one should expect, response condition interacted with response key position, $F1(1,19) = 8.3$, $p = .01$; $F2(1,11) = 93.5$, $p < .001$, indicating a right hand benefit for right hand responses at the left side in the crossed condition and at the right side in the uncrossed condition. Theoretically most important, temporal reference and response key position interacted, $F1(1,19) = 9.7$, $p = .01$; $F2(1,11) = 17.6$, $p = .002$. This time–space congruency effect was neither modulated by response condition, $F1(1,19) = 1.1$, $p = .31$; $F2(1,11) = 1.4$, $p = .27$, nor by SOA, $F1(2,38) = 1.2$, $p = .30$; $F2(2,22) = 1.0$, $p = .37$. All other effects were not significant, all $ps > .31$. Participants conducted more errors in the crossed than in the uncrossed response condition, $F1(1,19) = 24.3$, $p < .001$; $F2(1,11) = 264.3$, $p < .001$. The $F2$-analysis further revealed an interaction between response key position, SOA, and response condition $F2(2,22) = 3.9$, $p = .04$. There were no other significant effects for PC, all $ps > .07$.

Discussion

By requiring responses on keys placed on the left or right by crossed and uncrossed hands, we disentangled the egocentric spatial space and the effector-related "embodied" space. The presentation of a time word before a lateralized visual target evoked a space–time congruency effect, that is, responses were fastened for spatially left (right) responses when a past (future) word preceded the rectangle. Theoretically most important, this space–time congruency effect was not modulated when hands were crossed. This result indicates that temporal codes activate abstract spatial codes rather than effector-related spatial codes.

References

Bonato M, Zorzi M, Umiltá C (2012) When time is space: Evidence for a mental time line. Neurosci Biobehav Rev 36:2257–2273. doi:10.1016/j.neubiorev.2012.08.007

Boroditsky L, Fuhrman O, McCormick K (2010) Do English and Mandarin speakers think about time differently? Cognition 118:123–129. doi:10.1016/j.cognition.2010.09.010

Kintsch, W. (1998) Comprehension: A paradigm for cognition. Cambridge University Press, New York

Rolke B, Ruiz Fernández S, Schmid M, Walker M, Lachmair M, Rahona López JJ, Hervás G, Vázquez C (2013) Priming the mental time-line: Effects of modality and processing mode. Cogn Process 14:231–244. doi:10.1007/s10339-013-0537-5

Santiago J, Lupiáñez J, Pérez E, Funes MJ (2007) Time (also) flies from left to right. Psychon Bull Rev 14:512–516. doi:10.1007/s10339-013-0537-5

Is the novelty-P3 suitable for indexing mental workload in steering tasks?

Menja Scheer, Heinrich H. Bülthoff, Lewis L. Chuang
Max Planck Institute for Biological Cybernetics, Tübingen, Germany

Difficulties experienced in steering a vehicle can be expected to place a demand on one's mental resources (O'Donnell, Eggemeier 1986). While the extent of this mental workload (MWL) can be estimated by self-reports (e.g., NASA-TLX; Hart, Staveland 1988), it can also be physiologically evaluated in terms of how a primary task taxes a common and limited pool of mental re-sources, to the extent that it reduces the electroencephalographic (EEG) responses to a secondary task (e.g. an auditory oddball task). For example, the participant could be primarily required to control a cursor to track a target while attending to a series of auditory stimuli, which would infrequently present target tones that should be responded to with a button-press (e.g., Wickens, Kramer, Vanasse and Donchin 1983). Infrequently presented targets, termed oddballs, are known to elicit a large positive potential after approximately 300 ms of their presentation (i.e.,P3).

Indeed, increasing tracking difficulty either by decreasing the predictability of the tracked target or by changing the complexity of the controller dynamics has been shown to attenuate P3 responses in the secondary auditory monitoring task (Wickens et al. 1983; Wickens, Kramer and Donchin 1984).

In contrast, increasing tracking difficulty—by introducing more frequent direction changes of the tracked target (i.e. including higher frequencies in the function that describes the motion trajectory of the target)—has been shown to bear little influence on the secondary task's P3 response (Wickens, Israel and Donchin 1977; Isreal, Chesney, Wickens and Donchin 1980). Overall, the added requirement of a steering task consistently results in a lower P3 amplitude, relative to performing auditory monitoring alone (Wickens et al. 1983; Wickens et al. 1977; Isreal et al. 1980).

