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# List of Abbreviations

**2D:** Two-dimensional

**3D:** Three-dimensional

**ANS:** Autonomic Nervous System

**ASM:** Angular Second Moment

**AUC:** Area Under the Curve

**AV:** Audio-visual

**BVP:** Blood Volume Pulse

**CASE:** Continuously Annotated Signals of Emotion

**CDA:** Continuous Decomposition Analysis

**CNN:** Convolutional Neural Networks

**CNS:** Central Nervous System

**CWD:** Choi–Williams Distribution

**cvxEDA:** Convex Optimization based on EDA

**CWT:** Continuous Wavelet Transform

**DDA:** Discrete Decomposition Analysis

**DCM:** Dynamic Causal Modeling

**DR:** Dynamic Range

**ECG:** Electrocardiogram

**EDA:** Electrodermal Activity

**EEG:** Electroencephalogram

**EMG:** Electromyogram

**ER:** Emotion Recognition

**FDTA:** Fractal Dimension Texture Analysis

**FOS:** First-Order Statistics

**GADF:** Gramian Angular Difference Field

**GAF:** Gramian Angular Field

**GASF:** Gramian Angular Summation Field

**GLCM:** Gray Level Co-occurrence Matrix

**GLRLM:** Gray Level Run-Length Matrix

**GLU:** Gray-Level Uniformity

**HM:** Hu's Moments

**HR:** Heart Rate

**HRV:** Heart Rate Variability

**HVHA:** High Valence/High Arousal

**HVLA:** High Valence/Low Arousal

**KNN:** K-Nearest Neighbors

**KW:** Kruskal-Wallis

**LR:** Logistic Regression

**LRE:** Long Run Emphasis

**LTI:** Linear Time-Invariant

**LVHA:** Low Valence/High Arousal

**LVLA:** Low Valence/Low Arousal

**MAP:** Maximum Peak

**MASM:** Mean of Angular Second Moment

**MCN:** Mean of Contrast

**MCR:** Mean of Correlation

**MDE:** Mean of Difference Entropy

**MDN:** Median

**MDV:** Mean of Difference Variance

**ME:** Mean of Entropy

**MFD:** Mean of First Derivative

**MFCC:** Mel-Frequency Cepstral Coefficients

**MFC:** Mel-Frequency Cepstrum

**MIDM:** Mean of Inverse Difference Moment

**MIMC1:** Mean of Information Measures of Correlation-1

**MIMC2:** Mean of Information Measures of Correlation-2

**MIP:** Minimum Peak

**ML:** Machine Learning

**MN:** Mean

**MMCC:** Mean of Maximal Correlation Coefficient

**MSA:** Mean of Sum Average

**MSD:** Mean of Second Derivative

**MSE:** Mean of Sum Entropy

**MSV:** Mean of Sum Variance

**MSSV:** Mean of Sum of Squares Variance

**MTF:** Markov Transition Field

**PNS:** Peripheral Nervous System

**RASM:** Range of Angular Second Moment

**RCN:** Range of Contrast

**RCR:** Range of Correlation

**RDE:** Range of Difference Entropy

**RDV:** Range of Difference Variance

**RE:** Range of Entropy

**RIDM:** Range of Inverse Difference Moment

**RIMC1:** Range of Information Measures of Correlation-1

**RIMC2:** Range of Information Measures of Correlation-2

**RLU:** Run Length Uniformity

**RMCC:** Range of Maximal Correlation Coefficient

**RPC:** Run Percentage

**RP:** Recurrence Plot

**RSA:** Range of Sum Average

**RSE:** Range of Sum Entropy

**RSP:** Respiration

**RSV:** Range of Sum Variance

**RSSV:** Range of Sum of Squares Variance

**SAM:** Self-Assessment Manikin

**SFD:** Standard Deviation of First Derivative

**SKT:** Skin Temperature

**SparsEDA:** Nonnegative Sparse Deconvolution

**SRE:** Short Run Emphasis

**SSD:** Standard Deviation of Second Derivative

**SS:** Sum of Squares

**STD:** Standard Deviation

**STFT:** Short Time Fourier Transform

**SVM:** Support Vector Machine

**TFR:** Time-Frequency Representation

**VA:** Valence-Arousal

**WVD:** Wigner–Ville Distribution

**XGB:** XGBoost

**ZM:** Zernike’s Moments

# List of Symbols

$A$  : State transition matrix

$B$  : Tall matrix containing cubic B-spline basis functions as columns

$C$  : Observation matrix

$C_P$  : Coefficient matrix for the phasic component

$C_T$  : Coefficient matrix for the tonic component

$T(t)$  : Diffusion/reabsorption

$D_{ij}$  : Euclidean distance between any two points in the phase space

$f$  : Frequency

$f$  : Linear frequency

$f_m$  : Mel-frequency

$H$  : Matrix representation in the Laplace transform of  $h(t)$

$H_m(f_k)$  : Value of the m-th triangular filter at frequency  $f_k$

$h(t)$  : Impulse response shaped as a bi-exponential Bateman function

$I$  : Current

$j$  : Imaginary unit

$l$  : Vector of spline coefficients

$M$  : Tridiagonal matrix with moving average coefficients

$M_{ij}$  : Element of the MTF matrix representing the transition probability based on the time order of the original time series

$P(t)$  : Phasic component

$p$  : Sudo Motor Nerve Activity (SMNA)

$q$  : Auxiliary variable

$q$  : Vector in optimization problems

$q(x_i)$  : Bin to which the value  $x_i$  belongs

$R$  : Recurrence matrix

$R$  : Skin resistance

$r$  : Phasic activity

$ri$  : Radius in polar coordinates

$S(t)$  : Sweat secretion via pore opening

$S(f_k, t)$  : Spectrogram magnitude at frequency  $f_k$  and time  $t$

$SC(t)$  : Skin conductance at time  $t$

$SC_P(t)$  : Phasic component of skin conductance at time  $t$

$SC_T(t)$  : Tonic component of skin conductance at time  $t$

$t$  : Tonic component

$\tau$  : Delay coefficient in phase space reconstruction

$\tau$  : Variable representing time in STFT

$\tau_1$  : Slow time constant of the phasic curve shape

$\tau_2$  : Fast time constant of the phasic curve shape

$u(t)$  : Unitary step function

$u_k$  : Input at discrete time step  $k$

$U$  : Heaviside step function

$V$  : Voltage

$W$  : Markov transition matrix

$w(t - \tau)$  : Window function in STFT

$w_{ij}$  : Probability of transitioning from bin  $i$  to bin  $j$

$X$  : Original time series data

$X$  : Time series data

$X(t)$  : Time series data

$\hat{X}$  : Normalized time series

$x(t)$  : Time-domain signal

$x_k$  : State variable at discrete time step  $k$

$\epsilon$  : Additive independent and identically distributed zero-average Gaussian noise term

$\epsilon$  : Threshold distance in phase space reconstruction

$\mu S$  : MicroSiemens

$\phi$  : Angle

$\phi_i$  : Polar angle corresponding to the  $i$ -th element of the time series

$\nu(t)$  : Observation noise at time  $t$

$\nu_k$  : Observation noise at discrete time step  $k$