IARIA

MULTIMEDIA SIGNAL PROCESSING

UNIVERSITÀ DEGLI STUDI DI MILANO BICOCCA

DIPARTIMENTO DI INFORMATICA, SISTEMISTICA E COMUNICAZIONE

Human-Machine Interaction: EEG Electrode and Feature Selection Exploiting Evolutionary Algorithms in Motor Imagery Tasks

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Short Resume

PhD student in Computer Science at the University of Milano-Bicocca.

Main research interests:

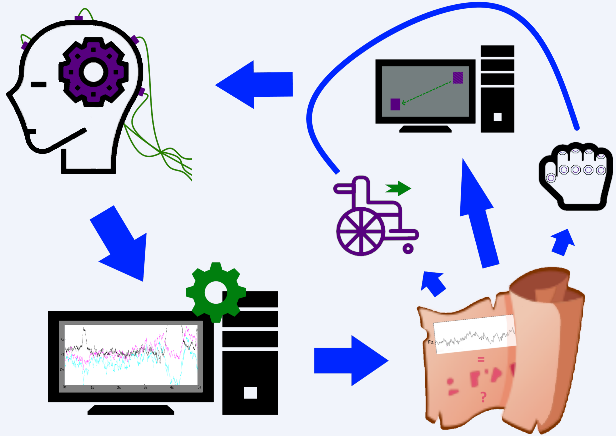
- Brain-related topics, especially brain computer interfacing;
- Signal processing: from electroencephalographic signals to underwater images;
- Artificial intelligence techniques in different applications: discriminate effects on time-series, learn new features, classify memes.

Trying to learn new things especially by interacting with other researchers and with the students I am tutoring, both in a Machine Learning course and for thesis completion.

Overview

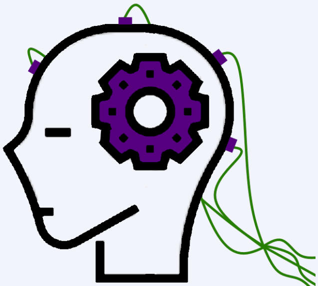
Introduction [1/4]

Human-Machine Interaction: EEG Electrode and Feature Selection Exploiting Evolutionary Algorithms in Motor Imagery Tasks



Human-Machine Interaction: EEG Electrode and Feature Selection Exploiting Evolutionary Algorithms in Motor Imagery Tasks

- is non-invasive;
- records brain activities and functions;
- is characterized by frequency bands;
- has temporal and spatial resolutions.



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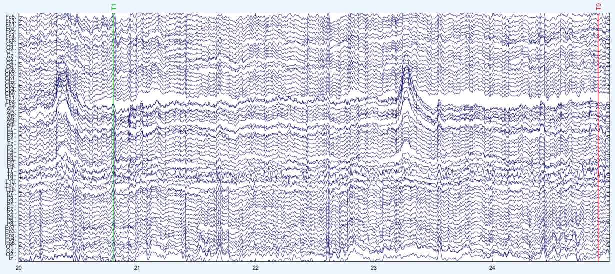

Introduction [2/4]

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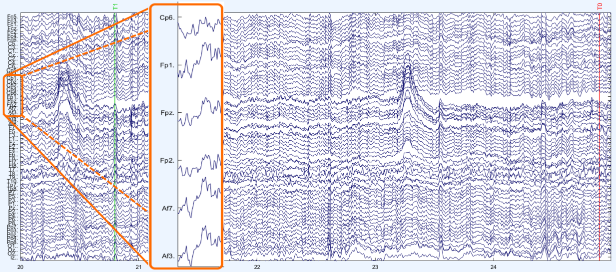
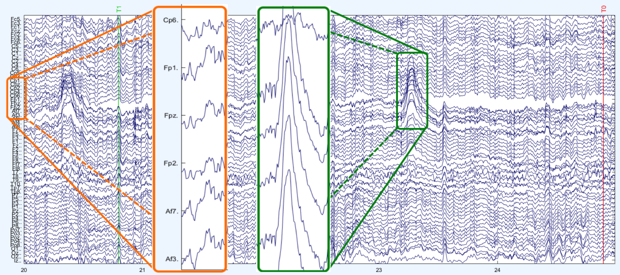


