LIST OF PUBLICATIONS

Journals:

1. Malan, N.S. and Sharma, S., 2019. Feature selection using regularized neighbourhood component analysis to enhance the classification performance of motor imagery signals. *Computers in biology and medicine*, *107*, pp.118-126. (IF=3.434)
2. Malan, N.S. and Sharma, S., Motor imagery EEG spectral-spatial feature optimization using Dual-Tree Complex Wavelet and Neighbourhood Component Analysis. *Innovation and Research in BioMedical Engineering* (IF=1.022).
3. Malan, N.S. and Sharma, S., Time window and frequency band optimization using regularized neighbourhood component analysis for Multi-View Motor Imagery EEG classification. *Biomedical Signal Processing and Control (Accepted)* (IF = 3.137).

Conference Papers:

1. Malan, N.S. and Sharma, S., 2018, July. Removal of Ocular Atrifacts from Single Channel EEG Signal Using DTCWT with Quantum Inspired Adaptive Threshold. In *2018 2nd International Conference on Biomedical Engineering (IBIOMED)* (pp. 94-99). IEEE.
2. Soni, D., Malan, N.S. and Sharma, S., 2019, July. CCA Model with Training Approach to Improve Recognition Rate of SSVEP in Real Time. In *Proceedings of the 2019 3rd International Conference on Artificial Intelligence and Virtual Reality* (pp. 56-59).

Book Chapter:

1. Malan, N.S. and Sharma, S., 2020. Introduction to Motor Imagery-Based Brain-Computer Interface: Time, Frequency, and Phase Analysis-Based Feature Extraction

for Two Class MI Classification. In *Biomedical and Clinical Engineering for Healthcare Advancement* (pp. 168-197). IGI Global.

Poster Presentations:

1. Malan, N. S., & Sharma, S. “Time-Frequency-Phase Feature extraction by DTCWT for Two-class Motor Imagery EEG”, ISC 2018: IEEE EMBS International Student Conference. (Awarded Best Poster)
2. Malan, N. S., & Sharma, S. “Frequency Band Optimization with neighbourhood component analysis to improve spatial filtering in motor imagery signals.”, ICBME 2019, Singapore, Dec 2019.

REFERENCES

[1] Chaudhary U, Birbaumer N, Ramos-Murguialday A. Brain-computer interfaces for communication and rehabilitation. Nat Rev Neurol 2016;12:513–25. https://doi.org/10.1038/nrneurol.2016.113.

[2] Bi L, Fan X, Liu Y. EEG-Based Brain-Controlled Mobile Robots: A Survey. IEEE Transactions on Human-Machine Systems 2013;43:161–76. https://doi.org/10.1109/TSMCC.2012.2219046.

[3] Sharanreddy PKK. Detection of primary brain tumor present in eeg signal using wavelet transform and neural network 2013. https://www.biomedscidirect.com/990/detection_of_primary_brain_tumor_present_in_eeg_signal_using_wavelet_transform_and_neural_network/articlescategories (accessed May 6, 2019).

[4] Rao RPN, Scherer R. Brain-Computer Interfacing [In the Spotlight]. IEEE Signal Processing Magazine 2010;27:152–150. https://doi.org/10.1109/MSP.2010.936774.

[5] Navarro AA, Ceccaroni L, Velickovski F, Torrellas S, Miralles F, Allison BZ, et al. Context-Awareness as an Enhancement of Brain-Computer Interfaces. IWAAL, 2011. https://doi.org/10.1007/978-3-642-21303-8_30.

[6] Burle B, Spieser L, Roger C, Casini L, Hasbroucq T, Vidal F. Spatial and temporal resolutions of EEG: Is it really black and white? A scalp current density view. Int J Psychophysiol 2015;97:210–20. https://doi.org/10.1016/j.ijpsycho.2015.05.004.

[7] Norcia AM, Appelbaum LG, Ales JM, Cottereau BR, Rossion B. The steady-state visual evoked potential in vision research: A review. Journal of Vision 2015;15:4–4. https://doi.org/10.1167/15.6.4.

[8] Yuan H, He B. Brain-computer interfaces using sensorimotor rhythms: current state and future perspectives. IEEE Trans Biomed Eng 2014;61:1425–35. https://doi.org/10.1109/TBME.2014.2312397.

[9] Pfurtscheller G, Neuper C. Motor imagery and direct brain-computer communication. Proceedings of the IEEE 2001;89:1123–34.

[10] Sur S, Sinha VK. Event-related potential: An overview. Ind Psychiatry J 2009;18:70–3. https://doi.org/10.4103/0972-6748.57865.

[11] Kamousi B, and. Classification of motor imagery tasks for brain-computer interface applications by means of two equivalent dipoles analysis. IEEE Transactions on Neural Systems and Rehabilitation Engineering 2005;13:166–71. https://doi.org/10.1109/TNSRE.2005.847386.

[12] Penn AA, Shatz CJ. Brain waves and brain wiring: the role of endogenous and sensory-driven neural activity in development. Pediatr Res 1999;45:447–58. https://doi.org/10.1203/00006450-199904010-00001.

[13] Neuper C, Pfurtscheller G. Event-related dynamics of cortical rhythms: frequency-specific features and functional correlates. International Journal of Psychophysiology 2001;43:41–58. https://doi.org/10.1016/S0167-8760(01)00178-7.

[14] Pfurtscheller G, Da Silva FL. Event-related EEG/MEG synchronization and desynchronization: basic principles. Clinical Neurophysiology 1999;110:1842–57.

[15] Blankertz B, Muller K-, Curio G, Vaughan TM, Schalk G, Wolpaw JR, et al. The BCI competition 2003: progress and perspectives in detection and discrimination of EEG single trials. IEEE Transactions on Biomedical Engineering 2004;51:1044–51. https://doi.org/10.1109/TBME.2004.826692.

[16] Tangermann M, Müller K-R, Aertsen A, Birbaumer N, Braun C, Brunner C, et al. Review of the BCI competition IV. Frontiers in Neuroscience 2012;6:55.
[17] Ming Cheng, Xiaorong Gao, Shangkai Gao, Dingfeng Xu. Design and implementation of a brain-computer interface with high transfer rates. IEEE Transactions on Biomedical Engineering 2002;49:1181–6. https://doi.org/10.1109/TBME.2002.803536.
[18] Chen X, Chen Z, Gao S, Gao X. A high-ITR SSVEP-based BCI speller. Brain-Computer Interfaces 2014;1:181–91. https://doi.org/10.1080/2326263X.2014.944469.
[19] Pun T, Alecu TI, Chanel G, Kronegg J, Voloshynovskiy S. Brain-computer interaction research at the computer vision and multimedia laboratory, University of Geneva. IEEE Transactions on Neural Systems and Rehabilitation Engineering 2006;14:210–3. https://doi.org/10.1109/TNSRE.2006.875544.
[20] Chaudhary U, Birbaumer N, Ramos-Murguialday A. Brain–computer interfaces for communication and rehabilitation. Nature Reviews Neurology 2016;12:513–25. https://doi.org/10.1038/nrneurol.2016.113.
[21] Mak JN, Wolpaw JR. Clinical Applications of Brain-Computer Interfaces: Current State and Future Prospects. IEEE Reviews in Biomedical Engineering 2009;2:187–99. https://doi.org/10.1109/RBME.2009.2035356.
[22] Fazel-Rezai R, Allison BZ, Guger C, Sellers EW, Kleih SC, Kübler A. P300 brain computer interface: current challenges and emerging trends. Front Neuroeng 2012;5:14. https://doi.org/10.3389/fneng.2012.00014.
[23] Pan J, Li Y, Zhang R, Gu Z, Li F. Discrimination Between Control and Idle States in Asynchronous SSVEP-Based Brain Switches: A Pseudo-Key-Based Approach. IEEE Transactions on Neural Systems and Rehabilitation Engineering 2013;21:435–43. https://doi.org/10.1109/TNSRE.2013.2253801.
[24] Arvaneh M, Robertson IH, Ward TE. A P300-Based Brain-Computer Interface for Improving Attention. Front Hum Neurosci 2019;12. https://doi.org/10.3389/fnhum.2018.00524.
[25] Mulder Th. Motor imagery and action observation: cognitive tools for rehabilitation. J Neural Transm 2007;114:1265–78. https://doi.org/10.1007/s00702-007-0763-z.
[26] Yuan H, He B. Brain-computer interfaces using sensorimotor rhythms: current state and future perspectives. IEEE Trans Biomed Eng 2014;61:1425–35. https://doi.org/10.1109/TBME.2014.2312397.
[27] Liu A, Chen K, Liu Q, Ai Q, Xie Y, Chen A. Feature Selection for Motor Imagery EEG Classification Based on Firefly Algorithm and Learning Automata. Sensors (Basel) 2017;17. https://doi.org/10.3390/s17112576.
[28] Zhang Y, Nam CS, Zhou G, Jin J, Wang X, Cichocki A. Temporally Constrained Sparse Group Spatial Patterns for Motor Imagery BCI. IEEE Transactions on Cybernetics 2018:1–11. https://doi.org/10.1109/TCYB.2018.2841847.
[29] Krusienski DJ, Grosse-Wentrup M, Galán F, Coyle D, Miller KJ, Forney E, et al. Critical issues in state-of-the-art brain–computer interface signal processing. J Neural Eng 2011;8:025002. https://doi.org/10.1088/1741-2560/8/2/025002.
[30] Jiang X, Bian G-B, Tian Z. Removal of Artifacts from EEG Signals: A Review. Sensors (Basel) 2019;19. https://doi.org/10.3390/s19050987.
[31] İşcan Z, Nikulin VV. Steady state visual evoked potential (SSVEP) based brain-computer interface (BCI) performance under different perturbations. PLOS ONE 2018;13:e0191673. https://doi.org/10.1371/journal.pone.0191673.

