



MARKUS RAAB^{1,2}, JÜRGEN PERL³ AND DIRK ZEHNALL^{4,5}

The Mapping of Intrinsic and Extrinsic Information in Continuous Visuo-Motor Control

Humans rely on eye-hand coordination in daily life. The term “visuo-motor mapping” describes the interaction between visual and motor processes, which determine the performance in eye-hand coordination problems. However, different concepts exist regarding what this interaction entails and how it is defined. For instance recent research by Rosenbaum and Chaiken (2001) demonstrated very fine motor control in a manual positioning task depends on extrinsic (spatial coordinates) and intrinsic (postural or body movements) information. The underlying representation of this extrinsic and spatial representation is defined in “world-based” coordinates, that is, x and y coordinates in the case of two-dimensional movements (see Carrozzo, McIntyre, Zago, & Lacquaniti, 1999, for detailed descriptions of different “world-based” representations). The reference frame coding bodily movements is defined as the intrinsic information.

The goal of our study is to test different models (see Rosenbaum & Chaiken, 2001, for an overview) that differ in the way how extrinsic and intrinsic information are mapped to enable precise motor control. To pursue our goal we use four models to generate different predictions for our study and evaluate these with our experimental and simulation results.

This goal is motivated by recent research that demonstrated encoding of extrinsic as well as intrinsic information with at least four potential models of motor control on behavioral level and for discrete movements only (Rosenbaum & Chaiken, 2001). That extrinsic and extrinsic information can coexist and interact is supported by behavioral and physiological experiments. For instance, psychophysical experiments confirm that two representations of space can coexist and can be modeled with

¹ Center for Adaptive Behavior and Cognition, Max Planck Institute for Human Development, Berlin, Germany

² Institute for Human Movement and Sport, University of Flensburg, Germany

³ Institute for Computer Science, University of Mainz, Germany

⁴ Institute for Sport and Sport Sciences, University of Heidelberg, Germany

⁵ Date of resubmission: 12th of August 2003

Authors note: The study was supported by a grant from TransCoop (III-TCFO-DEU/1023836) and the research pool of the University of Heidelberg. Correspondence regarding this article should be sent to the first author, Markus Raab now at University of Flensburg, Institute of Movement Science and Sport, Flensburg, Germany (raab@uni-flensburg.de).

The authors are grateful to Christel Fraser, Joe Johnson, and Anita Todd for their assistance with the English version.

neural network models (Andersen, Snyder, Bradley, & Xing, 1997; Andersen, Snyder, Li, & Stricanne, 1993). Behavioral research showed that transformations from one frame of reference to another frame of reference can be modeled for discrete movements (Flanders, Tillery, & Soechting, 1992). Yet, it remains unsolved if the acquisition of visuo-motor mapping takes place from the intrinsic to the extrinsic information, from the extrinsic to the intrinsic information, or if the mapping is acquired bi-directionally. Key research on the topic was conducted for reaching and pointing tasks (see Flanders et al., 1992, for an overview) but Flanders et al. (1992) speculated that the same methods applied for single-goal-orientated tasks could also be applied for continuous movements. For instance, Cordo and Flanders (1989) concluded that parameters of intended movements could be updated by the comparison of target and movement parameters that are represented in the same frame of reference. An advantage to test motor control models with pursuit tracking is that the desired response trajectory is objectively specified. In addition, this task allows for cumulative errors of ongoing movements, which will be implemented in our simulations to increase the weight of online and short-term feedback and feedforward processes. For instance, Weir, Stein, and Miall (1989) assumed that participants use the distance of target and control information (feedback) to plan the movement (feedforward) from extrinsic to intrinsic information. However, if only the target information was visible they used intrinsic information to plan the movement toward the target. Therefore, this movement plan requires intrinsic to extrinsic transition. In addition, to separate feedback and feedforward processes we applied one pursuit-tracking task with the occlusion of the control position to eliminate visual feedback processes (for input-blanking, see Stanley & Franks, 1990) instead of using compensatory (only error signal displayed) and pursuit tracking (target and control information displayed) to avoid the influence of other undesirable task effects (Weir et al., 1989). Note that we are only interested in the short time-scale of visuo-motor mapping and do not want to extend the types of mapping and the generalization of the findings to the long time-scale of observational learning or transfer tests (Hecht, Vogt, & Prinz, 2001; Rosenbaum & Chaiken, 2001).

One noteworthy exception of the studies that also include simulations for continuous visuo-motor mapping is the application of the “adaptive model theory” by Neilson, Neilson, and O’Dweyer (1993), comparing tracking behavior of humans using two simulations. The adaptive model theory uses parameters for the simulation that optimally adjusts the relation between motor program and motor output (Ghous & Nielson, 2002; Neilson & Neilson, 1999). The simulations incorporated either visual feedback processes alone (prediction parameter was set to zero) or visual feedback processes together with the predictions of the target information (feedforward). The simulation with a prediction of the target matched the human behavior better than the simulation without a prediction, indicating the use of a prediction of the target in pursuit tracking. In our view, these results are interesting and to some degree ambiguous for two reasons.

First, we believe that the tracking task applied by Neilson et al. (1993) allows for feedback processes and feedforward processes. Therefore fitting data with simulations which inherit both processes should result in a better fit compared to simulations in which only one of these processes is used to fit the data.

Second, we assume that -- contrary to the adaptive model theory -- the visuo-motor mapping can be represented by a parallel integration of visual and motor maps, which allows the visuo-motor mapping from extrinsic to intrinsic information as well as from intrinsic to extrinsic information. We also assume that simulations allowing parallel or sequential bi-directional transfer between intrinsic and extrinsic information should result in a better match between actual behavior and simulation behavior than models that process uni-directional information only from extrinsic to intrinsic information, or vice versa.

We will demonstrate in an experiment how to separate feedback and feedforward processes in tracking and how these processes can be used for mapping intrinsic and extrinsic information in four different ways we report next.

