Application of Biosignal-Driven Intelligent Systems for Multifunction Prosthesis Control

By

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Certificate

I, Rami N. Khushaba, declare that this thesis titled, Application of Biosignal-Driven Intelligent Systems for Multifunction Prosthesis Control, and the work presented in it are my own. I confirm that:

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Acronyms and Abbreviations

AAR: Adaptive Autoregressive
ACO: Ant Colony Optimization
ACV: Adaptive Cepstrum Vector
ANN: Artificial Neural Network
ANOVA: Analysis of Variance
AP: Action Potential
ARIMA: Autoregressive Integrated Moving Average
ARMA: Autoregressive Moving Average
BCI: Brain-Computer Interface
BE: Backward Elimination
BMI: Brain-Machine Interface
CCA: Canonical Correlation Analysis
CNS: Central Nervous System
CSP: Common Spatial Pattern
CSSD: Common Spatial Subspace Decomposition
CWD: Choi-Williams Distribution
CWT: Continuous Wavelet Transform
DB: Davies-Bouldin
DE: Differential Evolution
DEFLDA: Differential Evolution based Fuzzy Linear Discriminant Analysis
DMAV: Difference Mean Absolute Value
DOF: Degree-of-Freedom
DR: Dimensionality Reduction
DWT: Discrete Wavelet Transforms
EA: Evolutionary Algorithm
EDA: Estimation of Distribution Algorithm
EEG: Electroencephalogram
EMG: Electromyogram
EP: Evoked Potential
ERP: Event-Related Potential
EWP: Energy of the Wavelet Packet
FCM: Fuzzy C-Means
FDR: Fisher Discrimination Rate

FFT: Fast Fourier Transform
FIR: Finite Impulse Response
FITWPT: Fuzzy Information Theory based Wavelet Packet Transform method
FLDA: Fuzzy Linear Discriminant Analysis
FLDI: Fishers Linear Discriminant Index
fMRI: functional Magnetic Resonance Imaging
FNS: functional neural stimulation
FP: Feature Projection
FS: Feature Selection
FWP: Fuzzy Wavelet Packet
GA: Genetic Algorithm
GSVD: Generalized Singular Value Decomposition
HMI: Human-Machine Interfacing
IAV: Integral Absolute Value
ICA: Independent Component Analysis
JBB: Joint Best Basis
KDA: Kernel Discriminant Analysis
KFDA: Kernel Fuzzy Discriminant Analysis
KLPP: Kernel Locality Preserving Embedding
kNN: k-Nearest-Neighbor
KPCA: Kernel Principal Components Analysis
LCC: Linear Cepstrum Coefficients
LDA: Linear Discriminant Analysis
LDB: Local Discriminant Basis
LMS: Least-Mean-Square
LPP: Locality Preserving Projection
LS: Least-Squares
LSVM: Linear Support Vector Machine
MEG: Magnetoencephalogram
MES: Myoelectric Signal
MI: Mutual Information
MIEF: Mutual Information Evaluation Measure
MIFS: Mutual Information Feature Selection
MLP: Multilayer Perceptron
MRA: Multiresolution Analysis
MRD: Multiresolution Decomposition
mRMR: minimum-Redundancy-Maximum-Relevant
MU: Motor Unit
MV: Majority Vote
NB: Naive Bayes

NIRS: Near Infrared Spectroscopy
NMF: Nonnegative Matrix Factorization
NPE: Neighborhood Preserving Embedding
OFNDA: Orthogonal Fuzzy Neighborhood Discriminant Analysis
OLDA: Orthogonal Linear Discriminant Analysis
OPCA: Oriented Principal Component Analysis
OWP: Optimal Wavelet Packet
PCA: Principal Components Analysis
pdf: Probability Density Function
PSO: Particle Swarm Optimization
PWVD: Pseudo Wigner-Ville Distribution
RBF: Radial Basis Function
RMS: Root Mean Square
RWE: Relative Wavelet Energy
RWED: Running Windowed Exponential Distribution
SA: Simulated Annealing
SCP: Slow Cortical Potential
SFS: Sequential Forward Selection
SM: Selection Measure
SMR: Sensorimotor Rhythm
SOFM: Self Organizing Feature Map
SPR: Spectral Power Ratio
SSPR: Sandwich Spectral Power Ratio
SSVEP: Steady-State Visual Evoked Potential
STFT: Short Time Fourier Transform
SVD: Singular Value Decomposition
SVM: Support Vector Machine
T2FLDA: Type-2 Fuzzy Logic System
TD: Time Domain
TFR: Time-Frequency Representation
TMR: Targeted Muscle Reinnervation
TS: Tabu Search
TSP: Travelling Salesman Problem
ULDA: Uncorrelated Linear Discriminant Analysis
WPT: Wavelet Packet Transform
WT: Wavelet Transform

Abstract

Prosthetic devices aim to provide an artificial alternative to missing limbs. The controller for such devices is usually driven by the biosignals generated by the human body, particularly Electromyogram (EMG) or Electroencephalogram (EEG) signals. Such a controller utilizes a pattern recognition approach to classify the EMG signal recorded from the human muscles or the EEG signal from the brain. The aim of this thesis is to improve the EMG and EEG pattern classification accuracy. Due to the fact that the success of pattern recognition based biosignal driven systems highly depends on the quality of extracted features, a number of novel, robust, hybrid and innovative methods are proposed to achieve better performance. These methods are developed to effectively tackle many of the limitations of existing systems, in particular feature representation and dimensionality reduction. A set of knowledge extraction methods that can accurately and rapidly identify the most important attributes for classifying the arm movements are formulated. This is accomplished through the following:

1. Developing a new feature extraction technique that can identify the most important features from the high-dimensional time-frequency representation of the multichannel EMG and EEG signals. For this task, an information content estimation method using fuzzy entropies and fuzzy mutual information is proposed to identify the optimal wavelet packet transform decomposition for classification.

2. Developing a powerful variable (feature or channel) selection paradigm to improve the performance of multi-channel EMG and EEG driven systems. This will eventually lead to the development of a combined channel and feature selection technique as one possible scheme for dimensionality reduction. Two novel feature selection methods are developed under this scheme utilizing the ant colony and differential evolution optimization techniques. The differential evolution optimization technique is further modified in a novel attempt in employing a float optimizer for the combinatorial task of feature selection, proving powerful performance by both methods.

3. Developing two feature projection techniques that extract a small subset of highly informative discriminant features, thus acting as an alternative scheme for dimensionality reduction. The two methods represent novel variations to fuzzy discriminant analysis based projection techniques. In addition, an extension to the non-linear discriminant analysis is proposed based on a mixture of differential evolution and fuzzy discriminant analysis.

The testing and verification process of the proposed methods on different EMG and EEG datasets provides very encouraging results.