Neuroadaptive technology for Human Machine Teaming

16 Nov. 2023
Contributions from PhD theses of X. XU & G. ANGELOTTI

- “In search of invariants in varying electroencephalography signals for brain-computer interfaces”
defended by Xiaoqi XU on January 27th 2023.

- “Advances in Risk-Aware Offline Reinforcement Learning: A Study of Data Augmentation, Explainability, and Policy Selection”
defended by Giorgio ANGELOTTI on June 12th 2023.
Context and Contributions

Context
*How to improve Human-Machine Interaction (HMI) offline? (i.e. from previously collected data?)*

Data collection with Human in the Loop is expensive
→ Lack of HMI data
→ Data (inter-subject) variability *(cf. presentation X.Xu)*

Contributions in Offline Reinforcement Learning (ORL):
- Data augmentation
- Risk-aware Policy selection
- Application to HMI
Offline Reinforcement Learning

- No interaction to explore (no trial and error)
- Learns from a data set of experiences
- Possibly become better than the recorded agent

Levine et al.
Challenges

- **Vanilla Temporal Difference algorithms not good without exploration**

\[
\frac{\delta Q^*_i(s_t, a_t)}{\delta i} \approx \frac{Q^*_{i+1}(s_t, a_t) - Q^*_i(s_t, a_t)}{\alpha_i} = r_t + \gamma \max_{a} Q^*_i(s_{t+1}, a) - Q^*_i(s_t, a_t)
\]

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**Optimistic in front of Uncertainty**

Figure 2.4: Taken from the presentation of Kumar, Fu et al. (2019) at NeurIPS 2019. Q-function
**Works**

**Angelotti, Drougard, Chanel**
Offline Learning for Planning: A Summary
(2020) Proceedings of the 1st Workshop on Bridging the Gap Between AI Planning and Reinforcement Learning at the ICAPS

**Angelotti, Drougard, Chanel**
Expert-guided Symmetry Detection in MDPs
(2022) Proceedings of the 14th International Conference on Agents and Artificial Intelligence

**Angelotti, Drougard, Chanel**
Data Augmentation Through Expert-Guided Symmetry Detection to Improve Performance in Offline Reinforcement Learning
(2023) Proceedings of the 15th International Conference on Agents and Artificial Intelligence

**Angelotti, et al.**
Our method applied to HMI
Submitted to an International Conference

**Angelotti, Diaz Rodriguez**
Towards a more efficient computation of individual attribute and policy contribution for post-hoc explanation of cooperative multi-agent systems using Myerson values
(2023) Elsevier’s Knowledge-Based Systems

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**Review of the literature of offline learning (missing at the time)**

**Can we improve the data efficiency of algorithms in the offline context?**
Validation of expert proposed symmetries

**How to select a deterministic risk-sensitive policy between many?**
Robust offline policy selection with the Bayesian formalism

**Can we apply these methods to Human-Computer Interaction with Physiological computing?**
Robust application to Firefighter Robot use case

**Explainability for Multi-Agent Systems**
Contribution:

*Check if an alleged symmetry $k$ is valid* and use the resulting knowledge for data augmenting.

Estimate transitions → Transform data with $k$ → Evaluate probabilities

$\nu_k > \nu?$ → Augment or not $D$

proportional to the size of the intersection!
\[ U^\pi = \mathbb{E}_{s \sim \rho}[V^\pi(s)] \quad \Delta U = U^{\hat{\pi}_k} - U^{\hat{\pi}} \]
II Risk-aware Policy selection

Contribution:
A method to offline evaluate and select deterministic policies in a risk-sensitive way technique to do so for small finite states and actions MDPs.

![Diagram showing risk-sensitive metrics](image)

- **Exploitation vs Caution – step 1**
  - Data Set
  - Define Bayesian Prior Distribution on Model Uncertainty
  - Posterior Distribution on Model Uncertainty
II Risk-aware Policy selection

Exploitation vs Caution – step 2

Estimate the same value for every different policy in the candidate set, \( \{\text{Policy}_1, \ldots, \text{Policy}_n\} \)

then select the one that maximizes the Risk-sensitive metric!

Reiterate until the estimate has the wanted statistical significance
Environments
II Risk-aware Policy selection

Results

(< 10 states, < 10 actions)

Ring: NORBU ✔️, EvC ✔️

Chain: No best method

Usage of trivial policy increases with batch size
Application to Mixed-Initiative Human-Robot Interaction

- Human Supervision
- Dangerous consequences of bad policies
- Limited previously collected data set
- Partial observability
Application: Offline RL with Human-in-The-Loop and Physiological Computing
What is missing? A method to include model uncertainty for learned POMDPs and to compute a robust policy.

Contribution: technique to do so, specific to the application to our use case.