[32] Mellinger J, Schalk G, Braun C, Preissl H, Rosenstiel W, Birbaumer N, et al. An MEG-based brain-computer interface (BCI). Neuroimage 2007;36:581–93.
[33] Pfurtscheller G, Flotzinger D, Pregenzer M, Wolpaw JR, McFarland D. EEG-based brain computer interface (BCI). Search for optimal electrode positions and frequency components. Med Prog Technol 1995;21:111–21.
[34] Zhu Y, Xu K, Xu C, Zhang J, Ji J, Zheng X, et al. PET Mapping for Brain-Computer Interface Stimulation of the Ventroposterior Medial Nucleus of the Thalamus in Rats with Implanted Electrodes. J Nucl Med 2016;57:1141–5. https://doi.org/10.2967/jnumed.115.171868.
[35] Schalk G, Leuthardt EC. Brain-computer interfaces using electrocorticographic signals. IEEE Rev Biomed Eng 2011;4:140–54. https://doi.org/10.1109/RBME.2011.2172408.
[36] Naseer N, Hong K-S. fNIRS-based brain-computer interfaces: a review. Front Hum Neurosci 2015;9. https://doi.org/10.3389/fnhum.2015.00003.
[37] Howseman A, Zeki S, Gevins A, Smith ME, McEvoy LK, Leong H, et al. Electroencephalographic imaging of higher brain function. Philosophical Transactions of the Royal Society of London Series B: Biological Sciences 1999;354:1125–34. https://doi.org/10.1098/rstb.1999.0468.
[38] Al-Fahoum AS, Al-Fraihat AA. Methods of EEG Signal Features Extraction Using Linear Analysis in Frequency and Time-Frequency Domains. ISRN Neurosci 2014;2014. https://doi.org/10.1155/2014/730218.
[39] Easwaramoorthy D, Uthayakumar R. Analysis of biomedical EEG signals using Wavelet Transforms and Multifractal Analysis. 2010 INTERNATIONAL CONFERENCE ON COMMUNICATION CONTROL AND COMPUTING TECHNOLOGIES, 2010, p. 544–9. https://doi.org/10.1109/ICCCCT.2010.5670780.
[40] Zabidi A, Mansor W, Lee YK, Fadzal CWNFCW. Short-time Fourier Transform analysis of EEG signal generated during imagined writing. 2012 International Conference on System Engineering and Technology (ICSET), 2012, p. 1–4. https://doi.org/10.1109/ICSEngT.2012.6339284.
[41] Jung T-P, Makeig S, Westerfield M, Townsend J, Courchesne E, Sejnowski TJ. Removal of eye activity artifacts from visual event-related potentials in normal and clinical subjects. Clinical Neurophysiology 2000;111:1745–58. https://doi.org/10.1016/S1388-2457(00)00386-2.
[42] Jung T-P, Makeig S, Humphries C, Lee T-W, McKeown MJ, Iragui V, et al. Removing electroencephalographic artifacts by blind source separation. Psychophysiology 2000;37:163–78. https://doi.org/10.1111/1469-8986.3720163.
[43] Guerrero-Mosquera C, Navia-Vázquez A. Automatic removal of ocular artefacts using adaptive filtering and independent component analysis for electroencephalogram data. IET Signal Processing 2012;6:99–106. https://doi.org/10.1049/iet-spr.2010.0135.
[44] Lu J, McFarland DJ, Wolpaw JR. Adaptive Laplacian filtering for sensorimotor rhythm-based brain-computer interfaces. J Neural Eng 2013;10:016002. https://doi.org/10.1088/1741-2560/10/1/016002.
[45] McFarland DJ. The advantages of the surface Laplacian in brain-computer interface research. Int J Psychophysiol 2015;97:271–6. https://doi.org/10.1016/j.ijpsycho.2014.07.009.
[46] Brandl S, Frølich L, Höhne J, Müller K-R, Samek W. Brain-computer interfacing under distraction: an evaluation study. J Neural Eng 2016;13:056012. https://doi.org/10.1088/1741-2560/13/5/056012.

[47] Xu R, Jiang N, Mrachacz-Kersting N, Dremstrup K, Farina D. Factors of Influence on the Performance of a Short-Latency Non-Invasive Brain Switch: Evidence in Healthy Individuals and Implication for Motor Function Rehabilitation. Front Neurosci 2015;9:527. https://doi.org/10.3389/fnins.2015.00527.
[48] Park W, Kwon GH, Kim Y-H, Lee J-H, Kim L. EEG response varies with lesion location in patients with chronic stroke. J NeuroEngineering Rehabil 2016;13:21. https://doi.org/10.1186/s12984-016-0120-2.
[49] Yao L, Sheng X, Zhang D, Jiang N, Farina D, Zhu X. A BCI System Based on Somatosensory Attentional Orientation. IEEE Trans Neural Syst Rehabil Eng 2017;25:78–87. https://doi.org/10.1109/TNSRE.2016.2572226.
[50] Davies ME, James CJ. Source separation using single channel ICA. Signal Processing 2007;87:1819–32. https://doi.org/10.1016/j.sigpro.2007.01.011.
[51] Maddirala AK, Shaik RA. Removal of EOG Artifacts From Single Channel EEG Signals Using Combined Singular Spectrum Analysis and Adaptive Noise Canceler. IEEE Sensors Journal 2016;16:8279–87. https://doi.org/10.1109/JSEN.2016.2560219.
[52] Wu J. Wavelet domain denoising method based on multistage median filtering. The Journal of China Universities of Posts and Telecommunications 2013;20:113–9. https://doi.org/10.1016/S1005-8885(13)60037-0.
[53] Andria G, Attivissimo F, Cavone G, Giaquinto N, Lanzolla AML. Linear filtering of 2-D wavelet coefficients for denoising ultrasound medical images. Measurement 2012;45:1792–800. https://doi.org/10.1016/j.measurement.2012.04.005.
[54] Yanqin Z. Multi-level denoising and enhancement method based on wavelet transform for mine monitoring. International Journal of Mining Science and Technology 2013;23:163–6. https://doi.org/10.1016/j.ijmst.2013.03.008.
[55] Zhou Y, Li H. A denoising scheme for DSPI fringes based on fast bi-dimensional ensemble empirical mode decomposition and BIMF energy estimation. Mechanical Systems and Signal Processing 2013;35:369–82. https://doi.org/10.1016/j.ymssp.2012.09.009.
[56] Žvokelj M, Zupan S, Prebil I. Non-linear multivariate and multiscale monitoring and signal denoising strategy using Kernel Principal Component Analysis combined with Ensemble Empirical Mode Decomposition method. Mechanical Systems and Signal Processing 2011;25:2631–53. https://doi.org/10.1016/j.ymssp.2011.03.002.
[57] Ramanan SV, Kalpakam NV, Sahambi JS. A novel wavelet based technique for detection and de-noising of ocular artifact in normal and epileptic electroencephalogram. 2004 International Conference on Communications, Circuits and Systems (IEEE Cat. No.04EX914), vol. 2, 2004, p. 1027-1031 Vol.2. https://doi.org/10.1109/ICCCAS.2004.1346353.
[58] Kiamini M, Alirezaee S, Perseh B, Ahmadi M. A wavelet based algorithm for Ocular Artifact detection In the EEG signals. 2008 IEEE International Multitopic Conference, 2008, p. 165–8. https://doi.org/10.1109/INMIC.2008.4777729.
[59] Zhao Q, Hu B, Shi Y, Li Y, Moore P, Sun M, et al. Automatic identification and removal of ocular artifacts in EEG--improved adaptive predictor filtering for portable applications. IEEE Trans Nanobioscience 2014;13:109–17. https://doi.org/10.1109/TNB.2014.2316811.
[60] Krishnaveni V, Jayaraman S, Anitha L, Ramadoss K. Removal of ocular artifacts from EEG using adaptive thresholding of wavelet coefficients. J Neural Eng 2006;3:338–46. https://doi.org/10.1088/1741-2560/3/4/011.

[61] Wang Y, He Z, Zi Y. Enhancement of signal denoising and multiple fault signatures detecting in rotating machinery using dual-tree complex wavelet transform. Mechanical Systems and Signal Processing 2010;24:119–37. https://doi.org/10.1016/j.ymssp.2009.06.015.
[62] Miao M, Wang A, Zhao C, Liu F. EEG pattern recognition based on dual-tree complex wavelet transform and particle swarm optimization. 2016 10th International Conference on Sensing Technology (ICST), 2016, p. 1–5. https://doi.org/10.1109/ICSensT.2016.7796311.
[63] Peng ZK, Jackson MR, Rongong JA, Chu FL, Parkin RM. On the energy leakage of discrete wavelet transform. Mechanical Systems and Signal Processing 2009;23:330–43. https://doi.org/10.1016/j.ymssp.2008.05.014.
[64] The dual-tree complex wavelet transform - IEEE Journals & Magazine n.d. https://ieeexplore.ieee.org/document/1550194 (accessed March 4, 2021).
[65] Chaudhury KN, Unser M. On the Shiftability of Dual-Tree Complex Wavelet Transforms. IEEE Transactions on Signal Processing 2010;58:221–32. https://doi.org/10.1109/TSP.2009.2028962.
[66] Cantillo-Negrete J, Carino-Escobar RI, Carrillo-Mora P, Elias-Vinas D, Gutierrez-Martinez J. Motor Imagery-Based Brain-Computer Interface Coupled to a Robotic Hand Orthosis Aimed for Neurorehabilitation of Stroke Patients. Journal of Healthcare Engineering 2018;2018.
[67] Grosse-Wentrup M, Liefhold C, Gramann K, Buss M. Beamforming in noninvasive brain–computer interfaces. IEEE Transactions on Biomedical Engineering 2009;56:1209–19.
[68] Ang KK, Chin ZY, Wang C, Guan C, Zhang H. Filter Bank Common Spatial Pattern Algorithm on BCI Competition IV Datasets 2a and 2b. Front Neurosci 2012;6. https://doi.org/10.3389/fnins.2012.00039.
[69] Thomas KP, Guan C, Tong LC, Prasad VA. An adaptive filter bank for motor imagery based Brain Computer Interface. Conf Proc IEEE Eng Med Biol Soc 2008;2008:1104–7. https://doi.org/10.1109/IEMBS.2008.4649353.
[70] Yang R, Song A, Xu B. Feature extraction of motor imagery eeg based on wavelet transform and higher-order statistics. Int J Wavelets Multiresolut Inf Process 2010;08:373–84. https://doi.org/10.1142/S0219691310003535.
[71] Hu D, Li W, Chen X. Feature extraction of motor imagery EEG signals based on wavelet packet decomposition. The 2011 IEEE/ICME International Conference on Complex Medical Engineering, 2011, p. 694–7. https://doi.org/10.1109/ICCME.2011.5876829.
[72] Imran SM, Talukdar MTF, Sakib SK, Pathan NS, Fattah SA. Motor imagery EEG signal classification scheme based on wavelet domain statistical features. 2014 International Conference on Electrical Engineering and Information Communication Technology, 2014, p. 1–4. https://doi.org/10.1109/ICEEICT.2014.6919172.
[73] Boonyakitanont P, Lek-uthai A, Chomtho K, Songsiri J. A review of feature extraction and performance evaluation in epileptic seizure detection using EEG. ArXiv:190800492 [Eess] 2019.
[74] Tariq M, Trivailo PM, Simic M. Mu-Beta event-related (de)synchronization and EEG classification of left-right foot dorsiflexion kinaesthetic motor imagery for BCI. PLOS ONE 2020;15:e0230184. https://doi.org/10.1371/journal.pone.0230184.
[75] Hamner B, Leeb R, Tavella M, del R Millan J. Phase-based features for motor imagery brain-computer interfaces. 2011 Annual International Conference of the

