PROCESS: Projection-Based Classification of Electroencephalograph Signals

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Classification of EEG Signals as Time-series

Classification of electroencephalograph (EEG) signals is the common denominator in EEG-based recognition systems that are relevant to many applications ranging from medical diagnosis to EEG-controlled devices such as web browsers or typing tools for paralyzed patients [4].

- EEG signals can be considered as multivariate time-series.
- The k-nearest neighbor (k-NN) method using Dynamic Time Warping (DTW) as distance measure was reported to be competitive, if not superior, to many state-of-the-art time-series classifiers [2].

Our Contribution: PROCESS

We use DTW in order to construct real-valued features which results in projecting multivariate time-series into a vector space:

- A random subset $\mathcal{D}$ of the training data is selected;
- The distance of the *remaining* training data from the selected instances $\mathcal{D}$ is calculated using multivariate Dynamic Time Warping (DTW) [2];
- The training set is mapped into an $|\mathcal{D}|$-dimensional vector space, where each feature corresponds to the distance from a signal in $\mathcal{D}$.
- Any conventional classifier may be trained in this projected representation. We propose to use logistic regression [3].
- To classify a new instance x', its distances from $\mathcal{D}$ are calculated, hence the previously trained classifier (logistic regression) can predict its class label from the projected representation.

Figure 1 illustrates the mapping procedure, while Figure 2 shows an example two-dimensional projection.

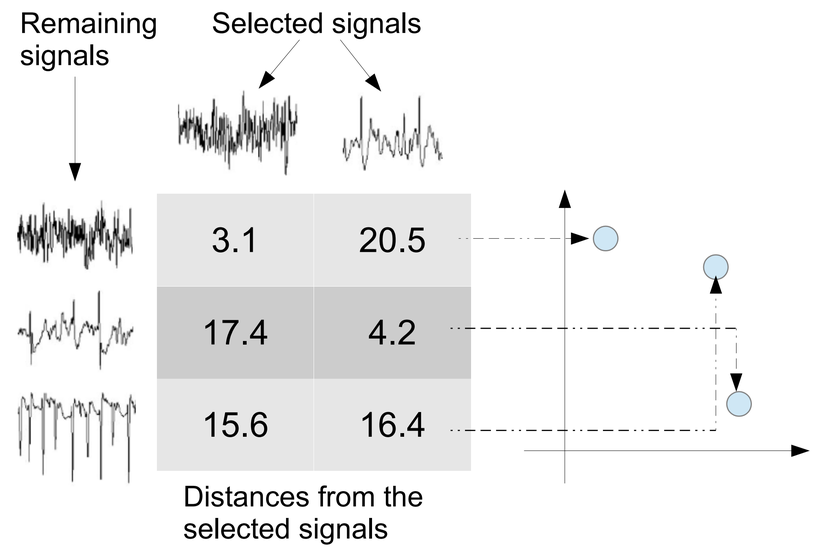

Figure 1: Projection of signals into a vector space by PROCESS. The horizontal (vertical) axis of the coordinate system correspond to the distances from the first (second) selected signal.

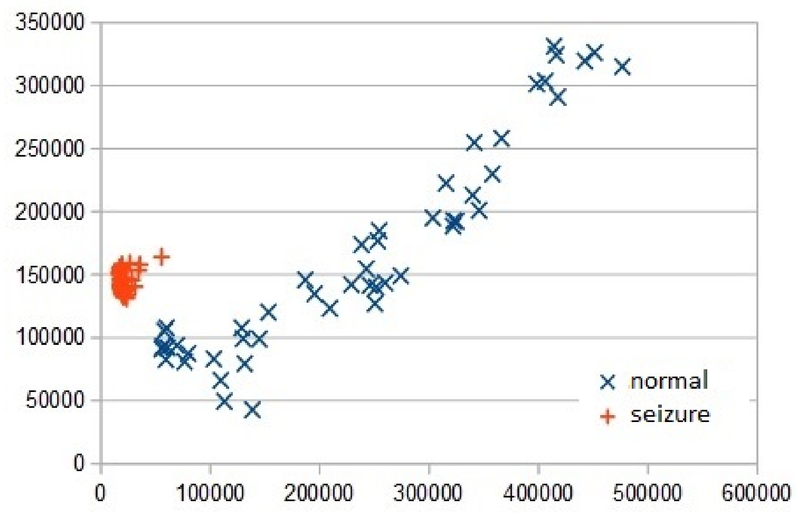

Figure 2: The result of projecting the EEG signals into a two dimensional vector space. Signal either correspond to normal brain activity or epileptic seizures [1].