Using a dual-task paradigm for indexing workload is not ideal. First, it requires participants to perform a secondary task. This prevents it from being applied in real-world scenarios; users cannot be expected to perform an unnecessary task that could compromise their critical work performance. Second, it can only be expected to work if the performance of the secondary task relies on the same mental resources as those of the primary task (Wickens, Yeh 1983), requiring a deliberate choice of the secondary task. Thus, it is fortunate that more recent studies have demonstrated that P3 amplitudes can be sensitive to MWL, even if the auditory oddball is ignored (Ullsperger, Freude and Erdmann 2001; Allison, Polich 2008). This effect is said to induce a momentary and involuntary shift in general attention, especially if recognizable sounds (e.g. a dog bark, opposed to a pure sound) are used (Miller, Rietschel, McDonald and Hatfield 2011).

The current work, containing two experiments, investigates the conditions that would allow 'novelty-P3', the P3 elicited by the ignored, recognizable oddball, to be an effective index for the MWL of compensatory tracking. Compensatory tracking is a basic steering task that can be generalized to most implementations of vehicular control. In both experiments participants were required to use a joystick to counteract disturbances of a horizontal plane. To evaluate the generalizability of this paradigm, we depicted this horizontal plane as either a line in a simplified visualization or as the horizon in a real-world environment. In the latter, participants experienced a large field-of-view perspective of the outside world from the cockpit of an aircraft that rotated erratically about its heading axis. The task was the same regardless of the visualization. In both experiments, we employed a full factorial design for the visualization (instrument, world) and 3 oddball paradigms (in experiment 1) or 4 levels of task difficulty (in experiment 2) respectively. Two sessions were conducted on separate days for the different visualizations, which were counter-balanced for order. Three trials were presented per oddball paradigm (experiment 1) or level of task difficulty (experiment 2) in blocks, which were randomized for order. Overall, we found that steering performance was worse when the visualization was provided by a realistic world environment in experiments 1 ($F (1, 11) = 42.8$, $p < 0.01$) and 2 ($F (1, 13) = 35.0$, $p < 0.01$). Nonetheless, this manipulation of visualization had no consequence on our participants' MWL as evaluated by a post-experimental questionnaire (i.e., NASA-TLX) and EEG responses. This suggests that MWL was unaffected by our choice of visualization.

The first experiment, with 12 participants, was designed to identify the optimal presentation paradigm of the auditory oddball. For the EEG analysis, two participants had to be excluded, due to noisy electrophysiological recordings (more than 50 % of rejected epochs). Whilst performing the tracking task, participants were presented with a sequence of auditory stimuli that they were instructed to ignore. This sequence would, in the 1-stimulus paradigm, only contain the infrequent odd-ball stimulus (i.e., the familiar sound of a dog's bark (Fabiani, Kazmerski, Cycowicz and Friedmann 1996)). In the 2-stimulus paradigm this infrequently presented oddball (0.1) is accompanied by a more frequently presented pure tone (0.9) and in