IEEE Engineering in Medicine and Biology Society, Boston, MA: IEEE; 2011, p. 2578–81. https://doi.org/10.1109/IEMBS.2011.6090712.
[76] Kumar S, Reddy T, Behera L. EEG Based Motor Imagery Classification Using Instantaneous Phase Difference Sequence. 2018 IEEE International Conference on Systems, Man, and Cybernetics (SMC), 2018, p. 499–504. https://doi.org/10.1109/SMC.2018.00094.
[77] Chen Y-C, Hsiao T-C. Instantaneous phase difference analysis between thoracic and abdominal movement signals based on complementary ensemble empirical mode decomposition. BioMedical Engineering OnLine 2016;15:112. https://doi.org/10.1186/s12938-016-0233-7.
[78] Oh S-H, Lee Y-R, Kim H-N. A Novel EEG Feature Extraction Method Using Hjorth Parameter. IJEEE 2014:106–10. https://doi.org/10.12720/ijeee.2.2.106-110.
[79] Lee HK, Choi Y-S. Application of Continuous Wavelet Transform and Convolutional Neural Network in Decoding Motor Imagery Brain-Computer Interface. Entropy 2019;21:1199. https://doi.org/10.3390/e21121199.
[80] Tangwiriyasakul C, Mocioiu V, van Putten MJAM, Rutten WLC. Classification of motor imagery performance in acute stroke. J Neural Eng 2014;11:036001. https://doi.org/10.1088/1741-2560/11/3/036001.
[81] Gibson RM, Chennu S, Owen AM, Cruse D. Complexity and familiarity enhance single-trial detectability of imagined movements with electroencephalography. Clin Neurophysiol 2014;125:1556–67. https://doi.org/10.1016/j.clinph.2013.11.034.
[82] Park W, Kwon GH, Kim D-H, Kim Y-H, Kim S-P, Kim L. Assessment of cognitive engagement in stroke patients from single-trial EEG during motor rehabilitation. IEEE Trans Neural Syst Rehabil Eng 2015;23:351–62. https://doi.org/10.1109/TNSRE.2014.2356472.
[83] Kamrunnahar M, Dias NS, Schiff SJ. Toward a Model-Based Predictive Controller Design in Brain–Computer Interfaces. Ann Biomed Eng 2011;39. https://doi.org/10.1007/s10439-011-0248-y.
[84] Zich C, Debener S, De Vos M, Frerichs S, Maurer S, Kranczioch C. Lateralization patterns of covert but not overt movements change with age: An EEG neurofeedback study. Neuroimage 2015;116:80–91. https://doi.org/10.1016/j.neuroimage.2015.05.009.
[85] Kitahara K, Hayashi Y, Kondo T, Yano S. Sound imagery contributes to foot Mi-based BCI even through it does not influence on the sensorimotor rhythms. 2016 Asia-Pacific Signal and Information Processing Association Annual Summit and Conference (APSIPA), 2016, p. 1–6. https://doi.org/10.1109/APSIPA.2016.7820835.
[86] Avilés-Cruz C, Villegas-Cortez J, Ferreyra-Ramírez A, López AZ. EEG Pattern Recognition: An Efficient Improvement Combination of ERD/ERS/Laterality Features to Create a Self-paced BCI System. In: Martínez-Trinidad JF, Carrasco-Ochoa JA, Ayala Ramirez V, Olvera-López JA, Jiang X, editors. Pattern Recognition, Cham: Springer International Publishing; 2016, p. 231–40. https://doi.org/10.1007/978-3-319-39393-3_23.
[87] Vuckovic A, Hasan MA, Osuagwu B, Fraser M, Allan DB, Conway BA, et al. The influence of central neuropathic pain in paraplegic patients on performance of a motor imagery based Brain Computer Interface. Clinical Neurophysiology 2015;126:2170–80. https://doi.org/10.1016/j.clinph.2014.12.033.

[88] Sburlea AI, Montesano L, Minguez J. Continuous detection of the self-initiated walking pre-movement state from EEG correlates without session-to-session recalibration. J Neural Eng 2015;12:036007. https://doi.org/10.1088/1741-2560/12/3/036007.
[89] Hashimoto Y, Ushiba J. EEG-based classification of imaginary left and right foot movements using beta rebound. Clin Neurophysiol 2013;124:2153–60. https://doi.org/10.1016/j.clinph.2013.05.006.
[90] Müller-Putz GR, Steyrl D, Faller J. Adaptive hybrid brain-computer interaction: ask a trainer for assistance! Annu Int Conf IEEE Eng Med Biol Soc 2014;2014:1493–6. https://doi.org/10.1109/EMBC.2014.6943884.
[91] Jian W, Chen M, McFarland DJ. EEG based zero-phase phase-locking value (PLV) and effects of spatial filtering during actual movement. Brain Res Bull 2017;130:156–64. https://doi.org/10.1016/j.brainresbull.2017.01.023.
[92] Daly I, Billinger M, Laparra-Hernández J, Aloise F, García ML, Faller J, et al. On the control of brain-computer interfaces by users with cerebral palsy. Clin Neurophysiol 2013;124:1787–97. https://doi.org/10.1016/j.clinph.2013.02.118.
[93] Jerbic AB, Horki P, Sovilj S, Isgum V, Cifrek M. Hilbert-Huang Time-Frequency Analysis of Motor Imagery EEG Data for Brain-Computer Interfaces. In: Lacković I, Vasic D, editors. 6th European Conference of the International Federation for Medical and Biological Engineering, Cham: Springer International Publishing; 2015, p. 62–5. https://doi.org/10.1007/978-3-319-11128-5_16.
[94] Hong J, Qin X, Bai J, Zhang P, Cheng Y. A combined feature extraction method for left-right hand motor imagery in BCI. 2015 IEEE International Conference on Mechatronics and Automation (ICMA), 2015, p. 2621–5. https://doi.org/10.1109/ICMA.2015.7237900.
[95] Reynolds C, Osuagwu BA, Vuckovic A. Influence of motor imagination on cortical activation during functional electrical stimulation. Clin Neurophysiol 2015;126:1360–9. https://doi.org/10.1016/j.clinph.2014.10.007.
[96] Meena YK, Cecotti H, Wong-Lin K, Prasad G. Towards increasing the number of commands in a hybrid brain-computer interface with combination of gaze and motor imagery. 2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), 2015, p. 506–9. https://doi.org/10.1109/EMBC.2015.7318410.
[97] Zhang R, Xu P, Chen R, Li F, Guo L, Li P, et al. Predicting Inter-session Performance of SMR-Based Brain-Computer Interface Using the Spectral Entropy of Resting-State EEG. Brain Topogr 2015;28:680–90. https://doi.org/10.1007/s10548-015-0429-3.
[98] Yi W, Qiu S, Wang K, Qi H, He F, Zhou P, et al. EEG oscillatory patterns and classification of sequential compound limb motor imagery. J Neuroeng Rehabil 2016;13:11. https://doi.org/10.1186/s12984-016-0119-8.
[99] Sollfrank T, Ramsay A, Perdikis S, Williamson J, Murray-Smith R, Leeb R, et al. The effect of multimodal and enriched feedback on SMR-BCI performance. Clinical Neurophysiology 2016;127:490–8. https://doi.org/10.1016/j.clinph.2015.06.004.
[100] Xiao R, Ding L. EEG resolutions in detecting and decoding finger movements from spectral analysis. Front Neurosci 2015;9. https://doi.org/10.3389/fnins.2015.00308.
[101] García-Cossio E, Severens M, Nienhuis B, Duysens J, Desain P, Keijsers N, et al. Decoding Sensorimotor Rhythms during Robotic-Assisted Treadmill Walking for

