 880
development of, 319
endmember extraction by, 323, 324, 325, 326, 327, 328
endmembers generated by, 344
for finding potential interferers, 430–431
in generating desired signatures, 626
pixels extracted by, 160, 342, 343, 532–533, 534
for producing background knowledge, 427
relationships with PPI and VCA, 319–323
simplex volumes and, 343, 344
stopping rule of, 960–961
used as an EIA, 344
Automatic target generation process (ATGP) algorithm, 881, 882, 883
in finding target locations, 882, 883, 886–887, 896
as an initialization algorithm, 595
in locating subpixel targets, 895–896
MATLAB codes for, 1040–1042
as an unsupervised method, 884–885
as an unsupervised target detection algorithm, 888–889
Automatic target generation process–EEA (ATGP-EEA), 243, 248–249, 255, 256, 257, 258, 259, 260, 261, 262, 263, 264, 272, 276, 277, 278, 317, 318, 320, 880, 881, 888. See also Endmember extraction algorithms (EEAs) algorithm for, 249
Automatic target generation process/Mahalanobis distance (ATGP/MD) approach, 960
Auxiliary functions, 59
Auxiliary signature vector, 827
Averaged panel pixel detection rates, 706, 713–714
Averaged risk, 36, 97
Averaged signature vectors, 813, 815
of gas data set, 753
Average Hamming spectra distance (AHSD), 720, 721, 725, 726, 727, 728, 729, 730, 731, 732, 733–735, 736–738, 739. See also AHSD entries; APDP/AHSD entries
AVIRIS Cuprite data, 577. See also Airborne visible infrared imaging spectrometer (AVIRIS)
AVIRIS Cuprite scene, 534–537
AVIRIS data experiments, 444–460, 746–749, 758–760
AVIRIS data simulation, classification results of, 749
AVIRIS experiments, 270–271, 309–313, 323, 815
AVIRIS image experiments, 478–482, 534
AVIRIS image scenes, 23–24
AVIRIS laboratory reflectance data, 725
AVIRIS reflectance data, 868
A-weighted AC-LSMA, types of, 414. See also Abundance-constrained LSMA (AC-LSMA); Linear spectral mixture analysis (LSMA)
A-weighted LSE problems, 413. See also Least-squares error entries
A-whitened LSE, 414. See also Least-squares error entries
Background (BKG), 333, 483, 484, 485. See also BKG entries; Clean background; Image background; Noisy background estimating, 43
Gaussian noise and clean panels embedded in, 110–112
implanting target pixels into, 105
target insertion into, 101
Background image, corrupted by Gaussian noise, 532
Background (BKG) knowledge
ATGP for providing, 427
from secondary data, 39
unsupervised, 429–432
Background (BKG) matrix, 54
Background (BKG) mean, 47
Background (BKG) pixels, 429, 466, 505
adding panel pixels to, 109
replaced with implanted panel pixels, 333
Background (BKG) signature matrix, 81
Background (BKG) signatures, 28–29, 89, 113, 511, 515, 525, 531
additional, 432
complete knowledge of, 420
determining numbers of, 485
no prior knowledge about, 420–426
radiance spectra of, 335
Background (BKG) signatures (Continued)
reflectance spectra of, 333
simulated, 333
spectral signatures of, 333, 334
Background (BKG) statistics, 41
Background (BKG) suppression, 503, 509, 511, 970
Background (BKG) virtual signatures (VSs), 491, 492, 503–505, 505–510, 519
Band correlation, 685
Band correlation constraint (BCC), 622, 624, 625, 626, 637, 650, 651, 652
algorithms/MATLAB codes for, 1047–1049
endmembers extracted by IN-FINDR corresponding to, 632, 635, 645, 649, 653–654
UFCLS-mixed panel results corresponding to, 642, 648
UFCLS-mixed panel results produced by, 631
Band correlation minimization (BCM), 621–622, 624, 625, 626, 637, 650, 651, 652.
See also LCMV-BCM
algorithms/MATLAB codes for, 1049–1050
endmembers extracted by IN-FINDR corresponding to, 632, 635, 645, 649, 653–654
UFCLS-mixed panel results corresponding to, 642, 648
UFCLS-mixed panel results produced by, 631
Band de-correlation (BD), 544, 614, 663, 678, 684–686, 686–687, 715. See also BD entries
BP followed by, 687
as a preprocessing step, 684
Band dependence constraint (BDC), 622, 624, 625, 626, 637, 650, 651, 652
endmembers extracted by IN-FINDR corresponding to, 632, 635, 645, 649, 653–654
UFCLS-mixed panel results corresponding to, 642, 648
UFCLS-mixed panel results produced by, 631
Band dependence minimization (BDM), 621–622, 624, 625, 626, 637, 650, 651, 652.
See also LCMV-BDM
algorithms/MATLAB codes for, 1050–1051
endmembers extracted by IN-FINDR corresponding to, 632, 635, 645, 649, 653–654
UFCLS-mixed panel results corresponding to, 642, 648
UFCLS-mixed panel results produced by, 631
Band dimensionality expansion (BDE), 18, 899–902, 919, 924. See also Progressive band dimensionality expansion (PBDE); Sequential band dimensionality expansion (SBDE)
in conjunction with FDE, 909
hyperspectral imaging techniques expanded by, 902–904
rationale for developing, 899–901
Band dimensionality expansion (BDE)-based LSMA, 897. See also Linear spectral mixture analysis (LSMA)
Band dimensionality expansion techniques, 904
Band expansion process (BEP), 18, 877, 897, 899, 901–902, 919, 924. See also BEP entries;
K-BEP entries
incorporated into LSMA, 923
LSMA performance and, 938
Band expansion process algorithm, 902
Band expansion process–based OSP (BEP-OSP), 927–928. See also Orthogonal subspace projection (OSP)
Band expansion process over-complete ICA, for MR image analysis, 931–932. See also Independent component analysis (ICA) entries
Band extraction, 816–818
Band generation process (BGP), 899, 924
Band image correlation matrix, 621
Band images, orthogonalizing, 685–686
Band image vectors, 892–893
Band-interleaved-by-pixel (BIP), 178
Band numbers
classification performance and, 658–661
for hyperspectral signatures, 682
Band prioritization (BP), 198, 199, 543, 544, 615–617, 683, 687, 715, 718
applications of, 624–651, 652
BD followed by, 616, 687–688
criteria for, 617–624
dimensionality prioritization vs., 614, 624
PBDP and, 613
progressive band dimensionality expansion via, 614, 655–656
progressive band dimensionality reduction via, 614, 654
Band prioritization, 540
Band prioritization/band de-correlation (BP/BD) approach, 616, 687–688. See also BP/BD entries
Band ratio, 891
Band ratio approach, 18
for CADCA, 880
Band reduction/expansion, 614
Band selection (BS), 31, 543, 616–617, 635, 663, 683–684, 715, 891–892, 981–983. See also BS entries; Constrained band selection (CBS); Progressive band selection (PBS) for CADCA, 880

crucial issues arising in, 614
dimensionality reduction by, 196–197
dimensionality reduction vs., 632–635
divergence measure for, 892
hyperspectral, 682
impact on signature analysis, 810
issues arising in, 613, 664–665
new approach to, 197–198
progressive band dimensionality process vs., 616

Band selection–based spectral compression, dimensionality reduction by, 556–557
Band selection procedure, 18
Band SeQuential (BSQ), 178
Band-to-band correlation, 820
Band variances, 617
Band vectors, 686
Basis functions, 59
Basis vectors, skewers as, 316
Bayes cost, 63
Bayes detector ($\delta^{\text{Bayes}}$), 36, 37, 38, 961
Bayes rule, 37
BBOPC band selection algorithm, 892, 893. See also Between-bands orthogonal projection correlation (BBOPC)

BD/BP-PBS algorithm, 687–688. See also Band de-correlation (BD); Band prioritization (BP); Band prioritization/band de-correlation (BP/BD) approach
BP/BD-PBS algorithm vs., 688
BD de-correlated bands, 691
BD preprocessing, 688
BD-removed bands, 695
BEP6 + KLSMA experiment, 912–916. See also Band expansion process (BEP); Kernel-based LSMA (KLSMA)
BEP6 + LSMA experiment, 910, 911, 912. See also Linear spectral mixture analysis (LSMA)
BEP9 + KLSMA experiment, 916–918. See also Kernel-based LSMA (KLSMA)
BEP9 + LSMA experiment, 910, 911–912. See also Linear spectral mixture analysis (LSMA)

BEP-based constrained energy minimization (BEP-CEM), 902, 903. See also Constrained energy minimization (CEM)
BEP-based maximum likelihood classifier (BEP-MLC), 904. See also Maximum likelihood classifier (MLC)
BEP-based orthogonal subspace projection (BEP-OSP), 902, 903
BEP-based RX-detector (BEP-RXD), 902, 903–904. See also RX detector (RXD, $\delta^{\text{RXD}}$)
BEP effectiveness tests, 910–911, 912
BEP-expanded bands, 941–942
BEP-expanded MR images, FCLS using, 939. See also BEP-preprocessed MR images; Magnetic resonance (MR) entries
BEP-FCLS method/technique, 924. See also Fully constrained least-squares (FCLS) method
BEP-generated bands, brain tissue classification and, 936–951
BEP-generated images, 953
BEP + LSMA (BEP-LSMA), 923. See also Linear spectral mixture analysis (LSMA) applying to magnetic resonance image classification, 918
BEP-LSOSP method/technique, 924. See also Least-squares-based orthogonal subspace projection (LSOSP)
BEP-NCLS method/technique, 924. See also Non-negativity abundance-constrained least-squares (NCLS) method
BEP-preprocessed MR images, 943. See also BEP-expanded MR images; Magnetic resonance (MR) entries
Best binary coding method, 728
Between-bands orthogonal projection correlation (BBOPC), 892, 896. See also BBOPC band selection algorithm
Between-class scatter matrices, 46, 47, 58, 360, 361, 362, 393, 396–397, 908
Between-class scatter matrix/within-class scatter matrix criterion, 362
Binary classification, 46, 47
Binary classification problems, reducing multiclass classification problems to, 53–54
Binary code words, 719, 720, 721, 722, 723, 724–725, 744
$L$-dimensional, 728
$L$-length, 736–739
$M$–block length, 776
Binary code word sets, 720
Binary coding, 9, 16–17, 717, 719, 720–723, 986
for spectral signatures, 719–740
in spectral identification, 729
Binary coding methods, 725
best, 728
results of, 727–730
spectral, 741
spectral identification and, 733–736
Binary composite hypothesis-testing approach, 62
Binary composite hypothesis-testing problem, 41
Binary decisions, 48
Binary encoders, progressive, 776
Binary hard decisions, 69
Binary hypothesis–based detectors, 36–38
Binary hypothesis test, 365, 959, 962
HFC vs. PCA methods and, 139
Binary hypothesis-testing problem, 36, 64, 66, 136–137
Binary images, 546
Binary signature coding schemes, 717, 719
Binary strings, encoding, 755–756
Binary-valued stage components, 775
Binary values, 719–720, 741, 742
Biometric recognition, 95–99
Biometric recognition system, evaluation of, 95
Bit allocation, 667
Bit plane coding, 719, 720
Bit position, 784
Bit rates, 764, 768, 771
Bits, 668
BKG class, signatures in, 485–486. See also Background (BKG) entries
BKG data sample vectors, 487
BKG signature extraction, 508–509
Blind source separation technique, 244
BP applications. See also Band prioritization (BP)
using highest-prioritized bands, 625–635
using least prioritized bands, 635–646
using mixed highest-prioritized and least-prioritized bands, 646–651
BP/BD bands, highest-prioritized, 692–693, 702–703. See also Band prioritization/band de-correlation (BP/BD) approach
BP/BD-PBS algorithm, 687, 688
BD/BD-PBS algorithm vs., 688
BP concept, 662–663
BP criteria (BPCs), 615–616, 674–677, 688, 806
BP/ID-BD algorithm and, 689
classification-based, 619–620
comparison of, 624, 650
FLDA-based, 619–620
highest-prioritized bands selected by, 651
highest-prioritized spectral bands selected by, 625
high-order statistics–based, 618, 658
infinite-order statistics–based, 618–619
for investigating DDA, 674
least-prioritized bands selected by, 652
OSP-based, 620
second-order statistics–based, 617–618, 674, 693
SNR-based, 618
variance-based, 617–618
BP experiments, 624–651, 652
BP/ID-BD algorithm, 688, 689
Brain imaging, 87–91
Brain MRI, 925. See also Magnetic resonance (MR) brain imaging; Magnetic resonance (MR) imaging (MRI)
Brain MR protocol, 951–952
Brain tissue classification, 87–91, 933–935, 935–936, 936–951
Brain tissues, 922
classification results of, 948, 951, 952, 953, 954
Brain tissue substances, 928, 930, 931, 933–935, 935–936, 936–951s
ground truth of, 89
BrainWeb MR image database, 920
Breast imaging, 83–87
Breast tissues, detection results for, 86, 87
Breast tumor detection, 84–87
BS/2D compression algorithm, 556. See also Band selection (BS)
BS/3D-cube compression algorithm, 557
BS-selected spectral bands, 982
BS techniques, 196–197, 800
CA-based unsupervised virtual signature finding algorithm (CA-UVSFA), 486, 488–489, 524. See also Component(s) analysis (CA)-based entries
Calcite signature, 112, 152, 296
CA-LSMA performance, 513. See also Linear spectral mixture analysis (LSMA)
Candidate algorithms, selecting, 102
Canonical analysis, 195
CA transform, 168, 170
Cauchy–Riemann equation, 5
CA-ULSMA procedure, 489–490, 499–503, 505–510. See also Linear spectral mixture analysis (LSMA); Unsupervised LSMA (ULSMA)
quantification results from, 513–517
CA-ULSMA/SLSMA comparative analysis, 501. See also Linear spectral mixture analysis (LSMA)
Causal processing, real-time, 991
Causal processing, 987–988
Causal RX detector (CRXD), 975. See also RX detector (RXD, dRXD)
CA-UVSFA procedure, 488–489. See also CA-based unsupervised virtual signature finding algorithm (CA-UVSFA); Unsupervised virtual signature finding algorithms (UVSFAs)
CB agents, quantification of, 825. See also Chemical/biological entries
CB data, 799
AVIRIS data vs., 818
CEM-based criteria, disadvantage of, 622. See also Constrained energy minimization (CEM)
CEM-based hyperspectral measure (MD_{CEM}), 475, 476, 479
CEM-based mixed sample classification techniques, 54
CEM detected panels, 567–569
CEM detection results, 119–121
CEM detector, 988
CEM filter (d_{CEM}), 374, 379–383
CEM implementation, 375–376, 376–377
CEM–matched filter distance (MFD_{CEM}), 476–477. See also Matched filter distance (MFD)
CEM solution, 375
Change detection, 773
Characteristic polynomial equation, 591, 595
Chemical/biological agent detection, 3D ROC analysis in, 91–95. See also CB agents
Chemical/biological (CB) defense, 799, 828. See also CB entries
Chemical/biological warfare (CBW) agents, 91
Chemical/biological warfare (CBW) defense, 10
Chemical data, spectral signatures of, 787
Chemical/infrared data signatures, spectral, 21
Cholesky decomposition, 175
Circular-SFPC (C-SFPC), 741, 751, 758, 759–760, 761, 762, 763, 764, 765, 766–768, 769, 770. See also Spectral feature probabilistic coding (SFPC)
performance of, 771
Classification, 195
CEM-based, 54
with hard decisions, 45–54, 62
linear spectral mixture analysis vs., 970
with soft decisions, 54–57, 62
supervised and unsupervised, 980
Classification-based BPC, 619. See also BP criteria (BPCs)
Classification-based criteria, 615
Classification error, 353
Classification performance
band number and, 658–661
quantitative analysis of, 445
Classification rates, 600–603
Classification results, 944, 945, 946, 947, 948 of brain tissues, 948, 951, 952, 953, 954
Classifiers, 29
hyperspectral measures working as, 482
kernelizing, 440–441, 980
“Class-map/pattern”-based spatial analysis, 503
Class membership–labeling process/technique, 392, 481
Class sample covariance matrices, 600
Clean background
clean panels embedded in/implanted into, 106–107, 109
endmembers embedded in/implanted into, 232–233, 235
Gaussian noise and clean panels implanted into, 108
Clean target panel pixels, 145, 146
Clean targets, 107
Clique, 922
Clustering algorithms, 275
Clutter space, 42
C-means clustering method, 584
C-means/K-means clustering algorithm, 266. See also k-means method
C-means method, 275. See also C-means entries; Fuzzy c-means (FCM) entries; ISODATA entries
Code, 774
Code book, 666, 774
Code words, 774, 986
M–block length binary, 776
Codings methods
DDA results by, 670–672
discrimination powers of, 758
Coding schemes, 666, 670, 717, 719
Coin flipping experiments, 287–288, 289, 290
Column vectors, 176, 484, 772, 773
Combinatorial vectors, 58
Complete knowledge
generating, 383
of target signatures, 372
Complete knowledge simulation, 402
Component(s) analysis (CA), 168
Component analysis (CA)-based techniques, 486
Component analysis (CA)-based transforms, 11
Component analysis–based ULSMA (CA-ULSMA), 483, 485, 486, 488–490. See also Unsupervised LSMA (ULSMA)
Component(s) analysis methods, 14
Component(s) analysis transform, 549
Component-based algorithms, 467
Component dimensionality, 125
Component prioritization-based projection pursuit, 191
Component spectral signatures, modeling, 214
Component transform techniques, 293
Compression performance, criteria used to measure, 546–547
Compression ratios (CRs), 542, 562, 981
Computational burden, reducing, 292
Computational complexity, 242, 247, 262, 264, 284, 290, 907, 908, 979, 980
Computational costs, 220–221, 239, 241, 244
Computer-aided detection and classification algorithm (CADCA), 880, 893, 894, 896 for concealed targets, 892–893
Computer-simulated data, 102
Computer simulations, 725–730
synthetic image–based, 868–871
using AVIRIS data, 831–842
using NIST-gas data, 843–852
Computing resources limits, 222
Concealed target detection, 879, 891–892, 895
applications of, 877
experiments for, 893–895
Concealed target detection problem, 896
Concealed targets computer-aided detection/classification algorithm for, 892–893
detecting unknown, 18
Concentration threshold, 92
Confusing data sample vectors, 52
Connectivity, four- and eight-neighbor, 803
Constant false alarm rate (CFAR) detector, 41. See also Generalized LRT (GLRT)-based CFAR
Constants, absorbing into threshold, 40
Constrained band correlation/dependence minimization, 620–624
Constrained band selection (CBS), 197–198, 620–621
algorithms/MATLAB codes for, 1046–1051
Constrained energy minimization (CEM), 8, 41, 43–44, 56, 61, 62, 114–122, 352, 357, 372, 392, 475, 476, 615, 621, 902, 980, 989. See also CEM entries
algorithms/MATLAB codes for, 1046, 1047–1049, 1049–1050, 1050–1051
alternative approach to implementing, 374–375
extending, 377
FVC-FLSMA vs., 395–396, 400–401, 403–405, 407–409
in hyperspectral target detection, 79
OSP vs., 57, 358, 376, 377, 379–383, 828
as partial knowledge version of OSP, 383–384
signature suppression by, 383
as a special case of TCIMF, 378–379
Constrained FIR linear filter, 623
Constrained least-squares methods, 409–410
Constrained linear spectral unmixing, 251
Constrained LSMA, 927. See also Linear spectral mixture analysis (LSMA)
ew application of, 895–896
Constrained LSMA methods, 955. See also Linear spectral mixture analysis (LSMA)
Constrained objective function, 198
Constrained optimization problem, 51, 66, 376, 377
Constraint constant, 52–53
Constraint matrix, 395
Constraint vectors, 56
Contaminated signatures, 872, 736
Contaminated spectral correlation, 479
Contiguous spectral bands, 356
Continuous approximations, 861
Continuous signal processing, 717
Continuous-value hyperspectral signal characterization, 797
Converged projection vector, 584
Convergence issues, 283
Convex cone analysis (CCA), 201, 202, 204, 207, 214–215, 240, 242, 967, 968
VCA vs., 247
Convex geometry algorithm, 201. See also Convexity geometry
Convex geometry–based criteria, 209–228
Convex geometry–based methods, 339
Convex geometry–based endmember extraction, 209–228
Convex hulls growing, 247–248
volumes of, 257, 349
Convexity-based endmember extraction algorithms, relationships among, 969
categorization of, 203
in endmember extraction, 202
COrdinate Rotation Digtal Computer (CORDIC) algorithm, 989–990
Corrected signatures, 869, 870
Correctly detected sample pool, 75
Correlation. See also De-correlated entries
band-to-band, 820
pixel-to-pixel, 820
Correlation-based least-squares error problem, 416
Correlation coefficient matrix, 172
Correlation coefficients (CCs), 369, 370, 371
Correlation eigenvalues, 127, 128, 135, 136
Correlation filter-based distance (RMFD), 237
Correlation matrix–calculated eigenvalues, 957–958
Correlation matrix–weighted hyperspectral measures, 475, 482
Correlation matrix–weighted matched filter distance, 476–477
Correlation-weighted hyperspectral measures, 469, 477
classification rates resulting from, 480, 481
confused with classifiers, 480
performance of, 479
for target discrimination/identification, 472–477
Correlation-weighted measures, 465–466
Corrupted detail/approximation signals, 865–866, 866–867
Corruption effect, 936
Cost functions, 37, 64
Cost matrix, 36
Co-variance–based PCA, 172
Covariance eigenvalues, 127, 128, 135, 136
Covariance matrix, 44, 172, 173, 180
of Gaussian–Markov noise, 369–370
Covariance matrix–calculated eigenvalue, 957–958
Covariance matrix–weighted hyperspectral measures, 474–475
Covariance matrix–weighted matched filter distance, 475
Creosote leaves
abundance fractions of, 369, 372
detection of, 382, 386–390
detection results of, 386, 388–390
Criteria. See also Convex geometry–based criteria; Custom-designed criteria; Data characterization–driven criteria; Data representation–driven criteria; Data characterization–driven criteria; Deflection criterion; Design criteria;
Eigen-based component analysis criteria; Eigenvalue distribution-based criteria; Endmember extraction criteria; FA-based criteria; NP detection–based criteria; Projection index (PI)-based criteria; Second-order component analysis (CA)-based criteria; Statistics-based criteria; Stopping criterion between-class scatter matrix/within-class scatter matrix, 362
for detection problems, 64
for DRT, 195
for finding endmember sets, 339
for kth moment–based SQ-EEA, 253
for optimality, 102
Cross-correlated band images, 943
Cross-correlated bands, 910, 938, 942, 943
Cross-correlated spectral band images, 901, 902
Cuprite AVIRIS image scene, 23
Cuprite image data scenes, 310
Cuprite image scene, 2, 326, 534–537
IN-FIND-extracted endmembers from, 690–692
Cuprite mining site, Nevada, 534
Cuprite reflectance, results for, 262
Cuprite reflectance data, 670–672, 688
“Curse of dimensionality,” 6, 209
Custom-designed criteria, 549
Custom-designed data processing techniques, 545
Custom-designed endmember initialization algorithm (EIA), 203, 204
Custom-designed initialization algorithms, 313, 588–589, 595
Custom-designed signal detection, in the noise model, 359