Visuo-motor Mapping 1 (Extrinsic to Intrinsic Mapping)

The Extrinsic to Intrinsic Mapping (EIM) approach assumes that from extrinsic information (Cartesian coordinates of the target), the movement of the hand (kinematics of angles, commands for muscles) is produced. This assumption is well supported by work on discrete (Hogan & Flash, 1987; Vetter, Goodbody, & Wolpert, 1999; Wolpert & Ghahramani, 2000) and continuous (Neilson et al., 1993) movements. In addition, Desmurget, Pelisson, Rossetti, and Prablanc (1998) sampled evidence on the physiological level that the central nervous system selects a given path in the space by Cartesian coordinates and then transforms this path into a pattern of joint covariation. Further support of transformation from viewer-centered to body-centered representation in direct visuo-motor mapping was established by Carrozzo et al. (1999). They introduced the notion of direct visuo-motor transformation because they applied continuously visible stimuli and, therefore, decreased the effects of memory processes on the direct visuo-motor mapping. This is a crucial extension of prior research, which applied memorized stimuli in experiments (Poizner et al., 1998).

Visuo-motor Mapping 2 (Intrinsic to Extrinsic Mapping)

The reference frames, on which the Intrinsic to Extrinsic Mapping (IEM) mapping is based, are internal models of movement (Miall & Wolpert, 1996). For instance, it is assumed that angle positions are used as a reference frame to generate movement trajectories (Rosenbaum, Loukopoulos, Meulenbroek, Vaughan, & Engelbrecht, 1995; Soechting, Buneo, Herrmann, & Flanders, 1995). The transformation of spatial

coordinates into a forearm movement defines the joint path required to move from the initial to the final posture (Desmurget, et al., 1998).

Visuo-motor Mappings 3 and 4 (sequential bi-directional mapping and parallel bi-directional mapping)

Andersen et al. (1993) argued that it is a very important issue to address how the transformation of different frames of references can be modeled beyond the two uni-directional mappings discussed above. The transformation can be carried out sequentially or in parallel and will be modeled in two types of visuo-motor mapping: sequential bi-directional mapping (SBM) and parallel bi-directional mapping (PBM). Space information (extrinsic) and angle information (intrinsic) structure the movement kinematics depending on situational factors (Rosenbaum et al., 1995). The transfer of extrinsic and intrinsic information occurs from the very beginning (see Hecht et al., 2001, for details on parallel bi-directional mapping) or after separate representations of visual and motor codes are built (see Ritter, 1990, for details on sequential bi-directional mapping). The transfer between intrinsic and extrinsic information is assumed to be organized in spatial maps, which represent the motion direction of a stimulus and an associated response (Flanders et al., 1992; Geisler, 1999).

SBM

Sequential visuo-motor mapping assumes a step-model of transformations from visual to motor codes that results in a unified sensorimotor representation. The step-model assumes that after the first transformation from extrinsic to intrinsic information (step 1) the transformation changes to a intrinsic to extrinsic information (step 2). Step 3 is a unified representation that combines intrinsic and extrinsic information (see Corrazzo & Lacquaniti, 1994, for details on hybrid-frame).

PBM

The assumed unified representation can also be acquired in parallel by changing, trial-by-trial, the order of mapping between intrinsic and extrinsic information.

The purpose of our experiment is two-fold. First, the experiment can inform about the importance different of information for visuo-motor control and learning. We predict that conditions with visual feedback result in better tracking performance than conditions without visual feedback but performance will improve in both conditions over acquisition based on the processing described in the EIM model. However if a movement is preprogrammed and controlled mainly by intrinsic information, then the occlusion of the visual information of the motion position should not cause the performance to deteriorate, compared to when target and movement information are displayed as the IEM model would predict. This should hold true at least in a constant environment, which would be the case in pursuit tracking of repeated tracking waveforms. Based on Elliot et al. (1998) findings that visual feedback is important even later in the course of visuo-motor mapping acquisition the difference between

conditions with and without visual feedback should remain constant over acquisition. In addition the PBM model based on early (and parallel) bi-directional mapping of intrinsic and extrinsic information would predict constant influence of visual feedback over acquisition. Contrary the SBM model would predict differences between the conditions with and without visual feedback on the movement at the beginning of acquisition and not at the end of acquisition in pursuit tracking. This effect can be tested by the interaction term of conditions with and without visual feedback over blocks of acquisition in the experiment presented below.

Second, we selected movement trajectories from participants and compared them to an objectively specified, optimal trajectory. This data can be used in the simulation for differentiating the four different models of visuo-motor mapping. This procedure is the important first step using simulations outcome to resemble actual tracking behavior for understanding the mapping of intrinsic and extrinsic information.

Method

Participants

Twenty-four participants (12 female and 12 male) had normal or corrected-to-normal vision abilities. Participants were all students from the Institute for Sport and Sport Science at the University of Heidelberg, Germany and participated voluntarily. Their ages ranged from 21 to 28 years and included 4 left-handers and 20 right-handers. All participants had no prior experience in tracking. Participants received course credits for participation and confirmed written consent.

Apparatus

A pursuit-tracking task (Heidelberg Tracking Task, Version 2.0; Raab & Schorer, 1998) was used. This tracking task was extended from the version used by Magill (1998). Participants had to follow a red cross (target), using a computer mouse, with a white cross (control). The tracking pattern was non-repeated for the first and last third of each trial, whereas the middle segment was repeated over all trials. The presentation of non-repeated and repeated information is necessary to separate acquisition of the tracking waveform from a simple practice effect. Each trial took 30 seconds. To generate the different tracking patterns, the formulas of Wulf and Schmidt (1997) were applied. The root mean square error (RMSE), indicating the average distance between target and control, was calculated every 50 milliseconds to measure performance. Two types of task were presented: In the first condition, visual feedback was available, that is, both the target and the control cross were displayed. In the second condition without visual feedback only the target cross was displayed and the control cursor was occluded so that no direct visual feedback on the distance between the control and target crosses could be used. In the latter condition, in every

of the three segment the movement cursor was visible for 1.5 seconds to allow participants to re-correct their position (input-blanking paradigm).

Procedure

Participants received the two conditions over two days (80 trials each day for a total of 160 trials). At the start of the experiment, participants received an additional 10 trials to warm up. The conditions were organized in 4 blocks of 40 trials, and each participant received two blocks in the condition with visual feedback and two blocks without visual feedback of their own movement. The order of blocks was counter-balanced between participants. After each trial, participants received RMSE information (displayed for approximately 5 seconds as a resting period) averaged over the 30-second trial.