Brain Computer Interface (BCI) Applications. PLOS ONE 2015;10:e0137910. https://doi.org/10.1371/journal.pone.0137910.
[102] Severens M, Perusquia-Hernandez M, Nienhuis B, Farquhar J, Duysens J. Using Actual and Imagined Walking Related Desynchronization Features in a BCI. IEEE Transactions on Neural Systems and Rehabilitation Engineering 2015;23:877–86. https://doi.org/10.1109/TNSRE.2014.2371391.
[103] Ibáñez J, Serrano JI, del Castillo MD, Monge-Pereira E, Molina-Rueda F, Alguacil-Diego I, et al. Detection of the onset of upper-limb movements based on the combined analysis of changes in the sensorimotor rhythms and slow cortical potentials. J Neural Eng 2014;11:056009. https://doi.org/10.1088/1741-2560/11/5/056009.
[104] López-Larraz E, Montesano L, Gil-Agudo Á, Minguez J. Continuous decoding of movement intention of upper limb self-initiated analytic movements from pre-movement EEG correlates. Journal of NeuroEngineering and Rehabilitation 2014;11:153. https://doi.org/10.1186/1743-0003-11-153.
[105] D H, K Q, Dy F, W J, X C, O B. Electroencephalography (EEG)-based brain-computer interface (BCI): a 2-D virtual wheelchair control based on event-related desynchronization/synchronization and state control. IEEE Trans Neural Syst Rehabil Eng 2012;20:379–88. https://doi.org/10.1109/tnsre.2012.2190299.
[106] Blokland Y, Spyrou L, Thijssen D, Eijsvogels T, Colier W, Floor-Westerdijk M, et al. Combined EEG-fNIRS decoding of motor attempt and imagery for brain switch control: an offline study in patients with tetraplegia. IEEE Trans Neural Syst Rehabil Eng 2014;22:222–9. https://doi.org/10.1109/TNSRE.2013.2292995.
[107] Song L, Gordon E, Gysels E. Phase Synchrony Rate for the Recognition of Motor Imagery in Brain-Computer Interface. In: Weiss Y, Schölkopf B, Platt JC, editors. Advances in Neural Information Processing Systems 18, MIT Press; 2006, p. 1265–72.
[108] Kevric J, Subasi A. Comparison of signal decomposition methods in classification of EEG signals for motor-imagery BCI system. Biomedical Signal Processing and Control 2017;31:398–406. https://doi.org/10.1016/j.bspc.2016.09.007.
[109] Jin Z, Zhou G, Gao D, Zhang Y. EEG classification using sparse Bayesian extreme learning machine for brain–computer interface. Neural Comput & Applic 2018:1–9. https://doi.org/10.1007/s00521-018-3735-3.
[110] Zhang Y, Zhou G, Jin J, Zhao Q, Wang X, Cichocki A. Sparse Bayesian Classification of EEG for Brain–Computer Interface. IEEE Transactions on Neural Networks and Learning Systems 2016;27:2256–67. https://doi.org/10.1109/TNNLS.2015.2476656.
[111] Wang H, Zhang Y, Waytowich NR, Krusienski DJ, Zhou G, Jin J, et al. Discriminative Feature Extraction via Multivariate Linear Regression for SSVEP-Based BCI. IEEE Transactions on Neural Systems and Rehabilitation Engineering 2016;24:532–41. https://doi.org/10.1109/TNSRE.2016.2519350.
[112] Zhang Y, Zhou G, Zhao Q, Jin J, Wang X, Cichocki A. Spatial-Temporal Discriminant Analysis for ERP-Based Brain-Computer Interface. IEEE Transactions on Neural Systems and Rehabilitation Engineering 2013;21:233–43. https://doi.org/10.1109/TNSRE.2013.2243471.
[113] Dong S, Kim B, Lee S. EEG-Based Classification of Implicit Intention During Self-Relevant Sentence Reading. IEEE Transactions on Cybernetics 2016;46:2535–42. https://doi.org/10.1109/TCYB.2015.2479240.

[114] Rakotomamonjy A, Guigue V, Mallet G, Alvarado V. Ensemble of SVMs for improving brain computer interface P300 speller performances. International conference on artificial neural networks, Springer; 2005, p. 45–50.
[115] Yu X, Chum P, Sim K-B. Analysis the effect of PCA for feature reduction in non-stationary EEG based motor imagery of BCI system. Optik-International Journal for Light and Electron Optics 2014;125:1498–502.
[116] Guo X, Wu X, Gong X, Zhang L. Envelope detection based on online ICA algorithm and its application to motor imagery classification. Neural engineering (NER), 2013 6th international IEEE/EMBS conference on, IEEE; 2013, p. 1058–61.
[117] Bhattacharyya S, Rakshit P, Konar A, Tibarewala DN, Janarthanan R. Feature selection of motor imagery EEG signals using firefly temporal difference Q-Learning and support vector machine. International Conference on Swarm, Evolutionary, and Memetic Computing, Springer; 2013, p. 534–45.
[118] Wang Y, Gonuguntla V, Shafiq G, Veluvolu KC. BMFLC with neural network and DE for better event classification. Brain-Computer Interface (BCI), 2013 International Winter Workshop on, IEEE; 2013, p. 34–5.
[119] Rakshit P, Bhattacharyya S, Konar A, Khasnobish A, Tibarewala DN, Janarthanan R. Artificial bee colony based feature selection for motor imagery EEG data. Proceedings of Seventh International Conference on Bio-Inspired Computing: Theories and Applications (BIC-TA 2012), Springer; 2013, p. 127–38.
[120] Uzer MS, Yilmaz N, Inan O. Feature Selection Method Based on Artificial Bee Colony Algorithm and Support Vector Machines for Medical Datasets Classification. ScientificWorldJournal 2013;2013. https://doi.org/10.1155/2013/419187.
[121] Ramos AC, Hernández RG, Vellasco M. Feature selection methods applied to motor imagery task classification. Computational Intelligence (LA-CCI), 2016 IEEE Latin American Conference on, IEEE; 2016, p. 1–6.
[122] Suraj null, Tiwari P, Ghosh S, Sinha RK. Classification of Two Class Motor Imagery Tasks Using Hybrid GA-PSO Based K-Means Clustering. Comput Intell Neurosci 2015;2015:945729. https://doi.org/10.1155/2015/945729.
[123] Gu Q, Li Z, Han J. Generalized Fisher Score for Feature Selection. ArXiv:12023725 [Cs, Stat] 2012.
[124] Ang KK, Chin ZY, Zhang H, Guan C. Filter bank common spatial pattern (FBCSP) in brain-computer interface. Neural Networks, 2008. IJCNN 2008.(IEEE World Congress on Computational Intelligence). IEEE International Joint Conference on, IEEE; 2008, p. 2390–7.
[125] Kononenko I. Estimating attributes: analysis and extensions of RELIEF. European conference on machine learning, Springer; 1994, p. 171–82.
[126] Guyon I, Elisseeff A. An Introduction to Variable and Feature Selection. Journal of Machine Learning Research 2003;3:1157–82.
[127] Tibshirani R. Regression shrinkage and selection via the lasso: a retrospective. Journal of the Royal Statistical Society: Series B (Statistical Methodology) 2017:273–82. https://doi.org/10.1111/j.1467-9868.2011.00771.x@10.1111/(ISSN)1467-9868.TOP_SERIES_B_RESEARCH.
[128] Yang W, Wang K, Zuo W. Neighborhood Component Feature Selection for High-Dimensional Data. JCP 2012;7:161–8.
[129] Lal TN, Schroder M, Hinterberger T, Weston J, Bogdan M, Birbaumer N, et al. Support vector channel selection in BCI. IEEE Transactions on Biomedical Engineering 2004;51:1003–10. https://doi.org/10.1109/TBME.2004.827827.

[130] Quinlan JR. Induction of Decision Trees. Mach Learn 1986;1:81–106. https://doi.org/10.1023/A:1022643204877.
[131] Quinlan JR. C4.5: Programs for Machine Learning. San Francisco, CA, USA: Morgan Kaufmann Publishers Inc.; 1993.
[132] Aggarwal S, Chugh N. Signal processing techniques for motor imagery brain computer interface: A review. Array 2019;1–2:100003. https://doi.org/10.1016/j.array.2019.100003.
[133] Li M, Cui Y, Hao D, Yang J. An adaptive feature extraction method in BCI-based rehabilitation. Journal of Intelligent & Fuzzy Systems 2015;28:525–35. https://doi.org/10.3233/IFS-141329.
[134] Jana GC, Swetapadma A, Pattnaik PK. Enhancing the performance of motor imagery classification to design a robust brain computer interface using feed forward back-propagation neural network. Ain Shams Engineering Journal 2018;9:2871–8. https://doi.org/10.1016/j.asej.2017.12.003.
[135] Yuksel A, Olmez T. A Neural Network-Based Optimal Spatial Filter Design Method for Motor Imagery Classification. PLOS ONE 2015;10:e0125039. https://doi.org/10.1371/journal.pone.0125039.
[136] Li Y, Zhang X-R, Zhang B, Lei M-Y, Cui W-G, Guo Y-Z. A Channel-Projection Mixed-Scale Convolutional Neural Network for Motor Imagery EEG Decoding. IEEE Transactions on Neural Systems and Rehabilitation Engineering 2019;27:1170–80. https://doi.org/10.1109/TNSRE.2019.2915621.
[137] Guan S, Zhao K, Yang S. Motor Imagery EEG Classification Based on Decision Tree Framework and Riemannian Geometry. Computational Intelligence and Neuroscience 2019;2019:e5627156. https://doi.org/10.1155/2019/5627156.
[138] Tang X, Wang T, Du Y, Dai Y. Motor imagery EEG recognition with KNN-based smooth auto-encoder. Artificial Intelligence in Medicine 2019;101:101747. https://doi.org/10.1016/j.artmed.2019.101747.
[139] Diana O, Mihaela A. Comparison of Classifiers and Statistical Analysis for EEG Signals Used in Brain Computer Interface Motor Task Paradigm. Ijarai 2015;4. https://doi.org/10.14569/IJARAI.2015.040102.
[140] Babiloni F, Bianchi L, Semeraro F, Millan J del R, Mourino J, Cattini A, et al. Mahalanobis distance-based classifiers are able to recognize EEG patterns by using few EEG electrodes. 2001 Conference Proceedings of the 23rd Annual International Conference of the IEEE Engineering in Medicine and Biology Society, vol. 1, 2001, p. 651–4 vol.1. https://doi.org/10.1109/IEMBS.2001.1019019.
[141] Trad D, Al-ani T, Jemni M. A feature extraction technique of EEG based on EMD-BP for motor imagery classification in BCI. 2015 5th International Conference on Information Communication Technology and Accessibility (ICTA), 2015, p. 1–6. https://doi.org/10.1109/ICTA.2015.7426931.
[142] Steyrl D, Scherer R, Müller-Putz G. Using random forests for classifying motor imagery EEG, 2013.
[143] He L, Liu B. Motor Imagery EEG Signals Analysis Based on Bayesian Network with Gaussian Distribution. In: Huang D-S, Han K, Gromiha M, editors. Intelligent Computing in Bioinformatics, Cham: Springer International Publishing; 2014, p. 241–7. https://doi.org/10.1007/978-3-319-09330-7_29.
[144] Maeder CL, Sannelli C, Haufe S, Blankertz B. Pre-stimulus sensorimotor rhythms influence brain-computer interface classification performance. IEEE Trans Neural Syst Rehabil Eng 2012;20:653–62. https://doi.org/10.1109/TNSRE.2012.2205707.