**d**, as orthogonal to **U**, 374. See also (d, U)-model
Dark-point-fixed (DPF) transform, 214
Data, 542. See also Information entries
for RN-FINDR, 291
Data analysis
multivariate, 585
random initial conditions in, 268
targets of hyperspectral, 13
Database identification, 34, 35
Data characterization–driven criteria, 138–140, 144–149, 164–166
virtual dimensionality as determined by, 126–140
Data compaction, 683. See also Data compression entries
Data compression, 15, 541, 545, 981. See also
information compression entries
endmember extraction–based hyperspectral, 542
exploitation-based hyperspectral, 542
exploitation-based lossy hyperspectral, 15
hyperspectral, 4
information compression vs., 8–9, 546, 547
LSMA-based hyperspectral, 542
success in, 545, 546
Data compression criteria, 541–542
Data compression issues, 15
Data compression ratio, 547
Data correlation matrix, 395
Data covariance matrix (K−1), 415
Data cube, full image, 230. See also Image cube
Data dilation, 231
Data dimensionality, 125, 589–590
reducing, 346
Data dimensionality reduction, 11, 168–199, 296,
305–306, 309, 346, 897
Data exploitation, hyperspectral, 7, 526
Data information, 542
PSDE, PSDP, and PSDR and, 581
Data matrix, 174
hyperspectral image and, 177–178
Data processing techniques, 80
custom-designed, 545
Data reduction, 683
Data representation
to determine virtual dimensionality, 140
PC-based, 584
Data representation–driven criteria, 149–155,
164–166
virtual dimensionality determined by, 140–144
Data representation system, selecting, 125
Data sample categories, 75
Data sample correlation, 469–470
Data sample correlation matrix, 136, 375
Data samples, 66, 180
projection values of, 488
unmixing, 492–499, 500, 501, 502
Data sample vectors, 49, 52, 54, 66, 175, 209, 210,
211, 249–250, 251, 273, 290, 309, 469, 484,
486, 603, 656, 964, 978, 979, 985
analyzing, 483
automatic target generation process and, 960
as endmembers, 316–317
finding maximum lengths of, 272–273
finding sample means of, 273–274
processed as 1D signals, 16
randomly selected, 265
RPPI-produced, 310
unmixing, 357
Data size reduction–based CF approach, 542
Data sphering, algorithms/MATLAB codes for,
1000–1001. See also Sphered data;
Sphering entries
Data training sample covariance matrix, 397
Data variances, 135, 176, 196–197
DDA results. See also Dynamic dimensionality
allocation (DDA)
by Purdue data coding methods, 672–673
by reflectance cuprite data coding methods,
670–672
DDA values, 693
Decision function, 53
Decision rules, 36
Decoded spectral signatures, 781
De-correlated bands, highest-prioritized, 695
De-correlated data, 183
De-correlated random process, 364
Deflection criterion, 971
δLS(r), 370, 371, 372, 380–382
δLS(r)/least-squares linear spectral mixture analysis
relationship, 362–364
Demixing matrix, 185
Dependent parameters, 95
Derivatives, calculating, 4–5
Design criteria, 542, 543
for EEAs, 330, 348–349
for SM-EEAs, 240
for SQ-EEAs, 264
Desired endmembers, 329
Desired signature knowledge, obtaining, 483–484
Desired signature matrix, 422–424
Desired target signature, 356
Desired target signature matrix (D), 56, 377, 378
Desired target signature vectors, 801
Detail signatures, 860, 863, 864
corruption of, 865–866, 866–867
signatures self-tuned by, 869–870
Detected abundance fractions, 92, 93
comparison of, 379, 382
Detected concealed targets, 895
Detection-based criteria, 615
“Detection” decision, 64
Detection methods/techniques, producing ROC
curves for, 73
Detection performance analysis, 78
Detection performance–based 2D receiver operating
characteristics (ROC) curves, 31
Detection power, 66, 137
Detection power/true-positive rate/probability, 73
Detection probability, 137, 366
Detection probability/rate, 66
Detection probability/rate/power, 68
Detection problems, criteria for, 64
Detection rate ($P_D$), 64, 69, 78, 99
Detection techniques, evaluating, 64
Detector performance, 69, 72, 99
Detectors, 29

evaluating, 64
Detector statistics, 67
Deterministic approach, 322
Deterministic detector, 38
Deterministic models, 928–929
Deviation from EPP (EPPD), 724, 725, 726, 727, 728, 729, 730, 731, 732, 733–735, 736–738, 739. See also Equal probability partition (EPP) binary coding
Diagonal matrix, 172, 173, 180
Digital Airborne Imaging Spectrometer (DAIS), 7915, 534, 537–539
Digital numbers (DNs), 54, 358
Dilation operations, 231
Dimensionality allocation, 668
Dimensionality constraints, intrinsic, 919
Dimensionality de-correlation, 984
Dimensionality expansion
band, 18
nonlinear, 18
Dimensionality expansion/reduction processes, progressive, 982
Dimensionality prioritization (DP), 199, 543, 544, 549, 581, 582, 583, 584–585, 683. See also DP entries
band prioritization vs., 614, 624
PSDP and, 589–590, 613
transformed components representation for, 585–589
Dimensionality reduction (DR), 31, 32, 168, 209, 212, 261, 293, 296, 320, 321, 328, 329, 340, 523–524, 549, 543, 582, 584, 626, 958, 981–983. See also DR entries; Progressive band dimensionality reduction (PBDR); Progressive spectral dimensionality reduction (PSDR); Variable dimensionality reduction (VDR)
applying ICA to, 185–186, 306
by band selection–based spectral compression, 556–557
band selection vs., 632–635
as a crucial preprocessing step, 326
for data, 296, 305–306, 309
by feature extraction–based transforms, 195–196
by high-order statistics–based components analysis transforms, 179–184
impact of, 349
impact on EEAs, 344–348
implementing, 581
by infinite-order statistics–based components analysis transforms, 184–190
issues in, 608, 613, 664–665
by projection pursuit–based components analysis transforms, 190–194
PSDP and, 613
for RN-FINDR, 291
by second-order statistics–based component analysis transforms, 170–179
spectral, 549, 550, 552
by transform-based spectral compression, 550–556
Dimensionality reduction by band selection (DRBS), 897, 899. See also DR by band selection (DRBS)
Dimensionality reduction by band selection (DRBS) techniques, 11
Dimensionality reduction by transform (DRT) techniques, 11. See also DR by transform (DRT)
Dimensionality reduction (DR) techniques, 11, 223, 245, 335, 337
best and worst, 520
Dimension expansion (DE), 931
Discrete approximations, 861
Discrete detail signal, 863
Discrete signal processing, 717
Discrete wavelet transform (DWT), 551, 558, 859, 860
Discriminant analysis, 195–196
Discriminant function, 366
Discriminant vectors, 393
Discriminating spectral signatures, 805
Discrimination
identification vs., 774
OSP-based hyperspectral measures for, 473
Discrimination power (DP), 805, 868.
See also Discriminatory powers for subpixel panel identification, 873, 874 of WSCA, 871
Discrimination threshold, 788
Discriminatory powers, 818. See also Discrimination power (DP); Relative spectral discriminatory power (RSDPW)
measurement of, 808
Distance measures
results of, 730
between signature vectors, 784
Distance metric, 481
Distinct panel signatures, extraction of, 637–646
Distribution asymmetry, 179
Distribution flatness, 179
Divergence measure, for band selection, 892
Divide-and-conquer strategy, 990
Dot products, 437, 438
DP criterion, 581. See also Dimensionality prioritization (DP); Discrimination power (DP)
DP-ranked priority scores, 581
DP via PIPP, 590. See also Projection index (PI)-based projection pursuit (PIPP)
DRBS/3D compression process, 557. See also Dimensionality reduction by band selection (DRBS) entries
DR by band selection (DRBS), 32, 168, 169–170, 196–197, 198, 199, 547, 548, 549, 556, 581. See also Dimensionality reduction (DR)
DR by transform (DRT), 32, 168, 198–199, 547, 548, 549, 556, 581, 582, 982, 983. See also Dimensionality reduction by transform (DRT) techniques algorithms/MATLAB codes for, 1001–1015 criteria for, 195 effectiveness of, 584
DR-processed dimensions, 982
DRT/DRBS, 547, 548, 549, 556. See also Dimensionality reduction by band selection (DRBS) entries; Dimensionality reduction by transform (DRT) techniques
DR transforms, 199, 247, 340–342, 344, 345 selecting, 212
Dual window–based eigen separation transform (DWEST), 975
Dummy source alphabet, 900–901
(d,U)-model, 357–358, 366, 383. See also d; U OSP-model vs., 379–380
signal detection perspective derived from, 359–360
Dynamic band selection (DBS), 686
Hamming code–based, 669
Huffman coding for, 668
Shannon coding for, 668
Early data processing, for Remote sensing data, 984 Echo time (TE), 930 EEA + LSMA approach, 519. See also Endmember extraction algorithms (EEAs); Linear spectral mixture analysis (LSMA) EEA-extracted pixels, 340, 535, 536, 539 EEA performance, DR impact on, 344 EEA performance evaluations, 344 EEA yield, 343 Effective dimensionality (ED), 124
Effective spectral dimensionality (ESD), 957 EIA approach, 278–280. See also Endmember initialization algorithms (EIAs)
EIA-driven EEAs, 278. See also Endmember extraction algorithms (EEAs); Endmember initialization algorithm (EIA)-driven EEAs (EIAD-EEAs)
EIA-EEAs, 205, 278, 315
EIA-FCLS-EEA, 278. See also Fully constrained least-squares (FCLS) method
EIA-generated initial endmembers, 265
EIA-HOS-EEA, 277. See also High-order statistics (HOS) entries; High-order statistics (HOS)-based EEAs
EIA-ICA-EEA, 277. See also Independent component analysis (ICA) entries
EIA-PP-EEAs, 278. See also Projection pursuit (PP) entries
EIA-SM-EEAs, 275, 277, 278. See also Endmember initialization algorithm (EIA)-driven SM-EEAs (EIAD-SM-EEAs); Simultaneous endmember extraction algorithms (SM-EEAs)
EIA-SQ-EEAs, 275, 278. See also Sequential endmember extraction algorithms (SQ-EEAs)
Eigen-analysis, 138
Eigen-based component analysis, 127
Eigen-based component analysis criteria, 128–129
Eigen component analysis transforms, 170–175
Eigenvalue categories, 129–130
Eigenvalue distribution, 166
Eigenvalue distribution-based criteria, 127–128
Eigenvalue locations, 131
Eigenvalue problem, generalized, 58
Eigenvalues maximum, 361 sample correlation matrix–calculated, 957–958 sample covariance matrix–calculated, 957–958
Eigenvector classes, 133
Eigenvector matrix, 171, 591
Eigenvector-prioritized PICA (eigen-PICA)
algorithm, 931–932. See also Prioritized ICA
(PICA)
Eigenvectors, 58
as initial projection vectors, 189
generating projection vectors as, 591
PCA-transformed components specified by,
582–583
Eight-neighbor connectivity, 803
Embedded block coding with block truncation
(EBCOT), 558
Embedded signatures, abundance fractions of,
840–841
EM-MRF-based approaches, 922. See also
Expectation-maximization (EM) algorithm;
Markov random field (MRF)
Empirical indicator function (EIF), 127, 130, 165
Empty intersection, 805
Encoding, SFPC algorithm for, 756
Encoding methods, 16–17
Endmember bundles, 517
Endmember determination, 969
Endmember extraction, 7–8, 12, 31, 101, 201–206,
256–263, 314, 315, 324, 325, 326, 327, 328,
340–341, 341–342, 467, 526–527, 559, 561,
See also Extracted endmembers
by FCLS-EEA, 226–228
by IN-FINDR, 632–635, 635–636, 637, 643–645,
649, 653–654, 656–658
improving, 296
linear spectral unmixing and, 519
PBS and, 688–690
PSDP, 598–599
second-order statistics–based, 228–230
statistics-based approaches to, 228
subpixel effects on, 332
terminologies related to, 969
ULSMA vs., 517–524
uniqueness of, 208
using DDA, 671, 672
using ICA, 344
Endmember extraction algorithms (EEAs), 12, 106,
See also Initialization-driven EEAs (ID-EEAs);
Random endmember extraction algorithms
(REEAs); Sequential endmember extraction
algorithms (SQ-EEAs)
algorithms/MATLAB codes for, 1015–1025
best design criteria for, 348–349
categorization of, 202, 205, 286, 968
classes of, 339
design criteria for, 330
design of, 208–209
development of, 207, 208, 967
effectiveness of, 111, 266, 282
endmember pixel generation and, 532
impact of dimensionality reduction on, 344–348
initial conditions to terminate, 267
initialization of, 266
least-squares–based, 968
major issues in, 265
pixels extracted by, 343–344, 533
relationships among, 316–349, 348, 969
selecting an initial set of endmembers for,
267–268
ultimate goal of, 266
using reduced data, 347
Endmember extraction application, 112–113
Endmember extraction–based hyperspectral data
compression, 542
Endmember extraction criteria, 202
Endmember extraction issues, 208
Endmember “finding,” 208, 241, 969
Endmember information, characterized by
high-order statistics, 347
Endmember initialization algorithm (EIA)-driven
EEAs (EIAD-EEAs), 266, 271, 275–277.
See also EIA-driven EEAs
Endmember initialization algorithm (EIA)-driven
SM-EEAs (EIAD-SM-EEAs), 271. See also
Simultaneous endmember extraction algorithms
(SM-EEAs)
Endmember initialization algorithms (EIAs), 265,
271, 315, 318
custom designed, 203
for SM-EEAs, 274–275
sharing features with SQ-EEAs, 274–275
Endmember matrix, 142, 393, 823
Endmember numbers
determining, 314
issues in, xxiii–xxiv
Endmember pixel generation, endmember extraction
algorithms and, 532
Endmember pixels, 254, 293, 325, 326, 527,
529–530, 531
extracted by algorithms, 261
extracted by PPI, 233–239, 340–341
extracted by SM-EEAs, 237
initial, 329
Endmember pixel vectors, 14
Endmember purity, 517
Endmembers, 7, 8, 32, 54, 207, 274–275, 411, 527. See also Final endmembers; Image endmembers; Initial endmembers; Virtue (virtual) endmembers (VEs)

accurate number of, 329
appropriate number of, 266
convex cone analysis and, 214–215
defined, 201
desired, 329
embedded in clean background, 235
embedded in noisy background, 235–236
extracted, 317
extracted by IN-FINDR, 599
extracted by N-FINDR, 520
falsely alarmed, 328
as hyperspectral signatures, 665
implanted into clean background, 232–233
implanted into noisy background, 233–234, 234–235
in simulated synthetic scene, 336
with IN-FINDR, 216–218, 218–222, 690–692
LSMA and, 351
manually selected, 289
mineral, 324
minimal simplex volume and, 214
number of image, 898
for PPI, 210, 211
presetting the number of, 267
random initial, 287, 289
required by linear spectral mixture analysis, 974
selecting an initial set for EEA, 267–268
selection of, 203
with SM-FINDR, 216
Statistics constituted by, 338
true, 288, 289
Endmember selection, 517–518, 969

Endmember sets

criteria for finding, 339
maximum simplex volume and, 339–344

endmembers extracted by IN-FINDR corresponding to, 632, 634, 644, 645, 649, 653–654
infinite-order statistics–based BPCs and, 619
maximum, 722
UFCLS-mixed panel results corresponding to, 640, 647
UFCLS-mixed panel results produced by, 629

ENVI 3.6, 212
Environment for visualizing images (ENVI), 207, 316. See also ENVI software
ENVI software, 177, 210, 212. See also Environment for visualizing images (ENVI); MATLAB-based PPI (MATLAB-PPI)
Equal probability partition (EPP) binary coding, 725, 726, 727, 728, 729, 730, 731, 732, 733–735, 736–738, 739, 986
spectral deviation of, 724
Equal probability partition (EPP) binary coding scheme, 717, 719, 720, 722–723
Error signature, 864
wavelet decomposition of, 865
Error threshold (γ), 127, 141, 142, 144, 960
selection of, 267
Error vectors, 227
Estimated abundance fractions, 250, 380, 924
of panel pixels, 514, 515, 518
Estimated abundance vector, 822
Estimates, notation for, 29
Estimation accuracy, 383
Estimation error(s), 55, 832 of α, 40
Estimation error ratios, 834, 843, 845–846, 852, 854
See also OSP-based Euclidean distance (EDOSP)
Euclidean distance (ED)-SDFC, implementation of, 745. See also Spectral derivative feature coding (SDFC)
Exhaustive searches, 267–268
Expand-and-reduce operations, 583
Expanded image cubes, 605
Expectation-maximization (EM) algorithm, 921, 922
Experiment design, 10
for synthetic image experiments, 101–123
Experiments. See also HYperspectral Digital Imagery Collection Experiment (HYDICE); Synthetic image experiments
benefits of, 578
at Purdue Indiana Indian Pine test site, 25–26
repeatable, 10, 102
synthetic image–based, 1
Experiments-based comparative study/analysis, 323–329
Exploitation algorithm, 527
Exploitation application, 553
Exploitation-based application compression, 547
Exploitation-based applications, 548, 559–561
Exploitation-based compression criteria, 545, 550
Exploitation-based criteria, 547
Exploitation-based hyperspectral data compression (EHDC), 542, 545–580, 981–982
Exploitation-based lossy hyperspectral data compression, xxiv, 15
Extracted endmembers, 317
simplexes formed by, 344
Extracted error (XE), 127, 129–130, 165
Extreme value theory, 961
FA-based criteria, 146. See also Factor analysis (FA)
Factor analysis (FA), 129. See also FA-based criteria
Factor analysis (FA)-based Malinowski’s error theory, 127, 129–130
“False alarm” (FA) decision, 68
False alarm probability (probabilities) (P_f), 37–38, 62, 137, 143, 326, 538, 577, 648, 959, 961
predetermined, 137
False alarm probability/rate (P_f), 64, 66, 69, 74, 99
Falsely alarmed endmember pixels, 295
Falsely alarmed endmembers, 328
Falsely alarmed pixels, 294
Falsely alarmed sample pool, 75
“False negative” (FN) decision, 64, 68
False negative rate/probability, 73
“False positive” (FP) decision, 64, 68
False positive rate/probability, 72
False rejection rate (FRR), 96, 98–99
FAST algorithm, 922
FastICA, 583, 604. See also My FastICA
algorithms/MATLAB codes for, 1005
learning algorithms with, 596
FastICA algorithm, 186, 188–190, 292–293, 489, 931
FastICA-generated ICs, 254, 572. See also Independent components (ICs)
Fast iterative PPI (FIPPI), 322. See also Pixel purity index (PPI) entries
algorithms/MATLAB codes for, 1015, 1017–1020
FCLS classification method, 626. See also Fully constrained least-squares (FCLS) method
FCLS classification results, 448, 605–607
FCLS-estimated abundance fraction map, 890
FCLS/IEA-EEA, 205. See also Endmember extraction algorithms (EEAs); Iterative error analysis (IEA)
FCLS/KFCLS curves, 451, 454, 457, 459, 460, 463. See also Kernel-based FCLS (KFCLS)
FCLS-mixed pixel quantification results, 118
FCLS performance, 445
FCLS quantification, for ATGP-FastICA cube, 608
FCLS unmixed pixels, abundance fractions of, 608
FCLS-unmixed results, 152–154, 607
FCM-based methods, 923. See also Fuzzy c-means (FCM) entries
FCM-MRF-based approaches, 922. See also Markov random field (MRF)
FDE by classification, 905, 907–908. See also Feature dimensionality expansion (FDE)
using intrapixel spectral correlation, 908
using sample spectral correlation, 907–908
FDE techniques, for multispectral imagery, 908, 909
Feature characterization, hyperspectral, 17
Feature dimensionality expansion (FDE), 897, 899, 919
by classification, 905, 907–908, 918
by nonlinear kernels, 904–909
by transformation, 905–907
Feature extraction (FE), 168
Feature extraction (FE)-based transforms, 11. See also FE transform
dimensionality reduction by, 195–196
Feature space, 46
Feature transforms, 195, 196, 199
Feature vector-constrained FLSMA (FVC-FLSMA), 391, 392–395, 409–410. See also Fisher’s LSMA (FLSMA); Linear spectral mixture analysis (LSMA)
FLDA and LSOSP vs., 399–400
FLDA, LSOSP, TCIMF, and CEM vs., 403–405, 406, 407–409
quantitative results produced by, 403, 405
relationship between OSP and, 396
relationship between LCDA and, 396–397
relationships with LCMV, TCIMF, and CEM, 395–396
TCIMF and CEM vs., 400–401
Feature vectors, 47, 48, 195, 196, 655
FE transform, 168. See also Feature extraction (FE) entries
Field programmable gate array (FPGA), 102, 989. See also FPGA designs
Fifth moment, 182
50–50% cross validation, for performance analysis, 600
Filter output SNR, 359
Filters
discrete wavelet transform and, 859
distinctions among, 378–379
LCMV, 972
Final endmembers extracted by a REEA, 288
inconsistent selection of, 314
Final results, inconsistency in, 315
Finite Gaussian mixture (FGM) model, 920
Finite impulse response (FIR), 44, 197, 373, 377
First endmember selection process, 273
for SGAs, 273
First-order coding methods, 771
First-order spectral statistics–based approaches, 957–959
First-order statistics, 959
HFC vs. PCA methods and, 139
First-order zero-mean Gaussian–Markov noise (GMN), 369
Fisher linear discriminant function, 360, 361
Fisher’s kernel, 981
Fisher’s linear discriminant analysis (FLDA), 624, 625, 637, 650, 651, 652, 907–908, 977–978. See also Fisher’s ratio–based linear discriminant analysis (FLDA); FLDA entries; Kernel-based Fisher’s linear discriminant analysis (KFLDA) endmembers extracted by IN-FINDR corresponding to, 632, 634, 644, 645, 649, 653–654
UFCLS-mixed panel results corresponding to, 641, 648
UFCLS-mixed panel results produced by, 630 weighting matrix derived from, 416–417
Fisher’s linear discriminant analysis (FLDA)-based BPC, 619–620. See also BP criteria (BPCs)
Fisher’s linear discriminant analysis perspective, from OSP-model, 360–362
Fisher’s LSMA (FLSMA), 8, 13, 352–353, 391–410, 435, 973. See also Linear spectral mixture analysis (LSMA) utility of, 398
Fisher’s ratio, 46, 47, 58, 195, 391, 393, 410, 908, 977
Fisher’s Rayleigh quotient, 361–362, 391, 393 Five-panel signature detection, 79–80, 83
Fixed-panel spectral signatures, 28
Fixed-dimensionality reduction (FDR), 983. See also Dimensionality reduction (DR)
Fixed dimensionality bad selection (FDBS), 983
Fixed-length coding, 666, 669, 986
Fixed-point algorithm, 596
Fixed-point-free (FPF) transform, 214
Fixed-size band allocation, dynamic dimensionality allocation and, 682
Fixed-size band selection (FSBS), PBS vs., 686–687
Fixed-size dimensionality, 543
FLDA-based binary classification, 47. See also Fisher’s linear discriminant analysis (FLDA)
FLDA-generated classifier, 46
FLDA-generated feature vectors, 393
FLSMA performance, 405, 407, 410. See also Fisher’s LSMA (FLSMA)
fMRI analysis, 930
Fourier transforms, 863
Fourier transform/series, 140
Four-neighbor connectivity, 803
Four-stage spectral/spatial hyperspectral compression, 560, 561
Fourth central moment, 179
Fourth-order statistics, 932
Fourth-order statistics–based kurtosis, 182
Fourth-order statistics–based SQ-EEA, 252–253. See also Kurtosis-EEA; Sequential endmember extraction algorithms (SQ-EEAs)
FPGA designs, for hardware implementation, 989–990. See also Field programmable gate array (FPGA)
Fractional abundance image, 395
Fractional abundance maps, 352, 392
Fractional abundance vector, 351–352
Full abundance constraints, 348–349
Full image data cube, 230
Fully abundance-constrained least-squares (FCLS) method, 81, 82, 83, 84, 85, 89–91, 229–230. See also FCLS entries; Full abundance constraints; Fully constrained least-squares (FCLS) method for spectral unmixing, 159
Fully abundance-constrained methods, 436, 884
Fully constrained least-squares–EEA (FCLS-EEA), 201, 204, 205, 209, 225, 226–227, 234–235, 240, 255, 278. See also Endmember extraction algorithms (EEAs) modification of, 227–228 results of, 232

AFCLS-FLSMA vs., 401–402, 403–405, 406, 407

algorithms/MATLAB codes for, 1026, 1028, 1034–1036

brain tissue classification by, 936–951

in detecting R panel pixels, 432

for material quantification, 880

operating on MR images, 935–936

quantitative results produced by, 402, 403, 405, 409

for spectral unmixing, 603–604, 605–607

total error from, 512, 513, 514

using BEP-expanded MR images, 939

 Functional magnetic resonance imaging (fMRI), 930
Fuzzy c-means (FCM), 920. See also FCM entries
Fuzzy c-means (FCM)-based techniques, 921–922

FVC-FLSMA-generated weighting matrix, 396. See also Feature vector–constrained FLSMA (FVC-FLSMA)

FVC-FLSMA performance, 409

Gas data, 751, 764, 786
classification results for, 752, 753

Gas data set, signature vectors and average signature vector of, 753. See also NIST entries

Gaussian assumption, 72

Gaussian distributions, 39, 73–74
zero-mean, 73

Gaussian-fitted 3D ROC curves, generating, 76.
See also Gaussian-fitted ROC curves; Three-dimensional (3D) ROC curves

Gaussian-fitted data, 95

Gaussian-fitted ROC curves, 94, 97–99, 100. See also Gaussian-fitted 3D ROC curves generating, 73–74

Gaussian kernels, 449

Gaussian–Markov model, 824. See also Gaussian–Markov process

Gaussian–Markov noise (GMN), 368–371 covariance matrix of, 369–370 detection results in, 370, 371, 373

Gaussian–Markov process, 826

Gaussian maximum likelihood (GML), 971

Gaussian maximum likelihood classifier (GMLC), 352. See also Maximum likelihood classifier (MLC)
using OSP-model, 366

Gaussian maximum likelihood detector/estimator, 355

Gaussian maximum likelihood estimator (\(\hat{\theta}_{GML}\)), 144, 357, 367, 377, 391, 412, 415, 436, 971

Gaussian maximum likelihood estimation (GMLE), 391, 412, 415, 436, 971

additive, 334
background image corrupted by, 532

in orthogonal subspace projection, 364–372

Gaussian noise assumption, 366

Gaussian noise–corrupted scenario, 303–305

Gaussian noise corruption, 299

Gaussian random variables, 290, 317, 322

Gaussian random vectors, 247, 272.
See also Gaussian vectors

Gaussian signal sources, 554

Gaussian skewers, 319, 320

Gaussian sources, 185, 929

Gaussian VCA, 290. See also Vertex component analysis (VCA)

Gaussian vectors, randomly generated, 321. See also Gaussian random vectors

Generalized eigenvalue problem, 58

Generalized LRT (GLRT), 41. See also Likelihood ratio test (LRT)

Generalized LRT (GLRT)-based CFAR, 62. See also Constant false alarm rate (CFAR) detector

Generalized OSP (GOSP), 899. See also Orthogonal subspace projection (OSP)

Geographical information system (GIS), 355

Geometry-based techniques, 46

Gershgorin circle theorem, 132–134

Gershgorin disks, 132, 133, 134

Gershgorin radii (GR), 127, 133–134, 134–135, 166

Gershgorin radius–based methods, 131–135

Givens rotations, 989

Global anomaly detector, 977

Global flat regions, 807

Global sample covariance matrix, 600

Glossary, 993–996

GLRT detector, 41. See also Generalized LRT (GLRT) entries

\(G_{mix}\), 751–753

Google Earth, 909
Gradient changes
- in spectral value, 744–745
- in spectral variation, 751–752, 771