Results

The significance criterion was established as $\alpha = 0.05$. The data were checked for outliers and for order effects of blocks. In addition -- and in line with previous research in pursuit tracking -- it was found that RMSE is significantly reduced over acquisition. Furthermore, the repeated tracking segment was learned significantly better than the non-repeated segments. An ANOVA on repeated measures showed significant improvement over time ($F(3, 23) = 5.82, p < 0.01, \eta^2 = 0.28$) from block 1 to block 4 collapsed over the conditions as well for each condition separately. The effect size of 0.28 is small. There was also an expected significantly better performance for the middle segment ($F_{(2, 23)} = 10.52, p < 0.01, \eta^2 = 0.41$) compared to the non-repeated segments, as was found in previous experiments (Schorer & Raab, 2000). The non-repeated segments showed no significant differences, as expected. These findings are not presented in detail; although they are necessary requirements to check the paradigm, they are not of relevance for the visuo-motor mapping.

We assumed that visual occlusion of the control cursor will deteriorate performance. This is indeed what we found. A large significant differences between conditions in the overall RMSE resulted from our ANOVA between the condition with and without visual feedback ($F_{(1, 23)} = 188.72, p < .01, \eta^2 = .93$). RMSE in the condition without visual feedback (after the last block in this condition) was still high and variable ($M = 55.82, SD = 18.8$). The RMSE in the condition with visual feedback was almost three times smaller and less variable ($M = 22.40, SD = 6.99$). This finding indicates that over acquisition the lack of extrinsic information can not be compensated by another source of information and that an intrinsic to extrinsic mapping alone seems less likely. There was no interaction of conditions and blocks, indicating that relative feedback control and relative feedforward control do not change over time as predicted by PBM but not by the SBM.

Summary

In summary, we applied the pursuit-tracking task to generate movement trajectories with an objective-defined trajectory criterion (target information) in two conditions. Two conditions could separate feedforward and feedback processes on the behavioral level. As assumed, tracking without the visible movement information produced higher RMSE. The absolute RMSE and the difference between conditions were so strong that we do not believe that the movement in the repeated segment was preprogrammed. In addition, the target information itself seems not to entail enough information to reduce RMSE in this condition. Therefore, a uni-directional transfer from one frame of reference to another seems questionable. Since we could not observe an interaction of conditions and blocks a pure step-model seems not likely (Flanders, et al., 1992). In addition our results support the fact that feedback is important at the end of acquisition (see Elliot, Ricker, & Lyons, 1998, for similar results in discrete tasks). The first experimental purpose to understand the importance of different sources of information is accomplished. However, this experimental design cannot distinguish the direction of acquisition of the different visuo-motor mappings in more detail and, therefore, the experimental data will be used as inputs into four different simulations representing the four visuo-motor mapping models as introduced as the second purpose of the experiment.

Simulations

One well-known and successful approach for analyzing and simulating processes is that of neural networks. In particular, self-organizing maps – the most famous representative of which is the Kohonen Feature Map (Haykin, 1999; Kohonen, 1995) – are able to classify processes into clusters and then, in turn, to recognize processes by identifying the corresponding cluster. Unsupervised correlation-based learning rules have been applied to reaching tasks previously (Gaudio & Grossberg, 1991; Kuperstein, 1988) and will now be extended to continuous movements. Feedback processes have previously been implemented in the lower-level sensorimotor formation of maps (Berthouz & Kuniyoshi, 1998) and also higher-level formation of maps (Jobst, 1992; Ritter, 1990). In addition, Flanders et al. (1992) argued that sensorimotor transformations can be implemented by a network of neurons with a parallel and a distributed structure, since it is realized and modeled by self-organizing maps. Although the KFM-approach is very helpful in the field of process analysis, there is a specific problem that makes it difficult to work with in the case of process analysis:

A KFM cannot learn continuously and so cannot adapt to dynamically changing information and learning situations. But this is what is required in the acquisition of continuous visuo-motor mapping. The reason for these disadvantage lies in the KFM-specific static external control-functions. Therefore, basing on the concept of KFM, DyCoN (i.e. Dynamically Controlled Network, Perl, 1998) has been developed, where every neurone dynamically controls its individual learning rate and radius of

activation, depending on its changing state (e.g., acquisition progress) and the learning content. This concept allows for continuous learning: A once prepared DyCoN can be trained again, with completing as well as with replacing information, and so can adapt to changing information profiles.

In addition, such a unified system should account for two types of participant behavior, exhibited when confronted with the two types of tasks in the experiment. This strategy lightens the learning problem, since there are fewer parameters (Szepesvari, Cimmer, & Lorincz, 1997), and allows for adaptive thresholds, as found in Hebbian synapses (Pennartz, 1997), and for a variable radius of activation of a neuron. This is a crucial difference to the Kohonen networks of constant radius activation because DYCON implements the concept of adaptive activation to learning impulses and allows for learned patterns to be superposed.

As a side-effect of the continuous-learning-ability DyCoN needs only a very small number of original training data: DyCoN can learn in phases and so allows for first preparing the network with Monte Carlo-generated data followed by specifically coining this reference network using the original data. This strategy has successfully been used in cases like analyses of rehabilitation processes where only a very small number of patients with very few test data had to be analyzed.

Finally, progress and result of network training can be measured and so helps for evaluating the corresponding learning process: The idea is that the 'representation' of a pattern – briefly spoken: the probability with which a corresponding test pattern can be recognized by the network – is an indicator for the success of the training process. Polani introduced the entropy as one measure function, which also in DyCoN has been used very successfully (see Polani, 2001; Perl, 2002a, 2002b, and Appendix, for technical details). As the examples from the Appendix show, the entropy reflects surprisingly well the training state of a network.

Simulation assumptions

Network: EIM

If participants used an uni-directional mapping from extrinsic to intrinsic information, than simulations in which networks are trained on the target information should reproduce the outcome resembling motor behavior (regardless of if they are tested and compared with conditions in which visual feedback was, or was not available) better than networks trained with any other mapping. In addition if participants apply an extrinsic to intrinsic mapping, then networks that model this direction of mapping should fit the trajectories produced by participants in the experiment better in the beginning of acquisition, than networks with the opposite or bi-directional mapping.

