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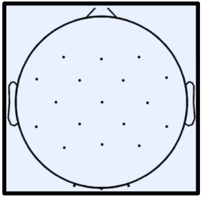
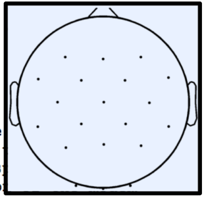
Vision and Motivation



Vision and Motivation

HIIT SCINET Robotics



Robotics

V Wigotsky (PLASTICS ENGINEERING, 1998-01-01)

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AI and robotics

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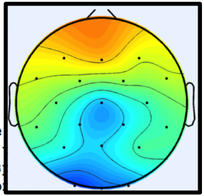

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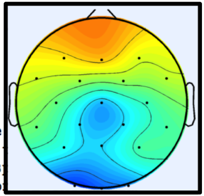

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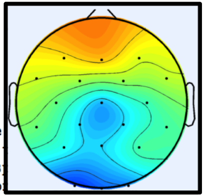

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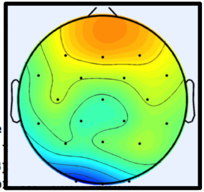

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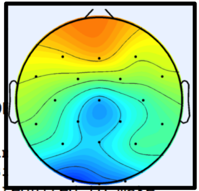


Turning Segways into soccer robots

B Browning, E Searock, P E Rybski, M Veloso (INDUSTRIAL RO
INTERNATIONAL JOURNAL, 2005-01-01)

Purpose - To adapt the segway RMP, a dynamically balanci
build robots capable of playing soccer autonomously. Des
approach - Focuses on the electro-mechanical mechanisms required to make
the Segway RMP autonomous, sensitive, and able to controla football.
Findings - Finds that turning a Segway RMP into a soccer-playing [...]

Multi-robot-systems in entertainment - Robot soccer

M W Han, G Novak (MULTI-AGENT-SYSTEMS IN PRODUCTION, 2000-01-01)

The robot soccer was introduced with the purpose to develop the intelligent cooperative multi-robot (agents) systems (MAS). From the scientific viewpoint the soccer robot is an intelligent autonomous agent, which carries outtasks with other agents in cooperative, coordinated and communicative way. The robot soccer provides a good opportunity to [...]

Modelling and control of a soccer robot

F Solc, B Honzik (7TH INTERNATIONAL WORKSHOP ON ADVANCED MOTION CONTROL, PROCEEDINGS, 2002-01-01)

The paper describes some results of development of robot soccer team

First steps toward our vision

Predicting term-relevance from brain signals:

1. A given topic T is relevant to a user
2. A term w is shown to the user
3. Brain signals are recorded using electroencephalography (EEG)
4. Classifier predicts the user's relevance of term w for topic T

Predicting term-relevance from brain signals

Research questions:

1. How well can we predict relevance judgements on terms from the brain signals of unseen users?
2. Which parts of the EEG signals are important for the prediction?

Experiment

"As realistic as possible/as controlled as possible."

Scenario:

- Each participant read and judged hand-picked terms in six topics
- One term at a time; no repetitions
- balanced ground-truth

Examples:

Entrepreneurship:	business risk, startup company, ...
Iraq war:	US army, Saddam Hussein, ...
Irrelevant words:	shopping, video-games, ...

Data:
38 participants, ca. 1368 relevance judgments

EEG feature representations

Views	$\mathbf{v}_k$	Features
Relevance judgement view:		
Relevance		A binary relevance judgement provided by a participant for a term for a given topic
Frequency-band-based views:		
Theta	1	40 features for each frequency band:
Alpha	2	20 features of average power over
Beta	3	1 second epochs before the relevance
Gamma1	4	judgement; 20 features of average
Gamma2	5	power over entire period, minus power
Engage	6	of the second before term onset
Event-related-potential-based view:		
ERPs	7	80 features of average amplitude: 20 features for 80–150 ms, P1; 20 features for 150–250 ms, N1/P2; 20 features for 250–450 ms, N2 or P3a; 20 features for 450–800 ms: N4 or P3b

Feature engineering in the *frequency domain* (i.e., frequency-band based) and in the *time domain* (i.e., event-related-potential based).

Classification setup

- Bayesian Efficient Multiple Kernel Learning [1],

$$y(\mathbf{x}_*) = \mathbf{a}^T \left(\sum_{k=1}^{K} e_k \mathbf{v}_{k,*} \right) + b$$

  with $\mathbf{y}$ the binary relevance judgements, $\mathbf{v}_k$ the views, and e_k the kernel weights (RQ2).

- Leave-one-participant-out strategy to estimate the classification accuracy (RQ1).

- Only observations that conformed to the ground truth, balance between relevant and irrelevant observations, five repetitions.

- Simple automatic feature selection procedure based on the t-statistic [7].