Gradient descent learning algorithm/program, 594, 596

Gram-Schmidt orthogonalization-based band de-correlation (GSO-BD) algorithm, 685–686

Gray level range, 893

Gray levels, maximal and minimal, 619

Gray-scaled images, 893–894, 895

Gray-scale fractional abundance images, 399

Ground sampling distance (GSD), 3, 879, 896

Ground truth, 25, 26, 305, 503, 505
- of brain tissue substances, 89
- Ground-truth-corresponding endmember (mineral) pixels, 270–271
- Ground-truth information, 537
- Ground truth map, 26, 27
- of panel targets, 882
- Ground truth mineral endmembers, 270
- Ground truth mineral pixels, 259, 270
- Ground-truth mineral spectra, 746, 749
- Ground truth pixels, 312. See also Ground truth mineral pixels
- Ground truth samples, 309

Gumbel distribution, 961, 962

Halfway partition (HP) binary coding, 725, 726, 727, 728, 729, 730, 731, 732, 733–735, 736–738, 739, 986

Halfway partition (HP) binary coding scheme, 717, 719, 720, 722

Halfway partition deviation (HPD), 724, 725, 726, 727, 728, 729, 730, 731, 732, 733–735, 736–738, 739

Hamming code–based DDA, 669. See also Dynamic dimensionality allocation (DDA)

Hamming coding, 666, 670, 672, 673, 678, 679–681
- for static dimensionality allocation, 669

Hamming distance (HD), 741, 746, 749, 784. See also Hamming spectral distance entries

Hamming distance (HD)-SDFC, 747, 748, 749, 750, 751, 753, 754, 764, 766. See also Spectral derivative feature coding (SDFC)
- implementation of, 745
- performance of, 764, 766
- RSDPW values for, 752, 766

Hamming spectral distance (HSD), 720, 721, 725, 726, 727, 728, 729, 730, 731, 732, 733–735, 736–738, 739. See also Hamming distance (HD)
- Hapke nonlinear mixing model, 921
- “Hard” coding, 773
- Hard decision–based quantizers, 774
- Hard-decision classification, 445
- Hard decision–made classifiers, 60
- Hard-decision-making detector, 79, 82
- Hard decisions, 33
- basis of, 39
- binary, 69
- classification with, 45–54, 62
- detectors with, 35
- Hard quantization, 774

Hardware implementation, FPGA designs for, 899–900

- algorithms/MATLAB codes for, 997–1000
- PCA method vs., 139–140
- principal components analysis vs., 959–960
- virtual dimensionality estimated by, 532

HFC/NWHFC method, 489–490, 532. See also Harsanyi–Farraud–Chang (HFC) method; Noise-whitened HFC (NWHFC) method

Hierarchical foreground/background analysis, 519

High compression ratios, 541

Higher-order statistics–based criteria, 615

Highest-prioritized bands, 636, 646–651
- BP applications using, 625–635
- selected by BP criteria, 651

Highest-prioritized BP/BD bands, 702–703. See also Band de-correlation (BD); Band prioritization (BP); Band prioritization/band de-correlation (BP/BD) approach

Highest-prioritized de-correlated bands, 695

Highest-prioritized/least-prioritized band mixing, BP applications using, 646–651

High-frequency domain information, 860

High interband correlation, 616

High-order IBSI, 466, 467. See also Interband spectral information (IBSI)

High-order spectral statistics–based approaches, 962–964

High-order spectral statistics (HOS) HFC (HOS-HFC) methods, 962–963. See also Harsanyi–Farraud–Chang (HFC) method; High-order statistics (HOS)
High-order spectral targets, 485
High-order statistics (HOS), 182–183, 202, 209, 230, 257, 282, 547, 596. See also HOS entries
endmember information characterized by, 347 of IBSI(S), 485, 486, 487, 488
types of, 932
High-order statistics band prioritization criteria, 662
High-order statistics–based BPC (BP criteria), 618, 658. See also BP criteria (BPCs)
High-order statistics–based components analysis transforms, dimensionality reduction by, 179–184
High-order statistics (HOS)-based DR (HOS-DR) transforms, 255, 326, 349. See also Dimensionality reduction (DR)
algorithms/MATLAB codes for, 1012–1015
High-order statistics (HOS)-based EEs (HOS-EEAs), 201, 204, 243, 252, 255, 272, 280. See also Endmember extraction algorithms (EEAs)
results produced by, 282, 285
High-order statistics–based PICA (HOS-PICA) algorithm, 931, 932. See also Prioritized ICA (ICA)
High-order statistics (HOS)-based SM-EEAs, 230, 252. See also Simultaneous endmember extraction algorithms (SM-EEAs)
High-order statistics (HOS)-based SQ-EEAs, 252–254, 260, 261. See also Sequential endmember extraction algorithms (SQ-EEAs)
High order statistics (HOS) methods, 962, 975
High-order target VSs, 505. See also Virtual signatures (VSs)
High-pass filters, discrete wavelet transform and, 859
High priority scores, 688
High priority sources, 684
High-resolution hyperspectral data, 674
High-spectral-resolution issues, 1
High spectral/spatial resolution, 483
Homogeneous background pixels, 531
Homogeneous pixels, 467, 526, 527, 531, 534, 539
HOS algorithms, 959. See also High order statistics (HOS) entries
HOS-based algorithms, 962. See also High order statistics (HOS)-based entries
HOS criteria, 688
HOS-ICPA, 254
Hotelling transform, 170
Householder transformation, 175
HSD/normalized HSD values, 733–735. See also Hamming spectral distance (HSD)
Huffman coding, 666, 670, 672, 673, 678, 679–681, 900–901
ternary, 900
Huffman coding–based DDA, 668. See also Dynamic dimensionality allocation (DDA)
Human eye inspection, 111
ICA-DR and, 346
panels in, 636
HYDICE data coding methods, DDA results by, 678
HYDICE data experiments, 460–462, 463
HYDICE data panel pixels, unmixed abundance fractions of, 679–681, 703–706
HYDICE experiments, 268–270, 305–309
HYDICE image experiments, 281, 477–478, 886–891
HYDICE image/imagery/image scenes, 399, 402, 419, 426, 503, 603, 624, 635, 660, 661, 694, 730, 764, 790, 852, 853, 880, 881, 893, 894–895
HYDICE panel scene, 27–28
HYDICE scene, 562, 570–571
CA-UTFA results for, 509
results for, 263
HYDICE vehicle scene, 26–27
Hyperplanes, normal vectors of, 49, 50
Hyperspectral analysis, unsupervised, 13–14
Hyperspectral band selection, 682
Hyperspectral compression, 549, 581, 981–984. See also Hyperspectral data compression
drawback of, 543
major approaches to, 549
mixed component transforms for, 554–556
by PBDP, 653–656
by PSDP, 597–598
Hyperspectral data, 772, 806–812
high-resolution, 674
as an information source, 665
virtual dimensionality of, 11, 124–167
Hyperspectral data analysis, targets of, 13
Hyperspectral data collection, 799
Hyperspectral data compression, 4, 546
endmember extraction–based, 542
exploitation-based, 542
exploitation-based lossy, 15
LSMA-based, 542
in preprocessing hyperspectral data, 580
Hyperspectral data exploitation, 7, 174, 526, 542
challenges to, 467
Index
Hyperspectral signals, 16
Kalman filter–based estimation for, 820–858
one-dimensional, 9
variable number variable band selection for,
799–819
wavelet representation for, 859–875
Hyperspectral signal subspace identification by
minimum error (HySime), 142–144, 149, 165,
166, 335. See also SSE/HySime-estimated values
Hyperspectral signature characterization, 9
progressive spectral signature coding for, 796
wavelets in, 859
Hyperspectral signatures, 488
dependents as, 665
proximity of, 872
tensor coding for, 741–771
Hyperspectral signature vectors, 9, 859
collecion of, 799
decomposing, 801, 802
Hyperspectral target detection, 79–80
applications of, 877
Hyperspectral variable band selection,
797–798
Hypothesis (hypotheses)
alternative, 66
null, 66
Hypothesis-testing problem, 38, 77
IBSI(S) sample spectral statistics, 483, 484, 485, 486,
488, 518, 985, 986. See also Interband spectral
information (IBSI)
high-order, 485, 486, 487, 488
IBSI(S)(\text{BKG}) sample spectral statistics, 484–485, 486
second-order, 485
IBSI(S)(\text{target}) sample spectral statistics, 484, 486
high-order, 485
ICA/2D compression, 551–552. See also Independent component analysis (ICA)
entries
ICA/2D compression algorithm, 551–552
ICA/3D compression algorithm, 552
ICA algorithms, use of random initial conditions by,
931
ICA-based spectral/spatial compression techniques, 569
ICA-based SQ-EEA, 969. See also Sequential endmember extraction algorithms (SQ-EEAs)
ICA-decompressed image cube, 573
ICA-DR transform, 347. See also Dimensionality reduction (DR)
HYDICE data and, 346
ICA-EEA. See Independent component analysis
(ICA)-based EEs; Independent component
analysis–based endmember extraction
algorithm (ICA-EEA)
ICA/JPEG2000 Multicomponent compression,
performance of, 563, 564, 568, 570
ICA (m = 0, n = 9) scenario, 572–573
ICA/spatial compression techniques,
569, 579
ICA transforms, 562
IC prioritization, 583, 932. See also Independent components (ICs)
by HOS-PICA, 932
ID-BD algorithm, 688, 689. See also Band
de-correlation (BD); Information divergence–based band de-correlation
approach
Idempotent projector, 359
Identification
discrimination vs., 774
OSP-based hyperspectral measures for, 473–474
Identification errors, 477, 478, 791, 852. See also Incorrect identification
Identity mapping, 437
Identity matrix (I), 173, 180, 368, 395, 413
ID-ICPA, 254
IDOSP identification measure, 474, 477, 478
IDOSP-identification measure, 474, 477, 478
ID-PCA algorithm, 595–596. See also Initialization-driven PCA (ID-PCA); Principal components
analysis (PCA)
ID-PIPP-generated PICs, 588. See also Initialization-driven PIPP (ID-PIPP); Projection index
(PI)-based projection pursuit (PIPP)
ID-PP algorithm, 194. See also Initialization-driven projection pursuit (IDPP, ID-PP)
ID-PPI, 204. See also Pixel purity index (PPI) entries
IEA-extracted pixels, 536. See also Iterative error
analysis (IEA)
IED-1-SGA, 273, 276, 278, 279, 280, 281, 282, 283,
284, 285. See also Initial endmember-driven
(EID) initialization; Simplex growing algorithms (SGAs)
IED-2-SGA, 273, 276, 278, 279, 280, 281, 282, 283,
284, 285
IED-ATGP, 278. See also Automatic target
generation process (ATGP)
IED-ATGP-EEAs, 272, 276, 278, 279, 280, 281, 282,
283, 284, 285. See also Endmember extraction
algorithms (EEAs)
IED-HOS-EEAs, 272, 278. See also High-order statistics (HOS)-based SQ-EEAs
IED-ICA-EEAs, 272, 278, 279, 280, 282, 283, 284, 285. See also Independent component analysis–based endmember extraction algorithm (ICA-EEA)

IED-IEA, 273–274. See also Iterative error analysis (IEA)

IED-kurtosis-EEA, 273, 278, 279, 280, 282, 283, 284, 285

IED-PP-EEA, 278. See also Projection pursuit (PP)

IED-SGAs, 273, 278. See also Simplex growing algorithms (SGAs)

IED-skewness-EEA, 278, 279, 280, 282, 283, 284, 285

IED-UFCLS, 272, 278. See also Unsupervised fully constrained least-squares (UFCLS) method

IED-UFCLS-EEA, 276, 278, 279, 280, 281, 282, 283, 284, 285

IED-UNCLS, 272. See also Nonnegativity constraint least-squares (NCLS) method; Unsupervised nonnegativity constrained least-squares (UNCLS) method

IED-VCA, 272, 276, 277, 278, 279, 280, 281, 282, 283, 284, 285. See also Initial endmember-driven (IED) initialization; Vertex component analysis (VCA)

IICA/2D compression algorithm, 553. See also Inverse transform of ICA (IICA)

IICA/3D compression, 554

IICA/3D compression algorithm, 554

IICA/3D Multicomponent JPEG2000 compression system, 553–554

IICA/3D-SPIHT compression system, 553–554. See also Set partitioning in hierarchical trees (SPIHT); SPIHT entries; 3D-SPIHT entries

IICA/JPEG2000 Multicomponent compression, performance of, 563, 564, 569, 570

Image analysis

pattern class–based vs. target class–based, 5 pixel-based, 33

Image background

characterized by supervised knowledge, 402–403

characterized by unsupervised knowledge, 405–409

experiments to represent, 426–427

target insertion into, 101

Image-based BS, 800. See also Band selection (BS)

Image-based BS techniques, variable-number variable-band selection vs., 805

Image compression

hyperspectral, 8–9

spatial, 542

Image cubes. See also Data cube expanded, 605

hyperspectral, 186

Image endmembers, 13

number of, 898

prior knowledge of, 825

Image pixels, 12

Image pixel vectors, 29, 466, 491–492, 823

Image processing

hyperspectral, 7

image classification in multispectral, 8

image quality/classification accuracy in, 64

progressive, 656

sequential, 656

Image resolutions, 860

multiple, 860

Images, dividing into tiles, 558

Image thresholding, 195

Image thresholding method, 47

Image vectors, 826

Imaging techniques, applications for

hyperspectral, 9

Imbedded error (IE), 127, 129–130, 165

Implanted panel pixels, replaced with background pixels, 333

Implanted panels

abundance fractions for, 565

synthetic image with, 419

Implanted targets, 108

Inconsistency issues, 283

Incorrect identification, on panel pixels, 875.

See also Identification errors

Independence-based ICA, 168. See also Independent component analysis (ICA) entries


algorithms/MATLAB codes for, 1004–1012 applying to dimensionality reduction, 185–186 implementing, 186, 929

in endmember pixels extraction, 341–342, 343, 344

to perform DR, 340

p values estimated by, 340–341

SGA in conjunction with, 338

use for DR, 306
Independent component analysis (ICA)-based EEAs, 243. See also Independent component analysis–based endmember extraction algorithm (ICA-EEA)

Independent component analysis (ICA)-based SQ-EEAs, 254. See also Sequential endmember extraction algorithms (SQ-EEAs)

Independent component analysis–based endmember extraction algorithm (ICA-EEA), 201, 203, 207, 209, 254, 257, 258, 260, 261, 262, 263, 264, 272. See also Independent component analysis (ICA)-based EEAs

Independent component analysis (ICA) transform, 169, 184–186

Independent components (ICs), 169, 188–190, 292–293, 551, 572, 573, 582–583, 584, 596, 930–931. See also FastICA-generated ICs; Prioritized ICs

generating, 583
produced by ATGP-FastICA algorithm, 604
ranking, 555, 583
ranking the orders of, 584
super-Gaussian, 186

Independent parameters, 95

Indiana Indian Pine test site, 2, 444–445, 459, 478–479, 599–603, 658–659, 672–674, 690. See also Purdue Indiana Indian Pine data

IN-FIND–extracted endmembers, from Cuprite scene, 690–692

IN-FIND–extracted mineral signatures, 688

IN-FINDR–found pixels, 650

IN-FINDR–generated endmembers, 431

Infinite-order (∞-order) statistics–based BPC, 618–619. See also BP criteria (BPCs)

Infinite-order statistics–based components analysis transforms, dimensionality reduction by, 184–190

Information. See also Data entries; Hyperspectral information compression; Pixel information; Spectral information entries

analysis of, 526
extracting from pixels, 526
from hyperspectral data, 665
generating from image data, 474
spectrally de-correlating, 551

Information bits, 668

Information compression, 546, 547. See also Data compression entries
data compression vs., 8–9, 546, 547
hyperspectral, 15

Information compression systems, key components of, 547–549

Information criterion (AIC), 6, 127, 130–131, 138, 165


d endmembers extracted by IN-FINDR
 corresponding to, 632, 634, 644, 645, 649, 653–654

infinite-order statistics–based BPCs and, 619
UFCLS-mixed panel results corresponding to, 640, 648
UFCLS-mixed panel results produced by, 629

Information divergence–based band de-correlation approach, 684. See also ID-BD algorithm

Information loss, 545

Information of endmembers, 288

Information-processed matched filter, 972

Information recovery, 546

Information retrieval, 545, 546

Information spectral dimension/bands, 669

Information theoretic criterion (ITC), 127, 130–131, 166

Information theory, 288

Inherent nonlinear spectral information, 920

Initial band selection, 687

Initial conditions, 266
categorization of, 204
impact of, 309
random, 329
selecting appropriate, 283
to terminate an EEA, 267

Initial endmember–driven EEAs (IED-EEAs), 204, 266, 271, 272–274, 278, 286
categorization of, 204

Initial endmember–driven SQ-EEAs (IED-SQ-EEAs), 271, 274, 278. See also Sequential endmember extraction algorithms (SQ-EEAs)

Initial endmember–driven (IED) initialization, 265, 276. See also IED entries

Initial endmember pixels, 329

Initial endmembers, 328. See also IED entries
appropriately selected, 265
EIA-generated, 265
generated by custom-designed initialization algorithms, 287
random, 313, 316, 325, 328
randomly generated, 265

Initialization algorithms, 322, 328, 329, 590
custom-designed, 287, 588–589, 595
Initialization-driven EEAs (ID-EEAs), 12, 203, 205, 206, 265–286, 271–277, 280, 315, 316, 318, 595, 968. See also Endmember extraction algorithms (EEAs) block diagram of, 277 categorization of, 266, 278 endmembers extracted by, 279–284 pixels extracted by, 284, 285 REEAs vs., 287

Initialization-driven ICA-DR (IDICA-DR, ICA-DR3), 169, 186, 189, 596, 604. See also Dimensionality reduction (DR); Independent component analysis (ICA) entries algorithms/MATLAB codes for, 1005, 1009–1010, 1010–1012

Initialization-driven PCA (ID-PCA), 591, 595–596. See also Principal components analysis (PCA) advantages of, 596

Initialization-driven PIPP (ID-PIPP), 588–589, 590. See also Projection index (PI)-based projection pursuit (PIPP)

Initialization-driven projection pursuit (IDPP, ID-PP), 191, 194

Initialization-driven VCA (ID-VCA), implementing VCA as, 277. See also Vertex component analysis (VCA)

Initialization issues, 266–271

Initial projection vectors, eigenvectors as, 189

Initial set of endmembers, selecting, 267–268

Initial vectors, randomly generating, 593. See also Initial projection vectors

Inner product matrix, 175

Innovation approximation signature, 867

Innovation detail signature, 867

Innovations signature, 864

In-reproducibility, 314

Interband correlation, 683, 684, 688, 803

Interband redundancy, 616

Interband spectral correlation, 805

Interband spectral information (IBSI), 466, 483, 484. See also IBSI(S) sample entries

Interband spectral information of signature r, \( IBSI[\{r]\}, \) 484

Interdistance-to-intradistance ratio, 391–392, 393, 396

Interference, eliminating, 421–422

Interference matrix, 81, 89

Interference/noise suppression, 378

Interferers, unknown, 56

Interferer signature, 511

Interpixel between-class scatter matrices, 908

Interpixel within-class scatter matrices, 908

Intersample spatial correlation, intrasample spatial correlation vs., 984

Intersection empty, 805

non-empty, 804

Intimate mixture, 921

Intimate spectral mixture, 435

Intraband criterion, 684

Intraband spectral information, 772

Intrapixel spectral correlation, 908

FDE by classification using, 908

Intrasample spatial correlation, intersample spatial correlation vs., 984

Intravoxel spectral information, 920

Intrinsinc dimensionality (ID), 124, 125, 126, 958

finding using eigenvalues, 127

Intrinsic dimensionality constraint, 919

INU (intensity nonuniformity) noise–corrupted brain MR images, 946

INU noise corruption, 944, 945, 946, 947

Inverse ICA/2D compression, 553. See also IICA entries

Inverse ICA/3D compression, 553–554

Inverse PCA/2D compression, 553. See also Principal components analysis (PCA)

Inverse PCA 3D compression, 553–554

Inverse transform of ICA (IICA), 553. See also IICA entries; Independent component analysis (ICA) entries

Inverse transform of PCA (IPCA), 553. See also IPCA entries; Principal components analysis (PCA)

IPCA/2D compression algorithm, 553. See also Inverse transform of PCA (IPCA)

IPCA/3D compression, 554

IPCA/3D compression algorithm, 554

IPCA/3D Multicomponent JPEG2000 compression system, 553–554

IPCA/3D-SPIHT compression system, 553–554. See also Set partitioning in hierarchical trees (SPIHT); SPIHT entries; 3D-SPIHT entries

IPCA/JPEG2000 Multicomponent compression, 564, 566, 567, 569, 570

ISODATA algorithm/process, 266, 274, 275, 276, 278, 283, 481

ISODATA (C-means) clustering method, 584. See also C-means entries

ISODATA-N-FINDR, 276, 278, 279, 280, 281, 282, 283, 284, 285. See also N-finder (N-FINDR) algorithm
ISODATA-PPI, 276, 278, 279, 280, 281, 282, 283, 284, 285. See also Pixel purity index (PPI) entries
Iterated constrained endmember (ICE), 265–266
Iterated constrained endmember (ICE) algorithm, 207, 209, 225
Iterative error analysis (IEA), 201, 204, 207, 209, 273, 339, 527, 538, 539, 967. See also Iterated constrained endmember (ICE) algorithm
Iterative error analysis–EEA (IEA-EEA), 243, 251, 275, 286. See also Endmember extraction algorithms (EEAs)
algorithm for, 251
UFCLS-EEA vs., 251
Iterative N-finder algorithm (IN-FINDR), 421, 429–430, 528, 966–967, 968. See also Iterative N-FINDR (IN-FINDR); N-finder (N-FINDR) algorithm
DDA values and, 671–672
Iterative N-FINDR (IN-FINDR), 206, 216–218, 240, 314–315. See also Iterative N-finder algorithm (IN-FINDR); Random IN-FINDR (RIN-FINDR)
comparative study of versions of, 222–223
domain pixels extracted via, 268–269, 270, 271
flow chart of, 218
implementation versions of, 218–222
random versions of, 296–305
results of, 297, 299, 301, 303, 306, 307, 310, 311
sequential versions of, 243
using a different set of random initial conditions, 306–309
Iterative process, 544
Iterative SC N-FINDR (ISC N-FINDR) algorithm, 966. See also Iterative N-finder algorithm (IN-FINDR)
Iterative SQ N-FINDR (ISQ N-FINDR) algorithm, 966. See also Iterative N-finder algorithm (IN-FINDR)
Joint Service Agent Water Monitor (JSAWM) program, 91
JPEG2000 algorithms, 541, 550–551, 551–552, 557–558. See also 3D Multicomponent JPEG
JPEG-2000 lossless compression, 546
JPEG2000 Multicomponent spatial compression, 561–562, 580
performance of, 566, 567, 568, 570
JSAWM hand-held assay (JSAWM-HHA), 91
Kalman filter–based estimation, for hyperspectral signals, 820–858. See also Kalman filter–based spectral signature estimator (KFSSE)
Kalman filter–based linear spectral unmixing (KFLU), 820–822, 822–824, 857, 858. See also KFLU entries
KFSCSP techniques vs., 821
KFSSE vs., 825–826
KFSSQ vs., 829
as 1D signal-processing technique, 822
panel pixels wrongly identified by, 856
performance of, 854
Kalman filter (KF)-based spectral characterization signal processing (KFSCSP) techniques, 820, 824–831. See also KFSCSP entries
Kalman filter–based spectral signature estimator (KFSSE), 798, 824, 825–826, 841, 849, 857, 858. See also KFSSE entries
algorithmic steps of, 829–830
in estimating spectral signatures, 832
implementing, 831–832, 843, 852
KFLU vs., 825–826
KFSSI vs., 827, 828
utility of, 843
Kalman filter–based spectral signature identifier (KFSSI), 798, 824–825, 826–828, 841, 857, 858
advantage of, 837, 847–848
algorithmic steps of, 829, 830
implementing, 832–839, 843–848, 852–856
KFSSE vs., 827, 828
mixed target identification by, 838–839, 848
panel pixels wrongly identified by, 856
state equation use by, 854
subpixel target identification by, 832–838, 843–848
utility and effectiveness of, 833, 846
Kalman filter–based spectral signature quantifier (KFSSQ), 798, 824, 825, 828–829, 857, 858
abundance fractions estimated by, 839–840, 857. See also KFSSQ entries
algorithmic steps of, 829, 830–831
implementing, 839–842, 856–857
KFLU vs., 829
mixed target quantification by, 840–842, 849–852
performance of, 856, 858
sensitivity to $\sigma_n$, 841–842, 850–852
subpixel target identification by, 849
Kalman filter–based spectral signature quantifier (KFSSQ) (Continued)
subpixel target quantification by, 839–840
use in quantification, 849–852
Kalman filtering–based techniques, 17, 798
Kalman filters (KFs), 991
advantages of, 821
applications of, 822–824
implementing, 823
as mixed pixel classifiers, 822
strengths of, 823
Kaolinite/alunite mixed pixel, 534
Karhunen–Loeve transform (KLT), 170–171, 542, 543
K-BEP-FCLS classification results, 945–946.
See also Band expansion process (BEP);
Kernel entries; Kernel-based FCLS (KFCLS)
K-BEP-FCLS method/technique, 925, 943, 944,
945–949, 950, 953–954. See also Fully
constrained least-squares (FCLS) method
K-BEP-LSOSP classification results, 945–946.
See also Least-squares-based orthogonal
subspace projection (LSOSP)
K-BEP-LSOSP method/technique, 925, 943, 944,
945–949, 950, 953–954
K-BEP-NCLS classification results, 945–946
K-BEP-NCLS method/technique, 925, 943, 944,
945–949, 950, 953–954. See also Non-
negativity abundance-constrained least-
squares (NCLS) method
Kernel-based adaptive CEM (KACEM), 907.
See also Adaptive CEM (ACEM); Constrained
energy minimization (CEM)
Kernel-based adaptive MLC (KAMLTC), 907.
See also Maximum likelihood classifier (MLC)
Kernel-based adaptive RXD (KARXD), 907.
See also Adaptive RXDs (ARXD);
RX detector (RX, 8RXD)
Kernel-based algorithms, 462
Kernel-based approaches, 52, 57, 905, 944–951,
977–981
Kernel-based ATGP (KATGP), 980. See also
Automatic target generation process (ATGP)
Kernel-based CEM (KCEM), 907, 980. See also
Constrained energy minimization (CEM)
Kernel-based classifiers, 463, 980–981
Kernel-based classification, 57–60
Kernel-based FCLS (KFCLS), 353, 434, 435,
439–440, 444, 451, 452, 454, 456, 457, 459,
460, 462, 463, 908, 912, 914, 915, 916, 917,
980. See also Fully constrained least-squares
(FCLS) method; K-BEP-FCLS entries;
K-FCLS entries
algorithms/MATLAB codes for, 1026, 1028,
1034–1035, 1038–1040
using an RBF kernel, 448, 451
Kernel-based Fisher’s linear discriminant
analysis (KFLDA), 58–59, 60, 907, 908, 980.
See also Fisher’s linear discriminant analysis
(FLDA)
Kernel-based FLSMA (KFLSMA), 980.
See also Fisher’s LSMA (FLSMA)
Kernel-based LSMA (KLSMA, K-LSMA), 8, 60,
434–463, 897, 910, 923, 980, 933. See also
Linear spectral mixture analysis (LSMA);
KLSMA entries
algorithms/MATLAB codes for, 1025–1040
applying to magnetic resonance image
classification, 918
benefits of, 444
extensions of least-squares–based techniques and,
436–441
kernelization and, 440–441
performance of, 947, 949–951, 953–954
relative performance of, 456, 463
to resolve nonlinear separability issue, 434
spectral unmixing and, 462
using polynomial kernels, 452
using RBF kernels, 452, 459
Kernel-based LSMA techniques, 943, 944
Kernel-based LSOSP (KLSOSP), 353, 434, 436–438,
443, 444, 445, 451, 452, 453, 454, 455, 456,
458, 461, 462, 908, 912, 913, 914, 916, 980.
See also Least-squares-based orthogonal
subspace projection (LSOSP)
algorithms/MATLAB codes for, 1026, 1027–1028
using an RBF kernel, 446, 449
Kernel-based MLC (KMLC), 907. See also Maximum
likelihood classifier (MLC)
Kernel-based methods/techniques, 18, 57
Kernel-based NCLS (KNCLS, KNCKLS), 353,
434, 435, 436–439, 444, 445, 449, 451,
452, 453, 454, 456, 458, 459, 460, 461, 462,
908, 912, 913, 915, 916, 917, 980. See also
Non-negativity abundance-constrained least-
squares (NCLS) method
algorithms/MATLAB codes for, 1026, 1028,
1032–1034
using an RBF kernel, 447, 450
Kernel-based OSP (KOSP), 353, 435, 462, 908. See also Orthogonal subspace projection (OSP).