the 3-stimulus paradigm the infrequently presented oddball (0.1) is accompanied by a more frequently presented pure tone (0.8) and an infrequently presented pure tone (0.1). These three paradigms are widely used in P3 research (Katayama, Polich 1996). It should be noted, however, that the target to target interval is 20 s regardless of the paradigm. To obtain the ERPs the epochs from 100 ms before to 900 ms after the onset of the recognizable oddball stimulus, were averaged. Mean amplitude measurements were obtained in a 60 ms window, centered at the group- mean peak latency for the largest positive maximum component between 250 and 400 ms for the oddball P3, for each of the three mid-line electrode channels of interest (i.e., Fz, Cz, Pz). In agreement with previous work, the novelty-P3 response is smaller when participants had to perform the tracking task compared to when they were only presented with the task-irrelevant auditory stimuli, without the tracking task (F (1, 9) = 10.9, $p < 0.01$). However, the amplitude of the novelty-P3 differed significantly across the presentation paradigms (F (2, 18) = 5.3, $p < 0.05$), whereby the largest response to our task-irrelevant stimuli was elicited by the 1- stimulus oddball paradigm. This suggests that the 1-stimulus oddball paradigm is most likely to elicit novelty-P3 s that are sensitive to changes in MWL. Finally, the attenuation of novelty-P3 amplitudes by the tracking task varied across the three mid-line electrodes (F (2, 18) = 28.0, $p < 0.001$). Pairwise comparison, Bonferroni corrected for multiple comparisons, revealed P3 amplitude to be largest at Cz, followed by Fz and smallest at Pz (all $p < 0.05$). This stands in contrast with previous work that found control difficulty to attenuate P3 responses in parietal electrodes (cf., Isreal et al. 1980; Wickens et al. 1983). Thus, the current paradigm that uses a recognizable, ignored sound is likely to reflect an underlying process that is different from previous studies, which could be more sensitive to the MWL demands of a tracking task.

Given the result of experiment 1, the second experiment with 14 participants, investigated whether the 1-stimulus oddball paradigm would be sufficiently sensitive in indexing tracking difficulty as defined by the bandwidth of frequencies that contributed to the disturbance of the horizontal plane (cf., Isreal et al. 1980). Three different bandwidth profiles (*easy*, *medium*, *hard*) defined the linear increase in the amount of disturbance that had to be compensated for. This manipulation was effective in increasing subjective MWL, according to the results of a post- experimental NASA-TLX questionnaire (F (2, 26) = 14.9, $p < 0.001$) and demonstrated the expected linear trend (F (1, 13) = 23.2, $p < 0.001$). This increase in control effort was also reflected in the amount of joystick activity, which grew linearly across the difficulty conditions (F (1, 13) = 42.2, $p < 0.001$). For the EEG analysis two participants had to be excluded due to noisy electrophysiological recordings (more than 50 % of rejected epochs). A planned contrast revealed that the novelty- P3 was significantly lower in the most difficult condition compared to the baseline viewing condition, where no tracking was done (F (1, 11) = 5.2, $p < 0.05$; see Fig. 1a). Nonetheless, novelty-P3 did not differ significantly between the difficulty conditions (F (2, 22) = 0.13, $p = 0.88$), nor did it show the expected linear trend (F (1, 11) = 0.02, $p = 0.91$). Like (Isreal et al. 1980), we find that EEG-responses do not discriminate for MWL that is associated with controlling increased disturbances. It remains to be investigated, whether the novelty-P3 is sensitive for the complexity of controller dynamics, like it has been shown for the P3.

The power spectral density of the EEG data around 10 Hz (i.e., alpha) has been suggested by (Smith, Gevins 2005) to index MWL. A post hoc analysis of our current data, at electrode Pz, revealed that alpha power was significantly lower for the medium and hard conditions, relative to the view-only condition (F (1, 11) = 6.081, $p < 0.05$; (F (1, 11) = 6.282, $p < 0.05$). Nonetheless, the expected linear trend across tracking difficulty was not significant (Fig. 1b).

To conclude, the current results suggest that a 1-stimulus oddball task ought to be preferred when measuring general MWL with the
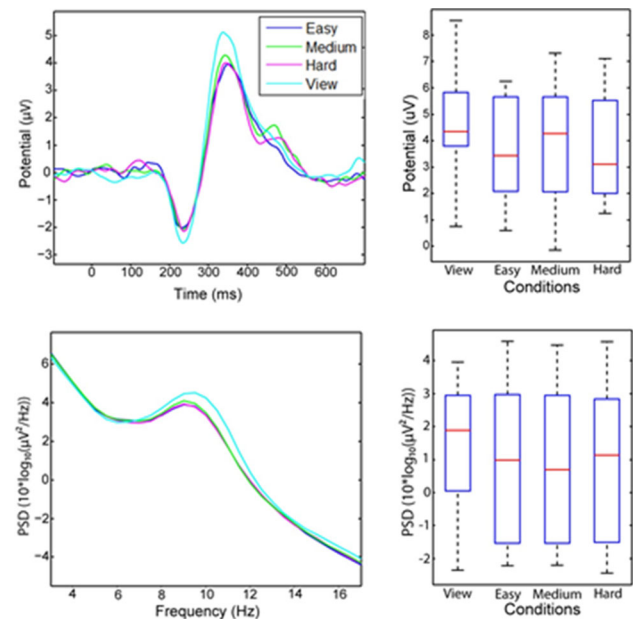
Fig. 1 a *left* Grand average ERP data of Experiment 2 averaged over Fz, Cz, Pz; *right* averaged amplitude of P3 as function of tracking difficulty. **b** *left* Averaged power spectral density (PSD) at Pz; *right* averaged PSD as a function of tracking difficulty