[145] Elias-Vinas D. An approach to improve the performance of subject-independent BCIs-based on motor imagery allocating subjects by gender n.d.
[146] Zich C, Debener S, Thoene A-K, Chen L-C, Kranczioch C. Simultaneous EEG-fNIRS reveals how age and feedback affect motor imagery signatures. Neurobiol Aging 2017;49:183–97. https://doi.org/10.1016/j.neurobiolaging.2016.10.011.
[147] Bamdadian A, Guan C, Ang KK, Xu J. Towards improvement of MI-BCI performance of subjects with BCI deficiency. 2015 7th International IEEE/EMBS Conference on Neural Engineering (NER), Montpellier, France: IEEE; 2015, p. 17–20. https://doi.org/10.1109/NER.2015.7146549.
[148] Liang S, Choi K-S, Qin J, Pang W-M, Wang Q, Heng P-A. Improving the discrimination of hand motor imagery via virtual reality based visual guidance. Comput Methods Programs Biomed 2016;132:63–74. https://doi.org/10.1016/j.cmpb.2016.04.023.
[149] Acqualagna L, Botrel L, Vidaurre C, Kübler A, Blankertz B. Large-Scale Assessment of a Fully Automatic Co-Adaptive Motor Imagery-Based Brain Computer Interface. PLOS ONE 2016;11:e0148886. https://doi.org/10.1371/journal.pone.0148886.
[150] Shin Y, Lee S, Lee J, Lee H-N. Sparse representation-based classification scheme for motor imagery-based brain-computer interface systems. J Neural Eng 2012;9:056002. https://doi.org/10.1088/1741-2560/9/5/056002.
[151] Hammer EM, Halder S, Blankertz B, Sannelli C, Dickhaus T, Kleih S, et al. Psychological predictors of SMR-BCI performance. Biol Psychol 2012;89:80–6. https://doi.org/10.1016/j.biopsycho.2011.09.006.
[152] Machado J, Balbinot A. Executed Movement Using EEG Signals through a Naive Bayes Classifier. Micromachines 2014;5:1082–105. https://doi.org/10.3390/mi5041082.
[153] Tang Z, Sun S, Zhang S, Chen Y, Li C, Chen S. A Brain-Machine Interface Based on ERD/ERS for an Upper-Limb Exoskeleton Control. Sensors (Basel) 2016;16. https://doi.org/10.3390/s16122050.
[154] Ren S, Wang W, Hou Z-G, Liang X, Wang J, Shi W. Enhanced Motor Imagery Based Brain- Computer Interface via FES and VR for Lower Limbs. IEEE Transactions on Neural Systems and Rehabilitation Engineering 2020;28:1846–55. https://doi.org/10.1109/TNSRE.2020.3001990.
[155] Kam T, Suk H, Lee S. Non-homogeneous spatial filter optimization for EEG-based brain-computer interfaces. 2013 International Winter Workshop on Brain-Computer Interface (BCI), 2013, p. 26–8. https://doi.org/10.1109/IWW-BCI.2013.6506618.
[156] Ono T, Kimura A, Ushiba J. Daily training with realistic visual feedback improves reproducibility of event-related desynchronisation following hand motor imagery. Clin Neurophysiol 2013;124:1779–86. https://doi.org/10.1016/j.clinph.2013.03.006.
[157] Yi W, Qiu S, Qi H, Zhang L, Wan B, Ming D. EEG feature comparison and classification of simple and compound limb motor imagery. J Neuroeng Rehabil 2013;10:106. https://doi.org/10.1186/1743-0003-10-106.
[158] Yi W, Qiu S, Wang K, Qi H, Zhao X, He F, et al. Enhancing performance of a motor imagery based brain-computer interface by incorporating electrical stimulation-induced SSSEP. J Neural Eng 2017;14:026002. https://doi.org/10.1088/1741-2552/aa5559.
[159] Li X, Zhang H, Guan C, Ong SH, Pan Y, Ang KK. Joint spatial-temporal filter design for analysis of motor imagery EEG. 2013 IEEE International Conference

on Acoustics, Speech and Signal Processing, 2013, p. 978–82. https://doi.org/10.1109/ICASSP.2013.6637795.
[160] Liu C, Wang H, Lu Z. EEG classification for multiclass motor imagery BCI. 2013 25th Chinese Control and Decision Conference (CCDC), 2013, p. 4450–3. https://doi.org/10.1109/CCDC.2013.6561736.
[161] Mondini V, Mangia AL, Cappello A. EEG-Based BCI System Using Adaptive Features Extraction and Classification Procedures. Computational Intelligence and Neuroscience 2016;2016:e4562601. https://doi.org/10.1155/2016/4562601.
[162] Shan H, Xu H, Zhu S, He B. A novel channel selection method for optimal classification in different motor imagery BCI paradigms. BioMedical Engineering OnLine 2015;14:93. https://doi.org/10.1186/s12938-015-0087-4.
[163] Roussel P, Negishi A, Mitsukura Y. Presentation of an SMR-based BCI using auditory feedback based on pitch. 2016 11th France-Japan 9th Europe-Asia Congress on Mechatronics (MECATRONICS) /17th International Conference on Research and Education in Mechatronics (REM), 2016, p. 174–7. https://doi.org/10.1109/MECATRONICS.2016.7547136.
[164] Thomas KP, Cuntai Guan, Chiew Tong Lau, Vinod AP, Kai Keng Ang. A New Discriminative Common Spatial Pattern Method for Motor Imagery Brain–Computer Interfaces. IEEE Trans Biomed Eng 2009;56:2730–3. https://doi.org/10.1109/TBME.2009.2026181.
[165] Li M, Liu H, Zhu W, Yang J. Applying Improved Multiscale Fuzzy Entropy for Feature Extraction of MI-EEG. Applied Sciences 2017;7:92. https://doi.org/10.3390/app7010092.
[166] Misawa T, Matsuda J, Hirobayashi S. A Single-Trial Multiclass Classification of Various Motor Imagery Tasks for EEG-Based Brain–Computer Interface Communication. Electronics and Communications in Japan 2017;100:18–26. https://doi.org/10.1002/ecj.11916.
[167] Ibáñez J, Serrano JI, del Castillo MD, Gallego JA, Rocon E. Online detector of movement intention based on EEG—Application in tremor patients. Biomedical Signal Processing and Control 2013;8:822–9. https://doi.org/10.1016/j.bspc.2013.07.006.
[168] Thomas KP, Guan C, Lau CT, Vinod AP, Ang KK. Adaptive tracking of discriminative frequency components in electroencephalograms for a robust brain-computer interface. J Neural Eng 2011;8:036007. https://doi.org/10.1088/1741-2560/8/3/036007.
[169] Feng J, Yin E, Jin J, Saab R, Daly I, Wang X, et al. Towards correlation-based time window selection method for motor imagery BCIs. Neural Networks 2018;102:87–95. https://doi.org/10.1016/j.neunet.2018.02.011.
[170] Jin J, Miao Y, Daly I, Zuo C, Hu D, Cichocki A. Correlation-based channel selection and regularized feature optimization for MI-based BCI. Neural Networks 2019;118:262–70. https://doi.org/10.1016/j.neunet.2019.07.008.
[171] She Q, Zou J, Luo Z, Nguyen T, Li R, Zhang Y. Multi-class motor imagery EEG classification using collaborative representation-based semi-supervised extreme learning machine. Med Biol Eng Comput 2020;58:2119–30. https://doi.org/10.1007/s11517-020-02227-4.
[172] Blankertz B, Tomioka R, Lemm S, Kawanabe M, Muller K. Optimizing Spatial filters for Robust EEG Single-Trial Analysis. IEEE Signal Processing Magazine 2008;25:41–56. https://doi.org/10.1109/MSP.2008.4408441.

[173] Higashi H, Tanaka T. Simultaneous Design of FIR Filter Banks and Spatial Patterns for EEG Signal Classification. IEEE Transactions on Biomedical Engineering 2013;60:1100–10. https://doi.org/10.1109/TBME.2012.2215960.
[174] Raza H, Cecotti H, Prasad G. Optimising frequency band selection with forward-addition and backward-elimination algorithms in EEG-based brain-computer interfaces. 2015 International Joint Conference on Neural Networks (IJCNN), 2015, p. 1–7. https://doi.org/10.1109/IJCNN.2015.7280737.
[175] Wei Q, Wei Z. Binary particle swarm optimization for frequency band selection in motor imagery based brain-computer interfaces. BME 2015;26:S1523–32. https://doi.org/10.3233/BME-151451.
[176] Dornhege G, Blankertz B, Krauledat M, Losch F, Curio G, Muller K-. Combined Optimization of Spatial and Temporal Filters for Improving Brain-Computer Interfacing. IEEE Transactions on Biomedical Engineering 2006;53:2274–81. https://doi.org/10.1109/TBME.2006.883649.
[177] Novi Q, Guan C, Dat TH, Xue P. Sub-band common spatial pattern (SBCSP) for brain-computer interface. Neural Engineering, 2007. CNE'07. 3rd International IEEE/EMBS Conference on, IEEE; 2007, p. 204–7.
[178] Thomas* KP, Guan C, Lau CT, Vinod AP, Ang KK. A New Discriminative Common Spatial Pattern Method for Motor Imagery Brain–Computer Interfaces. IEEE Transactions on Biomedical Engineering 2009;56:2730–3. https://doi.org/10.1109/TBME.2009.2026181.
[179] Zhang Y, Wang Y, Jin J, Wang X. Sparse Bayesian Learning for Obtaining Sparsity of EEG Frequency Bands Based Feature Vectors in Motor Imagery Classification. Int J Neural Syst 2017;27:1650032. https://doi.org/10.1142/S0129065716500325.
[180] Darvishi S, Gharabaghi A, Boulay CB, Ridding MC, Abbott D, Baumert M. Proprioceptive Feedback Facilitates Motor Imagery-Related Operant Learning of Sensorimotor β-Band Modulation. Front Neurosci 2017;11. https://doi.org/10.3389/fnins.2017.00060.
[181] Lisi G, Hamaya M, Noda T, Morimoto J. Dry-wireless EEG and asynchronous adaptive feature extraction towards a plug-and-play co-adaptive brain robot interface. 2016 IEEE International Conference on Robotics and Automation (ICRA), 2016, p. 959–66. https://doi.org/10.1109/ICRA.2016.7487227.
[182] Zhang Y, Zhou G, Jin J, Wang X, Cichocki A. Optimizing spatial patterns with sparse filter bands for motor-imagery based brain–computer interface. Journal of Neuroscience Methods 2015;255:85–91. https://doi.org/10.1016/j.jneumeth.2015.08.004.
[183] Song L, Epps J. Classifying EEG for Brain-Computer Interface: Learning Optimal Filters for Dynamical System Features. Comput Intell Neurosci 2007;2007. https://doi.org/10.1155/2007/57180.
[184] Higashi H, Tanaka T. Common Spatio-Time-Frequency Patterns for Motor Imagery-Based Brain Machine Interfaces. Computational Intelligence and Neuroscience n.d.:13.
[185] Yang Y, Chevallier S, Wiart J, Bloch I. Subject-specific time-frequency selection for multi-class motor imagery-based BCIs using few Laplacian EEG channels. Biomedical Signal Processing and Control 2017;38:302–11. https://doi.org/10.1016/j.bspc.2017.06.016.
[186] Ang KK, Chin ZY, Zhang H, Guan C. Mutual information-based selection of optimal spatial–temporal patterns for single-trial EEG-based BCIs. Pattern Recognition 2012;45:2137–44. https://doi.org/10.1016/j.patcog.2011.04.018.