Network: IEM

If mapping happens uni-directional from intrinsic to extrinsic information than this network should fit the behavioral trajectories of participants from the experiment better than the other mappings. In addition, networks that are trained on intrinsic information should fit trajectories generated in the experiment better in conditions in which no visual feedback is given compared to other training sets with pure extrinsic information. We do not know exactly what the motor program that generates the movement trajectories looks like (see Flanagan, Ostry, & Feldman, 1993; Worringham, 1991, for discussion). Thus, we will use the movement trajectories themselves for the modeling.

Network: SBM

Both uni-directional models described above can be compared to bi-directional mapping of intrinsic and extrinsic information. If the mapping of intrinsic and extrinsic information is bi-directional and sequential than the SBM-models outcome will fit behavioral data better than the other models. For the simulation, we expect outcome of networks that trained block-wise, first extrinsic to intrinsic mapping and then intrinsic to extrinsic mapping, should fit better with the participants trajectories than networks trained in another fashion. This effect should be present for all acquisition blocks in the simulations.

Network: PBM

We assume that the PBM trained network will match better with participants' behavior than the other trained networks, if parallel mapping of intrinsic and extrinsic mapping was mainly present in the acquisition of the tracking performance.

Simulation Procedure

We commenced simulations by choosing target information, which drives the extrinsic information. Movement error (RMSE in the experiment) was used to compare target location with participants' movements to drive intrinsic information. The procedure implementing RMSE has been used before in reaching tasks (Salinas & Abbott, 1995).

Input data

The analyzed tracking data were reduced for simulation purposes. First, only the data of the middle segment were used. This was done to secure a constant environment in which intrinsic and extrinsic information could be analyzed. Second, only the data from two participants were used to guarantee coherent behavioral strategies in the input data. The data from the selected participants presented mean RMSE and

normal standard deviations, compared to the Gaussian distribution of the sample in the experiment. Third, in the condition without visual feedback, tracking data from the middle segment were used only during the time the control cross was occluded. To keep the number of input vectors constant between the different nets, we also truncated the first and last 1.5 seconds in the condition with visual feedback.

The tracking data were recorded every 50 milliseconds, so that for the middle segment 180 data points could be used. The sampling rate of 50 milliseconds is consistent with the duration of electromyographic (EMG) bursts (Neilson et al., 1993). The data contain the space information in the \underline{x} and \underline{y} directions of the control and the target cross, as well as the Euclidean distance between the target and control cross in pixels. Redding and Wallace (1996) separated location codes (\underline{x} and \underline{y} information for feedforward) and difference codes (Euclidean distance between target and control cursor for feedback) for pointing tasks. We will apply this procedure for continuous input data. The separation of the target position and (internal estimated) difference vector is used when the data input of movements without visual distance is required. However, if the visual distance is not available, then the present position information is added (Bullock & Grossberg, 1988).

Speed on the \underline{x} -axis was held constant in the tracking task. Therefore, the only inputs, which are variable, are the \underline{y} -axis information of the target and the distance between crosses. Neilson and Neilson (1999) used an \underline{x} - and \underline{y} -coordinate system. However, we believe that the vector represents the degrees of freedom the task presents. Because the tracking task has a constant velocity ramp on the \underline{x} -axis, we used only the \underline{y} -axis information as input (McNeill & Card, 1999). We used direction and speed rather than derivatives (e.g., acceleration) since there is evidence that models can predict tracking performance better with functions rather than with derivatives (Engel & Soechting, 2000), which enables us to resemble the behavioral data more realistic. In addition, no noise was implemented (see Salinas & Abbott, 1995, for differences of implementation with and without noise).

We first presumed that an input vector should integrate data in the range of 200 milliseconds. We applied a four-dimensional input vector to ensure that this time frame would allow for the inclusions of the visually recognized information of target-control distance and its possible reaction on the motor side. Spijkers (1993) and Young and Zelaznik (1992), for example, found that visual feedback requires a time frame of between at least 100 and 200 milliseconds. In addition, there is evidence that ballistic movements have a duration of at least 100 milliseconds and, therefore, the prediction time should be at least in the range of a simple reaction time (Neilson et al., 1993). We also applied the minimal constraints of 200 milliseconds to represent predictions of small amplitude target moves of the tracking waveform. This differs from the constraints of the 30-step prediction of 1.5 seconds in the adaptive model theory (Neilson et al., 1993).

The second presumption was to accept quasi-continuous data input that was supported by prior experiments (Raab et al., 2001; Spijkers, 1993). We used overlapping input vectors of time $\underline{t_1-t_4}$, then $\underline{t_2-t_5}$, and so forth, to represent this

presumption in the simulation. In line with Viviani, Campadelli, and Mounoud (1987) we believe that visual error input and motor response are likely to be coded direct in vectorial terms.

Net Parameters

DYCON requires trained networks to run input data for learning and control processes. This initialization process (training of networks) allows for testing the actual value (behavioral data of the participants) on the set value (the target waveform), or vice versa. Kohonen (1995) describes for perception processes that at least 5,000 learning steps have to be iterated on the defined space (in this case the y -values of the target cross).

The entropy measure helps for evaluating the learning process: Each learning step improves the "representation" of the corresponding pattern in the network, which is reflected by an increasing entropy value of this pattern if tested on the network. As can be seen from the Appendix on DyCoN, the theoretical maximum of entropy depends on the number of neurons. In case of 20x20 neurons this maximum is equal to $^2\log(400)$, which is about "8.64". In practice, however, this maximum cannot be reached. If the learning data are noisy as original data usually are, an entropy value of about "5" can be considered as near to optimal. Even more important than the maximum value is the asymptotic behavior of the entropy: If the entropy becomes asymptotically constant this indicates a stable state of the network – meaning that no further learning step is useful or necessary.

This way, the number of learning steps, which varies in the literature (see Rojas, 1996, for an overview), can be adapted to the learning process: The training has to be continued until the entropy of the initialized network has reached asymptotically constant values. A very crucial point for later discussion is how actual and set values are represented in the initialized network.

Results

Training of Reference Networks

The training of reference networks with visual target information or movement indicate the effect of the training procedure. Analyses of the learning rate in every condition and for all participants from the start to the end of acquisition show, in an ANOVA (condition x test, repeated measures) with entropy as dependent variable that entropy values increase over acquisition significantly ($F_{(1,41)} = 11.86$, $p < .01$, $\eta^2 = .80$). This effect is high (Cohen, 1988) and can be replicated for each condition and participant in each simulated network using Scheffé for post-hoc comparison). Entropy values increase at least from one to close to five. The increase of entropy values can be understood as a very good mapping of actual and set values.