novelty-P3. Although changes in novelty-P3 can identify the control effort required in our compensatory tracking task, it is not sufficiently sensitive to provide a graded response across different levels of disturbances. In this regard, it may not be as effective as self-reports and joystick activity in denoting control effort. Nonetheless, further research can improve upon the sensitivity of EEG metrics to MWL by investigating other aspects that better correlate to the specific demands of a steering task.

References

Allison BZ, Polich J (2008) Workload assessment of computer gaming using a single-stimulus event-related potential paradigm. Biol Psychol 77 (3):277–283

Fabiani M, Kazmerski V, Cycowicz Y, Friedmann, D. (1996) Naming norms for brief environmental sounds. Psychol Rev 33:462–475

Hart SG, Staveland LE (1988) Development of NASA-TLX (Task Load Index). Results of empirical and theoretical research

Isreal JB, Chesney GL, Wickens CD, Donchin E (1980) P300 and tracking difficulty: evidence for multiple resources in dual-task performance. Psychophysiology 17 (3):259–273

Katayama J, Polich J (1996) P300 from one-, two-, and three-stimulus auditory paradigms. Int J Psychophysiol 23, 33–40

Miller MW, Rietschel JC, McDonald CG, Hatfield BD (2011) A novel approach to the physiological measurement of mental workload. Int J Psychophysiol 80 (1):75–78

O'Donnell RC, Eggemeier TF (1986) Workload assessment methodology. Handbook of Perception and Human Performance, 2:1–49

Smith ME, Gevins A (2005) Neurophysiologic monitoring of mental workload and fatigue during operation of a flight simulator. Defense and Security (International Society for Optics and Photonics) 116–126

Ullsperger P, Freude G, Erdmann U (2001). Auditory probe sensitivity to mental workload changes—an event-related potential study. Int J Psychophysiol 40 (3):201–209

Wickens CD, Kramer AF, Vanasse L, Donchin E (1983) Performance of concurrent tasks: a psychophysiological analysis of the reciprocity of information-processing resources. Science 221 (4615):1080–1082

Wickens CD, Israel J, Donchin E (1977) The event related potential as an index of task workload. Proceedings of the Human Factors Society Annual Meeting 21, 282–286

Wickens CD, Kramer AF, Donchin E (1984). The event- related potential as an index of the processing demands of a complex target acquisition task. Annals of the New York Academy of Sciences 425 (955610):295–299

Wickens CD, Yeh Y-Y (1983) The dissociation between subjective workload and performance: A multiple resource approach. In: Proceedings of the human factors and ergonomics society annual meeting, 27(3):244–248

Modeling perspective-taking by forecasting 3D biological motion sequences

Fabian Schrodt, Martin V. Butz
Cognitive Modeling, Computer Science Department, University of Tübingen, Germany

Abstract
The mirror neuron system (MNS) is believed to be involved in social abilities like empathy and imitation. While several brain regions have been linked to the MNS, it remains unclear how the mirror neuron property itself develops. Previously, we have introduced a recurrent neural network, which enables mirror-neuron capabilities by learning an embodied, scale- and translation-invariant model of biological motion (BM). The model allows the derivation of the orientation of observed BM by (i) segmenting BM in a common positional and angular space and (ii) generating short-term, top-down predictions of subsequent motion. While our previous model generated short-term motion predictions, here we introduce a novel forecasting algorithm, which explicitly predicts sequences of BM segments. We show that the model scales on a 3D simulation of a humanoid walking and is robust against variations in body morphology and postural control.