[187] Zhou G, Zhao Q, Zhang Y, Adali T, Xie S, Cichocki A. Linked Component Analysis From Matrices to High-Order Tensors: Applications to Biomedical Data. Proc IEEE 2016;104:310–31. https://doi.org/10.1109/JPROC.2015.2474704.
[188] Kalunga EK, Chevallier S, Barthélemy Q, Djouani K, Monacelli E, Hamam Y. Online SSVEP-based BCI using Riemannian geometry. Neurocomputing 2016;191:55–68. https://doi.org/10.1016/j.neucom.2016.01.007.
[189] Nakanishi M, Wang Y, Wang Y-T, Jung T-P. A Comparison Study of Canonical Correlation Analysis Based Methods for Detecting Steady-State Visual Evoked Potentials. PLOS ONE 2015;10:e0140703. https://doi.org/10.1371/journal.pone.0140703.
[190] Lin Z, Zhang C, Wu W, Gao X. Frequency recognition based on canonical correlation analysis for SSVEP-based BCIs. IEEE Transactions on Biomedical Engineering 2007;54:1172–6. https://doi.org/10.1109/TBME.2006.889197.
[191] Wang Y, Wang Y-T, Jung T-P. Visual stimulus design for high-rate SSVEP BCI. Electronics Letters 2010;46:1057–8. https://doi.org/10.1049/el.2010.0923.
[192] Bin G, Gao X, Wang Y, Hong B, Gao S. VEP-based brain-computer interfaces: time, frequency, and code modulations [Research Frontier]. IEEE Computational Intelligence Magazine 2009;4:22–6. https://doi.org/10.1109/MCI.2009.934562.
[193] Wang Y-T, Wang Y, Jung T-P. A cell-phone-based brain-computer interface for communication in daily life. J Neural Eng 2011;8:025018. https://doi.org/10.1088/1741-2560/8/2/025018.
[194] Pan J, Gao X, Duan F, Yan Z, Gao S. Enhancing the classification accuracy of steady-state visual evoked potential-based brain-computer interfaces using phase constrained canonical correlation analysis. J Neural Eng 2011;8:036027. https://doi.org/10.1088/1741-2560/8/3/036027.
[195] Zhang Y, Zhou G, Zhao Q, Onishi A, Jin J, Wang X, et al. Multiway Canonical Correlation Analysis for Frequency Components Recognition in SSVEP-Based BCIs. In: Lu B-L, Zhang L, Kwok J, editors. Neural Information Processing, Berlin, Heidelberg: Springer; 2011, p. 287–95. https://doi.org/10.1007/978-3-642-24955-6_35.
[196] Zhang Y, Zhou G, Jin J, Wang X, Cichocki A. Frequency Recognition in SSVEP-based BCI using Multiset Canonical Correlation Analysis. Int J Neur Syst 2014;24:1450013. https://doi.org/10.1142/S0129065714500130.
[197] Wang Y, Nakanishi M, Wang Y-T, Jung T-P. Enhancing detection of steady-state visual evoked potentials using individual training data. Annu Int Conf IEEE Eng Med Biol Soc 2014;2014:3037–40. https://doi.org/10.1109/EMBC.2014.6944263.
[198] Bin G, Gao X, Wang Y, Li Y, Hong B, Gao S. A high-speed BCI based on code modulation VEP. J Neural Eng 2011;8:025015. https://doi.org/10.1088/1741-2560/8/2/025015.
[199] Lotte F, Congedo M, Lécuyer A, Lamarche F, Arnaldi B. A review of classification algorithms for EEG-based brain–computer interfaces. J Neural Eng 2007;4:R1–13. https://doi.org/10.1088/1741-2560/4/2/R01.
[200] Malan NS, Sharma S. Feature selection using regularized neighbourhood component analysis to enhance the classification performance of motor imagery signals. Computers in Biology and Medicine 2019;107:118–26. https://doi.org/10.1016/j.compbiomed.2019.02.009.
[201] Zhang Y, Zhou G, Jin J, Wang M, Wang X, Cichocki A. L1-regularized Multiway canonical correlation analysis for SSVEP-based BCI. IEEE Trans Neural Syst Rehabil Eng 2013;21:887–96. https://doi.org/10.1109/TNSRE.2013.2279680.

[202] Fatourechi M, Bashashati A, Ward RK, Birch GE. EMG and EOG artifacts in brain computer interface systems: A survey. Clinical Neurophysiology 2007;118:480–94. https://doi.org/10.1016/j.clinph.2006.10.019.
[203] Wang P, Li J. Wavelet Denoising by Quantum Threshold Algorithm. Fourth International Conference on Image and Graphics (ICIG 2007), 2007, p. 62–6. https://doi.org/10.1109/ICIG.2007.41.
[204] Donoho DL, Johnstone IM. Ideal spatial adaptation by wavelet shrinkage. Biometrika 1994;81:425–55. https://doi.org/10.1093/biomet/81.3.425.
[205] Donoho DL. De-noising by soft-thresholding. IEEE Transactions on Information Theory 1995;41:613–27. https://doi.org/10.1109/18.382009.
[206] Zikov T, Bibian S, Dumont GA, Huzmezan M, Ries CR. A wavelet based de-noising technique for ocular artifact correction of the electroencephalogram. Engineering in Medicine and Biology, 2002. 24th Annual Conference and the Annual Fall Meeting of the Biomedical Engineering Society EMBS/BMES Conference, 2002. Proceedings of the Second Joint, vol. 1, IEEE; 2002, p. 98–105.
[207] Chaudhary U, Birbaumer N, Ramos-Murguialday A. Brain–computer interfaces for communication and rehabilitation. Nature Reviews Neurology 2016;12:513.
[208] Hamedi M, Salleh S-H, Noor AM. Electroencephalographic Motor Imagery Brain Connectivity Analysis for BCI: A Review. Neural Computation 2016;28:999–1041. https://doi.org/10.1162/NECO_a_00838.
[209] Chaudhury KN, Unser M. On the shiftability of dual-tree complex wavelet transforms. IEEE Transactions on Signal Processing 2010;58:221–32.
[210] Chaurasiya RK, Londhe ND, Ghosh S. Statistical wavelet features, PCA, and SVM based approach for EEG signals classification. International Journal of Electrical, Computer, Electronics and Communication Engineering 2015;9:182–6.
[211] Resalat SN, Saba V. A Study of Various Feature Extraction Methods on a Motor Imagery Based Brain Computer Interface System. Basic Clin Neurosci 2016;7:13–9.
[212] Kim C, Sun J, Liu D, Wang Q, Paek S. An effective feature extraction method by power spectral density of EEG signal for 2-class motor imagery-based BCI. Medical & Biological Engineering & Computing 2018:1–14.
[213] Hsu W-Y. Wavelet-coherence features for motor imagery EEG analysis posterior to EOG noise elimination. Int J Innov Comput Inform Control 2013;9:465–75.
[214] Whitley D. A genetic algorithm tutorial. Statistics and Computing 1994;4:65–85.
[215] Babatunde OH, Armstrong L, Leng J, Diepeveen D. A genetic algorithm-based feature selection 2014.
[216] Boutsidis C, Mahoney MW, Drineas P. Unsupervised feature selection for principal components analysis. Proceedings of the 14th ACM SIGKDD international conference on Knowledge discovery and data mining, ACM; 2008, p. 61–9.
[217] Song F, Guo Z, Mei D. Feature selection using principal component analysis. System science, engineering design and manufacturing informatization (ICSEM), 2010 international conference on, vol. 1, IEEE; 2010, p. 27–30.
[218] Goldberger J, Hinton GE, Roweis ST, Salakhutdinov RR. Neighbourhood components analysis. Advances in neural information processing systems, 2005, p. 513–20.
[219] Shawe-Taylor J, Sun S. A review of optimization methodologies in support vector machines. Neurocomputing 2011;74:3609–18.
[220] Schlogl A, Kronegg J, Huggins J, Mason S. 19 evaluation criteria for bci research. Toward Brain-Computer Interfacing 2007.