Visual target maps. In our initialization, a constant high entropy value with a mean of 4.79 was reached within 10,797 learning steps, which is equal to 61 trials of the middle segment. Each model network was given input of the behavioral data of participants in two experimental conditions. Therefore, a total of eight networks were trained and tested for the comparison.

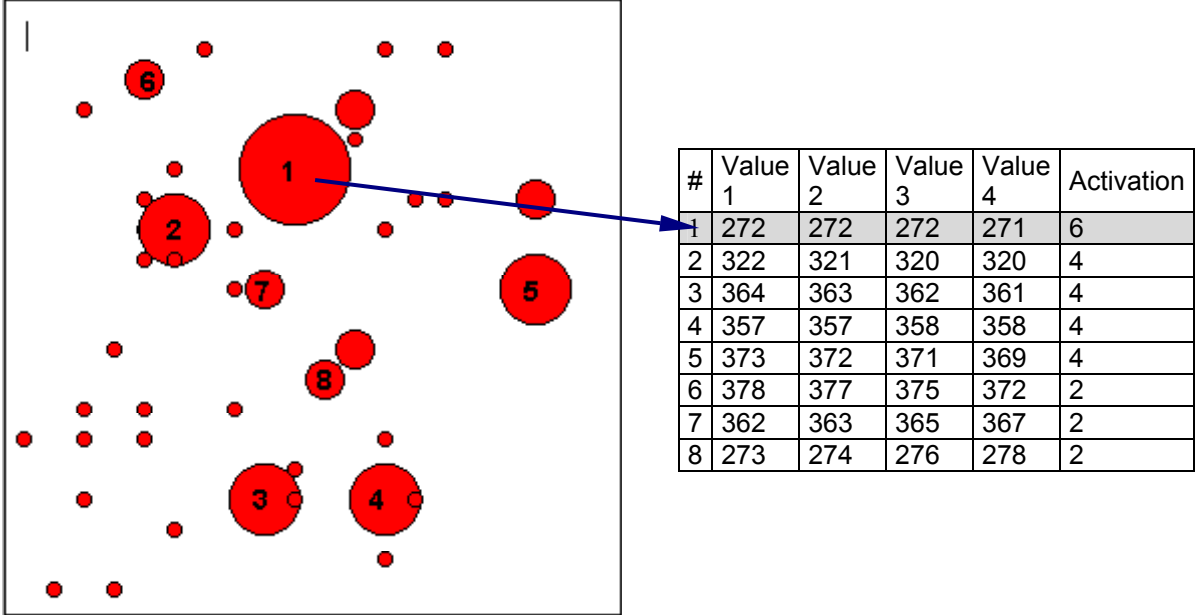


Fig 1: The neuronal representation of set values of the target waveform. Left: neuron 1 represents the y-pixel vector of 272, 272, 272, 271 and was activated six times, as shown on the right side of the figure.

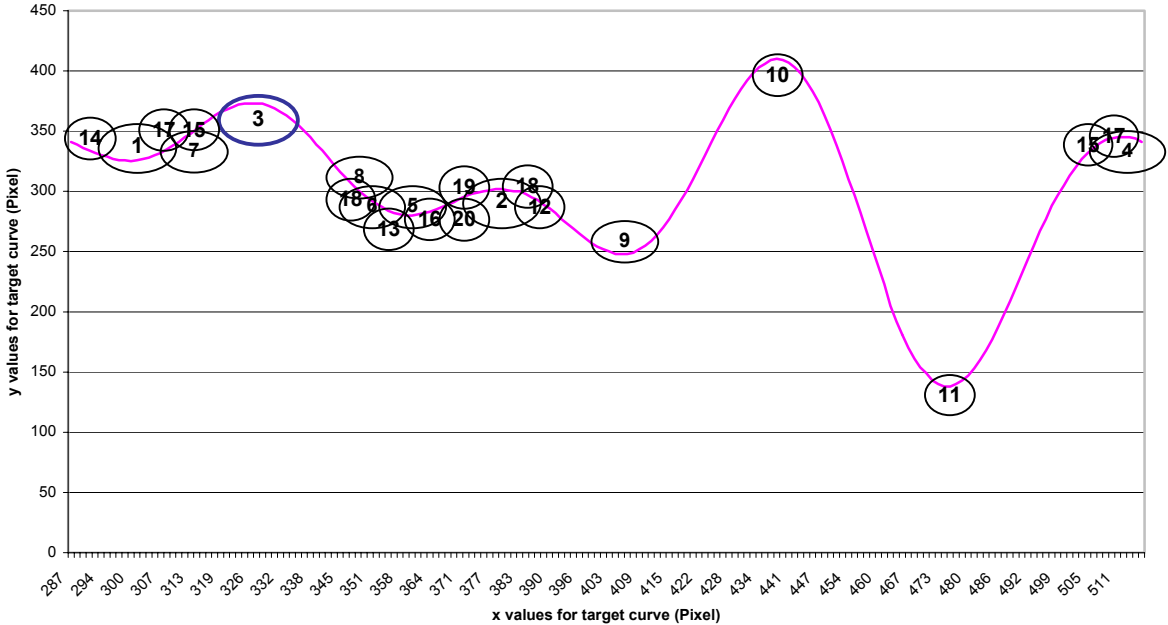


Fig. 2. The neuronal representation of set values of the target waveform in the middle segment of every trial (in pixels). For example, neuron 3 represents the second reversal point of the tracking pattern.

Figure 1 shows the distribution of activation in the 20×20 matrix of the net. In addition, for instance, in Figure 1 the y -pixel information (272, 272, 272, 271) is represented by neuron 1 with an activation rate of 6 (see Table on the right side of Fig. 1). In other words, six inputs with a vectors length of four activate neuron 1 and describe a clustering process. Because this y -pixel information is more often activated than others (e.g., neuron 8 representing pixels 273, 274, 276, and 278 with an activation rate of 2), neuron 1 is presented larger, which reflects the fact that it contains more clustered information. 20 clusters were necessary to represent the target waveform. Figure 2 demonstrate how these 20 clusters are distributed over the waveform; more activations of the net at the reversal points of the target curve can be recognized. Furthermore, Figure 2 shows that more neurons concentrate on very fine visual differences compared to extremes after higher amplitudes of the waveform, which can be separated and represented by their unique pattern more easily.

