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Glossary of Terms

EMG	Electromyogram
μC	Microcontroller
IF	Information Fusion
HMD	Health Monitoring Devices
MV	Multi-view
fMRI	Functional magnetic resonance imaging
EEG	Electroencephalogram
sMRI	Structural magnetic resonance imaging
FF	Feature fusion
PCA	Principal components analysis
LDA	Linear discriminant analysis
ULDA	Uncorrelated linear discriminant analysis
NLDA	Non-linear linear discriminant analysis
SOFM	Self-organizing feature map
MLP	Multilayer perceptron
CCA	Canonical correlation analysis
FV	Feature vectors
MCCA	Multi-canonical correlation analysis
FbOMCCA	Multi-canonical correlation analysis based on fractional-order
GCCA	Generalized canonical correlation analysis
GCPV	Generalized canonical projective vectors
LDCCA	Local discrimination canonical correlation analysis
BCI	Brain computer interface
ECG	Electrocardiography
CPVs	Canonical projected vectors
MVL	Multi-view learning
PSDA	power spectral density analysis
SVM	Support vector machine
MUs	Motor units
MUAPs	Motor Unit Action Potentials
NDs	Neuromuscular disorders
ALS	Amyotrophic lateral sclerosis

EMGPAD	Electromyogram precision decomposition
ANN	Artificial neural network
RBF-ANN	Radial basis function neural network
FT	Fourier transformation
STFT	Short-term Fourier transformation
WT	Wavelet transformation
IP	Interference pattern
DWT	Discrete wavelet transformation
F-SVM	fuzzy-support vector machine
SD	Standard deviations
PSO	Particle swarm optimization
MLPNN	Multilayer perceptron neural networks
DFNN	Dynamic fuzzy neural network
ANFIS	Adaptive neuro-fuzzy inference system
PNN	Probabilistic neural network
dMUAP	Dominated motor unit action potential
DCA	Discriminate correlation analysis
MVDCA	Multi-domain multit-view discriminate correlation analysis
MUPT	Motor unit train
nEMG	Needle electromyogram
NJs	Neuromuscular junctions
NCS	Nerve conduction studies
SP	Spontaneous activity
SDMS	Storage and data management system
DA	Differential amplifier
ADC	Analog-to-digital converter
SNR	Signal-to-ratio
CMRR	Common-mode rejection ratio
GNRC	Guwahati Neurological Research centre
IRB	Institutional review board
SVD	Singular value decomposition
VWS	Variability within-subjective
rF-SVD	Regularized frame-singular value decomposition
CCCM	Collective correlation coefficient matrix
OC	Overall correlation
VIS	Variability in intra-subjective
FES	Feature extraction and selection
TD	Time-domain
AR	Autoregressive features
PVs	Projected vectors
EMD	Empirical mode decomposition
CCDF	Canonical correlation discriminant features

db	Daubechies wavelet
k -nn	k -nearest neighbors algorithm
ER	Error rate
SSS	Small-sample size
JSRC	Joint sparse representation classification
HMI	Human-machine-interaction
LDC	Normal densities based linear (multi-class) classifier
QDC	Quadratic (multi-class) classifier
SE	Separability evaluation
FC	Fisher criteria
EEMD	Ensemble empirical mode decomposition
IMFs	Intrinsic mode functions
SF	Statistical feature