[221] (PDF) Translation of EEG Spatial Filters from Resting to Motor Imagery Using Independent Component Analysis. ResearchGate n.d. http://dx.doi.org/10.1371/journal.pone.0037665.
[222] Corralejo R, Hornero R, Álvarez D. Feature selection using a genetic algorithm in a motor imagery-based Brain Computer Interface. 2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 2011, p. 7703–6. https://doi.org/10.1109/IEMBS.2011.6091898.
[223] Nakisa B, Rastgoo MN, Rakotonirainy A, Maire F, Chandran V. Long Short Term Memory Hyperparameter Optimization for a Neural Network Based Emotion Recognition Framework. IEEE Access 2018;6:49325–38. https://doi.org/10.1109/ACCESS.2018.2868361.
[224] Bashashati H, Ward RK, Bashashati A. Bayesian optimization of BCI parameters. 2016 IEEE Canadian Conference on Electrical and Computer Engineering (CCECE), 2016, p. 1–5. https://doi.org/10.1109/CCECE.2016.7726801.
[225] Cervera MA, Soekadar SR, Ushiba J, Millán J del R, Liu M, Birbaumer N, et al. Brain-computer interfaces for post-stroke motor rehabilitation: a meta-analysis. Ann Clin Transl Neurol 2018;5:651–63. https://doi.org/10.1002/acn3.544.
[226] Fazel-Rezai R, Allison BZ, Guger C, Sellers EW, Kleih SC, Kübler A. P300 brain computer interface: current challenges and emerging trends. Front Neuroeng 2012;5. https://doi.org/10.3389/fneng.2012.00014.
[227] Pan J, Li Y, Zhang R, Gu Z, Li F. Discrimination Between Control and Idle States in Asynchronous SSVEP-Based Brain Switches: A Pseudo-Key-Based Approach. IEEE Transactions on Neural Systems and Rehabilitation Engineering 2013;21:435–43. https://doi.org/10.1109/TNSRE.2013.2253801.
[228] Soni D, Malan NS, Sharma S. CCA Model with Training Approach to Improve Recognition Rate of SSVEP in Real Time. Proceedings of the 2019 3rd International Conference on Artificial Intelligence and Virtual Reality, Singapore, Singapore: Association for Computing Machinery; 2019, p. 56–9. https://doi.org/10.1145/3348488.3348498.
[229] Mulder Th. Motor imagery and action observation: cognitive tools for rehabilitation. J Neural Transm 2007;114:1265–78. https://doi.org/10.1007/s00702-007-0763-z.
[230] Ang KK, Guan C. EEG-Based Strategies to Detect Motor Imagery for Control and Rehabilitation. IEEE Transactions on Neural Systems and Rehabilitation Engineering 2017;25:392–401. https://doi.org/10.1109/TNSRE.2016.2646763.
[231] Widmann A, Schröger E, Maess B. Digital filter design for electrophysiological data – a practical approach. Journal of Neuroscience Methods 2015;250:34–46. https://doi.org/10.1016/j.jneumeth.2014.08.002.
[232] Widmann A, Schröger E. Filter Effects and Filter Artifacts in the Analysis of Electrophysiological Data. Front Psychology 2012;3. https://doi.org/10.3389/fpsyg.2012.00233.
[233] Carrera-León O, Ramirez JM, Alarcon-Aquino V, Baker M, D'Croz-Baron D, Gomez-Gil P. A motor imagery BCI experiment using wavelet analysis and spatial patterns feature extraction. 2012 Workshop on Engineering Applications, 2012, p. 1–6. https://doi.org/10.1109/WEA.2012.6220084.
[234] Malan NS, Sharma S. Removal of Ocular Atrifacts from Single Channel EEG Signal Using DTCWT with Quantum Inspired Adaptive Threshold. 2018 2nd International Conference on Biomedical Engineering (IBIOMED), 2018, p. 94–9. https://doi.org/10.1109/IBIOMED.2018.8534915.

[235] Ming M, Shaona L, Haitao M, Yuliang M, Yunyuan G. Feature extraction method of motor imagery EEG based on DTCWT sample entropy. 2015 34th Chinese Control Conference (CCC), 2015, p. 3964–8. https://doi.org/10.1109/ChiCC.2015.7260250.
[236] Taran S, Bajaj V. Motor imagery tasks-based EEG signals classification using tunable-Q wavelet transform. Neural Comput & Applic 2018. https://doi.org/10.1007/s00521-018-3531-0.
[237] Xu B, Zhang L, Song A, Wu C, Li W, Zhang D, et al. Wavelet Transform Time-Frequency Image and Convolutional Network-Based Motor Imagery EEG Classification. IEEE Access 2019;7:6084–93. https://doi.org/10.1109/ACCESS.2018.2889093.
[238] Peng ZK, Jackson MR, Rongong JA, Chu FL, Parkin RM. On the energy leakage of discrete wavelet transform. Mechanical Systems and Signal Processing 2009;23:330–43.
[239] Goldberger J, Roweis S, Hinton G, Salakhutdinov R. Neighbourhood Components Analysis n.d.:8.
[240] Malan NS, Sharma S. Feature selection using regularized neighbourhood component analysis to enhance the classification performance of motor imagery signals. Computers in Biology and Medicine 2019;107:118–26. https://doi.org/10.1016/j.compbiomed.2019.02.009.
[241] Tangermann M, Müller K-R, Aertsen A, Birbaumer N, Braun C, Brunner C, et al. Review of the BCI Competition IV. Front Neurosci 2012;6. https://doi.org/10.3389/fnins.2012.00055.
[242] Blankertz B, Muller K-R, Krusienski DJ, Schalk G, Wolpaw JR, Schlogl A, et al. The BCI competition III: validating alternative approaches to actual BCI problems. IEEE Transactions on Neural Systems and Rehabilitation Engineering 2006;14:153–9. https://doi.org/10.1109/TNSRE.2006.875642.
[243] Thomas E, Dyson M, Clerc M. An analysis of performance evaluation for motor-imagery based BCI. J Neural Eng 2013;10:031001. https://doi.org/10.1088/1741-2560/10/3/031001.
[244] Shan H, Xu H, Zhu S, He B. A novel channel selection method for optimal classification in different motor imagery BCI paradigms. Biomed Eng Online 2015;14. https://doi.org/10.1186/s12938-015-0087-4.
[245] Mahmoudi M, Shamsi M. Multi-class EEG classification of motor imagery signal by finding optimal time segments and features using SNR-based mutual information. Australas Phys Eng Sci Med 2018;41:957–72. https://doi.org/10.1007/s13246-018-0691-2.
[246] Corralejo R, Hornero R, Álvarez D. Feature selection using a genetic algorithm in a motor imagery-based Brain Computer Interface. 2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 2011, p. 7703–6. https://doi.org/10.1109/IEMBS.2011.6091898.
[247] Kai Keng Ang, Zhang Yang Chin, Haihong Zhang, Cuntai Guan. Filter Bank Common Spatial Pattern (FBCSP) in Brain-Computer Interface. 2008 IEEE International Joint Conference on Neural Networks (IEEE World Congress on Computational Intelligence), Hong Kong, China: IEEE; 2008, p. 2390–7. https://doi.org/10.1109/IJCNN.2008.4634130.
[248] Jiang L, Wang Y, Cai B, Wang Y, Wang Y. Spatial-Temporal Feature Analysis on Single-Trial Event Related Potential for Rapid Face Identification. Front Comput Neurosci 2017;11. https://doi.org/10.3389/fncom.2017.00106.

[249] Zhao Y, Han J, Chen Y, Sun H, Chen J, Ke A, et al. Improving Generalization Based on l1-Norm Regularization for EEG-Based Motor Imagery Classification. Front Neurosci 2018;12. https://doi.org/10.3389/fnins.2018.00272.
[250] Kumar S, Sharma A, Tsunoda T. An improved discriminative filter bank selection approach for motor imagery EEG signal classification using mutual information. BMC Bioinformatics 2017;18:545. https://doi.org/10.1186/s12859-017-1964-6.
[251] Zhang Y, Nam CS, Zhou G, Jin J, Wang X, Cichocki A. Temporally Constrained Sparse Group Spatial Patterns for Motor Imagery BCI. IEEE Trans Cybern 2019;49:3322–32. https://doi.org/10.1109/TCYB.2018.2841847.
[252] He L, Kong X, Yu PS, Ragin AB, Hao Z, Yang X. DuSK: A Dual Structure-preserving Kernel for Supervised Tensor Learning with Applications to Neuroimages. ArXiv:14078289 [Cs] 2014.
[253] Higashi H, Rutkowski TM, Tanaka T, Tanaka Y. Multilinear Discriminant Analysis With Subspace Constraints for Single-Trial Classification of Event-Related Potentials. IEEE J Sel Top Signal Process 2016;10:1295–305. https://doi.org/10.1109/JSTSP.2016.2599297.
[254] Soni D, Malan NS, Sharma S. CCA Model with Training Approach to Improve Recognition Rate of SSVEP in Real Time. Proceedings of the 2019 3rd International Conference on Artificial Intelligence and Virtual Reality, Singapore, Singapore: Association for Computing Machinery; 2019, p. 56–9. https://doi.org/10.1145/3348488.3348498.
[255] Introduction to Motor Imagery-Based Brain-Computer Interface: Time, Frequency, and Phase Analysis-Based Feature Extraction for Two Class MI Classification: Medicine & Healthcare Book Chapter | IGI Global n.d. https://www.igi-global.com/chapter/introduction-to-motor-imagery-based-brain-computer-interface/239081 (accessed February 5, 2021).
[256] Krusienski DJ, Grosse-Wentrup M, Galán F, Coyle D, Miller KJ, Forney E, et al. Critical issues in state-of-the-art brain–computer interface signal processing. J Neural Eng 2011;8:025002. https://doi.org/10.1088/1741-2560/8/2/025002.
[257] Malan NS, Sharma S. Motor Imagery EEG Spectral-Spatial Feature Optimization Using Dual-Tree Complex Wavelet and Neighbourhood Component Analysis. IRBM 2021. https://doi.org/10.1016/j.irbm.2021.01.002.
[258] Wei QG, Wan B, Lu ZW. Classification of EEG Signals Using Filter Bank Common Spatial Pattern Based on Fisher and Laplacian Criteria. Applied Mechanics and Materials 2013. https://www.scientific.net/AMM.239-240.1033 (accessed March 3, 2020).
[259] Kumar S, Sharma A, Tsunoda T. An improved discriminative filter bank selection approach for motor imagery EEG signal classification using mutual information. BMC Bioinformatics 2017;18. https://doi.org/10.1186/s12859-017-1964-6.
[260] Jiang J, Wang C, Wu J, Qin W, Xu M, Yin E. Temporal Combination Pattern Optimization Based on Feature Selection Method for Motor Imagery BCIs. Front Hum Neurosci 2020;14. https://doi.org/10.3389/fnhum.2020.00231.
[261] Klonowski W. Everything you wanted to ask about EEG but were afraid to get the right answer. Nonlinear Biomed Phys 2009;3:2. https://doi.org/10.1186/1753-4631-3-2.
[262] Akay M. Wavelets in biomedical engineering. Ann Biomed Eng 1995;23:531–42. https://doi.org/10.1007/BF02584453.
[263] Akay M, Mello C. Wavelets for biomedical signal processing. Proceedings of the 19th Annual International Conference of the IEEE Engineering in Medicine and Biology Society. “Magnificent Milestones and Emerging Opportunities in Medical