Kernel-based RXD (KRXD), 907, 980. See also RX detector (RXD, S_KRXD).

Kernel-based support vector machine (KSVM), 59–60, 353, 440, 908, 980. See also Support vector machines (SVMs).

Kernel-based techniques, 435–436 results of, 946–951

Kernel-based transformations, 979

Kernel-based UFCLS (KUFCLS), 980. See also Unsupervised fully constrained least-squares (UFCLS) method.

Kernel-based UNCLS (KUNCLS), 980. See also Nonnegativity constraint least-squares (NCLS) method; Unsupervised nonnegativity constrained least-squares (UNCLS) method.

Kernel-based WAC-LSMA (KWACLSMA), 980. See also Abundance-constrained LSMA (AC-LSMA); Weighted abundance–constrained LSMA (WAC-LSMA).

Kernel counterparts, 449, 454, 455, 462

Kernelization, 440–441, 979–980 experiments using, 912–916, 916–918 kernel trick for, 877

LSMA and, 443, 444 role of, 441

Kernel orthogonal subspace projection (KOSP), 933 algorithms/MATLAB codes for, 1026, 1027

Kernel PCA (K-PCA), 906. See also Principal components analysis (PCA).

Kernels, 59, 230–231. See also RBF kernels effectiveness of, 449

nonlinear, 57, 933

polynomial, 452–454

types of, 980–981

Kernel support vector machine (K-SVM), 59–60. See also Support vector machines (SVMs).

Kernel trick, 57, 58, 437, 440 for kernelization, 877

Kernel types, 57

KFCLS algorithm, 439–440. See also Fully constrained least-squares (FCLS) method;

Kernel-based FCLS (KFCLS).

K-FCLS classification results, 945–946

K-FCLS method/technique, 924–925, 933, 943, 944, 945–949, 950, 953–954

KFLU-performed abundance fraction estimation, 824. See also Kalman filter–based linear spectral unmixing (KFLU).

KFLU-unmixed results, for lined-up pixels, 853, 856

KFSCS techniques, 822, 857–858. See also Kalman filter (KF)-based spectral characterization signal processing (KFSCSP) techniques.

Kalman filter–based linear spectral unmixing vs., 821

as signature vector–based techniques, 842, 843 utility of, 831

KFSSE-estimated reflectance spectra, 832. See also Kalman filter–based spectral signature estimator (KFSSE); Signal subspace estimation (SSE).

KFSSE-estimated spectra, 833, 843, 844, 853

KFSSE estimation, 829

KFSQ-estimated abundance fractions, 842. See also Kalman filter–based spectral signature quantifier (KFSQQ).

KFSQQ-estimated abundance fractions, 840–841

KFSQQ-estimated quantification results, 849, 850

KL expansion, 170, 171. See also Karhunen–Loeve transform (KLT).

KLMSA classifiers, 457. See also Kernel-based LSMA (KLMSA, K-LSMA).

KLMSA experiment, 912

KLMSA performance, evaluating, 445

K-LSOSP classification results, 945–946. See also Least-squares-based orthogonal subspace projection (LSOSP).


k-means method, 275. See also C-means/K-means clustering algorithm.

KNCLS algorithm, 439, 440. See also Nonnegativity abundance-constrained least-squares (NCLS) method.

K-NCLS classification results, 945–946

K-NCLS method/technique, 924–925, 933, 943, 944, 945–949, 950, 953–954. See also Nonnegativity constraint least-squares (NCLS) method.

kth moment–based SQ-EEA, criterion for, 253. See also Sequential endmember extraction algorithms (SQ-EEAs).

kth moment of statistics, 187, 193

kth normalized central moment, 182–183

kth order statistics, 184, 187, 193, 588

Kuhn–Tucker conditions, 438

Kullback–Leibler information measure, 472


endmembers extracted by IN-FINDR corresponding to, 632, 633, 643, 645, 649, 653–654
Kurtosis (Continued)
equations of, 586
fourth-order statistics–based, 182
UFCLS-mixed panel results produced by, 628
UFCLS-mixed panel results corresponding to, 639, 647
Kurtosis transform, 184
Kurtosis transform DR (Kurtosis-DR), 169. See also Dimensionality reduction (DR)
Laboratory data, 19–20, 786
Lagrange (Lagrangian) multiplier method, 181, 376
Lagrange multipliers, 52–53, 394
Lagrange multiplier vectors, 52, 60, 438
Lagrange multiplier vector set, 51
Lagrangians, 51, 182, 376, 394
“Land cover” classes, 25
Land cover/use classification, 599–603, 658–660, 672, 690–694
“Land use” classes, 25
LCMV-based optimization problem, 623. See also Linearly constrained minimum variance (LCMV) entries
LCMV-BCC, 624. See also Band correlation constraint (BCC)
LCMV-BCM, 623. See also Band correlation minimization (BCM)
LCMV-BDC, 624. See also Band dependence constraint (BDC)
LCMV-BDM, 623. See also Band dependence minimization (BDM)
LCMV filter, 972
LCMV-generated weighting matrix, 396
LCMV-weighted abundance fully constrained LSE problem, 416
LCMV-weighted abundance nonnegativity-constrained LSE problem, 416
LCMV-weighted abundance sum-to-one constrained LSE problem, 416
LCMV-weighted AC-LSMA, 412, 415–416, 422, 424, 425, 427, 431, 432. See also Abundance-constrained LSMA (AC-LSMA)
LCMV-weighted FCLS, 416. See also Fully constrained least-squares (FCLS) method
LCMV-weighted NCLS, 416. See also Non-negativity abundance-constrained least-squares (NCLS) method
LCMV-weighted SCLS, 416. See also Sum-to-one constrained least-squares (SCLS) entries
LCVF data, 156, 157, 158, 159, 161, 164, 165
L-dimensional binary code words, 721, 722, 723, 724–725, 728, 741–742, 743
L-dimensional column vectors, 176
L-dimensional data samples, 54
L-dimensional mixed signal source vector, 185
L-dimensional signature vectors, 741
L-dimensional weighting vector, 373
Learning algorithms, 593–594, 596
Learning rules, 266–267
Least-prioritized bands, 636–637, 638–642, 646–651, 652
BP applications using, 635–646
selected by BP criteria, 652
Least-prioritized/highest-prioritized band mixing
BP applications using, 646–651
Least-priority scores, 635, 636
Least-squares AC-LSMA, 432–433. See also Abundance-constrained LSMA (AC-LSMA)
Least-squares (LS) approach, 47, 362
Least-squares (LS)-based algorithms, 467, 487
Least-squares (LS)-based endmember extraction algorithms, 968
Least-squares–based estimator, 55–56
Least-squares–based linear spectral mixture analysis (LS-LSMA), 355, 391, 434, 435, 501. See also LS-LSMA techniques
relationship between $\hat{D}_LS(r)$ and, 362–364, 369
relationships with OSP and LSOSP, 364, 390
algorithms/MATLAB codes for, 1026, 1027
brain tissue classification by, 936–951
FVC-FLSMA vs., 399–400, 403–405, 406, 407–409
operating on MR images, 935–936
relationships with OSP and LS-LSMA, 364, 390
total error from, 512, 513, 514
Least-squares (LS)-based techniques, 352
Least-squares (LS)-based ULSMA (LS-ULSMA), 483, 485, 486–488, 491–499. See also Unsupervised LSMA (ULSMA)
Least-squares (LS)-based unsupervised virtual signature finding algorithm (LS-UVSFA), 487–488, 524. See also Unsupervised virtual signature finding algorithms (UVSFAs)


corresponding to panel pixels, 855

as a distance measure, 745

for quantitative analysis, 159

relationship to $\sigma_w$, 847

of virtue endmembers, 165

Least-squares error–based approach, 318

Least-squares error–based constrained spectral unmixing methods, 339

Least-squares error (LSE)-based EEAs, 243, 248, 249–250. See also Endmember extraction algorithms (EEAs)

Least-squares error (LSE)-based transform, 170

Least-squares error (LSE) criterion, 352

Left singular vector matrix, 175


Linear binary classifier, 49

Linear data representations, 140

Linear discriminant function, 48, 49–50, 59

Linear filters, finite impulse response, 44

Linear hyperspectral imaging, issues in, xxiii

Linear hyperspectral mixture analysis, 80–83. See also Linear spectral mixture analysis (LSMA)

Linearly constrained discriminant analysis (LCDA)

relationship between FVC-FLSMA and, 396–397

Linearly constrained discriminant analysis (LCDA), 352–353, 392

Linearly constrained minimum variance (LCMV), 43, 392

Linearly constrained minimum variance (LCMV), 615

Linearly constrained minimum variance (LCMV), 622–623

Linearly constrained minimum variance (LCMV) adaptive beamforming, 197–198

Linearly constrained minimum variance (LCMV) approach, 392

Linearly constrained minimum variance (LCMV) approach relationship between FVC-FLSMA and, 395–396

Linearly constrained optimization problem, 377

Linearly constrained optimization problem, 44

Linearly mixed data, 184–185

Linear mixing model, 113, 435, 445, 519, 520, 559, 822, 957, 970. See also Linear mixture model

Linear mixture analysis theory, 434

Linear mixture model(s), 54, 185, 358, 824, 825

Kalman filters and, 821

Linear mixture model–based OSP, 11, 168. See also Orthogonal subspace projection (OSP)

Linear nonseparability, 904–905, 979

Linear nonseparable problems, 52, 57

Linear optimal filter, 360

Linear programming–based minimal volume enclosing simplex (MVES), 965

Linear regression model, 140, 144

Linear separability problem, 50

for support vector machines, 51–54

Linear spectral mixture analysis (LSMA), xxiv, 12, 32, 45, 152, 157, 161, 225–228, 351–353, 355, 391–410, 411, 434, 441, 442, 459, 462, 463, 469, 483, 542, 559, 603–608, 660–661, 682, 694–714, 898, 909, 910–912, 918, 957, 967, 969, 970–974. See also BEP-LSMA; Fisher’s LSMA (FLSMA); Kernel-based LSMA (KLSMA); LSMA entries; Normalized LSMA; Supervised LSMA (SLSMA); Unsupervised LSMA (ULSMA); Weighted abundance–constrained LSMA (WAC-LSMA)

advantages of, 923

algorithms/MATLAB codes for, 1025–1040

brain tissue classification by, 936–951
classification vs., 970
drawbacks of, 924
drawbacks required by, 974

Kalman filter–based linear spectral unmixing and, 821

kernelization and, 443, 444

for MRI, 923–928

operating on MR images, 935–936, 936–951

OSP-based approach to, 971, 972, 973

in partial volume estimation, 955

for performance evaluation, 159

problems solved by, 411–413

QLSE performance of, 939–941

in remote sensing image classification, 921

spectral processing and, 955

tactical unmixing and, 664, 878

techniques developed for, 352, 353

Linear spectral mixture analysis (LSMA) applications, 113–114

Linear spectral mixture analysis (LSMA)-based SQ-EEAs, 248–251. See also Sequential endmember extraction algorithms (SQ-EEAs)
Linear spectral mixture analysis (LSMA) methods, 896
Linear spectral random mixture analysis (LSRMA), 435
for MRI, 928–932
Linear spectral unmixing (LSU), 81, 125, 152, 969–970
endmember extraction and, 519
Linear spectral unmixing (LSU) techniques, 215, 351–352, 435
Linear SVM, 59. See also Support vector machines (SVMs)
Linear transformation, 40
Linear transforms, 591
Linear unmixing, 358. See also Linear spectral unmixing (LSU) entries
Lined-up pixels, KFLU-unmixed results for, 853, 856
Literal analysis, 1
spatial domain–based, 7
L-length binary code words, 736–739
Lloyd’s algorithm I, 758
Loading factors, 617, 618, 620
Lossless data compression, 546
Lossy compression, 542, 543
Lossy compression techniques, 561–562, 569
Lossy hyperspectral data compression, 15
Low-frequency domain information, 860
Low-pass filters, discrete wavelet transform and, 859
Low probability detector (LPD, 8LPD), 384–385
Low signal/high noise bands, 27
Low spectral resolution multispectral imagery, 5
LS-based algorithms, 485, 492. See also
Least-squares entries
LS-based LSMA/CA-based ULSMA, 517–518.
See also Component(s) analysis entries; Linear spectral mixture analysis (LSMA);
Unsupervised LSMA (ULSMA)
LSE-based AC-LSMA, 412, 927. See also
Abundance-constrained LSMA (AC-LSMA);
Least-squares error entries
LSE-based endmember extraction algorithms, 967
relationships among, 969
LS-estimated abundance vector, 363
LS estimation error, 367
LS-LSMA performance, 513. See also Least-squares–based linear spectral mixture analysis (LS-LSMA). See also Linear spectral mixture analysis (LSMA)
LSMA-based hyperspectral data compression, 542
LSMA-based hyperspectral image compression, 550
LSMA-based intrapixel techniques, 951
LSMA-based methods, 924–925
quantitative analysis among, 945–946
LSMA-based techniques, 80–81, 82, 89, 143–144, 922–923
LSMA classifiers, 449, 452, 454, 455, 457
LSMA experiments, 911
LSMA extensions, 434, 435, 436
LSMA models, 351
LSMA performance, 505, 511, 524–525
evaluation of, 460–462
LSMA performance evaluation, 503
LSOSP-based methods, 953–954. See also Least-squares-based orthogonal subspace projection (LSOSP)
LSOSP classification results, 446
LSOSP/KLSOSP curves, 449, 452, 453, 455, 458, 461. See also Kernel-based LSOSP (KLSOSP)
LSOSP-mixed pixel classification results, 115–117
LSOSP performance, 407
LSOSP-unmixed abundance fractions, 114
LS-SLSMA techniques, 352, 353. See also Least-squares entries; Supervised LSMA (SLSMA)
LS-ULSMA procedure, 503–505. See also
Unsupervised LSMA (ULSMA)
quantification results from, 513–517
LS-UVSFA/CA-UVSFA, 518–519, 525. See also
Component(s) analysis entries; Unsupervised virtual signature finding algorithms (UVSFAs)

$(m = 1, n = 8)$-PCA/ICA transform scenario, 574, 576. See also Independent component analysis (ICA); Principal components analysis (PCA)
$(m = 2, n = 7)$-PCA/ICA transform scenario, 575
Macro spectral mixture, 921
Magnetic resonance (MR) brain imaging, 87–91. See also Brain MRI
Magnetic resonance (MR) brain wave library, 102
Magnetic resonance (MR) breast imaging, 83–87
Magnetic resonance (MR) image analysis, multispectral, 19
Magnetic resonance (MR) image classification, applying BEP + LSMA and KLSMA to, 918
Magnetic resonance (MR) imaging (MRI), 920–921. See also MR entries
band expansion process over-complete ICA for, 931–932
connection to spectral unmixing, 925
future development of, 955
linear spectral random mixture analysis for, 928–932
LSMA for, 923–928
multispectral, 19, 920–955
orthogonal subspace projection to, 925–927
Magnetic resonance (MR) imaging problems,
hyperspectral imaging for, 877–878
Magnetic resonance tissue parameters, 930
Mahalanobis classifier/maximum likelihood
classifier, 482
Mahalanobis distance (MD), 40, 367, 384, 412,
465, 978
Mahalanobis distance–based filters, 975
Mahalanobis distance–based Gaussian maximum
likelihood estimation (GMLE), 391, 412
Mahalanobis distance (MD)-based measures, 470
Mahalanobis distance kernel, 981
Mahalanobis distance (MD)-like measure (MDRX),
474, 475, 476, 479
Malinowski’s error theory, 127, 129–130, 166
Mallat’s algorithm, 859, 860, 863
Margin of separation, 50
Markov random field (MRF), 920, 922
Matched filter, 360, 363–364, 482
Matched filter–based detectors, 975
Matched filter–based distance, 465. See also
Matched filter distance (MFD)
Matched filter–based hyperspectral measures,
470
Matched filter distance(MFD). See also Correlation
filter-based distance; MFD-based hyperspectral
measures
correlation matrix–weighted, 476–477
covariance matrix–weighted, 475
Matching signal, 40
Matching signature vectors, 827, 833, 858
Material quantification, FCLS method for, 880
Material signature vector, 472
MATLAB-based PPI (MATLAB-PPI), 204, 206,
210, 211–214, 240. See also ENVI software;
Pixel purity index (PPI) entries
panel pixels extracted by, 213
MATLAB codes, 997–1051
MATLAB software package, 1–2
Matrices, 29
Matrix factorization, 174–175
Matrix inversion, 989
Matrix projection matrix, 253
Maximal gray levels, 619
Maximal linear spectral unmixed error (MLSUE),
225
Maximal/minimal OP, 319. See also Orthogonal
projections (OPs)
Maximal/minimal simplex volume (MSV), 266
Maximal OPs, 325, 329, 337. See also Orthogonal
projections (OPs)
Maximal orthogonal subspace projection, 323
Maximal projection learning algorithm, 593
Maximal projections, 211–212, 321
Maximal variance, 595
Maximal volume, VCA-found, 329
Maximal volume–based EEAs. See also
Endmember extraction algorithms (EEAs)
Maximum eigenvalues, 361
Maximum entropy, 722
Maximum filter output SNR, 360
Maximum IC projection, 505. See also Independent
components (ICs)
Maximum likelihood–based classification/ estimation, 898
Maximum likelihood classifier (MLC), 474–475,
599–603, 674, 977–978. See also MLC entries
Maximum likelihood detector, 41, 366
OSP as, 365
Maximum likelihood estimates, of abundance
fraction, 367
Maximum likelihood estimator, OSP as, 365
Maximum noise fraction (MNF), 168, 169, 176–177,
212, 232, 255, 268–269, 270, 271, 293, 294,
295, 306, 307, 310, 320, 325, 337, 338, 345,
346, 347, 519, 520–524
algorithms/MATLAB codes for, 1003–1004
in endmember pixels extraction, 341–342, 343
p values estimated by, 340–341
Maximum noise fraction (MNF) transform, 112, 618
Maximum orthogonal complement algorithm
(MOCA), 960, 061
Maximum orthogonal projection, 227, 247
Maximum orthogonal subspace projection (MOSP)
approach, 960
Maximum PC projections, 505. See also Principal
components (PCs)
Maximum SID ratio, 815. See also Spectral
information divergence (SID)
Maximum simplex volume, 518
endmember sets and, 339–344
Maxmin-distance algorithm, 274, 275, 276, 278.
See also Minimax detector
Maxmin-N-FINDR, 276, 278, 279, 280, 281, 282,
283, 284, 285. See also N-finder (N-FINDR)
algorithm
Maxmin-PPI, 276, 278, 279, 280, 281, 282,
283, 284, 285. See also Pixel purity index (PPI)
entries
M–block length binary code word, 776
MD-based hyperspectral measures, 479. See also Mean deviation (MD) performance of, 480
M-dimensional priority unit vector, 784
MD-weighted abundance fully constrained LSE problem, 415. See also Least-squares error entries
MD-weighted abundance nonnegativity-constrained LSE problem, 415
MD-weighted abundance sum-to-one constrained LSE problem, 415
MD-weighted AC-LSMA, 412, 415, 422, 424, 425, 427, 431, 432. See also Abundance-constrained LSMA (AC-LSMA)
MD-weighted FCLS, 415. See also Fully constrained least-squares (FCLS) method
MD-weighted NCLS, 415. See also Non-negativity abundance-constrained least-squares (NCLS) method
MD-weighted SCLS, 415. See also Sum-to-one constrained least-squares (SCLS) entries
Mean detection rate ($R_D$), 78
Mean deviation (MD), 723, 744
Mean false alarm rate ($R_F$), 78
Mean squared error (MSE), 142, 312, 542, 543, 547, 594. See also MSE entries used for compression, 570, 580
Mean squared error approach, 318
Mean squared error (MSE)-based approaches, 820
Mean squared error (MSE)-based transform, 170
Mean squared error (MSE) estimation algorithms, 956
Measurement equation, 820–821, 822, 826, 828, 858 modified, 825 remodeling, 826–827
Measurement matrix, 823
Measurement noise, 827, 858 standard deviation of, 837
Median partition (MP) binary coding, 725, 726, 727, 728, 729, 730, 731, 732, 733–735, 736–738, 739, 986
Median partition (MP) binary coding scheme, 717, 719, 720, 721–722
Median partition deviation (MPD), 723–724, 725, 726, 727, 728, 729, 730, 731, 732, 733–735, 736–738, 739
Memory coding method, 757
Memoryless coding, 986
Mercer’s theorem, 57, 60
MFD-based hyperspectral measures, 479. See also Matched filter distance (MFD)
Mineral endmembers, 324
Mineral signatures, 112, 113, 114, 144, 146, 281, 535 extracting, 298 extracting panel pixels corresponding to, 301–303 pure, 309, 312 true, 259
Mineral signature vectors, discrimination among, 747
Mineral spectra, USGS ground-truth, 746, 749
Mineral spectral signatures, 331, 441
Minimal gray levels, 619
Minimal/maximal OP, 319. See also Orthogonal projections (OPs)
Minimal projections, 211–212, 488
Minimal projection value, 488
Minimal simplex volume, 214–215
Minimal volume constrained non-negative matrix factorization (MVC-NMF), 965
Minimal volume enclosing simplex (MVES), 965
Minimal volume transform (MVT)-based approach, 965
Minimax detector, 37, 38. See also Maxmin entries
Minimum description length (MDL), 6, 127, 130–131, 138, 165
Minimum IC projection, 505. See also Independent components (ICs)
Minimum misclassification canonical analysis (MMCA), 619–620
Minimum simplex volume, 518
Minimum volume transform (MVT), 201, 202, 207, 208–209, 214, 215, 240, 242, 317. See also MVT/N-FINDR VCA vs., 247
Minor components (MCs), 616–617, 635–636 “Miss” decision, 64, 68
Mixed ($m$, $n$)-PCA/ICA compression algorithm, 555. See also Independent component analysis (ICA); Mixed PCA/ICA entries; Principal components analysis (PCA)
Mixed ($m$, $n$)-PCA/ICA transform, 555, 556. See also PCA/ICA
Mixed component analysis, for spectral/spatial compression, 570–576
Mixed component–compressed/decompressed image cubes, 574, 575
Mixed component transforms, for hyperspectral compression, 554–556
Mixed highest-prioritized and least-prioritized bands, BP applications using, 646–651
Mixed panel classifiers, 81
Mixed panel pixels, simulated, 105
Mixed PCA/ICA approach, 577, 579. See also Mixed ($m$, $n$)-PCA/ICA entries
Mixed PCA/ICA component analysis, 587
for hyperspectral imagery, 571
Mixed pixel analysis, 580
Mixed pixel–based techniques, 392
Mixed pixel classification, 114, 395, 410, 445, 492
Kalman filters and, 821
performance in, 575–576
RBF kernels and, 451
Mixed pixel classification problem, 358
Mixed pixel classification/quantification, 567
Mixed pixel classifiers, 399
Mixed pixel information, 479
Mixed pixel panel quantification, 569–570, 577–580
Mixed pixel panels, 331–332
abundance fractions for, 566, 570
Mixed pixel quantification, 114, 576–577
Mixed pixels, 26, 32, 33, 467, 526, 527, 539
Mixed-pixel self-classification, 871
Mixed pixel vectors, 14, 838–839, 840–841, 848, 849–850. See also \( \text{mix mixed pixel vector} \)
Mixed projection index–based prioritized PP (M-PIPP), 587. See also Projection index (PI)-based projection pursuit (PIPP)
Mixed sample analyses, 10, 31, 33–62
classification of, 45
subsample analysis vs., 34–35
Mixed sample classification, 34, 45, 60
Mixed sample classification techniques, CEM-based, 54
Mixed sample identification, prior knowledge of, 34
Mixed sample quantification, 34
Mixed samples, 33
subsamples vs., 60
subsample target vs., 34
Mixed-sample targets, simulation of, 104
Mixed sample vectors, 525
Mixed signature classification, 748–749, 751–755
Mixed signature discrimination/identification, 470
Mixed signatures
noisy, 811
spectral identification for, 789–790
Mixed signature vectors, 789, 809, 810, 819
Mixed target identification, by KFSSI, 838–839, 848
Mixed target quantification, by KFSSQ, 840–842, 849–852
Mixed target signature vector, identifying unknown, 841
Mixing effect, 921
Mixing matrices, 185, 186
for signal source separation, 930
MLC-classification, 658–659, 672. See also Maximum likelihood classifier (MLC)
MLC class rates
in Purdue data, 699–702
using PBS prioritized bands, 694–699
MLC performance, 690
MLC rates, 691–694
of PBS, 693
MNF-DR transform, 345. See also Dimensionality reduction (DR); Maximum noise fraction (MNF) entries
Model error, 970
Models, interpreting, 77
Modified spectral mixture analysis, 517
Monte Carlo simulations, 102
Morphological eccentricity index (MEI), 231
Moving target detection, 988
MP binary code word, 724. See also Median partition (MP) binary coding entries
MPCM-based progressive spectral signature coding (MPCM-PSSC), 772, 773–774, 783–786, 796, 986. See also MPCM-PSSC entries; Multistage pulse coding modulation (MPCM); Progressive spectral signature coding (PSSC)
applications of, 786
discrimination results obtained by, 791
panel pixel identification by, 791–796
performance of, 789
results produced by, 791
unique features of, 796
versatility of, 786
MPCM decoded signal points, 783
MPCM decoding algorithm, 777–778, 783
MPCM encoded priority code words, 779
MPCM-encoded progressive spectral signatures, 780
MPCM-encoded signal samples, 782
signal reconstruction of, 783
MPCM encoding, stages required for, 778
MPCM encoding algorithms, 776–783
MPCM-PSSC spectral discrimination algorithm, 784–785. See also MPCM-based progressive spectral signature coding (MPCM-PSSC)
MPCM-PSSC spectral identification algorithm 1, 785–786, 791
MPCM-PSSC spectral identification algorithm 2, 786, 791
MR brain image analysis, 922. See also Magnetic resonance (MR) entries
MR brain image experiments, real, 951–954
MR brain images, 933–934
MRI experiments, K-LSMA and, 933
MR image (MRI) analysis, 955
source separation–based OC-ICA for, 930–931
MR image data, 921
MR images
combined with BEP-generated bands, 936–951
as multispectral images, 877, 924
quantitative, 878
MR image voxels, classifying, 923
MR instruments, advances in, 955
MR tissue signatures, 925–926
MR tissue substance signatures, 926
MSE estimation error covariance matrix, 823–824.
See also Mean squared error (MSE) entries
MSE prediction error covariance matrix,
823–824
MSE values, 564, 566, 567
MSI data, expanded, 919. See also Multispectral imaging (MSI)
MSI techniques, 899
M-stage thresholds, 785
Multichannel erosion, 231
Multi-channel morphological processing,
230–231
Multiclass classification problems, reducing to
binary classification problems, 53–54
Multidimensional data, representing, 124, 125
Multiple background synthetic image experiment,
564–567
Multiple-class classification, 47
Multiple correlation coefficient, 173
Multiple endmember spectral mixture analysis, 517
Multiple image resolutions, 860
Multiple regression theory, 173
Multiple-replacement IN-FINDR, 218, 219–220.
See also Iterative N-finder algorithm
(IN-FINDR)
Multiple-signal detection, 63
Multiple signal detection/classification, generating
3D ROC curves for, 77–78
Multiple-signal detection model, 77–78
Multiple signals
joint detection of, 82
single signal detection of, 82–83
Multiple-stage PCM (MPCM), 772, 773. See also
MPCM entries; Multistage pulse coding modulation
(MPCM)
Multiple subsample targets, 56
Multiple-window anomaly detection (MWAD), 977
Multiscale approximation, 860
Multiscale approximation space, 862
Multiscale signal representation, 860
Multiscale wavelet transform, 863
Multisignal detection, 65
Multisignal detection/classification, 70
Multispectral brain MR images, 925
Multispectral data, 3-band SPOT, 6
Multispectral image experiments, 463, 909–918
Multispectral image processing, image classification
in, 8
Multispectral imagery
FDE techniques for, 908, 909
hyperspectral imagery vs., xxiv–xxv, 4–7, 897, 957
issues of, 3–4
low spectral resolution, 5
nonlinear dimensionality expansion to, 18,
897–919
processing, 974
Multispectral imagery vs. hyperspectral imagery
issue, xxiv–xxv, 4–7, 897, 957
Multispectral images
defined, 898
MR images as, 877, 924
Multispectral imaging (MSI), 877, 920, 921.
See also MSI entries
hyperspectral imaging vs., 897, 987
Multispectral imaging techniques, spatial domain–
based, 355–356
Multispectral magnetic resonance (MR) image
analysis, 19
Multispectral magnetic resonance (MR) imaging, 19,
920–955
Multispectral MR images, special processing of, 955
Multispectral signature vector, 9
Multispectral-to-hyperspectral approaches, 355
Multistage pulse coding modulation (MPCM), 718,
772, 773, 774–783. See also MPCM entries
applying to SSC, 778
Multivariate data, determining ID in, 124
Multivariate data analysis, 585
Muscovite signature, 114
Mutual information concept, 185
MVT/N-FINDR, 968. See also Minimum volume
transform (MVT); N-finder (N-FINDR)
algorithm
My FastICA, algorithms/MATLAB codes for,
1005–1007, 1010–1012. See also FastICA
entries
NAPC transform algorithm, 178–179. See also
Noise-adjusted principal component (NAPC)
entries
National Institute of Standards and Technology
(NIST), 19, 749. See also NIST entries
Natural logarithm function, 760
NCLS classification results, 447. See also Non-
negativity abundance-constrained least-squares
(NCLS) method
NCLS/KNCLS curves, 450, 456, 458, 459, 461, 462. See also Kernel-based NCLS (KNCLS, KNCKLS)