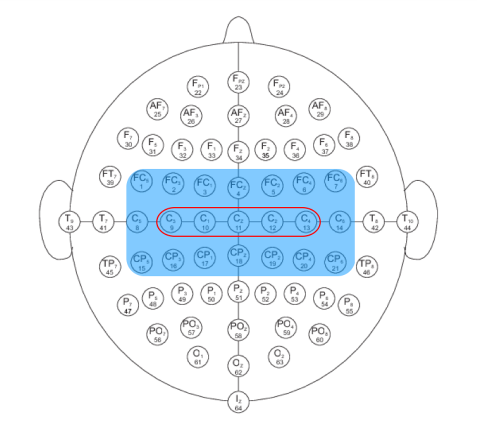
Human-Machine Interaction: EEG Electrode and Feature Selection Exploiting Evolutionary Algorithms in Motor Imagery Tasks

- is easily affected by noise;
- is heterogeneous.



Introduction [3/4]

Human-Machine Interaction: EEG Electrode and Feature Selection Exploiting Evolutionary Algorithms in Motor Imagery Tasks



Features

- Type: limited;
- Selection/Extraction: a priori, dimensionality reduction, ignores spatial and type contributions;
- Purpose: improve performance.

Introduction [4/4]

Human-Machine Interaction: EEG Electrode and Feature Selection Exploiting Evolutionary Algorithms in Motor Imagery Tasks

Literature

- Type: limited;
- Selection/Extraction: a priori, dimensionality reduction, ignores spatial and type contributions;
- Purpose: improve performance.

Proposed

- Type: combinations of heterogeneous features;
- Selection: ignores a priori knowledge;
- Purpose: access spatial and type contributions.

Aim

Provide a benchmark to highlight spatial and feature type contributions

Contributions

1. Population-based approach;
2. Heterogeneous features;
3. Evolutionary Feature Selection (EFS);
4. Analyses of electrodes and feature type contributions.

Background

- **Core**: EFS $\rightarrow$ minimum number of features, maximum classification accuracy;
- **Advantages**: no field knowledge, different solutions with single execution.
- **Literature**: electrode set reduction, subject-based approach, poor number of instances [1][2][3].

Background

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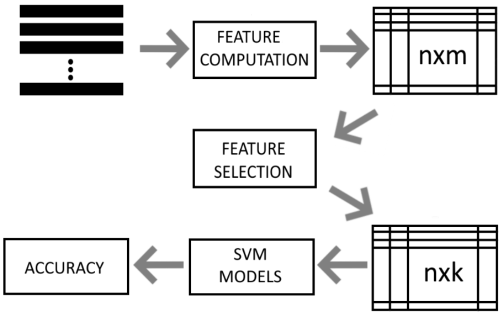
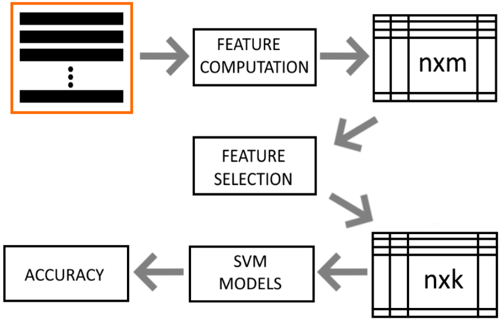
Dataset: EEG Motor Movement/Imagery Dataset [4][5]

- Subjects: 109;
- Instances for motor movement task: $4924 = 2469$ LH $+ 2455$ RH;
- Instances for motor imagery task: $4915 = 2479$ LH $+ 2436$ RH;
- Sampling rate: 160 Hz;
- Normalization: min-max, Z-score.