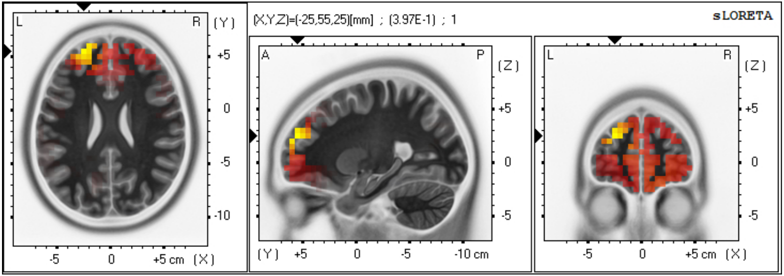
Predictive power

Views	Mean accuracy	p-value	Mean improvement
All	0.5415	**0.0003**	8.30%
Selected combined views:			
Al+Ga1	0.5429	0.0014	8.59%
Al+E	0.5475	**0.0007**	9.50%
Ga1+E	0.5528	**0.0002**	10.55%
Al+Ga1+Be	0.5369	0.0022	7.37%
Al+Ga1+E	0.5586	<**0.0001**	11.72%
Individual views:			
Alpha (Al)	0.5242	0.0265	4.83%
Gamma1 (Ga1)	0.5143	0.1445	2.86%
Beta (Be)	0.5005	0.4838	0.10%
Gamma2	0.5101	0.2003	2.02%
Theta	0.5000	0.4984	0.01%
ERPs (E)	0.5312	0.0092	6.24%
Engage	0.4773	0.9673	−4.55%

Bold entries denote that improvements are statistically significant at a level $\alpha = 0.01$, p-value $< \alpha$ with correction for multiple testing.

Physiological findings

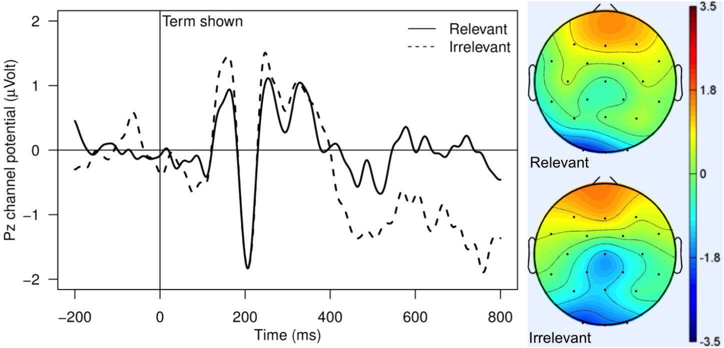
Localization of Alpha change assoziated with relevance mapped to a normalized brain:



Brodmann Area 10 associated with a range of cognitive functions that are important for relevance judgments, such as recognition, semantic processing, memory recall, and intentional planning [5, 4, 2].

Physiological findings

Grand average of the ERP in the Pz channel:



ERP after irrelevant and relevant term onset with significance difference after 450ms, maximizing at 747ms. The latency and topography of the potential suggest the involvement of a P3-like potential [3].

Why interesting for IR?

- In certain IR applications the target is to detect true positive terms (i.e., relevant with very high probability) that represent a user's search intent [6].
- In such applications, a classifier that trades recall for the benefit of precision can be used to maximize user experience.
- We can take advantage of the fact that brain signals can be captured continuously and with high throughput—compared to signals that require explicit user interaction.
- As a result, a large number of relevance judgments can be observed in a relatively short time.

Application: Topic representation

Topic-wise prediction using a **high-precision classifier** with $p > 0.99$ as threshold for a term being classifed as relevant:

Topic	Count all	Count relevant	Precision	Recall	Top 5 relevant terms
Climate change and global warming	209	111	0.5238	0.0991	Snowmelt, Elevated CO2, Climate change, *hardware synchronization*, *sightseeing*
Entrepreneurship	199	110	0.6897	0.1818	business risk, startup company, business creation, *shopping*, *virtual relationships*
Immigration integration	204	105	0.5238	0.1048	citizenship, ethnic diversity, xenophobia, *arsonist*, *morse code*
Intelligent Vehicles	185	109	0.8000	0.1101	pedestrian tracking, collision sensing, remote driving, radar vision, *arsonist*
Iraq war	208	111	0.6296	0.1532	Saddam Hussein, US army, Tony Blair, *morse code*, *rock n roll*
Precarious employment	204	106	0.5714	0.1132	minimum wage, employment regulation, job instability, *virtual relationships*, *video-games*
Mean	202	109	0.6231	0.1270	

Normal font indicats a relevant term according to the ground truth, italics indicates an irrelevant term according to the ground truth.

Summary

- Relevance judgments happen in the brain and therefore the most intriguing way to predict relevance is to directly use the brain signals.
- We showed that term-relevance prediction using only brain signals captured via EEG is possible. We demonstrated its usage to construct meaningful sets of terms for unknown topics.
- Currently, we are expanding this idea towards usage in a real information retrieval system by utilizing an IR-suitable modification of the semantic oddball paradigm.

For future developments and all our other research related to IR, visit `http://augmentedresearch.hiit.fi/`.

Appendix

Publication

Manuel J. A. Eugster*, Tuukka Ruotsalo*, Michiel M. Spapé*, Ilkka Kosunen, Oswald Barral, Niklas Ravaja, Giulio Jacucci, and Samuel Kaski. **Predicting term-relevance from brain signals.** In Proceedings of the 37th International ACM SIGIR Conference on Research & Development in Information Retrieval, pages 425–434, 2014. (* equal contribution). http://dx.doi.org/10.1145/2600428.2609594.

Acknowledgments

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