NCLS performance, 445

N-coin flipping experiments, 287–288, 289, 290

N-dimensional column vectors, 176. See also L-dimensional entries

Nearest neighbor rule–based classifiers, 481–482


Neural networks, 435

Newton’s method, 266

Neyman–Pearson (NP) detector (δNP), 37, 38, 41, 64, 66, 68, 137, 958, 959, 960, 961

normalized, 75

Neyman–Pearson (NP) detection problem, 65–67

Neyman–Pearson (NP) detection theory, 41, 65, 69, 127, 958. See also NP detection–based criteria

Neyman–Pearson (NP) lemma, 66–67


algorithms/MATLAB codes for, 1015, 1020–1023
development of, 965–967
dilemmas related to, 967

for endmember extraction, 314, 520

implemented as SM-EEA, 317–318

initial conditions in, 966

maximal volume simplexes and, 342–343

pixel extraction using, 532–533, 534

pixels extracted by, 158–159, 162, 163, 164, 165, 341, 342, 343

simplex volumes and, 343, 344, 345, 346, 347, 348

versions of, 205, 206

N-FINDR + LSMA, 519, 520. See also Linear spectral mixture analysis (LSMA); N-finder (N-FINDR) algorithm

N-FINDR difficulties, 330

N-FINDR–extracted endmember pixels, 535, 536, 537–539

N-FINDR extraction, of mineral signatures, 671–672

Nine-replacement IN-FINDR (9-IN-FINDR), 223, 224. See also Iterative N-finder algorithm (IN-FINDR)

9-signature matrix, 28–29

NIST/EPA gas-phase infrared database, 19–20, 21. See also National Institute of Standards and Technology (NIST)

NIST-gas data, 813–818

computer simulations using, 843–852

NIST-gas data experiments, 749–755, 760–764, 786–790

NIST-gas data set, 760, 813. See also Gas data entries

NIST website, 813

NMF-based minimal volume constrained non-negative matrix factorization (MVC-NMF), 965

Noise. See also Gaussian noise; Non-Gaussian noise:

White noise
effect on VNVBS, 811–812
in hyperspectral imagery, 112
statistics of, 41
unstructured, 43

Noise-adjusted principal component (NAPC), 212

Noise-adjusted principal component (NAPC) transform, 169, 176, 177–179, 618

Noise assumptions, 356–357

experiments to examine, 367–372

Noise class, 127, 131

Noise-corrupted matching spectral signature vector, 826

Noise-corrupted signatures, 790

Noise corruption, 108, 944, 945, 946, 947

Noise covariance matrix, 178
estimating, 179

Noise detection, 84

Noise effect, 532–533

Noise fraction (NF), 176–177

Noise models, signal detection in, 359

Noise suppression, 378

Noise-whitened Harsanyi–Farraud–Chang (NWHFC) method, 138, 143, 144, 155–163, 165, 420–421, 423. See also HFC/NWHFC method

algorithms/MATLAB codes for, 999–1000

virtual dimensionality estimated by, 532

Noise whitening, effect of, 371–373

Noisy background
clean panels embedded in/implanted into, 107–108, 109–110
endmembers embedded in/implanted into, 233–234, 235–236
noisy endmembers embedded in/implanted into, 234–235, 236

Noisy endmembers
embedded in noisy background, 236
implanted into noisy background, 234–235
Noisy mixed signatures, 811
Non-empty intersection, 804
Non-Gaussianity, 186
Non-Gaussian noise, 131, 135
Non-kernel-based LSMA methods, 953
Nonlinear band dimensionality expansion techniques, 877, 878
Nonlinear dimensionality expansion (NDE), 919
to multispectral imagery, 18, 897–919
Nonlinear dimensionality expansion techniques, 918
Nonlinear functions, 435
Nonlinear kernels, 18, 57, 933
feature dimensionality expansion by, 904–909
Nonlinearly correlated images, 900
Nonlinear separability, 434
Nonlinear spectral information, inherent, 920
Nonliteral analysis, 1, 6–7
Nonliteral hyperspectral imaging techniques, design principles for, 956–965
Non-negative matrix factorization (NMF), 965
Non-negativity abundance-constrained least-squares (NCLS) method, 80–81, 82, 83, 84, 85, 89–91
effectiveness of, 83
See also NCLS entries
algorithms/MATLAB codes for, 1026, 1028–1032
brain tissue classification by, 936–951
kernel version of, 462
operating on MR images, 935–936
total error from, 512, 513, 514
Nonparametric methods, 921–922
Nonstationary data, 821
Normalization constant, 40
Normalized AMD (NAMD), 40, 61. See also
Adaptive matched detector (AMD)
Normalized CEMs, in hyperspectral target detection, 79. See also
Constrained energy minimization (CEM)
Normalized correlation eigenvalues, 128
Normalized covariance eigenvalues, 128
Normalized detected signal strength, 75
Normalized ED values, 726. See also Euclidean distance (ED)
Normalized eigenvalue distribution, finding first sudden drop in, 128
Normalized endmember matrix, 228, 229
Normalized Hamming spectral distance values, 726, 727, 728, 729, 733–736
Normalized LSMA, 81. See also
Linear spectral mixture analysis (LSMA)
Normalized Neyman–Pearson detector, 75
Normalized spectral matched filter, 374
Normal vectors, of hyperplanes, 49, 50
Notations, 29–30
“Not true” decision, 64
NP detection–based criteria, 14, 166. See also
Neyman–Pearson (NP) detection theory
Null hypothesis, 66

Object function, 52
Objective functions, 196–197. See also
Constrained objective function
Oblique subspace projection, 362
Observable signature vector, 827, 829
On-board data processing, 989
1D discrete-value signal processing, 987
1D hyperspectral signal processing, 16
One-dimensional (1D) continuous signal processing, 797
One-dimensional hyperspectral signal, 9
One-dimensional (1D) signal-processing techniques
KFLU as, 822
KFSCSP technique as, 821
One-dimensional signature–based BS, 800. See also
Band selection (BS)
One-dimensional (1-D) spectral signature, 783
One-dimensional (1D) transform coding technique, 773
1D-spectral/2D-spatial compression, 550
1D spectral compression, 550
One-step MSE estimation error covariance matrix, 823–824. See also
Mean squared error (MSE) entries
One-step MSE prediction error covariance matrix, 823–824
OP-based algorithms, 328. See also
Orthogonal projections (OPs)
OP-based EEA s, 202, 339. See also
Endmember extraction algorithms (EEAs)
Optical real-time adaptive spectral identification system (ORASIS), 517
Optimal abundance vector, 438
Optimal code, 668
Optimal coding performance, 664–665
Optimal component transform, 549
Optimal feature matrix, 59
Optimality, specifying criteria for, 102
Optimal projection vector, 184
Optimal threshold ($t$), 74
Optimal weighting vector, 374, 377
Optimal weight vector, 50, 52, 57
Optimization problems, linearly constrained, 44
Orthogonal complement space, 249
Orthogonal complement subspaces, 319
Orthogonal complement vector space, 862
Orthogonal detail spaces, 862
Orthogonality principle, 686, 956, 963–964
Orthogonalization-based band de-correlation, 684, 685–686
Orthogonal projection (OP)-based EEAs, 242–243, 318–329. See also Endmember extraction algorithms (EEAs)
Orthogonal projection divergence (OPD), 14, 465, 470–471, 473
Orthogonal projections (OPs), 208, 209–214, 266, 317, 319, 320, 323, 329, 967
for CADCA, 880
as EEA design criteria, 330
in endmember extraction, 202
maximal, 329
maximum residuals of, 961
uses of, 318
Orthogonal projection subspaces, 320, 322. See also Orthogonal subspace projection (OSP)
Orthogonal projection vector, 317
Orthogonal subspace projection (OSP), 6, 8, 43, 45, 48, 54–56, 61, 62, 80, 114, 140–142, 143–144, 168, 189, 196, 199, 243, 248–249, 352, 353, 356, 357–358, 902, 925, 926. See also Least-squares-based orthogonal subspace projection (LSOSP); Linear mixture model–based OSP; OSP entries algorithms/MATLAB codes for, 1026–1028
band expansion process–based, 927–928
capability of, 56
CEM vs., 358, 379–383, 828
derivation of, 390
Gaussian noise assumption in, 365
Gaussian noise in, 364–372
implemented without knowledge, 383–390
implemented with partial knowledge, 372–383
implementing, 13
interpreting, 971–972
kernel-based, 933
maximal, 323
to MRI, 925–927
perspectives to derive, 358–364
relationship between FVC-FLSMA and, 396
relationships with LSOSP and LS-LSMA, 364
relationship with CEM, 57, 376, 377
as a special case of TCIMF, 378
success of, 365
weighting matrix derived from, 417–418
Orthogonal subspace projection (OSP) approach, 318, 355–390. See also OSP approach
Orthogonal subspace projection (OSP)-based algorithm, 487
Orthogonal subspace projection (OSP) operator, 592
Orthogonal subspace projector (OSP), 89, 183, 192, 248–249, 359, 411, 436, 586, 624, 625, 637, 650, 651, 652, 883. See also OSP projector ($\mathbf{8_{OSP}}$)
endmembers extracted by IN-FINDR corresponding to, 632, 634, 644, 645, 649, 653–654
UFCLS-mixed panel results corresponding to, 641, 648
UFCLS-mixed panel results produced by, 630
Orthogonal subspace projector (OSP) approach, 801. See also OSP approach
Orthogonal subspace projector–based band prioritization criterion (OSP-BPC). See BP criteria (BPCs); OSP-based BPC (OSP-BPC); OSP-BPC algorithm
Orthogonal subspace projector (OSP) detector, 963–964
Orthonormalized eigenvectors, 174
OSP anomaly detector (OSPAD, $\mathbf{8_{OSPAD}}$), 383, 384, 385, 386–390. See also Orthogonal subspace projection entries; Orthogonal subspace projector entries
OSP approach, 356, 473. See also Orthogonal subspace projection (OSP) approach; Orthogonal subspace projector (OSP) approach; OSP-based approach
OSP-based algorithms, applications for, 356–357
OSP-based approach, to linear spectral mixture analysis, 971, 972, 973
OSP-based BPC (OSP-BPC), 620, 799, 800, 801–803, 806. See also BP criteria (BPCs)
OSP-based divergence, 473
OSP-based Euclidean distance (EDOSP), 473, 475
OSP-based hyperspectral measures, 479, 480
for discrimination, 473
for identification, 473–474
OSP-based maximum likelihood classifier (MLCOSP), 475. See also Maximum likelihood classifier (MLC)
OSP-based methods, 149–151, 152–155, 339
pixels extracted by, 159–162, 163, 164, 165
VD estimated by, 157, 166
OSP-based signal detector (OSP), 361
OSP-BPC algorithm, 802–803, 818. See also BP criteria (BPCs)
reference signature vector for, 813
OSP classifier (OSP), 357, 361, 367, 368, 370, 372, 378, 380–382
OSP learning rule, 227
OSP-model, 357–358, 364
(d,U)-model vs., 379–380
Fisher's linear discriminant analysis perspective from, 360–362
Gaussian maximum likelihood classifier using, 366
parameter estimation perspective from, 362
signal detection perspective derived from, 359–360
signal detector in Gaussian noise, 365–366
whitening according to, 369
OSP performance, 899
improving, 371
OSP-projected data sets, 192, 253
OSP projector (OSP), 55–56. See also Orthogonal subspace projector (OSP)
OSP-weighted abundance-constrained LSE problems, types of, 417–418. See also Least-squares error(s) (LSE, LSEs)
OSP-weighted abundance fully constrained LSE problem, 418. See also Least-squares error(s) (LSE, LSEs)
OSP-weighted abundance nonnegativity-constrained LSE problem, 418. See also Least-squares error(s) (LSE, LSEs)
OSP-weighted abundance sum-to-one constrained LSE problem, 417. See also Least-squares error(s) (LSE, LSEs)
OSP-weighted AC-LSMA, 413, 417–418, 422, 424, 425, 427, 431, 432. See also Abundance-constrained LSMA (AC-LSMA); Linear spectral mixture analysis (LSMA)
OSP-weighted FCLS, 418. See also Fully constrained least-squares (FCLS) method
OSP-weighted NCLS, 418. See also Non-negativity abundance-constrained least-squares (NCLS) method
OSP-weighted SCLS, 418. See also Sum-to-one constrained least-squares (SCLS) entries
Outer product matrix, 175
Over-complete ICA (OC-ICA), 18, 899, 929, 930, 931, 957. See also Independent component analysis (ICA) entries
utility of, 933
Over-complete linear spectral mixture analysis (OC-LSMA), 898, 899
Over-complete LSMA, 957. See also Linear spectral mixture analysis (LSMA)
Panel-based hyperspectral measures, 477
Panel center pixels, 503
Panel detection, 567–569
Panel pixel detection rates, averaged, 706, 713–714
Panel pixel groups, 660–661, 661–662
Panel pixel identification
incorrect, 854, 856
KFSSI in, 852
by MPCM-PSSC, 791–796
abundance fractions of, 423, 425, 426, 427, 428, 429
abundance fractions simulated for, 529
AMEE-extracted, 531
averaged detection rates of, 698–706
detection rates of, 443
detection results of, 632, 645
endmembers corresponding to, 632, 645
extracted by MATLAB-PPI, 213
extracted by PPI and N-FINDR, 113
extracted by SGA, 337
extracted by VCA, 336
extracting, 239
failure to extract, 281–282
HYDICE data, 679–681, 703–706
incorrect identification on, 875
mixed pixel, 299, 504–505
quantification results of, 856
sample correlation among, 853
superimposed over background pixels, 301
target, 499
types of, 530
unmixed results of, 509
unmixing, 511–512, 523
visible, 111
wrongly identified, 854, 856
Panel pixel superimposition, 108–109
Panel pixel vectors, abundance fractions of, 886–887, 890
Panels
abundance fraction results of, 421, 427–429, 431, 432
abundance fractions of, 563, 564, 888–889
mixed pixel, 566, 569–570, 577–580
simulated, 332–334
single pixel, 564
subpixel target, 852
unmixed results of, 513, 521–523
Panel shrinking process, 843
Panel signature corruption, 111
Panel signatures, 268–269, 326, 398, 419, 460–462, 477, 508, 515
complete knowledge of, 420
as endmembers, 306, 309
no prior knowledge about, 420–426
Panel signature vectors, 791–792
discrimination among, 791
Panel simulations, 104–106
Panel targets, ground truth map of, 882
Parallel processing, 990
Parameter estimation, 414, 820, 822
weighting matrix derived from, 414–416
Parameter estimation perspective, 412
from OSP-model, 362
Parameters, uncontrollable, 1
Parametric methods, 921–922
Parity-check bands, 983
Parity-check transformed dimensions, 983
Partial derivatives, 5
Partial knowledge, 380–383
OSP implemented with, 372–383
Partially abundance-constrained least-squares
unmixing method, 882
Partially abundance-constrained LSMA method, 967
Partially abundance-constrained methods, 436
Partially abundance NCLS method, 924. See also Non-negativity abundance-constrained least-squares (NCLS) method
Partial volume effect, 921
Partial volume estimation (PVE), 920, 923, 949, 952, 953, 955
approaches to solving, 921–922
Passive sensor array processing, 131
Pattern-based multispectral imaging techniques, 4
Pattern class–based image analysis, 5
Pattern classification, 3, 266, 352, 362, 391, 414
target classification vs., 8
Pattern classification techniques, 416
spatial-based, 8
Pavia image scene, 537, 538, 539
PBDE process, 655. See also Progressive band dimensionality expansion (PBDE)
PBDP prioritized cuprite scene, endmember extraction results of, 657. See also Progressive band dimensionality process (PBDE)
PBDR process, 654. See also Progressive band dimensionality reduction (PBDR)
PBS band prioritization (BP), 718. See also Band prioritization (BP); Progressive band selection (PBS)
PBS prioritized bands, MLC class rates using, 694–699
PCA/2D compression, 551–552. See also Principal components analysis (PCA)
PCA/2D compression algorithm, 551–552
PCA/3D compression algorithm, 552
PCA/ATGP relationship, 321–322. See also Automatic target generation process (ATGP)
PCA-based DR (PCA-DR), 169. See also Dimensionality reduction (DR); PCA-DR transform; Principal components analysis (PCA)
PCA-based priority score, 617–618
PCA-based spectral compression, 571–572
PCA-decompressed image cube, 572
PCA-DR transform, simplex volumes and, 345. See also Dimensionality reduction (DR); PCA-based DR (PCA-DR)
PCA-generated principal components, 177
PCA/ICA, obstacles to implementing, 551.
See also Independent component analysis (ICA); (m = 1, n = 8)-PCA/ICA transform scenario; Mixed (m,n)-PCA/ICA transform
PCA/ICA 2D compression system, 551
PCA/ICA 3D compression system, 552
PCA/JPEG2000 Multicomponent compression, performance of, 564, 566, 568, 570
PCA (m = 9, n = 0) scenario, 571–572
PCA method, HFC method vs., 139–140
PCA/spatial compression techniques, 569, 579
PCA-transformed components, specified by eigenvectors, 582–583
PCA-transformed data space, 584
PCA transforms, 562
PC-based data representation, 584. See also Principal components (PCs)
PC sequence, 592
PCs/ICs, number retained, 551. See also Independent components (ICs)
p-dimensional unity vector, 225
Peak SNR (PSNR), 542. See also Signal-to-noise ratio (SNR)
Performance analysis, 329
Performance criteria, 542
Performance evaluation quantification analysis for, 463
3D ROC analysis for, 89
Performance measures, implementing, 745
PG-PCA algorithm, 592. See also Principal components analysis (PCA); Progressive PCA (PG-PCA)
Phantoms, 102
PICA-based algorithms, 931–932
PIC prioritization, 609. See also Projection index components (PICs)
PIC prioritization index, 587
Pigeon-hole principle, 4, 5–7, 18, 356, 613, 615, 665, 897, 898, 956–963, 983
PI/PI, 608. See also Projection index (PI) for PSDP, 598–599
PIPP-generated PICs, 587, 590. See also Projection index (PI)-based projection pursuit (PIPP); Projection index components (PICs)
Pixel-based hyperspectral measures, 477
Pixel-based image analysis, 33
Pixel extraction, 149–151, 159–162, 163, 164, 165
Pixel extraction/information, 526–540
Pixel information, 536, 538
algorithms selected to extract, 528
extracted from hyperspectral imagery, 466
extracting, 526, 532
Pixel information analysis, 467
algorithms for, 539
via synthetic images, 528–534
Pixel information extraction, 467
Pixel information processing, 14
Pixel-level spectral information, 356
Pixel panels, 419. See also Panel pixels mixed, 331–332, 577–580
pure, 331–332
Pixel purity index (PPI), 201, 202, 203, 204, 205, 209–214, 243, 255, 232–233, 241, 288, 339, 348, 488, 518, 527, 528, 538, 539, 964–965, 967, 968. See also Automatic PPI (APPI); MATLAB-based PPI (MATLAB-PPI); PPI entries; Random PPI (RPPI)
algorithms/MATLAB codes for, 1015–1017
design rationale of, 316
development of, 207
drawbacks of, 212
dependent pixels extracted via, 268–269, 270, 271
dependent members extracted by, 294–295, 306, 307, 310, 323, 324, 325, 326, 327
in finding appropriate skewers, 282
implemented as SM-EEA, 317–318
issues in, 210
pixels extracted by, 340–341, 343, 532–533, 534
as a random algorithm, 314
relationships with VCA and ATGP, 319–323
sequential versions of, 318
simplex volumes and, 343
versions of, 204, 205
Pixel purity index (PPI) algorithm, 112–113, 142
Pixels, 12, 14, 29. See also Two-pixel panels abundance fractions of, 423, 425, 426, 427, 428, 429
alumina/kaolinite mixed, 534
AMEE-extracted, 535, 536, 537, 539
anomalous, 467, 526, 527, 530, 534, 537–538
ATGP-extracted, 536
ATGP-generated, 407
background, 333, 429, 505
detection rates of, 443
EEA-extracted, 340, 535, 536, 539
dependent member, 254, 261, 293, 325, 527, 529–530, 531
extracted by ID-EEAs, 284, 285
falsely alarmed, 294, 295
ground-truth-corresponding endmember (mineral), 270–271
ground truth mineral, 270
homogeneous, 467, 526, 527, 531, 534, 539
homogeneous background, 531
IEA-extracted, 536
implanted panel, 333
mixed, 26, 32, 33, 467, 526, 527, 539
N-FINDR–extracted endmember, 535, 536, 537–539
panel center, 503
performance of unmixing, 698, 707–712
PPI-extracted endmember, 535, 536, 537–539
pure, 21–22, 295, 296, 467, 526, 527, 531, 541, 887
spatial locations of, 312
spectral signatures of, 26
subpanel, 441
target, 791
target panel, 499
total number of, 78
Index