Introduction

This paper investigates how we may be able to recognize BM sequences and mentally transform them to the egocentric frame of reference to bootstrap mirror neuron properties. Our adaptive, self-supervised, recurrent neural network model (Schrodt et al. 2014) might contribute to the understanding of the MNS and its implied capabilities. With the previous model, we were able to generate continuous mental rotations to learned canonical views of observed 2D BM—essentially taking on the perspective of an observed person. This self-supervised perspective taking was accomplished by back-propagating errors stemming from top-down, short-term predictions of the BM progression.

In this work, we introduce an alternative or complementary, time-independent forecasting mechanism of motion segment sequences to the model. In the brain, prediction and forecasting mechanisms may be realized by the cerebellum, which is involved in the processing of BM (Grossman et al. 2000). In addition, it has been suggested that the cerebellum may also support the segmentation of motion patterns via

the basal ganglia, thereby influencing the learning of motor sequences in parietal and (pre-)motor cortical areas (Penhune and Steele 2012). Along these lines, the proposed model learns to predict segments of motion patterns given embodied, sensorimotor motion signals. Due to the resulting perspective taking capabilities, the model essentially offers a mechanism to activate mirror neuron capabilities.

Neural Network Model

The model consists of three successive stages illustrated in the overview given in Fig. 1. The first stage processes relative positional and angular values into mentally rotated, motion-direction sensitive population codes. The second stage performs a modulatory normalization and pooling of those. Stage III is a self-supervised pattern segmentation network with sequence forecasting, which enables the back-propagation of forecast errors. We detail the three stages and the involved techniques in the following sections.

Stage I: Feature Preprocessing

The input of the network is driven by a number of (not necessarily all) relative joint positions and joint angles of a person. Initially, the network can be driven by self-perception to establish an egocentric perspective on self-motion. In this case, the relative joint positions may be perceived visually, while the perception of the joint angles may be supported by proprioception in addition to vision. When actions of others are observed, joint angles may be solely identified visually.

In each single interstage Ia in the relative position pathway, a single, positional body landmark relation is transformed into a directional velocity by time-delayed inhibition, in which way the model becomes translation-invariant. Interstage Ib implements a mental rotation of the resulting directional velocity signals using a neural rotation module R_μ. It is driven by auto-adaptive mental rotation angles (Euler angles in a 3D space), which are implemented by bias neurons. The rotational module and its influence on the directional velocity signals are realized by gain field-like modulations of neural populations (Andersen et al. 1985). All positional processing stages apply the same mental rotation R_μ, by which multiple error signals can be merged at the module. This enables orientation-invariance on adequate adaptation of the module's biases. In interstage Ic, each (rotated) D-dimensional directional motion feature is convolved into a population of $3^D - 1$ direction-responsive neurons.
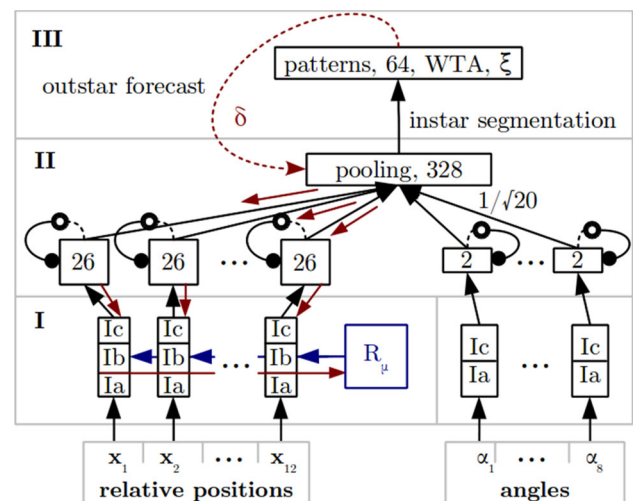
Fig. 1 Overview of the three-stage neural modeling approach in a 3D example with 12 joint positions and 8 joint angles, resulting in n = 20 features. *Boxes* numbered with *m* indicate layers consisting of *m* neurons. *Black arrows* describe weighted forward connections, while *circled arrowheads* indicate modulations. *Dashed lines* denote recurrent connections. *Red arrows* indicate the flow of the error signals