Classifier confusion matrix: Dirichlet Prior for POMDP Observation

SOLVE ROBUSTLY THE POMDP AND THE MDP TAKING INTO ACCOUNT MODEL UNCERTAINTY
Evaluate the mixed-initiative interaction policy

compare following policies:

1. **Data collector policy (Random)**
2. **Full automatic policy**
3. **MDP adaptive strategy** with physiological and behavioural data
4. **POMDP adaptive strategy** with physiological and behavioural data
### III Application to HMI

<table>
<thead>
<tr>
<th>Policy</th>
<th>mean</th>
<th>std</th>
<th>min</th>
<th>25%</th>
<th>Median</th>
<th>75%</th>
<th>max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Random ($D$)</td>
<td>22.1</td>
<td>10.0</td>
<td>1.0</td>
<td>12.8</td>
<td>26.5</td>
<td>29.3</td>
<td>36.0</td>
</tr>
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<td>Random ($D_{val}$)</td>
<td>17.9</td>
<td>9.6</td>
<td>4.0</td>
<td>8.3</td>
<td>20.0</td>
<td>26.8</td>
<td>32.0</td>
</tr>
<tr>
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<td>22.7</td>
<td>7.6</td>
<td>6.0</td>
<td>18.0</td>
<td>22.5</td>
<td><strong>28.8</strong></td>
<td><strong>39.0</strong></td>
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<tr>
<td>POMDP ($D_{val}$)</td>
<td><strong>23.4</strong></td>
<td><strong>5.7</strong></td>
<td><strong>14.0</strong></td>
<td><strong>18.5</strong></td>
<td><strong>24.0</strong></td>
<td><strong>27.5</strong></td>
<td><strong>37.0</strong></td>
</tr>
<tr>
<td>FA ($D_{val}$)</td>
<td>25.6</td>
<td>5.0</td>
<td>9.0</td>
<td>25.3</td>
<td>27.0</td>
<td>28.0</td>
<td>32.0</td>
</tr>
</tbody>
</table>
Belief of performance

Spearman’s $\rho = 0.325$

$p(\beta)$-value < 0.001
Offline Reinforcement Learning could improve Human Machine Interaction.

Teaming up better with people,

by better understanding their state.

→ EEG-based Brain Computer Interface!
Context and Contributions

Context:

How to design a classifier for BCI that tackles inter-subject EEG variability?

Contributions:

- Laplacian (spatial)
- Path signature (temporal)
- Topological data analysis (spatio-temporal)
EEG varies between sessions and subjects

EEG variability

<table>
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<th>Internal</th>
<th>Macroscopic</th>
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</thead>
<tbody>
<tr>
<td>cellular noise</td>
<td>environmental noise</td>
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<tr>
<td>electrical noise</td>
<td>task</td>
</tr>
<tr>
<td>synaptic noise</td>
<td></td>
</tr>
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</table>

<table>
<thead>
<tr>
<th>Microscopic</th>
<th>External</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Gibson, E., Lobaugh, N. J., Joordens, S., &amp; McIntosh, A. R. (2022)</td>
</tr>
</tbody>
</table>

Masquelier, T. (2013)
Scrivener, C. L. & Reader, A. T. (2022)
Solutions

Transfer learning

Adaptive waveform learning

Model the neural events through adaptive kernels


Objectif: robust features against inter-subject variability

- Laplacian: hierarchical representation that encodes the intrinsic geometry
- Path signature: invariant under time reparametrization and captures order
- TDA: extracts topological properties of the attractor of EEG dynamics
• X. Xu, N. Drougard, R. N. Roy (2021). Dimensionality Reduction via the Laplace-Beltrami Operator: Application to EEG-based BCI, *IEEE EMBS Conf. NER*


• X. Xu, D. Lee, N. Drougard, R. N. Roy (accepted for publication in Scientific Reports). Signature methods for brain-computer interfaces. Preprint available at Research Square [https://doi.org/10.21203/rs.3.rs-2476159/v1]

• X. Xu, N. Drougard, R. N. Roy (to be submitted). Tackling inter-subject variability in brain-computer interface via topological data analysis.
Data availability:

All of the datasets analysed during the thesis are publicly available. The links for download:

- *BCI competition IV 2a dataset*: https://www.bbci.de/competition/iv/
- *Physionet motor imagery dataset*: https://physionet.org/content/eegmmidb/1.0.0/
- *Passive BCI competition dataset*: https://zenodo.org/record/4917218#.Y8pgFKfMI5k

Code availability:

Code of these methods can be found on github:

- *Path signature*: https://github.com/XiaoqiXu77/Signature_BCI
- *TDA*: https://github.com/XiaoqiXu77/TDA_BCI
Path signature

- Originated in pure math to solve stochastic differential equations
- Borrowed by machine learning community as a feature map for time series (e.g. handwritten character recognition, diagnosis of bipolar disorder etc.)
- Never used for BCI

Path signature

Path $X_t : [a, b] \rightarrow \mathbb{R}^d$  

Signature $S(X)_{a,b} = (1, S(X)_{a,b}^1, \ldots, S(X)_{a,b}^n, S(X)_{a,b}^{1,1}, S(X)_{a,b}^{1,2}, \ldots)$

level 1

level 2

$S(X)^i_{a,b} = \int_a^b dX_t^i = X_b^i - X_a^i = \Delta X^i$

$S(X)_{a,b}^{i_1,\ldots,i_k} := \int_{a<t<b} S(X)_{a,t}^{i_1,\ldots,i_{k-1}} dX_t^{i_k}$