1113

types of, 526, 527–528, 530
UFCLS-extracted, 536
UTDA-extracted, 535, 536, 538
utility of, 527
Pixel-to-pixel correlation, 820, 854
Pixel vectors, 14, 29, 368, 526, 822, 887, 890, 891
convex cone analysis and, 214–215
extracted by PPI, 293–294
target, 792–796
Polynomial kernels, 452–454, 455–456, 980
kernel-based LSMA using, 452
Power of the test, 72
p parameter, estimating, 351
PP-EEAs, initializing, 278. See also Endmember extraction algorithms (EEAs); Projection pursuit (PP)
PPI/ATGP relationship, 319–320. See also
Automatic target generation process (ATGP);
Pixel purity index (PPI) entries
PPI counts, 211, 212, 269, 289, 290, 316–317, 319, 965
PPI-extracted endmember pixels, 535, 536, 537–539
PPI failure, 280–281
PPI uncertainty, 322
PPI/VCA relationship, 320–321. See also Vertex component analysis (VCA)
Predicted false alarm probability, 137
Predicted signature, 864
Prescribed stage threshold, 784
Prewhitenning process, 365
Primary set of eigenvalues, 129
Principal components (PCs), 169, 171–172, 486, 488, 489, 543, 551, 571–572, 584, 586, 616–617, 635–636, 906
algorithms/MATLAB codes for, 1001–1003
band usage and, 635
in endmember pixels extraction, 341–342, 343
Harsanyi–Farraud–Chang method vs., 959–960
properties of, 584
p values estimated by, 340–341
Principal components analysis–EEA (PCA-EEA), 201, 230. See also Endmember extraction algorithms (EEAs)
Principal components transformation (PCT), 170.
See also Principal component transform
Principal component transform, 906. See also
Principal components transformation (PCT)
Prioritization criteria, 543
Prioritized bands, with PBS, 706
Prioritized ICA (PICA), 931. See also PI-C-based algorithms
Prioritized ICs, 254. See also Independent components (ICs)
Prioritized PCs, 595. See also Principal components (PCs)
Priority codes, 772, 773–774, 796
Priority code words, 774, 776–777, 784
graphical plot of, 778–779
MPCM encoded, 779
Priority-ranked band sets, 803, 804
Priority scores, 617, 618, 620, 651–653, 803, 982
PCA-based, 617–618
of a spectral band, 621
for spectral dimensions, 582
Priority unit vectors, 784
Prior knowledge
contaminated or inaccurate, 516
of image endmembers, 825
unavailability of, 517
Prior target knowledge, 356
Probability density function, 66, 73
Probability distributions, 36–37, 66, 188, 961
Probability of rejection, 65
Processes, iterative, progressive, and sequential, 544
Process-then-forget benefit, 990
Progressive band dimensionality expansion (PBDE), 653, 655–656, 662
terminating, 655
unmixing performance of, 660
via BP, 614, 655–656
See also PBDP prioritized cuprite scene
advantages of, 616
band selection vs., 616
experiments for, 656–661
hyperspectral compression by, 653–656
issues addressed/mitigated by, 664
performing, 651–653
potentials of, 662–663
progressive performance of, 669–670
PSDP vs., 613, 658, 683
in spectral unmixing, 660
Progressive band dimensionality reduction (PBDR), 653, 655, 656, 662
as a sequential backward process, 655
starting, 654
Progressive band dimensionality reduction (PBDR)  
(Continued)  
unmixing performance of, 660 via BP, 614, 654  
Progressive band selection (PBS), 15, 544, 616, 663,  
683–715, 718, 798, 984. See also PBS entries  
effects of, 715  
effectiveness of, 688  
FSBS vs., 686–687  
implementing, 687–688  
MLC rates of, 693  
origination of, 683–684  
with prioritized bands, 706  
Progressive band selection experiments, 688  
Progressive band/spectral dimensionality processing,  
991  
Progressive binary encoders, 776  
Progressive coding, 9, 17  
for spectral signatures, 772–796  
Progressive dimensionality expansion/reduction  
processes, 982  
Progressive dimensionality reduction (PDR), 683  
Progressive edge detection, 773  
Progressive high-order statistics component analysis,  
596  
Progressive hyperspectral processing, 990–991  
Progressive image processing, 656  
Progressive independent component analysis,  
596  
Progressive MPCM-encoded signal, 778. See also  
Multistage pulse coding modulation (MPCM)  
Progressive PCA (PG-PCA), 591. 592. See also  
Principal components analysis (PCA)  
SM-PCA vs., 592  
Progressive principal components analysis, 591–596  
Progressive process, 544  
sequential process vs., 655–656  
Progressive processing, 773  
Progressive signature coding (PSC), 718, 772  
Progressive spectral dimensionality expansion  
(PSDE), 581, 597–598, 605, 653. See also  
PSDE entries  
as a sequential forward process, 598  
Progressive spectral dimensionality expansion via  
PPIP (PSDE-PIPP), 583, 585. See also  
Projection index (PI)-based projection pursuit (PPIP)  
Progressive spectral dimensionality process (PSDP),  
15, 199, 543, 544, 581–612  
algorithms in, 589–596  
experiments for, 598–608  
hyperspectral compression by, 597–598  
issues addressed/mitigated by, 664  
PBDP vs., 613, 658, 683  
progressive performance of, 669–670  
PSDE and PSDR implementation and, 610  
Progressive spectral dimensionality process via PIPP  
(PSDP-PIPP), 583. See also Projection index  
(PI)-based projection pursuit (PPIP)  
Progressive spectral dimensionality reduction  
(PSDR), 581, 597, 653  
as a sequential backward process, 598  
Progressive spectral dimensionality reduction via  
PPIP (PSDR-PIPP), 583, 585, 600. See also  
Projection index (PI)-based projection pursuit  
(PPIP)  
Progressive spectral identification process, 789  
Progressive spectral signature changes, 786  
Progressive spectral signature coding (PSSC),  
772–796. See also MPCM-based progressive  
spectral signature coding (MPCM-PSSC)  
advantages of, 773  
for hyperspectral signature characterization, 796  
MPCM-based, 772, 773–774, 783–786  
SSC and, 773  
Progressive spectral signatures  
MPCM-encoded, 780  
Progressive spectral/spatial compression, 557, 558  
Progressive stage-by-stage decoded spectral  
signatures, 781  
Projection direction matrix, 585  
Projection index (PI), 190–194  
Projection index (PI), 585, 586, 587, 599  
role in producing projection vectors, 608  
Projection index (PI)-based criteria, 193–194,  
587–588  
Projection index (PI)-based PRioritized Projection  
Pursuit (PI-PRPP), 191, 193–194, 587–588,  
590  
Projection index (PI)-based projection pursuit  
See also Projection index–projection pursuit  
(PIPP) algorithm; R-PIPP algorithm  
Projection index components (PICs), 191, 192, 193,  
194, 583, 586, 599, 669  
ID-PIPP-generated, 588  
PIPP-generated, 587, 590  
Projection index–projection pursuit (PIPP)  
algorithm, 192, 586. See also Projection index  
(PI)-based projection pursuit (PIPP)  
in conjunction with DP, 608–609  
Projection pursuit (PP), 191, 585  
Projection pursuit (PP) approach, 184  
Projection pursuit (PP)-based algorithms, 272
Projection pursuit (PP)-based components analysis transforms, dimensionality reduction by, 190–194
Projection pursuit (PP)-based DRT, 583. See also Dimensionality reduction by transform (DRT) techniques
Projection pursuit (PP)-based EEAs, 243. See also Endmember extraction algorithms (EEAs)
Projection sequence, 253
Projection subspaces, 322
Projection values, of data samples, 488
Projection vector generation algorithm (PVGA), 184, 253–254
Projection vectors, 46, 47, 179, 193, 226, 252–254, 317, 587, 593, 683, 932
algorithm for finding, 183–184, 253–254
generating, 584
generating as eigenvectors, 591
kernelizing, 979–980
maximum of residuals of, 962
orthogonal, 317
randomly generated, 590
Projection vector sequence, 586
Projectors. See also Orthogonal subspace projector (OSP); OSP projector ($\delta^{OSP}$); Signal subspace projector
idempotent, 359
random, 254
PSDE algorithm, 597–598. See also Progressive spectral dimensionality expansion (PSDE)
PSDE implementation, 610
PSDE/PSDR, 603–604. See also Progressive spectral dimensionality reduction (PSDR)
PSDE via DP, 609. See also Dimensionality prioritization (DP)
PSDP endmember extraction, 598–599. See also Progressive spectral dimensionality process (PSDP)
PSDR algorithm, 597. See also Progressive spectral dimensionality reduction (PSDR)
PSDR implementation, 610
PSDR via DP, 609. See also Dimensionality prioritization (DP)
p-SGA, 967. See also Simplex growing algorithms (SGAs)
p-signal projection matrix, 141, 142
p-successive replacement IN-FINDR (p-SC IN-FINDR), 221–222, 244. See also Iterative N-finder algorithm (IN-FINDR)
Pulse code modulation (PCM), 772, 774, 775.
See also Multistage pulse coding modulation (MPCM)
Purdue data classes, 694–699, 699–702
classification rates of, 675–677
Purdue data coding methods, DDA results by, 672–673
Pure mineral signatures, 309, 312
Pure/mixed-sample classifiers, 61, 62
Pure panel pixels, 299, 504–505. See also Pure pixel
panels
superimposed over background pixels, 301
Pure panel signatures, 632
Pure pixel–based 3D image compression techniques, 541
Pure pixel–based class-labeling classifier, 399
Pure pixel panels, 331–332. See also Pure panel pixels
Pure pixels, 21, 295, 296, 467, 526, 527, 531, 887
Pure pixel vectors, 887
Pure-sample classification, 45
Pure-sample target detection, 35–38
Pure signatures, 257, 531
Purest signatures, 299, 306, 309
Pure/subsample detectors, 61, 62
Pure target VSs, 505. See also Virtual signatures (VSs)
p values
determining, 484
determination of, 335–336
estimated by SSE, 335–336, 337
estimated by VD, 334, 335–336, 338
estimating, 340–341
p-vertex simplexes, 317, 339
Pyramid example, 904
Pyramid method, 882
QR decomposition, 175
Quantification algorithms, 828
Quantification analysis, for performance evaluation, 463
Quantification errors, 512–513
Quantification least-squares error (QLSE), 939–941
Quantification values, graphical plots of, 429
Quantitative analysis, 403, 404, 409
of classification performance, 445
Quantitative MR imaging, 878. See also Magnetic resonance (MR) entries
Quantization levels, 774, 775, 777
Quantization results, 774
Quantized values, 742
Quantizers, 774–775

Radial basis function (RBF), 943–944. See also RBF kernels
Radial basis function (RBF) neural networks, 435
Radiance data, 324–325
real images with, 327–328
Radiance data–based synthetic images, 324
Radiance spectra
of background signatures, 335
of real images, 334
Random algorithms, 287–288
PPI as, 314
Random EEA (REEA), 12. See also Endmember extraction algorithms (EEAs)
Random endmember extraction algorithms (REEAs), 186, 203–204, 205, 206, 287–315, 316, 318, 968
categorization of, 204
computing time needed by, 299
in extracting endmembers, 305, 315
performance of, 293
Random generators, 313, 320
Random ICA–based EEA (RICA–EEA), 292–293. See also Independent component analysis (ICA) entries
Random ICA-DR (RICA-DR, ICA-DR2), 169, 186, 188, 189–190, 192, 292, 596. See also Dimensionality reduction (DR) algorithms/MATLAB codes for, 1005, 1008–1009
Random IN-FINDR (RIN-FINDR), 292, 296–297, 315. See also Iterative N-FINDR (IN-FINDR) computing time and iterations of, 301, 305, 312 results of, 297, 300, 302, 304, 306, 307, 311 using two different thresholds, 309
Random initial condition issues, 268–271
Random initial conditions, 313, 329. See also Randomly generated initial conditions
Random initial endmembers, 202, 203, 212, 271, 274, 287, 289, 313, 316, 322, 325, 328. See also Randomly generated initial endmembers
Random initial projection vectors, 929, 930, 931. See also Randomly generated projection vectors; Random projection vectors
Random initial projection unit vectors, use by FastICA, 186
Randomized decision, 67
Randomized decision rule, 37
Randomized detector, 37, 65
Randomly generated Gaussian vector, 321
Randomly generated initial conditions, 283, 284
Randomly generated initial endmembers, 265
Randomly generated projection vectors, 590. See also Random projection vectors
Randomly generated skewers, 289
Randomly selected data sample vectors, 265
Random N-FINDR (RN-FINDR), 288, 290–292, 296–297, 314, 966. See also N-finder (N-FINDR) algorithm in AVIRIS experiments, 310–313
computing time and iterations of, 299, 301, 303, 305, 313
disadvantage of, 291
in HYDICE experiments, 306–309
Random noise corruption, 867
Random PCs, finding, 593. See also Principal components (PCs)
Random p initial endmembers, 292
Random PPI (RPPI), 288–290, 313–314. See also Pixel purity index (PPI) entries; RPPI entries advantages of, 290
in AVIRIS experiments, 309–310
computing time and iterations of, 296, 310
in HYDICE experiments, 306, 307
Random projection index–based projection pursuit (RPI-PP, R-PIPP), 191, 192–193. See also Projection index–based projection pursuit (PIPP)
Random projection vectors, 272, 292–293
Random projector, 254
Random SC N-FINDR (RSC N-FINDR), 292, 296–297, 309, 315. See also SuCcessive N-FINDR (SC N-FINDR) computing time and iterations of, 299, 301, 303, 305, 312
results of, 297, 298, 300, 304, 306, 308, 311
using two different thresholds, 309
Random SGA (RSGA), 288, 292. See also RSGA entries; Simplex growing algorithms (SGAs)
Random SQ N-FINDR (RSQ N-FINDR), 292. See also SeQuential N-FINDR (SQ N-FINDR)
Random unit vectors, 210, 211
Random variable concept, 287. See also Gaussian random variables
Random variables, Gaussian, 322
Random VCA (RVCA), 288, 290. See also Vertex component analysis (VCA)
Ranked band sets, 803, 804
Rayleigh’s quotient, 46, 360, 391, 393
Fisher’s, 361–362, 391, 393
RBF kernels, 445, 449–451, 457, 980–981. See also
Radial basis function (RBF) entries
kernel-based LSMA using, 452
KFCLS using, 448, 451
KLSOSP using, 446, 449
KNCLS using, 447, 450
mixed pixel classification and, 451
Real data, generating a 3D ROC curve for, 75–76
Real data–based ROC analysis, 72–78. See also
Three-dimensional receiver operating
characteristics (3D ROC) analysis
Real data experiments, 852–857
Real error (RE), 127, 129–130, 165
Real hyperspectral image experiments, 258–262,
725, 730–739
Real hyperspectral images, virtual dimensionality
estimated for, 155–163, 164, 165
Real image experiments, 281–282, 305–313,
325–329, 398, 402–409, 426–432, 503–517,
534–539, 567–580, 598–608, 764–771,
871–875
guidelines for, 338
Real image hyperspectral experiments, 790–796
Real image pixels, 577–578
Real images
with radiance data, 327–328
radiance spectra of, 334
with reflectance data, 328
reflectance spectra of, 333
Realizations, 288
Real MR brain image experiments, 951–954.
See also Magnetic resonance (MR) entries
Real MR images, classification results of, 951, 952,
953, 954
Real-time causal processing, 991
Real-time N-FINDR processing, 966
Real time process algorithms, 977
Real-time processing, 821, 975, 988, 990
Real-to-complex analysis, 4
Real-valued functions, 29
Receiver operating characteristics (ROC), 10.
See also ROC curves; Three-dimensional receiver operating characteristics (3D ROC)
analysis; Three-dimensional (3D) ROC curves;
Two-dimensional (2D) ROC curves
Receiver operating characteristics (ROC) analysis,
10, 41, 63–100, 925. See also Three-dimen-
sional receiver operating characteristics (3D ROC) analysis
real data–based, 72–78
traditional, 72
uses for, 63
Reconstructed signature, 865
Reduce-and-expand operations, 583
Redundant spectral information, 801
References, choosing, 872
Reference signatures, 667, 747, 766
selection of, 819
Reference signature vectors, 752–754, 760, 768, 771,
800, 801–802, 808, 810, 814–815
for OSP-BPC, 813
selecting, 758
Reflectance cuprite data, 670–672
Reflectance cuprite data coding methods, DDA
results by, 670–672
Reflectance Cuprite data scene, 688
Reflectance data, 323–324, 327, 336
real images with, 328
Reflectance data–based synthetic images, 324
Reflectance spectra, 104, 367, 528
of background signatures, 333
KFSSE-estimated, 832
of a real image, 333
Relative entropy, 472
Relative spectral discriminatory probabilities
(RSDPB), 544, 665
Relative spectral discriminatory power (RSDPW),
747, 748, 749, 750, 758, 759, 808–809.
See also Discrimination power (DP); RSDPW
entries
Remotely sensed data samples, 719
Remote sensing, 859, 920
applications of, 989
Remote sensing data, early data processing for,
984
Remote sensing image analysis, 821
Kalman filters and, 821
Remote sensing image classification, 225
linear spectral mixture analysis in, 921
Remote sensing image processing, 467
Remote sensing image processing techniques, 974
Remote sensing images, 898
Remote Sensing Signal and Image Processing
Laboratory (RSSIPL), xxiii
algorithms developed in, 2, 997
Remove-before-extract strategy, in AMEE, 533
Repeatability experiments, 10
Repetition time (TR), 930
Replacement rule, 217, 218
Reproducing kernel theory, 58
Rescaled discrimination, 808
RICA-EEA algorithm, 293. See also Random ICA
entries
Right singular vector matrix, 175
“Right” vectors, 319
Risk, averaged, 97
Risk function, 37
RN-FINDR algorithm, 291–292. See also Random N-FINDR (RN-FINDR)
ROC curves, 10, 38, 63, 64, 68–69, 70, 71, 936, 937, 938–939, 940, 944, 945, 946, 947, 949.
See also Receiver operating characteristics (ROC); Three-dimensional (3D) ROC curves; Two-dimensional (2D) ROC curves
Gaussian-fitted, 73–74
generating from real data, 72–73
R panel pixels
abundance fraction results of, 427–429, 431, 432
identification errors of, 477–478
R-PIPP algorithm, 192–193. See also Projection index–based projection pursuit (PIPP)
R pixel vectors, 887, 890–891
abundance fractions of, 891
abundance fraction estimates of, 889–890, 891
RPPI, 204. See also Random PPI (RPPI)
RPPI algorithm, 289–290
RPPI experiments, 293–296
RSDPW curves, 811. See also Relative spectral discriminatory power (RSDPW)
RSDPW values, 750–751, 759–760, 761, 762, 764, 765, 766, 767, 768, 769, 808, 809, 810, 812, 813, 814, 815, 816, 817, 818
comparative graphical plots of, 759, 763, 764, 765, 770
for HD-SDFC and AVD-SDFC, 752
RSGA algorithm, 292, 296–297, 309. See also Random SGA
computing time and iterations of, 299, 301, 303, 305, 312, 313
results of, 297, 298, 301, 303, 305, 306, 308, 312
RVCA algorithm, 290. See also Random VCA (RVCA); Vertex component analysis (VCA)
RX algorithm, 358, 528, 531, 535, 536, 538, 539
pixel extraction using, 533, 534
RX-anomaly detection algorithm, 539
RXD-based detectors, 975–977. See also RX detector (RXD, \(\delta^{RXD}\))
RXD-based matched filter distance (MFD\(_{RX}\)), 475, 476
RXD detection algorithm, 352
anomaly detection by, 122–123
RX detector (RXD, \(\delta^{RXD}\)), 384–385, 386–390, 474, 475, 482, 518, 902, 972, 975–977, 980, 988.
See also RXD entries
RXDF, 976, 977
RX filter, 537
SAM-based spectral similarity values, 539. See also Spectral angle mapper (SAM)
Sample band correlation matrix, 623
Sample correlation/covariance matrix, 174, 175, 482
Sample correlation information, 482
Sample correlation matrix, 44. See also Sample correlation spectral matrix (R)
Sample correlation matrix–calculated eigenvalues, 957–958
Sample correlation spectral matrix (R), 414, 415
Sample covariance matrix, 44, 977. See also Sample covariance spectral matrix (K); Sample data covariance matrix
ways of calculating, 600
Sample covariance matrix–calculated eigenvalue, 957–958
Sample covariance spectral matrix (K), 414
Sample data covariance matrix, 178
Sample intra-pixel IBSI, 466. See also Interband spectral information (IBSI)
Sample means, 152, 336
of data sample vectors, 273–274
Sample mean vector (\(\mu\)), 141, 251
Sample pools, 75–76
number of samples in, 76
Sample spectral correlation, 470, 907
FDE by classification using, 907–908
Sample spectral correlation matrix, 29
Sample spectral covariance/correlation matrix, 470
Sample spectral covariance matrix, 29
Sample spectral statistics, 138, 466
Sample vectors, 978, 979
SAM values, 807, 808, 809, 837, 847, 875. See also Spectral angle mapper (SAM)
for subpixel panel identification, 874
Satellite data communication, 718
Satellite Pour l’Observation de la Terra (SPOT) system, 909. See also SPOT data
\(S^{BK}\) signatures, 484, 485, 490
Scalar parameter estimate, 363
Scaling constants, 40, 43, 55, 362, 374
Scaling function, 859, 860, 861
Scatter matrices, 46, 47, 360, 361, 908
Schwarz’s inequality, 42, 359
Score function, 53–54
SDFC-based measures, performance of, 754.
See also Spectral derivative feature coding (SDFC)
Search processes, limiting, 222. See also Exhaustive searches
Secondary data, background knowledge from, 39
Secondary set of eigenvalues, 129
Second-order BP criteria, 693. See also Band prioritization (BP)

Second-order coding methods, 771

Second-order component analysis (CA)-based criteria, 209. See also Component(s) analysis (CA) entries

Second-order data statistics, 347–348

Second-order hyperspectral measures, 477

Second-order IBSI, 466, 467. See also Interband spectral information (IBSI)

Second-order spectral measures, 470

Second-order spectral statistics–based approaches, developing, 960

Second-order spectral statistics–based HFC methods, 959–961. See also Harsanyi–Farraud–Chang (HFC) method

Second-order spectral targets, 485

Second-order-statistical spectral band images, 901

Second-order-statistical spectral bands, 899–900

Second-order-statistic BPC, 674. See also BP criteria (BPCs); Second-order statistics–based BPC