Engineering” (Cat. No.97CH36136), vol. 6, 1997, p. 2688–91 vol.6. https://doi.org/10.1109/IEMBS.1997.756888.
[264] Rafiee J, Rafiee MA, Prause N, Schoen MP. Wavelet basis functions in biomedical signal processing. Expert Systems with Applications 2011;38:6190–201. https://doi.org/10.1016/j.eswa.2010.11.050.
[265] Feng J, Yin E, Jin J, Saab R, Daly I, Wang X, et al. Towards correlation-based time window selection method for motor imagery BCIs. Neural Networks 2018;102:87–95. https://doi.org/10.1016/j.neunet.2018.02.011.
[266] Blankertz B, Muller KR, Krusienski DJ, Schalk G, Wolpaw JR, Schlogl A, et al. The BCI Competition III: Validating Alternative Approaches to Actual BCI Problems. IEEE Trans Neural Syst Rehabil Eng 2006;14:153–9. https://doi.org/10.1109/TNSRE.2006.875642.
[267] Ramoser H, Muller-Gerking J, Pfurtscheller G. Optimal spatial filtering of single trial EEG during imagined hand movement. IEEE Transactions on Rehabilitation Engineering 2000;8:441–6. https://doi.org/10.1109/86.895946.
[268] Dornhege G, Blankertz B, Krauledat M, Losch F, Curio G, Muller K-. Combined Optimization of Spatial and Temporal Filters for Improving Brain-Computer Interfacing. IEEE Transactions on Biomedical Engineering 2006;53:2274–81. https://doi.org/10.1109/TBME.2006.883649.
[269] Higashi H, Tanaka T. Simultaneous Design of FIR Filter Banks and Spatial Patterns for EEG Signal Classification. IEEE Transactions on Biomedical Engineering 2013;60:1100–10. https://doi.org/10.1109/TBME.2012.2215960.
[270] Xygonakis I, Athanasiou A, Pandria N, Kugiumtzis D, Bamidis PD. Decoding Motor Imagery through Common Spatial Pattern Filters at the EEG Source Space. Computational Intelligence and Neuroscience 2018. https://doi.org/10.1155/2018/7957408.
[271] Velásquez-Martínez LF, Álvarez-Meza AM, Castellanos-Domínguez CG. Motor Imagery Classification for BCI Using Common Spatial Patterns and Feature Relevance Analysis. In: Ferrández Vicente JM, Álvarez Sánchez JR, de la Paz López F, Toledo Moreo FcoJ, editors. Natural and Artificial Computation in Engineering and Medical Applications, Berlin, Heidelberg: Springer; 2013, p. 365–74. https://doi.org/10.1007/978-3-642-38622-0_38.
[272] Tan C, Sun F, Zhang W, Liu S, Liu C. Spatial and Spectral Features Fusion for EEG Classification during Motor Imagery in BCI. ArXiv:180804443 [Eess, q-Bio] 2018.
[273] Tariq M, Trivailo PM, Simic M. EEG-Based BCI Control Schemes for Lower-Limb Assistive-Robots. Front Hum Neurosci 2018;12. https://doi.org/10.3389/fnhum.2018.00312.
[274] Zhou G, Zhao Q, Zhang Y, Adalı T, Xie S, Cichocki A. Linked Component Analysis From Matrices to High-Order Tensors: Applications to Biomedical Data. Proceedings of the IEEE 2016;104:310–31. https://doi.org/10.1109/JPROC.2015.2474704.
[275] Zhu X, Li X, Zhang S, Ju C, Wu X. Robust Joint Graph Sparse Coding for Unsupervised Spectral Feature Selection. IEEE Transactions on Neural Networks and Learning Systems 2017;28:1263–75. https://doi.org/10.1109/TNNLS.2016.2521602.
[276] Zhu X, Li X, Zhang S. Block-Row Sparse Multiview Multilabel Learning for Image Classification. IEEE Transactions on Cybernetics 2016;46:450–61. https://doi.org/10.1109/TCYB.2015.2403356.

[277] Liu M, Zhang D. Pairwise Constraint-Guided Sparse Learning for Feature Selection. IEEE Transactions on Cybernetics 2016;46:298–310. https://doi.org/10.1109/TCYB.2015.2401733.
[278] Nie D, Wang L, Adeli E, Lao C, Lin W, Shen D. 3-D Fully Convolutional Networks for Multimodal Isointense Infant Brain Image Segmentation. IEEE Transactions on Cybernetics 2019;49:1123–36. https://doi.org/10.1109/TCYB.2018.2797905.
[279] Zhang Y, Shi F, Cheng J, Wang L, Yap P-T, Shen D. Longitudinally Guided Super-Resolution of Neonatal Brain Magnetic Resonance Images. IEEE Transactions on Cybernetics 2019;49:662–74. https://doi.org/10.1109/TCYB.2017.2786161.
[280] Zhou T, He X, Xie K, Fu K, Zhang J, Yang J. Robust visual tracking via efficient manifold ranking with low-dimensional compressive features. Pattern Recognition 2015;48:2459–73. https://doi.org/10.1016/j.patcog.2015.03.008.
[281] Lv J, Kang Z, Wang B, Ji L, Xu Z. Multi-view Subspace Clustering via Partition Fusion. ArXiv:191201201 [Cs, Stat] 2019.
[282] Fu Y, Cao L, Guo G, Huang TS. Multiple feature fusion by subspace learning. CIVR ’08, 2008. https://doi.org/10.1145/1386352.1386373.
[283] Li Y, Yang M, Zhang Z. A Survey of Multi-View Representation Learning. IEEE Trans Knowl Data Eng 2019;31:1863–83. https://doi.org/10.1109/TKDE.2018.2872063.
[284] Zhang Y, Zhou G, Jin J, Zhang Y, Wang X, Cichocki A. Sparse Bayesian multiway canonical correlation analysis for EEG pattern recognition. Neurocomputing 2017;225:103–10. https://doi.org/10.1016/j.neucom.2016.11.008.
[285] Nie D, Trullo R, Lian J, Wang L, Petitjean C, Ruan S, et al. Medical Image Synthesis with Deep Convolutional Adversarial Networks. IEEE Transactions on Biomedical Engineering 2018;65:2720–30. https://doi.org/10.1109/TBME.2018.2814538.
[286] Jiao Y, Zhang Y, Wang Y, Wang B, Jin J, Wang X. A Novel Multilayer Correlation Maximization Model for Improving CCA-Based Frequency Recognition in SSVEP Brain-Computer Interface. Int J Neural Syst 2018;28:1750039. https://doi.org/10.1142/S0129065717500393.
[287] Cao Z, Prasad M, Tanveer M, Lin C-T. Tensor Decomposition for EEG Signal Retrieval. 2019 IEEE International Conference on Systems, Man and Cybernetics (SMC) 2019:2423–7. https://doi.org/10.1109/SMC.2019.8914076.
[288] Chaudhary U, Birbaumer N, Ramos-Murguialday A. Brain-computer interfaces for communication and rehabilitation. Nat Rev Neurol 2016;12:513–25. https://doi.org/10.1038/nrneurol.2016.113.
[289] Abdulkader SN, Atia A, Mostafa M-SM. Brain computer interfacing: Applications and challenges. Egyptian Informatics Journal 2015;16:213–30. https://doi.org/10.1016/j.eij.2015.06.002.
[290] Nicolas-Alonso LF, Gomez-Gil J. Brain Computer Interfaces, a Review. Sensors (Basel) 2012;12:1211–79. https://doi.org/10.3390/s120201211.
[291] Lin Z, Zhang C, Wu W, Gao X. Frequency recognition based on canonical correlation analysis for SSVEP-based BCIs. IEEE Transactions on Biomedical Engineering 2007;54:1172–6. https://doi.org/10.1109/TBME.2006.889197.
[292] Huang D, Quan Y, He M, Zhou B. Comparison of linear discriminant analysis methods for the classification of cancer based on gene expression data. J Exp Clin Cancer Res 2009;28:149. https://doi.org/10.1186/1756-9966-28-149.

[293] Lei B, Yang P, Wang T, Chen S, Ni D. Relational-Regularized Discriminative Sparse Learning for Alzheimer's Disease Diagnosis. IEEE Transactions on Cybernetics 2017;47:1102–13. https://doi.org/10.1109/TCYB.2016.2644718.
[294] Liu L, Chen L, Chen CLP, Tang YY, pun CM. Weighted Joint Sparse Representation for Removing Mixed Noise in Image. IEEE Transactions on Cybernetics 2017;47:600–11. https://doi.org/10.1109/TCYB.2016.2521428.
[295] Zhou T, Liu F, Bhaskar H, Yang J. Robust Visual Tracking via Online Discriminative and Low-Rank Dictionary Learning. IEEE Transactions on Cybernetics 2018;48:2643–55. https://doi.org/10.1109/TCYB.2017.2747998.
[296] Wen Z, Hou B, Jiao L. Discriminative Dictionary Learning With Two-Level Low Rank and Group Sparse Decomposition for Image Classification. IEEE Transactions on Cybernetics 2017;47:3758–71. https://doi.org/10.1109/TCYB.2016.2581861.
[297] Zhang Y, Zhang H, Chen X, Liu M, Zhu X, Lee S-W, et al. Strength and similarity guided group-level brain functional network construction for MCI diagnosis. Pattern Recognition 2019;88:421–30. https://doi.org/10.1016/j.patcog.2018.12.001.
[298] Zhang C, Fu H, Hu Q, Zhu P, Cao X. Flexible Multi-View Dimensionality Co-Reduction. IEEE Transactions on Image Processing 2017;26:648–59. https://doi.org/10.1109/TIP.2016.2627806.