$= \int_{a<t_k<b} \int_{a<t_{k-1}<t_k} \ldots \int_{a<t_1<t_2} \int_a^{i_1} dX_{t_1}^{i_1} dX_{t_2}^{i_2} \ldots dX_{t_k}^{i_k}$
Path signature

Path \( X_t : [a, b] \rightarrow \mathbb{R}^d \) → Signature \( S(X)_{a, b} = (1, S(X)^1_{a, b}, \ldots, S(X)^n_{a, b}, S(X)^{1,1}_{a, b}, S(X)^{1,2}_{a, b}, \ldots) \)

level 1

level 2

(a) \( S(X)^{1,2}_{a, b} \)
(b) \( S(X)^{2,1}_{a, b} \)
(c) \( \frac{1}{2}(S(X)^{1,2}_{a, b} - S(X)^{2,1}_{a, b}) \) → lead matrix
Properties

- It fully characterizes paths up to tree-like equivalence (paths which retrace themselves along some subsection)
- Any continuous classification boundary in the path space can be approximated by a linear boundary in the signature space
- Can be efficiently computed, and used in an online setting
- Invariant under translation and time reparametrization
Application on BCI
Results

Features: study of truncation levels

<table>
<thead>
<tr>
<th></th>
<th>level</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
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<tbody>
<tr>
<td>intra</td>
<td>SVM</td>
<td>50.5(12.9)</td>
<td>66.1(15.2)</td>
<td>55.7(13.3)</td>
<td>36.9(13.9)</td>
</tr>
<tr>
<td></td>
<td>LDA</td>
<td>51.0(12.6)</td>
<td>63.4(14.0)</td>
<td>54.7(14.2)</td>
<td>54.6(14.2)</td>
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<tr>
<td></td>
<td>LR</td>
<td>50.9(11.3)</td>
<td>67.1(13.5)</td>
<td>56.0(13.3)</td>
<td>56.6(14.0)</td>
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<tr>
<td></td>
<td>RF</td>
<td>49.7(11.6)</td>
<td>59.7(16.1)</td>
<td>58.2(16.8)</td>
<td>36.6(18.0)</td>
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<tr>
<td></td>
<td>MLP</td>
<td>52.3(11.2)</td>
<td>61.6(16.4)</td>
<td>54.8(13.3)</td>
<td>56.8(15.1)</td>
</tr>
<tr>
<td>inter</td>
<td>SVM</td>
<td>52.6(3.6)</td>
<td>53.9(6.1)</td>
<td>44.2(6.2)</td>
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<tr>
<td></td>
<td>LDA</td>
<td>52.5(4.9)</td>
<td>53.5(6.2)</td>
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<td>LR</td>
<td>53.5(4.4)</td>
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<td>58.7(8.3)</td>
<td>56.3(5.2)</td>
<td>52.2(5.7)</td>
</tr>
</tbody>
</table>

- The lead-lag relationship captured by the level 2 signature seems to be relevant with the underlying neural mechanisms.
Application on BCI
## Results

<table>
<thead>
<tr>
<th></th>
<th>#channels</th>
<th>#classes</th>
<th>Signature (intra)</th>
<th>Signature (inter)</th>
<th>Covariance (intra)</th>
<th>Covariance (inter)</th>
</tr>
</thead>
<tbody>
<tr>
<td>BCI Competition IV 2a</td>
<td>22</td>
<td>2</td>
<td>71.4 (18.1)</td>
<td>66.1 (11.8)</td>
<td>81.1 (16.6)</td>
<td>69.2 (15.9)</td>
</tr>
<tr>
<td>Physionet MI-BCI</td>
<td>64</td>
<td>2</td>
<td>60.1 (23.9)</td>
<td>47.0 (11.0)</td>
<td>63.8 (24.2)</td>
<td>46.2 (14.8)</td>
</tr>
<tr>
<td>Passive BCI competition</td>
<td>61</td>
<td>3</td>
<td>88.9 (10.5)</td>
<td>41.4 (7.4)</td>
<td>90.9 (9.3)</td>
<td>42.0 (5.6)</td>
</tr>
<tr>
<td>BCI Competition IV 2a</td>
<td>22</td>
<td>2</td>
<td>71.4 (18.1)</td>
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<td>2</td>
<td>58.2 (24.5)</td>
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<td>64.1 (24.7)</td>
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<tr>
<td>Passive BCI competition</td>
<td>21</td>
<td>3</td>
<td>58.0 (17.7)</td>
<td>39.7 (6.1)</td>
<td>71.2 (15.9)</td>
<td>36.9 (5.4)</td>
</tr>
</tbody>
</table>

- The signature-based matrices are more robust to inter-subject variability than covariance matrices, especially on noisy and low-quality data.

Xiaoqi Xu, Darrick Lee, Nicolas Drougard, Raphaëlle N. Roy (2023). Signature methods for brain-computer interfaces. Accepted for publication in Scientific Reports.