Motor maps. The same procedure was applied for the actual values of the behavior to initialize a neural network (Fig. 3). The high activation of the actual motor value is mainly based on the hold component in the y direction that can be interpreted as a freezing of degrees of freedom (Bernstein, 1967). So how can we separate the quality of matches between actual motor and visual set values in the simulation? The answer lies in the entropy values. In the condition without visual feedback, representations are smaller compared to the condition with visual feedback, in which entropy receives a value of 3.36 for the same participant. Because of a general correlation of $r = 0.98$ between activation and entropy values (Zechnall, 2001), higher activation of many neurons result in higher entropy values.

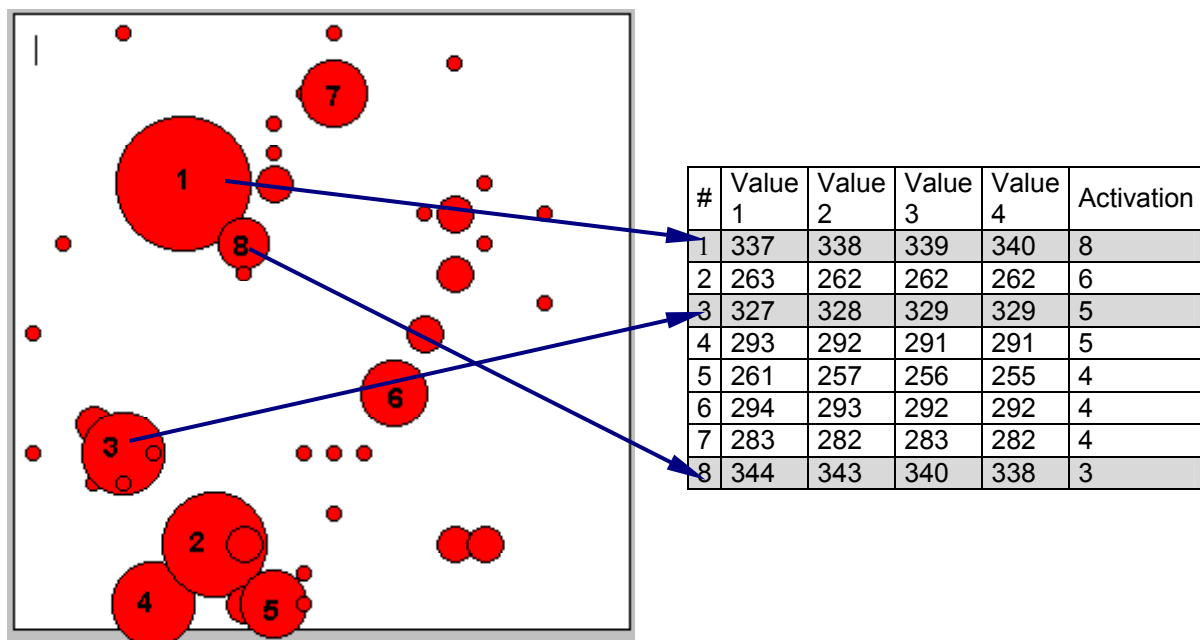


Fig. 3: The neuronal representation of action values of the movement pattern. On the right side the pixel vector and activation are shown. Diameters of the neurons on the left side represent the activation rate.

Feedback and feedforward motor maps. Overall, the acquisition of motor maps, without the visual information on the position of the own movement, does result in lower entropy values, the same applying at the beginning and at the end of

acquisition for conditions with visual feedback (Figure 4a) and for conditions without visual feedback (Figure 4b).

