Data Mining and Machine Learning for Classification and Clustering of NIRS signals

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Collaboration

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LABEX NUMEV

10/04/2014

Institut Mines-Télécom

2f-NIRS - ISAE / M2H - Toulouse
Aim and Outline

Interest of DM and ML for NIRS Data Analysis and BCI

What could be the contribution of Mines Alès in the French Community for functional NIRS?

- Machine Learning and Data Mining
- Brain Computer Interface (BCI)
- Main issues
- Applications
  - Graph-based transfer learning for managing brain signals variability in NIRS-based BCIs
  - Estimation of operator attentional state
Machine Learning

« Field of study that gives computers the ability to learn without being explicitly programmed »
Arthur Samuel 1959

« Instead of trying to produce a programme to simulate the adult mind, why not rather try to produce one which simulates the child's ? If this were then subjected to an appropriate course of education one would obtain the adult brain. » Alan Turing 1963
Data Mining

« The non-trivial process of identifying valid, novel, potentially useful and ultimately understandable patterns in data »
Fayyad, Shapiro et Smyth 1996
Knowledge Discovery from Data

Data sources

Consolidation

Selection

Data Mining / Machine Learning

Evaluation

Formated Data

Consolidated Data

y=ax²

Models

Data sources
Classification / Clustering

<table>
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Classification

- SVM
- LDA
- K-means
- Decision trees
- Neural networks
- Fuzzy Logic clustering
- Regression
- Rules
- Case based reasoning
- Bayesian networks
- ...

Clustering

Attribut 1

Attribut 2

Attribut 1

Attribut 2
General principles of BCI

Biological Signals → Electrical Analogic signals → Analogic Signal processing → Analogic to Digital Conversion → Digital Signal Processing → Numerical Data

Sensor

decision-making tools → Classification Clustering → Features Selection
NIRS based BCI

NIRS
Near-Infrared Spectroscopy

Classification
Features Selection
Digital Signal Processing

HbO2 HHb

Time

HbO2 HHb

Time
Main issues

- Variability Inter subjects and Inter sessions
- Long calibration time for BCI
- Choice of the ML / DM classification method
- Off line / On line approach
- Lack of data for benchmark
Graph-based transfer learning for managing brain signals variability in NIRS-based BCIs

- Long calibration time needed before every use in order to train a subject-specific classifier.
- One way to reduce this calibration time is to use data collected from other users or from previous recording sessions of the same user as a training set.
- However, brain signals are highly variable and using heterogeneous data to train a single classifier may dramatically deteriorate classification performance.
- Transfer learning framework in which we model brain signals variability in the feature space using a bipartite graph.
Graph-based transfer learning for managing brain signals variability in NIRS-based BCIs

- Open Data provided by Abibullaev et al., 2013
- NIRS signals recorded from seven healthy subjects using 16 measurement channels on pre-frontal cortex
- Two experiments - four sessions:
  - discern brain activation patterns related to imagery movement of right forearm from the activation patterns related to relaxed state
  - discern brain activation patterns related to imagery movement of left forearm from the activation patterns related to relaxed state.
- During each session, participants performed three trials

Graph-based transfer learning for managing brain signals variability in NIRS-based BCIs

Prototypical brain activity pattern using NIRS technology
Graph-based transfer learning for managing brain signals variability in NIRS-based BCIs

Brain signals variability in NIRS-based BCIs:
(a) Inter-sessions variability of explanatory channels for subject 5 in experiment 1.
(b) Inter-subjects variability of explanatory channels for subjects 3 and 4 in experiment 2.

White dots represent explanatory channels and black dots represent non-explanatory channels.
Graph-based transfer learning for managing brain signals variability in NIRS-based BCIs

Bipartite graph model for characterizing brain signals variability in the features space between different users
Estimation of operator attentional state

Towards a near infrared spectroscopy-based estimation of operator attentional state.
Gérard Derosière, Sami Dalhoumi, Stéphane Perrey, Gérard Dray, Tomas Ward
PLoS ONE 01/2014

7 subjects
Estimation of operator attentional state

B. NIRS signals preprocessing

C. Pattern classification (SVM)

Signals from the first 10 minutes of task (data from 6 of the 7 subjects)

Signals from the last 10 minutes of task (data from 6 of the 7 subjects)

SVM training

First 10 min

Last 10 min

Signals from the first 10 and last 10 minutes of task (data from the remaining subject)

SVM test

Calculation of % of correctly classified epochs
# Estimation of operator attentional state

## A. Subject [O2Hb] [HHb] [O2Hb] and [HHb]

<table>
<thead>
<tr>
<th>Subject</th>
<th>[O2Hb]</th>
<th>[HHb]</th>
<th>[O2Hb] and [HHb]</th>
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## B. Mean ± SD [O2Hb] [HHb] [O2Hb] and [HHb]

<table>
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</table>

## C. Mean ± SD [O2Hb] [HHb] [O2Hb] and [HHb]

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### Mean ± SD

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<td>77 ± 20.2</td>
<td>66.2 ± 35.1</td>
<td>83.5 ± 23.1</td>
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Estimation of operator attentional state

On line
K-means custering
Estimation of operator attentional state

On line K-means clustering
Estimation of operator attentional state

On line
K-means clustering
Estimation of operator attentional state

On line K-means clustering

20 min.
Estimation of operator attentional state

On line
K-means clustering

25 min.
Estimation of operator attentional state

On line
K-means clustering

Graph showing data points with different colors representing different groups clustered by K-means algorithm.
Future work

- On line data analysis
- Fuzzy clustering
- Multi Classifier aggregation

- NIRS Open Data Repository
- NIRS Open Data Analysis Software
Data Mining and Machine Learning for Classification and Clustering of NIRS signals

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