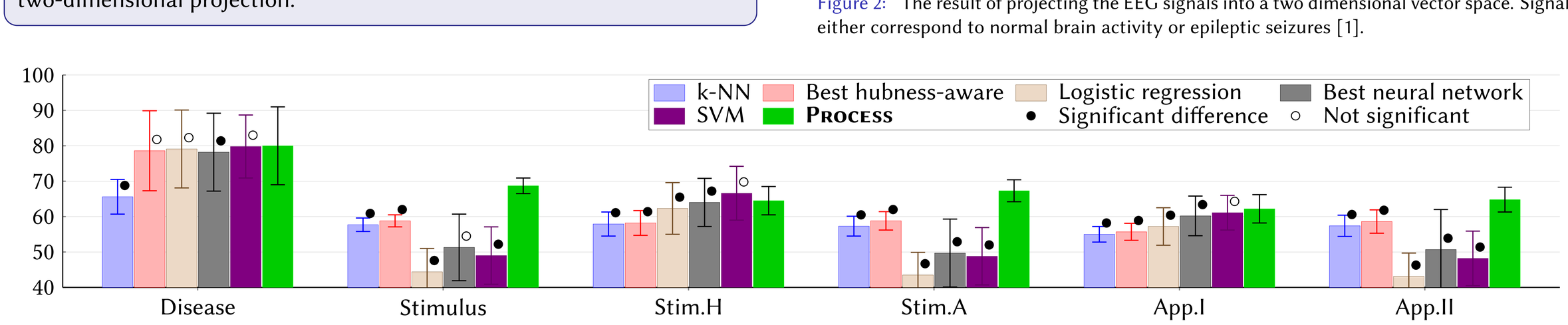

Figure 3: Average accuracy of classifiers over 10×10-fold cross-validation. The bullets show whether the accuracies significantly ($p < 0.01$) differ from those of PROCESS. The numeric values of average accuracies and standard deviations are reported in the Proceedings.

Experiments

In order to evaluate our approach, we used the publicly available EEG dataset[a] from the UCI machine learning repository [6].

- In the *Disease* context the task is to recognize whether a person is affected by the disease (alcoholism) or not.
- In the *Stimulus* context we classified signals according to stimuli.
- The *Stim.H*, *Stim.A*, *App.I* and *App.II* contexts extend *Stimulus* by restricting the data used in training/testing phases to signals from healty/alcoholic individuals only.

We compared the accuracy of PROCESS to the following baselines:

- k-nearest neighbor using Dynamic Time Warping (DTW) distance;
- Hubness-aware classifiers hw-kNN, HFNN, NHBNN and HIKNN [5];
- Logistic regression, Support Vector Machines (SVMs) and neural networks from the Weka software package.[b]

[a]http://archive.ics.uci.edu/ml/datasets/EEG+Database
[b]http://www.cs.waikato.ac.nz/ml/weka/

Conclusions and Outlook

- The proposed projection approach may be useful to represent EEG signals of a real dataset in a low dimensional vector space and may allow exploratory analysis of the data by visual inspection.
- One may consider more advanced selection strategies for $\mathcal{D}$ other than random selection.
- The vector representation of the data constructed by PROCESS allows to use (almost) any vector classifiers including ensemble methods and semi-supervised classifiers. The projection might be useful for clustering or anomaly detection.

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[1] R. G. Andrzejak et al. Indications of nonlinear deterministic and finite-dimensional structures in time series of brain electrical activity: Dependence on recording region and brain state. *Physical Review E*, 64(6):061907, 2001.

[2] K. A. Buza. *Fusion Methods for Time-Series Classification*. Peter Lang Verlag, 2011.

[3] S. le Cessie and J. van Houwelingen. Ridge Estimators in Logistic Regression. *Applied Statistics*, 41(1):191–201, 1992.

[4] M. Sabeti et al. A new approach for eeg signal classification of schizophrenic and control participants. *Expert Systems with Applications*, 38(3):2063 – 2071, 2011.

[5] N. Tomašev et al. Hubness-aware classification, instance selection and feature construction: Survey and extensions to time-series. In *Feature Selection for Data and Pattern Recognition*, pages 231–262. Springer, 2015.

[6] X. L. Zhang et al. Event related potentials during object recognition tasks. *Brain Research Bulletin*, 38(6):531–538, 1995.