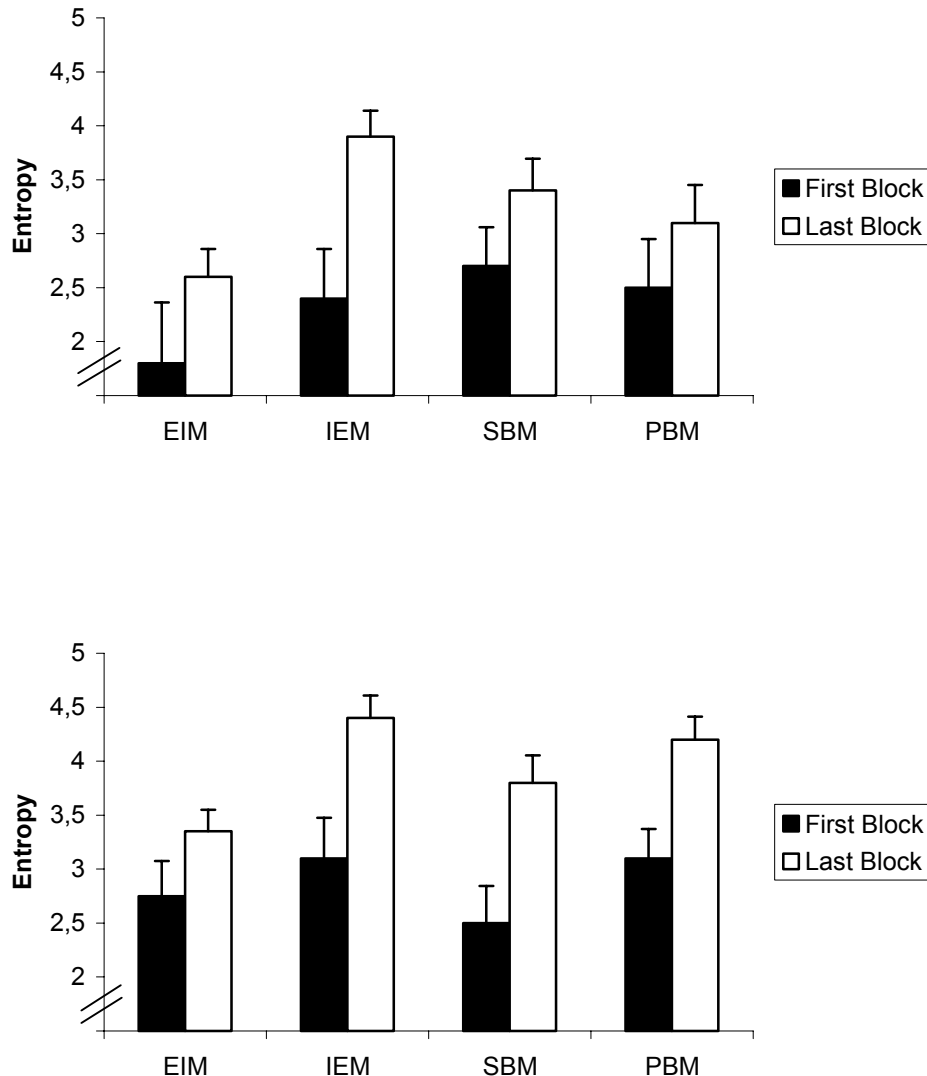


Fig. 4a and 4b. The Mean entropy of the four networks for conditions with visual feedback (upper panel) and without visual feedback (lower panel) averaged for all participants. (EIM = extrinsic to intrinsic network, IEM = intrinsic to extrinsic network, SBM = sequential bi-directional mapping, PBM = parallel bi-directional mapping).

The RMSE data from the experiment, therefore, is represented by the difference between absolute entropy levels of the simulations with and without visual feedback, because more motor noise of the movements, in conditions without visual feedback, served as input for the simulations. Therefore, the starting entropy values of the trained nets were used for covariation of the final entropy values. However, this does not change the observed result pattern.

Testing the Four Visuo-motor Mapping Models

The testing of the trained target and motor maps allows to separate the four models (see Introduction) and guaranteeing a cross-validation check of the model fitting procedure used in the training situation. However, because of the mean entropy value of 4.79 in average of the trained nets, it is clear that testing the four models in these reference nets results in maximal the same average level of entropy, if a total match between trained and tested nets is optimal. In addition, and to ensure that motor and visual clusters are not different in their total activation rate, which may influence the total entropy values (see Simulations), we compared the distribution of the number of activated neurons in the motor and target maps. The motor maps show an expected smaller number of activations of the same neurons ($\underline{M} = 4.9$, $\underline{SD} = 1.55$) compared to the target maps ($\underline{M} = 3.5$, $\underline{SD} = 1.41$). More importantly, the distribution of the matrix of 20×20 neurons was equal in both target and motor maps, indicating no influence on the test of simulations that allow either uni-directional or bi-directional mapping of intrinsic and extrinsic information to be superior due to the prior distribution of the activation. Simulations were carried out separately for each of the four networks representing the four visuo-motor mappings. To make comparisons between different networks, all networks learned with the same input data. The extrinsic to intrinsic mapping network (EIM-net) learned on a reference network that was trained with the target map (extrinsic information). The intrinsic to extrinsic mapping network (IEM-net) learned on a reference network with information from the motor map (intrinsic information). The sequentially and simultaneously bi-directional, sequential bi-directional mapping networks learned either after every 40 trials (SBM-net) or every trial (PBM-net), with a combination of extrinsic and intrinsic information. To interpret the clustering of intrinsic and extrinsic information, entropy values were compared. The primary question is, how do participants acquire the visuo-motor mapping to reduce RMSE in tracking? The network differences in the final entropy levels are significant ($F_{(1,3)} = 5.45$, $p < .05$, $\eta^2 = .73$; see Figs. 4a and 4b). Post hoc analyses show differences between the IEM-net and the other three networks ($p < .05$), and between the SBM and PBM networks and EIM-net ($p < .05$). That is, EIM-net results in the lowest entropy values compared to the SBM-nets and the PBM-net. No differences could be found between the SBM and PBM networks. No interaction between acquisition, conditions, or nets was significant. In addition, the IEM-net shows the highest entropy values in conditions with and without visual feedback, whereas the SBM-net and the PBM-net shows the second highest values.

Summary

The results of the simulations indicate that the outcome with different mappings can resemble participants behavior in the experimental conditions. The development of a representation of intrinsic information after approximately 10,000 steps, replicates prior findings of the artificial movements of a robot arm (Ritter, Martinetz, & Schulten, 1989). We showed that extremes of the tracking waveform are represented in the networks and that small differences of intrinsic or extrinsic information require the representation of more clusters in the networks. In short, it can be summarized that reversal points of the curve are represented significantly more than trajectories toward these reversal points. In error analyses of tracking behavior, it could also be confirmed that participants allocate their attention toward these reversal points (Raab, Schorer, & Magill, submitted). Furthermore, small amplitudes result in the

initialization of more information (y values) than high amplitudes. Improvement in the entropy of all four networks (for both conditions with and without visual feedback) was found significantly after the training of DYCoN. However, feedforward processes results in lower entropy values, compared to feedback processes. This finding reflects the RMSE differences between the two types of tasks in the pursuit-tracking behavior in the experiment. Therefore, we can assume that all our networks acquired visuo-motor mapping. Yet, the IEM-net best matches the tracking data for the feedforward condition, in which intrinsic to extrinsic mapping seems to be the most important mapping, whereas the EIM-net received the lowest entropy value. The main difference effect score was high ($\eta^2 = 0.73$), however, the performance of the SBM and PBM networks was, in both conditions, lower than that of the IEM-net. This finding partly supports our assumption that the visuo-motor mapping should be better if a bi-directional mapping between extrinsic and intrinsic information is offered. It has to be taken into account that the difference between the SMI networks and the IEM-net are not large in the feedback conditions, therefore, it can be summarized that at least the uni-directional transfer only from extrinsic to intrinsic cannot be supported by our study. In addition, because no interaction between acquisition, conditions, and networks was found, the difference between networks cannot be explained by the relative control of feedback and feedforward processes (see Raab et al., submitted, for evidence at the behavioral level).

General Discussion

This article focuses on the mapping of intrinsic and extrinsic information in continuous movements. Four different models of visuo-motor mapping were tested. We used an unsupervised, dynamically controlled neuronal network to investigate possible mappings of these information. Data from continuous pursuit-tracking movements allows us, on the one hand, to separate different visuo-motor processes (feedback, feedforward) and, on the other hand, to shed light on the more complex interplay between intrinsic and extrinsic information. The results of acquisition in DYCoN showed that essential parameters (e.g., changes of target direction at the reversal points of the tracking waveform) from the visual information of a repeated waveform were selected (see Wünstel, Boll, Polani, Uthmann, & Perl, 1999, and Schöllhorn & Perl, 2002, for similar approaches).