Second-order statistics, 209, 959, 978

Second-order statistics–based criteria, 615

Second-order statistics–based endmember extraction, 229–230, 280

Second-order statistics–based SQ-EEAs, 248. See also Sequential endmember extraction algorithms (SQ-EEAs)

Second-order statistics–based transform, 959. See also Second-order statistics transform

Second-order statistics band prioritization criteria, 662

Second-order statistics methods, 975

Second-order statistics transform, 554. See also Second-order statistics–based transform

Security, convenience, threshold, and cost relationship, 98–99

“Seeing-is-believing” concept, 1

Segmentation, 920–921

Segmentation algorithms, 921

Self-classification

mixed-pixel, 871

signature, 870–871

Self-correction, 872, 873

Self-denosing, signature, 869–870

Self-discrimination, signature, 867–868, 870–871

Self-identification

signature, 870–871

subpixel, 871

using WSCA-SSC, 873–875

Self-information, 667–668

Self-tuning, signature, 869–870

Sensitivity, 83

Sensor data, acquiring, 799

Sequential backward processes, PSDR as, 598

Sequential backward selection (SBS), 598, 655

Sequential band dimensionality expansion (SBDE), 656

Sequential band dimensionality reduction (SBDR), 656

Sequential endmember extraction algorithms (SQ-EEAs), 12, 202, 204, 205, 206, 207–208, 222, 230, 234, 241–264, 255–258, 271, 274–275, 286, 298, 316, 318, 968. See also Endmember extraction algorithms (EEAs);


converting SM-EEAs into, 242

design criteria for, 264

design criteria for, 264

endmember numbers and, 264

linear spectral mixture analysis–based, 248–251

in sequential endmember generation, 258–259

types of, 242–244

Sequential forward processes, PSDE as, 598

Sequential forward selection (SFS), 598, 655

Sequential image processing, 656

SeQuential N-FINDR (SQ N-FINDR), 241, 255, 318, 966, 968. See also Random SQ N-FINDR (RSQ N-FINDR)

Sequential PCA (SQ-PCA), 591, 593–595. See also Principal components analysis (PCA)

advantages of, 596

Sequential process, 544

progressive process vs., 655–656

Sequential processing, 990

Sequential searches, 266

Set partition, 722

Set partitioning in hierarchical trees (SPIHT), 558. See also SPIHT entries; 3D-SPIHT entries

SFBC binary code word, 744. See also Spectral feature–based binary coding (SFBC); Spectral feature binary coding (SFBC)

SFBC methods, 725

SFPC encoding algorithm, 756. See also Spectral feature probabilistic coding (SFPC)
SFPC measure, 756–757
SGA performance, 336–337. See also Simplex
growing algorithms (SGAs)
Shannon coding, 666, 670, 672–673, 678, 679–681
Shannon coding–based DDA, 667–668. See also
Dynamic dimensionality allocation (DDA)
Shannon–Fano coding, 720, 722
SID-generated spectral similarity values, 817.
See also Spectral information divergence (SID)
SID-measured spectral similarity values, 811–812
SID ratio, 815
SID-SAM mixed measures, 472, 477. See also
Spectral angle mapper (SAM)
SID values, 807, 808, 809, 810, 811–812, 813, 814,
815, 816, 817, 818, 837, 847
Sigma u. See Standard deviation of measurement
noise (\sigma_u)
Sigmoid function kernel, 980
Sigmoid kernels, 452, 454–460
Signal-background-noise (SBN) model, 39, 77, 81,
82, 83, 84, 89
Signal characterization, 717
Signal class, 127, 131
Signal classification, 70
Signal classification problems, 65
Signal coding, 16–17, 717, 986
 hyperspectral, 9, 717–718
types of, 9
Signal-decomposed interference-annihilated (SDIA)
model, 417
Signal-decomposed interference/noise (SDIN)
model, 39, 77, 81, 83, 84, 85, 89
Signal detectability, 356
deterioration of, 380
Signal detected sample pool, 75
Signal detection, 65, 70, 109, 414
 in the noise model, 359
 primary task in, 362
 standard model for, 358
Signal detection approach, 357
Signal detection in noise (SN) model, 77
Signal detection model(s), 964
 applying, 38–39
 OSP-model as, 365
 simulating, 101
Signal detection performance, 971
Signal detection perspective, 361, 412
derived from (d,U)-model and OSP model,
359–360
Signal detection problems, 36, 109
Signal detection techniques, effectiveness of, 111
Signal detection theory, 38, 67
Signal detector in Gaussian noise, in OSP-model,
365–366
Signal estimation, 986–987
Signal function, 864
Signal identification, 797
Signal models, 359
Signal/noise detection model, 503
Signal processing
 continuous, 717
discrete, 717
 hyperspectral, 7
Signal processing perspectives, 357
Signal processing techniques, xxiii, 128
Signal profile, 70
Signals
 3D ROC curves for, 93–99, 100
ticket samples of, 91–92, 93
Signal samples, MPCM-encoded, 782
Signal sensitivity, analysis of, 94
Signal source distinction, 131
Signal sources, 124, 127, 135, 137, 140–141, 929,
964. See also Spectral signal sources
 estimating number of, 126–127
Signal source separation, mixing matrix for, 930
Signal sources/signatures, number of, 163–164
Signal source vectors, 185
 uncorrelated, 185
Signal subspace, 41–42
Signal subspace estimation (SSE), 142–144, 149,
See also SSE/HySime-estimated values
values estimated by, 336, 340
Signal subspace projector, 56
Signal-to-clutter ratio (SCR), 42
Signal-to-noise ratio (SNR), 43, 107, 176, 177,
178–179, 352, 357, 359–360, 368, 369, 370,
371, 386, 490–491, 542, 547, 624, 625, 637,
650, 651, 652, 657, 675–677, 689, 690, 692,
694–699, 699–702, 703–706, 707–712,
713–714, 786, 971. See also SNR entries
anomaly detection and, 387
dimension members extracted by IN-FINDR corresponding
to, 632, 633, 643, 645, 649, 653–654
in hyperspectral imagery, 365
UFCLS-mixed panel results corresponding to,
638, 647
UFCLS-mixed panel results produced by, 627
used for compression, 570, 580
Signal-to-noise-ratio–based BPC, 618. See also BP
criteria (BPCs)
Signal-to-noise ratio (SNR)-based components
analysis transforms, 176–179
Signal-to-noise ratio (SNR)-based maximum noise fraction (MNF), 168. See also Maximum noise fraction (MNF) entries

Signal-to-noise ratio (SNR)-derived orthogonal subspace projection (OSP), 352

Signature(s), 29. See also Background (BKG) signatures; Component spectral signatures; Chemical/infrared data signatures; Panel signatures; Signal sources/signatures; Spectrally distinct signatures; Spectral signature entries; Target signature matrices; Virtual signatures (VSs)
alunite, 312
calcite, 112, 152
contaminated, 736
developing algorithms to extract, 485
differing thresholds for, 752
finding, 974
finding a set of p, 484
finding categories of, 485
mineral, 112, 113, 114, 144, 146
muscovite, 114
noise-corrupted, 790
pure, 257
pure panel, 632
purest, 299, 306, 309
reference, 747, 766
separating, 511
spectrally distinct, 429, 957, 958, 974
spectra of, 382
undesired, 460
Signature accommodation, 667
Signature analysis, impact of BS on, 810
Signature-based measures, 465
Signature-based spectral similarity measures, 466
Signature characterization, hyperspectral, 9
Signature classification, 746, 748–749, 867–868
Signature classification/identification, 809–811, 814–815
Signature coding, 9, 771
Signature corruption, 111
Signature detection, five-panel, 79–80
Signature discrimination, 665, 746, 747, 750–751, 804, 805, 806–809, 813–814
between signatures with different band numbers, 816–818
Signature discrimination performance, 815
Signature discriminatory probabilities, 667
Signature finding, 518
Signature identification, 867–868
Signature knowledge
accurate, 973–974
obtaining desired, 483–484
Signature matrix, 427, 432, 492, 524, 983–984
desired, 422–424
undesired target, 356
undesired, 417
Signature self-correction (SSC), 863
Signature self-discrimination/classification/identification, 867–868
Signature self-discrimination/self-classification/self-identification, 870–871
Signature self-tuning (SST), 863
Signature self-tuning/self-denoising, 869–870
Signature subspace projection (SSP), 492
Signature subspace projection (SSP) matrix, 413
Signature subspace projector (SSP, PM), 418
Signature suppression, 378
Signature variance, 138
Signature vector–based hyperspectral measures, 482
classification resulting from, 479
for target discrimination/identification, 470–472
Signature vector–based spectral measures, 470–471, 472, 469
Signature vector–based spectral similarity measures, 469
Signature vector–based techniques, 831
KFSCSP techniques as, 842, 843
Signature vector behavior, 728
Signature vector coding methods, 741
Signature vector estimators, 825
Signature vectors, 16, 29, 719, 729, 730, 741, 758, 783, 822. See also Mixed signature vectors; Panel signature vectors
abundance fractions of, 850
auxiliary, 827
averaged, 813, 815
correlation associated with, 819
decomposing hyperspectral, 801, 802
discrimination among, 747, 788
distance measure between, 784
of gas data set, 753
hyperspectral, 9, 799
matching, 827, 833, 858
M-stage thresholds for, 785
multispectral, 9
observable, 827, 829
quantification results of, 850
reference, 752–754, 760, 768, 771, 800, 801–802, 808, 810, 813, 814–815
relative discrimination among, 807–808
selecting reference, 758
Signature vectors (Continued)
spectral, 29, 721, 742, 760, 806, 985
spectral similarity among, 837
subset of, 752
target, 785, 789, 801, 825–826, 827, 829, 833, 837, 839, 858
true, 841
Signature vector similarity, measuring, 784
Signature verification/identification, 482
Similarity values, 739
obtained by subpixel panel comparison, 855
Simplex-based EEAs, 202. See also Endmember extraction algorithms (EEAs)
Simplex-based methods, 323
Simplex-based SGA, 968. See also Simplex growing algorithms (SGAs)
Simplexes
formed by extracted endmembers, 344
growing, 245–247
algorithm/MATLAB codes for, 1015, 1023–1025
in conjunction with ICA, 338endmember pixels extracted by, 237
panel pixels extracted by, 337
pixels extracted by, 342, 343
results of, 297, 298, 300, 302, 304, 306, 308, 310, 312, 331
SC N-FINDR vs., 245–247
simplex volumes and, 343, 344, 345, 346, 347, 348
VCA vs., 247, 330–338
Simplex inflation process, 215
Simplex volume(s), 208–209, 214, 329, 518
calculating, 342, 343
as EEA design criteria, 330
in endmember extraction, 202
minimal, 214–215
Simulated abundance fractions, 332–333
Simulated background signature, 333
Simulated panel composition, 578
Simulated panels, 332–334
Simulated pixel vectors, 386
Simulated subpixel target panels, 843, 846
Simulated synthetic scene, endmembers in, 336
Simultaneous endmember extraction algorithms (SM-EEAs), 12, 202, 204, 205, 206, 230, 207–240, 266, 286, 271, 278, 288, 316, 317–318, 968. See also Endmember extraction algorithms (EEAs)
converting into SQ-EEAs, 242
design criteria for, 240
drawbacks of, 239–240
EIAs for, 274–275
endmember initialization algorithms for, 274–275
endmember pixels extracted by, 237
implementing, 262–263
performance analysis studies of, 231–239
SQ-EEAs vs., 241–242
Simultaneous N-FINDR (SM-NFINDR), 215, 216, 222, 223, 240, 243. See also N-finder (N-FINDR) algorithm
flow chart of, 217
Simultaneous PCA (SM-PCA), 591–592. See also Principal components analysis (PCA)
PG-PCA vs., 592
s-IN-FINDR algorithm, 967. See also Iterative N-finder algorithm (IN-FINDR)
Single-background signature, 427–429
Single background synthetic image experiment, 562–564
Single desired-signal source (d) detection, in the noise model, 359
Single pixel panels, abundance fractions of, 564
Single-replacement IN-FINDR (1-IN-FINDR), 218–219, 223. See also Iterative N-finder algorithm (IN-FINDR)
Single signature vector–based spectral measures, 470
p values estimated by, 340–341
Singular vector matrices, 175
Sixth moment, 182
Skewer number, impact of, 214
as basis vectors, 316
finding appropriate, 282
Gaussian, 319, 320
randomly generated, 289
endmembers extracted by IN-FINDR corresponding to, 632, 633, 643, 645, 649, 653–654
equations of, 586
third-order statistics–based, 181
UFCLS-mixed panel results corresponding to, 639, 647
UFCLS-mixed panel results produced by, 628
Skewness-EEA, 255, 256, 257, 258, 259, 260, 261, 262, 263, 264. See also Endmember extraction algorithms (EEAs); Third-order statistics–based SQ-EEA
Skewness transform, 184
Slack variables, 52–53, 59, 979
SLSMA/CA-ULSMA comparative analysis, 501. See also Component analysis–based ULSMA (CA-ULSMA); Linear spectral mixture analysis (LSMA); Supervised LSMA (LSMA); Unsupervised LSMA (ULSMA)
SLSMA using OSP, 352
SNR-based OSP, 391. See also Signal-to-noise ratio (SNR)
SNR level, 785
SNR values, 564, 565, 566, 567, 812
“Soft” coding, 773
Soft-decision classification, 445
Soft decision–made classifiers, 60
Soft decisions, 33, 45
basis of, 39
classification with, 54–57, 62
detectors with, 35
Soft quantization, 775
Soft quantizers, 775
Soft target detector, 44
Software algorithms, 922
Source alphabet probabilities, 665
Source alphabets, 665–666
dummy, 900–901
Source alphabet set, 722
Source coding, 665–666
Source separation–based OC-ICA, for MR image analysis, 930–931. See also Independent component analysis (ICA) entries; Overcomplete ICA (OC-ICA)
Space-based vector parameter estimation methods, 364
SPAM-based binary coding methods, 725. See also Spectral analysis manager (SPAM)
SPAM binary coding, 717, 719–720, 720–721, 741
extended, 723
Spatial analysis, “class-map/pattern”–based, 503
Spatial-based pattern classification techniques, 8
Spatial compression, 15, 541, 549–557
Spatial compression techniques, 548
Spatial domain analysis, 355
Spatial domain–based data analysis, 984
Spatial domain–based image processing techniques, 484
Spatial domain–based literal analysis, 7
Spatial domain–based methods, 974
Spatial domain–based multispectral imaging techniques, 355–356
Spatial domain–based techniques, 3–4, 963
Spatial image compression, 542
Spatial information, AMEE-related, 539
Spatial properties, 484
Spatial/spectral correlation, 209
Spatial targets, 466, 484
Specificity, 83
Spectra, steps in producing, 22
Spectra, target-based, 503
Spectral analysis manager (SPAM), 717, 719, 725, 726, 727, 728, 729, 730, 731, 732, 733–735, 736–738, 739, 740, 747, 748, 749, 750, 751, 753, 754, 758, 759, 760, 761, 762, 763, 764, 765, 766, 767, 768, 769, 770, 771, 986. See also SPAM entries
as an encoder, 742
improving performance of, 742
reinterpretation of, 743–744
Spectral angle mapper (SAM), 14, 22, 26, 152, 188, 231, 270, 275, 290, 312, 422, 431, 465, 469, 470–471, 472, 476, 477, 482, 593, 667, 670, 674, 684, 736, 753, 852, 854. See also SAM values
events made by, 854–856
extracted pixels measured by, 309
performance of, 875
RSDPW values of, 809
threshold used for, 432
Spectral band, priority score of, 621
Spectral band images, 621, 901, 902
auto-correlated, 902
cross-correlated, 901, 902
second-order-statistical, 901
of SPOT data, 909
Spectral band image vectors, 621, 622
Spectral bands, 5, 6, 624, 651, 683, 688, 877, 957
adding, 655
contiguous, 356
effective use of, 356
highest-prioritized, 625
interpreting, 615
Spectral bands (*Continued*)

reducing the number of, 654
signal energies of, 111
Spectral band selection/ranking, 652
Spectral band-to-band correlation, 800
Spectral binary coding methods, 741
Spectral channels, 772, 799–800, 897
Spectral channels/bands, number of, 898
Spectral characteristics, 470
Spectral characterization, 6, 9, 772, 857–858
VNVBS for, 818
Spectral compression, 15, 541, 542–543, 549–557
transform-based, 550–556
Spectral compression criterion, 550
Spectral compression techniques, 548
Spectral correlation, 470
whitened, 374
Spectral correlation matrix, 29
Spectral covariance matrix, 29
Spectral data, applying binary coding to, 719
Spectral de-correlation, 551
Spectral derivative feature coding (SDFC), 717–718, 741, 743–755, 764–766, 986
development of, 742, 744–746
performance of, 764, 766, 771
Spectral deviation, 728
Spectral deviation from EPP (EPPD), 724. *See also* Equal probability partition (EPP) binary coding
Spectral dimensionality, 539. *See also* Spectral dimensions of a remotely sensed data set, 125
Spectral dimensionality processing, 589–596
Spectral dimensionality reduction, 552, 547–548, 549, 550
Spectral dimension/bands, 665, 666, 668, 669
Spectral dimensions, 624, 651. *See also* Spectral dimensionality prioritizing, 544
priority scores for, 582
Spectral discriminatory probabilities, 665
Spectral discrimination, 730, 784–785, 790–791
using MPCM-PSSC, 786–788
Spectral discrimination capability, 808
Spectral distance measures, 729
results of, 730
Spectral feature–based coding, 723–725
Spectral feature binary coding (SFBC), 741, 747, 748, 749, 750, 751, 753, 754, 758, 759, 760, 761, 762, 763, 764, 765, 766, 767, 768, 769, 770, 771, 986. *See also* Spectral feature–based binary coding (SFBC)
as an encoder, 742
improving performance of, 742
reinterpretation of, 743–744
Spectral feature characterization, 819
as an arbitrary-bit encoder, 771
development of, 756–758
as a discrimination measure, 757–758
generalization capability of, 759–760
with higher bit rates, 763–764
performance of, 768, 770–771
Spectral features, characterizing, 772
Spectral halfway partition deviation (HPD), 724. *See also* Halfway partition deviation (HPD)
Spectral identification, 730, 785–786, 788–790, 791–796
binary coding in, 729, 733–736
for a mixed signature, 789–790
Spectral identification algorithms, 785–786, 791
Spectral identification process, progressive, 789
Spectral information, 138, 484, 547
accomplishments of, 772
advantages of, 4
exploring, 717
pixel-level, 356
redundant, 801
as a BD criterion, 691
errors made by, 854–856
infinite-order statistics–based BPCs and, 619
RSDPW values of, 809
spectral similarity values of, 813, 815
Spectral library, 101, 785, 788, 819
Spectral library/database, 469
“Spectrally” distinct hyperspectral data, HFC vs. PCA methods and, 139
Spectrally distinct signatures, 232, 235, 272, 405, 429, 596, 603, 665, 668, 958, 974
defining, 957
number of, 124
Spectral matched filter, normalized, 374
Spectral mean deviation (MD), 744
Spectral measure–based band de-correlation, 684–685
See also Band de-correlation (BD)
Spectral measures
discriminatory power of, 807
signature vector–based, 469
single signature vector–based, 470
Spectral processing, 955
Spectral profile information, 15
Spectral profiles, 773, 796, 806, 812. See also Spectral signature profiles
Spectral properties, 126
Spectral quantification, 825, 828
Spectral redundancy, in 3D cube compression, 550
Spectral resolution, 168, 877
improved, 201, 503
Spectral sample correlation, 617
Spectral signal sources, number of, 142
Spectral signature characterization, 821
Spectral signature coding (SSC), 741, 772
applications of, 772–773
applying MPCM to, 778
arithmetic coding in, 742–743
PSSC and, 773
Spectral signature identification, 826–828
Spectral signature matrix, 358
Spectral signature mean deviation (MD), 723, 725, 726, 727, 728, 729, 730, 731, 732, 733–735, 736–738, 739
Spectral signature median, 721
Spectral signature profiles, 809. See also Spectral signature profiles
Spectral signatures, 20, 21, 125, 293, 421, 530
of background signatures, 333, 334
binary coding for, 719–740
of chemical data, 787
of chemical/infrared data signatures, 21
discriminating, 805
five-panel, 28
KFSSE in estimating, 832
of pixels, 26, 527
progressive coding for, 772–796
progressive stage-by-stage decoded, 781
Spectral signature unmixing, 351
Spectral signature vectors, 29, 721, 742, 760, 806, 826, 985
characterizing, 800
discriminated by WSCA-SSC, 873
encoding in multiple stages, 772
progressive decomposition of, 774
Spectral similarity measuring, 292, 469, 696
among signature vectors, 837
Spectral similarity measures, 470, 804
signature vector–based, 469
Spectral similarity values, 747, 748, 749, 750, 751, 758, 762, 810
comparative plots of, 754, 759, 761, 763, 764, 766, 768, 769
comparative results of, 764, 766–767, 768, 769
SAM-based, 539
of SID, 813, 815, 817
Spectral/spatial compression, 549–557
mixed component analysis for, 570–576
3D-cube compression vs., 549–550
Spectral/spatial compression techniques, 580
Spectral statistics, 466
for designing EEAs, 209
Spectral targets, 466, 484, 485
high-order, 485
second-order, 485
Spectral unmixing, 32, 45, 159, 356, 362, 434–435, 501, 503, 519, 559, 626
FCLS method for, 603–604, 605–607
KLSMA and, 462
LSMA and, 664, 878
PBDP in, 660
Spectral unmixing applications, in hyperspectral imagery, 356
Spectral unmixing–based EEAs, 339
Spectral unmixing methods, 822
Spectral value, gradient changes in, 744–745
Spectral variability, 470. See also Spectral variation(s)
Spectral variation(s), 744–745
capturing subtle, 792
gradient changes in, 751–752, 771
progressive changes in, 773
subtle, 743
Spectral-varying system gain parameters, 827
Sphered data, 297, 298, 299, 300–301, 302, 303–305, 307–308, 309, 312, 314, 347, 349. See also Data
sphering
removing first- and second-order statistics in, 348
for RN-FINDR, 291
Sphering, whitening vs., 179–180
Sphering method, 179–181, 252, 253
SPICA-DR algorithm, 187–188. See also
Dimensionality reduction (DR); Prioritized ICA (PICA); Statistics-prioritized ICA-DR (SPICA-DR)
SPIHT (Set Partition in Hierarchical Tree) algorithms, 541, 550–551, 551–552, 558–559. See also Set partitioning in hierarchical trees (SPIHT); 3D-SPIHT entries; 2D-SPIHT entries

Split-SFPC (S-SFPC), 741, 757, 758, 759–760, 761, 762, 763, 764, 765, 766–768, 769, 770. See also Spectral feature probabilistic coding (SFPC)

performance of, 770, 771

SPM 5/8 algorithm, 922

SPOT data. See also Satellite Pour l’Observation de la Terra (SPOT) system
spectral band images of, 909
unmixed results of, 910–918

SPOT multispectral data, 3-band, 6

SQ-EEA–generated endmembers, 274. See also Sequential endmember extraction algorithms (SQ-EEAs)

SQ-EA performance, 261

SQ-PCA algorithm, 595. See also Principal components analysis (PCA); Sequential PCA (SQ-PCA)
s-replacement IN-FINDR (s-IN-FINDR), 220, 222. See also Iterative N-finder algorithm (IN-FINDR)

SSE estimates, 335–336, 337. See also Signal subspace estimation (SSE)

SSE/HySime-estimated values, 156–157, 158, 159, 160, 161, 166. See also Hyperspectral signal subspace identification by minimum error (HySime)
s-SGA, 967. See also Simplex growing algorithms (SGAs)

SSP-weighted AC-LSMA, 413, 418. See also Abundance-constrained LSMA (AC-LSMA)
s-successive replacement IN-FINDR (s-SC IN-FINDR), 221, 222, 244. See also Iterative N-finder algorithm (IN-FINDR)

Stage thresholds, 785, 788

for panel signatures, 790

Standard BS techniques, 818. See also Band selection (BS)

Standard detection theory, decisions in, 67

Standard deviation, of state noise, 826, 827, 835, 843

Standard deviation of measurement noise (\(\sigma_0\)), 837, 843

KFSSQ sensitivity to, 841–842, 850–852

KFSSQ vs. values of, 851–852

LSE relationship to, 847

Standardized data sets, for hyperspectral imaging algorithms, 123

Standardized PCA–based EEA (SPCA-EEA) algorithm, 228–230, 240, 252. See also Endmember extraction algorithms (EEAs); Principal components analysis (PCA); Standardized principal components analysis (SPCA)-EEA

nine endmembers extracted by, 229–230

Standardized principal components analysis (SPCA), 172–173, 183, 228

Standardized principal components analysis (SPCA)-EEA, 201, 204, 205, 209

\(S_{\text{target}}\) signatures, 484, 485. See also Target signature entries

State equation, 821, 822, 823, 825, 826, 828, 858

KFSSI use of, 854

modified, 825

remodeling, 826–827

State noise, 858

standard deviation of, 826, 827, 835, 843

Static dimensionality allocation (SDA), 666

Hamming coding for, 669

Statistical decision theory, 67

Statistical signal processing algorithms, designing, 919

Statistics
categorization of, 203

in endmember extraction, 202

high-order, 182–183

Statistics-based component transforms, 198–199

Statistics-based criteria, 187, 189

for endmember extraction, 202

Statistics-based EEAs, 201. See also Endmember extraction algorithms (EEAs)

Statistics-based techniques, 45

Statistics prioritized ICA-DR (SPICA-DR, ICA-DR1), 169, 186, 187–188, 189–190, 596. See also Dimensionality reduction (DR); Independent component analysis (ICA); Prioritized ICA (PICA)

algorithms/MATLAB codes for, 1005, 1007–1008

Stopping criterion (criteria), 184, 253, 266

Stopping rule, 227, 249, 251, 291, 615, 654, 655, 661

ATGP, 960–961

Structuring element (SE), 231

Subpanel pixels, 441

Subpixel analyses, 33, 580

Subpixel detection, 567, 879–880

Subpixel discrimination/identification, 736

Subpixel effects, on endmember extraction, 332

Subpixel identification, APDP values for, 736

Subpixel panel comparison, similarity values obtained by, 855
SVM-generated classifier, 46. See also Support vector machines (SVMs)

$S_W^{-1}$-weighted abundance fully constrained LSE problem, 417

$S_W^{-1}$-weighted abundance nonnegativity-constrained LSE problem, 416

$S_W^{-1}$-weighted abundance sum-to-one constrained LSE problem, 416

$S_W^{-1}$-weighted AC-LSMA, 422, 424, 425, 427, 431, 432. See also Abundance-constrained LSMA (AC-LSMA); Linear spectral mixture analysis (LSMA)

types of, 416–417

$S_W^{-1}$-weighted FCLS, 417. See also Fully constrained least-squares (FCLS) method

$S_W^{-1}$-weighted NCLS, 417. See also Nonnegativity constraint least-squares (NCLS) method

$S_W^{-1}$-weighted SCLS, 417. See also Sum-to-one constrained least-squares (SCLS) entries

Synthetic aperture radar (SAR)-ATR systems, 65

Synthetic image-based computer simulations, 419–426, 868–871

Synthetic image–based experiments, 1

importance of, 501–503

Synthetic image-based scenarios, 297–305


design of, 10, 101–123
goal of, 441

Synthetic images, 1, 102

benefits of using, 152–154

pixel information analysis via, 528–534

radiance data–based, 324

reflectance data–based, 324

simulated by radiance data, 324

standardized, 101

Synthetic image scenarios, 104–112

value of, 503

Synthetic linear image experiments, LSMA and KLSMA resulting images of, 442

Synthetic mixed-sample targets, simulation of, 104

Synthetic MR brain image experiments, 933–951.