Proposed Approach



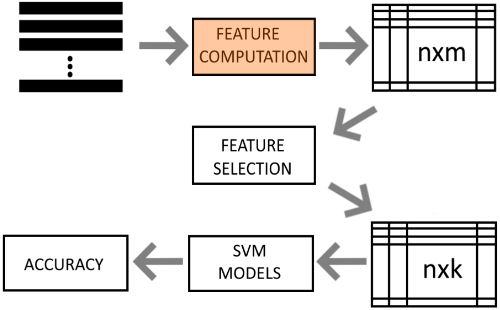
Proposed Approach



Pre-processing and tests

1. Notch filter: 50 Hz;
2. FIR filter: 7 - 31 Hz;
3. Test on non-normalized (NN-DS), min-max normalized (MM-DS) and z-score normalized (ZS-DS) data.

Proposed Approach

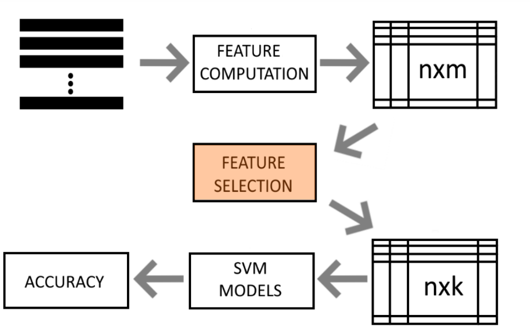


Feature Computation

1280 features $=$ 64 electrodes $\times$[3 Hjorth params $+$ 2 frequency bands $\times$ (PSD through Welch $+$ 3 modalities $\times$ PSD through Morlet) $+$ statistical measures].

- Time-domain: Hjorth parameters [6];
- Frequency-domain: PSD estimation through Welch's method [7];
- Time-frequency domain: PSD extraction through Morlet wavelet convolution [8].

Proposed Approach



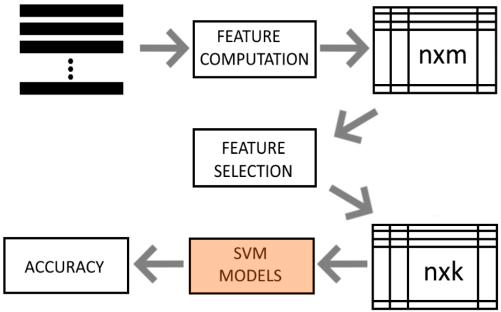
Feature Selection

- Benchmark: principal component analysis and a priori selection;
- EFS techniques: genetic algorithm, particle swarm optimization, simulated annealing
  - wrapper approach $\rightarrow$ SVM with radial basis and scaled gamma;
  - objective functions: performance only, performance/number of features [9]

$$f(x) = \alpha(1-acc)+(1-\alpha)\left(1-\frac{N_{sf}}{N_{if}}\right)$$

  - Output: binary vector.

Proposed Approach



Classifiers

- Binary classification of LH/RH movement/imagination;
- Models: Linear, Quadratic, Cubic, Fine/Medium/Coarse Gaussian SVM models (5-fold cross validation);
- Dataset: (1) all the features; (2) a priori selected; (3) PCA dimensions; (4) EFS selected;
- Total number of tests: 11.

Discussion [1/3]

Table: Best results obtained in each test on motor left/right hand movement[1]

Test	*SVM model*	*Dataset*	*# features*	*Accuracy (%)*
all features	**cubic**	**ZS-DS**	**1280**	**67.8**
a priori	mean Gaussian	ZS-DS	100	62.7
PCA	quadratic	MM-DS	43	62.3
GA accuracy	cubic	ZS-DS	662	67.2
GA trade-off	**cubic**	**ZS-DS**	**646**	**67.8**
PSO accuracy	cubic	ZS-DS	620	67.3
PSO trade-off	**quadratic**	**ZS-DS**	**675**	**68.0**
SA accuracy	**cubic**	**ZS-DS**	**1117**	**68.3**
SA trade-off	cubic	ZS-DS	1116	67.8
agreement accuracy	quadratic	ZS-DS	264	66.4
agreement trade-off	cubic	ZS-DS	308	67.5

[1] NN-DS = non-normalized, MM-DS = min-max normalized, ZS-DS normalized data.