See also Magnetic resonance entries

Synthetic MR images, of brain, 934

Synthetic subsample targets, simulation of, 103

System gain parameters, spectral-varying, 827s

System gain vectors, 825

Systolic arrays, 989

Target abundance–constrained classifiers, 401

Target abundance–constrained mixed pixel classification (TACMPC), 391, 392

Target analysis, 465–467

Target-based detection, 4

Target-based spectral analysis, 503

Target capture, 102

Target class–based image analysis, 5

Target classes, 506–508

Target classification, pattern classification vs., 8

Target-constrained interference-minimized filter (TCIMF, $\delta^{\text{TCIMF}}$), 45, 54, 56–57, 61, 62, 357, 377–379, 380–383, 396. See also TCIMF

entries


Target detection, 43–44, 110, 355

applications of, 17–18, 879–896

automatic, 18

CEM and, 118–122

hyperspectral, 79–80

subpixel, 114–122

unsupervised, 527, 796

Target detection applications, 114–122

Target detection/classification, 13

Target discrimination, 465, 975

signature vector–based hyperspectral measures for, 470–472

Target discrimination/identification, correlation-weighted hyperspectral measures for, 472–477.

See also Target identification

Target embeddedness (TE), 101, 102–103, 106, 255–258, 441


target panel pixels in, 499

Target estimation error, 896

Target identification, 469. See also Target discrimination/identification

signature vector–based hyperspectral measures for, 470–472

Target implantation (TI), 101, 105, 441


Target information, in OSP, 358

Target insertion, 101, 102–103

into image background, 101

Target knowledge, 35, 45, 356, 499, 902

Target mean, 47
Target panel pixels, 499
Target panels
  subpixel, 839, 852
  visible, 111
Target pixels, 321–322, 506–508, 791
  ATGP-generated, 407, 422, 431
  finding, 248
Target pixel vectors, 29, 792–796, 832–833
  excluding, 375
Targets, 29
  spectral characteristics of, 3–4
  spectrally distinct, 5–6
  subtle substance, 974
Target sample vectors, 273, 489
Target signal sources, 484, 957–958
  features of, 975
Target signature(s), 363, 364, 380, 485, 505, 525
  abundance fractions of, 894
  complete knowledge about, 372, 379
  constraining, 372
  desired, 356
  number of, 466
  partial knowledge about, 384
Target signature–constrained classifiers, 400
Target signature–constrained mixed pixel
classification (TSCMPC), 391, 392
Target signature discrimination, 482
Target signature matrices, desired and undesired,
  56, 377
Target signature substance estimates, 653
Target signature vectors, 785, 789, 825–826, 827, 829, 833, 837, 858
  desired and undesired, 801
  identifying, 839
  known, 839–840, 840–841, 849, 850
  unknown, 840, 841, 849
Target signature vector separation, 473
Targets of interest
  complete knowledge of, 380
  simulation of, 103–104
Target spectral signature matrix, 358
Target substances, complete prior knowledge of, 35
Target verification, 469
Target VS extraction, 491, 492. See also Virtual
  signatures (VSs)
Target VSSs, 491, 492, 503–505, 519
  extracting, 485–486
  high-order, 505
  pure, 505
TCIMF performance, 407. See also Target-
  constrained interference-minimized filter
  (TCIMF, $\delta^{TCIMF}$)
TCIMF scenarios, 382–383
Terminologies, 29–30
Ternary Huffman coding, 900
Texture feature coding method (TFCM),
  742, 744
Third central moment, 179
Third-order statistics, 932
Third-order statistics–based skewness, 181
Third-order statistics–based SQ-EEA, 252. See also
  Sequential endmember extraction algorithms
  (SQ-EEAs); Skewness-EEA
3-band SPOT multispectral data, 6
3-bit coders, 764
3-bit SFBC, 2-bit SPAM vs., 758. See also Spectral
  feature–based binary coding (SFBC); Spectral
  feature binary coding (SFBC)
3D compression, 547, 548–549
3D combinational curves, 98–99
3D combinational performance cost curve, 99
3D combinational performance ROC curve, 99.
  See also Three-dimensional (3D) ROC curves
3D compression, 552, 553–554, 557–559
3D compression techniques, 15. See also 3D-cube
  compression techniques; Three-dimensional
  (3D) image compression techniques
3D cost curve, 98
3D-cube compression, 549
  spectral redundancy in, 550
  spectral/spatial compression vs., 549–550
3D-cube compression techniques, 550, 557
3D de-compression, 552, 557
Three-dimensional (3D) image compression
  techniques, pure pixel–based, 541
Three-dimensional receiver operating characteristics
  (3D ROC), 10
  developing, 64–65
Three-dimensional receiver operating characteristics
  (3D ROC) analysis, 31, 63–100, 91, 443, 445,
  460, 463, 608, 920, 925, 936, 937, 938–939,
  940, 944, 945, 946, 947, 949, 970
  applications of, 78–83, 84, 85
  in chemical/biological agent detection, 91–95
  issues arising in, 69–72
  in magnetic resonance breast imaging, 83–87
  for performance evaluation, 89, 878
Three-dimensional (3D) ROC curves, 63, 65, 70, 71,
  79, 86, 87, 445, 449, 450, 451, 452, 453, 454,
  455, 456, 457, 458, 459, 460, 461, 462, 463,
  608, 936, 937, 938, 939, 940, 944, 945, 946,
  947, 949
  Gaussian fitted, 76
  generating, 75–77
Three-dimensional (3D) ROC curves (Continued) generating for multiple signal detection/classification, 77–78
for mean classification rates, 940
for performance evaluation, 94
for signals, 93–99, 100
3D lossy compression, 569
3D lossy compression techniques, 580
3D mean-ROC curve, 78. See also Three-dimensional (3D) ROC curves
3D Multicomponent JPEG, 557–558, 563, 564. See also JPEG2000 algorithms
3D-SPIHT (Set Partition in Hierarchical Tree) algorithm, 541, 550–551, 552. See also Set partitioning in hierarchical trees (SPIHT); SPIHT entries
3D-SPIHT compression, 558–559, 580
performance of, 563, 564, 566, 567, 568, 570
3D-SPIHT spatial compression, 561–562
3D techniques, 955
Three-source model, 357
Three-stage hyperspectral information compression, 545, 548
Three-stage spectral/spatial hyperspectral compression, 560, 561
Threshold (\(\tau\)), 64, 65, 67, 69–72, 299, 309. See also Concentration threshold
adjusting, 74
choosing, 72
fixed and same, 78
optimal, 74
as a parameter, 98–99, 100
role of costs in, 95–96
varying, 75
Thresholded binary images, 894, 895
Thresholding difference, between normalized correlation eigenvalues and normalized covariance eigenvalues, 128
Thresholding difference Gershgorin radii, 134–135
Thresholding energy percentage, 127–128
Thresholding Gershgorin radii, 134
Threshold values, 290, 299, 309, 399, 432
Ticket samples, of signals, 91–92, 93
Tiles, dividing images into, 558
Tissue classes, 933, 934
Tissue classification, 920–921, 923, 933–935, 935–936, 936–951
Tissue quantification, 955
Tissue signatures, prior knowledge of, 942
Tissues training sample regions, 934
\(t^{mix}\) mixed pixel vector, 810, 811, 812, 814, 815, 838–839, 840–841, 848, 849–850
Total error, 512, 513
Total scatter matrix, 397
Training data, 409
Training sample covariance matrix, 600
Training samples, 420, 431–432
for target classification, 466
Training sample vectors, 46
Transformations, kernelizing, 440
Transform-based spectral compression, dimensionality reduction by, 550–556
Transform coding methods, 550
Transforms
component analysis–based, 11
feature extraction–based, 11
Transform techniques, 168
Trial-and-error approach, to \textit{a posteriori} knowledge, 841
Trial-and-error estimation, 6
“True” decision, 64
True endmembers, 288, 289
True mineral signatures, 259
“True negative” (TN) decision, 64, 68
True-negative rate/probability, 73
True pixels, total number of, 78
“True positive” (TP) decision, 64, 68
True signature vector, 826, 841
2-bit coders, 764
2-bit SPAM, 3-bit SFBC vs., 758. See also Spectral analysis manager (SPAM)
Two-class classification problem, 48
2D compression technique, 551–553
2D de-compression, 553, 554, 556
2D discrete wavelet transform (DWT), 551
Two-dimensional (2D) degenerated simplex, 317
Two-dimensional (2D) image compression algorithms, 541
Two-dimensional (2D) image processing, 526
Two-dimensional receiver operating characteristics (2D ROC) analysis, 31, 936, 937, 938, 939, 940, 944, 945, 946, 947, 949
issues arising in, 70–72
traditional, 72
plots of areas under, 612, 706, 713–714
2D spatial compression, 549
2D spectral images, 85
2D-SPIHT (Set Partition in Hierarchical Tree) algorithm, 541, 552
2D-SPIHT compression, 558, 559
Two-pixel panels, 27–28
Two-replacement IN-FINDR (2-IN-FINDR), 219–220, 224. See also Iterative N-finder algorithm (IN-FINDR)
Two signal-source (d, U)-model, 359. See also (d, U)-model
Two-stage compression process, 15
Two-stage spectral/spatial hyperspectral compression, 560, 561
U, 380, 383. See also (d, U)-model; Undesired signature matrix (U); Undesired target signature matrix (U)
CEM implementation and, 375
d as orthogonal to, 374
undesired target signatures in, 372
UFCLS estimated abundance fractions, 579. See also Fully constrained least-squares (FCLS) method;
Unsupervised fully constrained least-squares (UFCLS) method
UFCLS-extracted pixels, 536
UFCLS-generated BKG/target VSs, 504. See also Background (BKG) entries; Virtual signatures (VSs)
UFCLS-generated target pixels, 508
UFCLS-mixed panel abundance fractional maps, 636
UFCLS-mixed panel results, 627–631, 638–642, 647–648
UFCLS-mixed pixel classification, 575, 626
UFCLS-unmixed abundance fractions, 569
UFCLS-UVSFA, 512, 513. See also Unsupervised virtual signature finding algorithms (UVSFAs)
target VSs extracted by, 491, 492, 494, 496
ULSMA performance, 511. See also Linear spectral mixture analysis (LSMA); Unsupervised LSMA (ULSMA)
UNCLS-generated BKG/target VSs, 504. See also Nonnegativity constraint least-squares (NCLS) method
UNCLS-generated target pixels, 507
Unconstrained-abundance least-squares algorithm, 248
Unconstrained LSMA, 926–927. See also Linear spectral mixture analysis (LSMA)
Unconstrained LSMA methods, 955
Unconstrained LSOSP, 420, 422, 424, 425, 427, 428, 431, 432. See also Least-squares-based orthogonal subspace projection (LSOSP)
Unconstrained spectral unmixing method, 114
Uncorrelated noise, 364
Uncorrelated signal source vector, 185
Under-complete ICA (UC-ICA), 18, 898–899, 929, 930, 931, 957. See also Independent component analysis (ICA) entries
Under-complete linear spectral mixture analysis (UC-LSMA), 898, 899
Under-complete LSMA, 957. See also Linear spectral mixture analysis (LSMA)
Undesired signal matrix, 55
Undesired signal source annihilator, 972
Undesired signature annihilation, 378
Undesired signature annihilator, 384, 475
Undesired signature matrix (U), 473. See also U
Undesired signature projector, CEM implementation and, 375–376, 376–377
Undesired signature rejection matrix, 412–413
Undesired signatures, 460. See also Undesired target signatures
performance and, 379
Undesired target signature matrix (U), 56, 356, 377, 378. See also U
Undesired target signatures, 372, 384
Undesired target signature vectors, 801 eliminating, 801
Unified kernel theory, 436
Uniformly most powerful (UMP) detector, 41
Uniform random variables, 272
Uniform target detector (UTD, δUTD), 384
Unitary matrices, 174
Unit (unity) vectors, 225 random, 210, 211
Unknown concealed targets, detecting, 18
Unknown interferers, 56
Unmixed abundance fractions, 420, 445, 512–517, 520
of HYDICE data panel pixels, 679–681, 703–706
Unmixed error, 225
Unstructured noise, 43
Unsupervised algorithms, 357
Unsupervised background knowledge, 429–432
Unsupervised classification, 980
Unsupervised FLSMA (UFLSMA), 410. See also Fisher’s LSMA (FLSMA); Linear spectral mixture analysis (LSMA)
Unsupervised fully constrained least-squares EEA (UFCLS-EEA), 243, 248, 250, 255, 256, 257, 258, 259, 260, 261, 262, 263, 264, 272, 278. See also Endmember extraction algorithms (EEAs)
algorithm for, 250
IEA-EEA vs., 251
Unsupervised fully constrained least-squares (UFCLS) method, 142, 149–151, 152, 154, 157, 160, 161, 162, 163, 164, 165, 201, 204, 225, 339, 467, 487, 527, 528, 538, 539, 563, 565, 626, 791, 880, 967, 969
abundance quantification by, 576
algorithms/MATLAB codes for, 1040, 1044–1046
classification by, 572–575
dermember pixels generated by, 531
maximal volume simplexes and, 342–343
pixel extraction using, 532–533, 534
pixels extracted by, 342, 343
quantitative unmixed results obtained by, 578
simplex volumes and, 343, 344
in unmixing abundance fractions, 566
in unmixing panels, 571
Unsupervised hyperspectral analysis, 13–14
Unsupervised hyperspectral image analysis, 465–467
Unsupervised hyperspectral target detection, algorithms/MATLAB codes for, 1040–1046
Unsupervised image classification, 31
Unsupervised knowledge, image background characterized by, 405–409
See also Linear spectral mixture analysis (LSMA)
dermember extraction vs., 517–524
qualitative and quantitative analyses of, 511–517
Unsupervised LSOSP (ULSOSP) algorithm, 967. See also Least-squares-based orthogonal subspace projection (LSOSP)
Unsupervised nonnegativity constrained least-squares (UNCLS) method, 142, 149–151, 152, 157, 162, 163, 164, 165, 248, 272, 467, 487, 967
Unsupervised nonnegativity constrained least-squares (UNCLS) method. See also Non-negativity abundance-constrained least-squares (NCLS) method
algorithms/MATLAB codes for, 1040, 1042–1044
Unsupervised nonnegativity least-squares EEA (UNCLS-EEA), 243, 248, 249–250, 255, 256, 257, 258, 259, 260, 261, 262, 263, 264, 278. See also Endmember extraction algorithm (EEAs); Linear spectral mixture analysis (LSMA); Non-negativity abundance-constrained least-squares (NCLS) method; Nonnegativity constraint least-squares (NCLS) method algorithm for, 250
Unsupervised OSP (UOSP), 248, 928. See also Orthogonal subspace projection (OSP)
Unsupervised target classification, 465
Unsupervised target detection, 31, 465, 467, 527, 796
Unsupervised target detection algorithms (UTDAs), 323, 527. See also UTDA-extracted pixels automatic target generation process algorithm as, 888–889
pixel extraction using, 532–533, 534
Unsupervised target-generation algorithms, 466
Unsupervised target sample–finding algorithm (UTSFA), 467
Unsupervised virtual signature finding algorithms (UVSFAs), 669, 970. See also ATGP-UVSFA; CA-based unsupervised virtual signature finding algorithm (CA-UVSFA); Least-squares (LS)-based unsupervised virtual signature finding algorithm (LS-UVSFA); LS-UVSFA/CA-UVSFA; UFCLS-UVSFA
Unwanted signature matrix, 417
Unweighted AC-LSMA, 433. See also Abundance-constrained LSMA (AC-LSMA); Linear spectral mixture analysis (LSMA)
U.S. Army Joint Service Agent Water Monitor (JSAWM) program, 91. See also USGS entries
Used image processing techniques, 355
User-synthetic aperture radar (SAR)-ATR systems, 65
USGS ground-truth mineral spectra, 19, 20, 746, 749
USGS quadrangle map, 25
UTDA-extracted pixels, 535, 536, 538. See also Unsupervised target detection algorithms (UTDAs)
Variable dimensionality band selection (VDBS), 983, 984
Variable dimensionality reduction (VDR), 983, 984. See also Dimensionality reduction (DR)
Variable-length code words, 667
Variable-length coding, 666, 682, 798
Variable-length optimal codes, 664–665
Variable-number variable-band selection (VNVBS), 17, 666, 803–806. See also VNVBS entries
effectiveness of, 808
as a feature selection method, 800–801
for hyperspectral signals, 799–819
image-based BS techniques vs., 805
noise effect on, 811–812
performance of, 815
performed on hyperspectral signature vectors, 806
RSDPW vs., 814, 815
as a signature classifier, 805
signatures with different band numbers and, 816–818
for spectral characterization, 818
endmembers extracted by IN-FINDR corresponding to, 632, 633, 643, 645, 649, 653–654.
UFCLS-mixed panel results corresponding to, 638, 647.
UFCLS-mixed panel results produced by, 627.
Variance-based BPC, 617–618. See also BP criteria (BPCs).
VCA-found maximal volume, 329. See also Vertex component analysis (VCA).
VCA performance, 336–337.
VCA/PPI relationship, 320–321. See also Pixel purity index (PPI) entries.
VCA uncertainty, 322–323.
VD applications, 126. See also Virtual dimensionality (VD).
VD determination problem, 136.
VD-determined spectral compression, 561.
VD-estimated PCs, 488. See also Principal components (PCs).
VD-estimated values, 322, 491, 543, 563, 565. See also VD value estimators.
VD estimation, 131, 648, 658.
avgorithms for, 997–1000.
VD estimation techniques, 143–144, 149–151, 157, 159, 167.
VDHySime techniques, 143–144.
VDOSP techniques, 143–144, 167.
VD spectral dimensions, 137.
VDSE techniques, 143–144. See also Signal subspace estimation (SSE).
VD value estimators, 147–149.
VD values, determining, 165.
Vector coding, 9, 17, 717, 986.
for hyperspectral signatures, 741–771.
Vector coding techniques, 771.
Vector parameter estimate, 363.
Vector quantization, 266.
Vectors, 29.
endmember extraction by, 323, 324, 325, 326, 327, 328.
improvement of, 337–338.
panel pixels extracted by, 336.
pixels extracted by, 342, 343.
relationships with PPI and ATGP, 319–323.
results produced by, 331.
SGAs vs., 330–338.
simplex volumes and, 343, 344.
as a variant of ATGP, 323.
Vertices.
insufficient number of, 328.
selecting, 244–245.
Very high spectral resolution, 526.
Very large scale integration (VLSI) technology, 989.
VE selection, 518. See also Virtue (virtual) endmembers (VEs).
defined, 124, 125.
detectors determining, 963.
determined by data characterization-driven criteria, 126–140.
determined by data representation–driven criteria, 140–144.
as an estimate, 613, 614, 682.
estimated by HFC and NWHFC, 532.
estimated for real hyperspectral images, 155–163, 164, 165.
for estimating number of dimensions, 340.
as an estimation method, 511.
estimation of, 423.
for HYDICE data, 305.
HFC method-produced, 534.
HFC vs. PCA methods and, 140.
interpretation of, 958.
$p$ values estimated by, 338.
$q$ value estimated by, 596.
reinterpretation of, 126.
reliability of, 336.
in target pixel number estimation, 885.
values estimated by, 341.
Virtual dimensionality (VD) concept, xxiv, 163–166.
BKG, 485–486.
extracting target, 485–486.
Virtue (virtual) endmembers (VEs), 125, 142, 159, 162–163, 517, 974.
least-squares errors for, 165.
Visible panel pixels, 111
Visible target panels, 111
Visual assessment, 111
Visualization tools, 314
VNVBS-based hyperspectral signature discrimination (VNVBS-HSD), 804, 805. See also
Variable-number variable-band selection (VNVBS)
VNVBS experiments, 806–818
Voxels, 921
classifying MR image, 923
VS extraction, 501. See also Virtual signatures (VSs)
VS matrix, 499, 501

WAC-LSMA performance, evaluating, 419. See also
Abundance-constrained LSMA (AC-LSMA);
Linear spectral mixture analysis (LSMA);
Weighted abundance–constrained LSMA (WAC-LSMA)
Water absorption bands, 25
Water vapor absorption bands, 27
Wavelet analysis, 860–863
application of, 859, 860
multiscale approximation of, 860
Wavelet-based compression technique, 557–558
See also WSCA entries
applications of, 875
discrimination power of, 871
Kalman filtering and, 860
Wavelet-based techniques, 17
Wavelet decomposition, 864
of error signature, 865
Wavelet function, 859, 862–963
Wavelet reconstruction, 864
Wavelet representation, 140
for hyperspectral signals, 859–875
Wavelet transform, 860
Weighted abundance–constrained LSMA (WAC-LSMA), 8, 13, 353, 411–433, 435, 469, 973, 981. See also
Abundance-constrained LSMA (AC-LSMA); Linear spectral mixture analysis (LSMA); Weighted AC-LSMA methods
LSE problems derived from, 413–418
types of, 411
Weighted LSE, 13. See also Least-squares error entries, 13
Weighted LSE approach, 412
Weighting correlation matrix, 469
Weighting matrices, 396, 432–433. See also
Weighting matrix (A)
Weighting matrix (A), 412, 413
approaches to selecting, 414
derived from Fisher’s linear discriminant analysis perspective, 416–417
derived from orthogonal subspace projection perspective, 417–418
derived from parameter estimation perspective, 414–416
Weighting (weight) vectors, 42, 48, 49, 50, 59, 623
L-dimensional, 373
optimal, 374
White Gaussian noise (WGN), 135, 236, 365, 367, 386
white uniform noise vs., 367–368
Whitened spectral correlation, 374
Whitened vectors, 42
Whitening
according to OSP-model, 369
effect of, 371–373
sphering vs., 179–180
Whitening matrix, 40–41, 55, 171, 185, 906
Whitening process, 40
White noise, 138. See also White Gaussian noise (WGN); White uniform noise (WUN)
CEM implementation and, 376–377
White noise vectors, 825
White uniform noise (WUN), white Gaussian noise vs., 367–368
Window-based adaptive anomaly detectors, 975
Winner-Take-All (WTA) rule, 894
Winter N-FINDR, 965–966. See also N-finder (N-FINDR) algorithm
Within-class scatter matrices, 46, 47, 58, 360, 361, 362, 393, 396, 397, 409, 412, 908
WSCA for signature self-correction (WSCA-SSC), 860, 863, 866–867. See also Signature self-correction (SSC); Wavelet-based signature characterization algorithm (WSCA);
WSCA-SSC entries
evaluating performance of, 875
subpixel self-identification using, 873–875
WSCA signature self-tuning (WSCA-SST), 860, 863–866, 868
WSCA-SSC procedure, 867–868. See also WSCA for signature self-correction (WSCA-SSC)
WSCA-SST real image experiment, 872–873
WSCA-SST flowchart, 866. See also WSCA signature self-tuning (WSCA-SST)
WSCA-SST implementation procedure, 865–866
Y pixel vectors, 887, 890, 891
  abundance fractions of, 891
Zero-holder interpolator, 858
Zero-mean data sample matrix, 180
Zero-mean de-correlated random process, 364

Zero-mean Gaussian distribution, 73
Zero-mean Gaussian noise, 111, 365
Zero-mean noise, 366
Zero-mean white noise, 364,
  365, 368
Zero-padding, 816