Discussion [2/3]

Table: Best results obtained in each test on motor left/right hand imagination[2]

Test	*SVM model*	*Dataset*	*# features*	*Accuracy (%)*
all features	**linear**	**NN-DS**	**1280**	**64.3**
a priori	linear	ZS-DS	100	59.7
PCA	quadratic	MM-DS	41	59.5
GA accuracy	**cubic**	**ZS-DS**	**641**	**63.8**
GA trade-off	quadratic	ZS-DS	608	63.7
PSO accuracy	cubic	MM-DS	622	61.7
PSO trade-off	**quadratic**	**ZS-DS**	**714**	**64.0**
SA accuracy	cubic	ZS-DS	1114	63.6
SA trade-off	**cubic**	**ZS-DS**	**1117**	**63.8**
agreement accuracy	cubic	ZS-DS	272	62.4
agreement trade-off	quadratic	ZS-DS	313	63.3

[2] NN-DS = non-normalized, MM-DS = min-max normalized, ZS-DS normalized data.

Discussion [3/3]

Electrodes agreement

- Left/right hand movement: a priori electrodes selected + frontal, parietal and occipital electrodes;
- Left/right hand imagination: a priori electrodes selected + fronto-central, parietal and occipital electrodes;

Feature types

- Left/right hand movement: great influence of statistical measures;
- Left/right hand imagination: great contribution from Hjorth activity parameter;
- Both tasks: presence of time-frequency related features;

Conclusion and Future Work

- ☑ Dataset: EEG Motor Movement/Imagery Dataset;
- ☑ Better results on: z-score normalized dataset → heterogeneity mitigation;
- ☑ Different feature types → broaden the analysis;
- ☑ The EFS techniques contributes in the feature selection without the influence of expert knowledge;
- ☑ Different contributions of the brain areas and feature types;
- ☐ Test with different fitness functions and on different datasets;
- ☐ Define experimental protocol considering ergonomic issues.

Thank you

Bibliography

1. A. Atyabi, M. Luerssen, S. Fitzgibbon, and D. M. Powers, "Evolutionary feature selection and electrode reduction for EEG classification," in 2012 IEEE congress on evolutionary computation. IEEE, 2012, pp. 1–8.
2. K. Amarasinghe, P. Sivils, and M. Manic, "EEG feature selection for thought driven robots using evolutionary algorithms," in 2016 9th International Conference on Human System Interactions (HSI). IEEE, 2016, pp. 355–361.
3. K. Amarasinghe, P. Sivils, and M. Manic, "EEG feature selection for thought driven robots using evolutionary algorithms," in 2016 9th International Conference on Human System Interactions (HSI). IEEE, 2016, pp. 355–361.
4. A. L. Goldberger, L. A. Amaral, L. Glass, J. M. Hausdorff, P. C. Ivanov, R. G. Mark, J. E. Mietus, G. B. Moody, C.-K. Peng, and H. E. Stanley, "PhysioBank, PhysioToolkit, and PhysioNet: components of a new research resource for complex physiologic signals," circulation, vol. 101, no. 23, 2000, pp. e215–e220.
5. G. Schalk, D. J. McFarland, T. Hinterberger, N. Birbaumer, and J. R. Wolpaw, "BCI2000: a general-purpose brain-computer interface (BCI) system," IEEE Transactions on biomedical engineering, vol. 51, no. 6, 2004, pp. 1034–1043.
6. S.-H. Oh, Y.-R. Lee, and H.-N. Kim, "A novel EEG feature extraction method using Hjorth parameter," International Journal of Electronics and Electrical Engineering, vol. 2, no. 2, 2014, pp. 106–110.
7. P. Welch, "The use of fast Fourier transform for the estimation of power spectra: a method based on time averaging over short, modified periodograms," IEEE Transactions on audio and electroacoustics, vol. 15, no. 2, 1967, pp. 70–73.
8. M. X. Cohen, "A better way to define and describe Morlet wavelets for time-frequency analysis," NeuroImage, vol. 199, 2019, pp. 81–86.
9. S. M. Vieira, L. F. Mendonça, G. J. Farinha, and J. M. Sousa, "Modified binary PSO for feature selection using SVM applied to mortality prediction of septic patients," Applied Soft Computing, vol. 13, no. 8, 2013, pp. 3494–3504.

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