The goal of this research was to understand the visuo-motor mapping in more detail. Therefore, four mapping were manipulated systematically. A visuo-motor mapping from the extrinsic to intrinsic information (EIM-net) received the worst match between the simulation and human tracking data. The IEM-net, which describes the mapping from intrinsic information to extrinsic information, received the best match. As shown previously in discrete tasks, a single model using both mappings is also possible (Rogosky & Rosenbaum, 2000; Rosenbaum et al., 1995). In our simulation, good matches of simulation and tracking data of the sequential and parallel SBM-nets and PBM-nets support this approach. The SBM-net and PBM-net showed differences in the distribution of entropy level over acquisition, but difference in the final entropy score was shown only on a descriptive level. This finding tentatively supports the concept that different intrinsic and extrinsic information are not intensified separately and sequentially, but are mutually connected in the acquisition. This result cannot be explained by a step-model (Flanders et al., 1992) that assumes a sequential transformation from extrinsic to intrinsic and intrinsic to extrinsic information. Because Flanders et al. (1992) used 70 trials for the transformation change and we used 80

trials in each condition we do not think that we modeled only the first part of the step-model. However, the high entropy values of the IEM-net indicate at least a potential parallel visuo-motor mapping. We cannot be sure if the IEM-net or the SBM/PBM networks represent a better description of the participants' behavior. The results do not support the notion of a mapping solely from extrinsic to intrinsic information as assumed in the EIM model.

The underlying interface representing this finding could be explained either by a transformation process (Neilson & Neilson, 1999), which acquires a common code (Prinz, 1997), or a unified sensorimotor representation (Carrozzo et al., 1999). The support for one of the alternatives is beyond the scope of this research. We tentatively would interpret our results so far as showing that, for continuous movements, a transformation from intrinsic to extrinsic information could be acquired by a parallel acquisition of extrinsic to intrinsic and intrinsic to extrinsic information that accentuate the bi-directional transfer of these information (Henriques, Klier, Smith, Lowy, & Crawford, 1998). The posterior parietal cortex could serve as a psychophysically plausible interface to simultaneously represent different frames of reference (Andersen, et al., 1997; Pouget & Sejnowski, 1995; Salinas & Abbott, 1995). We also would like to reiterate that it is not our intention to generalize these findings to discrete movements or long time-scale behaviors. The number of participants used for the simulations, the sensitivity of all parameters, and the details of the simulations employed do not allow us to broaden our interpretation. However, they serve as a starting point to understand the specific types of visuo-motor mapping in continuous movements.

References

- Andersen, R. A., Snyder, L. H., Bradley, D. C., & Xing, J. (1997). Multimodal representation of space in the posterior parietal cortex and its use in planning movements. *Annual Review in Neurosciences*, 20, 303–330.
- Andersen, R. A., Snyder, L. H., Li, C.-S., & Stricanne, B. (1993). Coordinate transformation in the representation of spatial information. *Current Opinion in Neurobiology*, 3, 171–176.
- Bernstein, N. A. (1967). *The coordination and regulation of movements*. UK, Oxford: Pergamon.
- Berthouz, L., & Kuniyoshi, Y. (1998). Emergence and categorization of coordinated visual behavior through embodied interaction. *Machine Learning*, 31, 187–200.
- Bullock, D., & Grossberg, S. (1988). Neural dynamics of planned arm movements: Emergent invariants and speed-accuracy properties during trajectory formation. *Psychological Review*, 95(1), 49–90.
- Carrozzo, M., & Lacquaniti, F. (1994). A hybrid frame of reference for visuo-manual coordination. *NeuroReport*, 5, 453–456.
- Carrozzo, M., McIntyre, J., Zago, M., & Lacquaniti, F. (1999). Viewer-centers and body-centered frames of reference in direct visuomotor transformations. *Experimental Brain Research*, 129, 201–210.
- Cohen, J. (1988). *Statistical power analysis for the behavioral sciences*. Hillsdale, NJ: Erlbaum.
- Cordo, P. J., & Flanders, M. (1989). Sensory control of target acquisition. *Trends in Neurosciences*, 12(3), 110–117.
- Desmurget, M., Pelisson, D., Rossetti, Y., & Prablanc, C. (1998). From eye to hand: Planning goal-directed movements. *Neuroscience and Biobehavioral Reviews*, 22(6), 761–788.

- Elliot, D., Ricker, K. L., & Lyons, J. (1998). The control of sequential goal-directed movement: Learning to use feedback or central processing? *Motor Control*, 2, 61–80.
- Engel, K. C., & Soechting, J. F. (2000). Manual tracking in two dimensions. *Journal of Neurophysiology*, 83, 3483–3494.
- Flanagan, J. R., Ostry, D. J., & Feldman, A. G. (1993). Control of trajectory modifications in target-directed reaching. *Journal of Motor Behavior*, 25(3), 140-152.
- Flanders, M., Tillery, S. I. H., & Soechting, J. F. (1992). Early stages in a sensorimotor transformation. *Behavioral and Brain Sciences*, 15(2), 309–320.
- Gaudiano, P., & Grossberg, S. (1991). Vector associative maps: Unsupervised real-time error based learning and control of movement trajectories. *Neural Networks*, 4, 147–183.
- Geisler, W. S. (1999). Motion streaks provide a spatial code for motion direction. *Nature*, 400(1), 65–69.
- Ghous, A., & Neilson, P. D. (2002). Evidence for internal representation of a static nonstationarity in a visual tracking task. *Human Movement Science*, 21, 847-879.
- Haykin, S. (1999). *Neural networks: A comprehensive foundation* (2nd ed.). Englewood Cliffs, NJ: Prentice Hall.
- Hecht, H., Vogt, S., & Prinz, W. (2001). Motor learning enhances perceptual judgment: A case for action-perception transfer. *Psychological Research*, 65, 3–14.
- Henriques, D. Y. P., Klier, E. M., Smith, M. A., Lowy, D., & Crawford, J. D. (1998). Gaze-centered remapping of remembered visual space in an open-loop pointing task. *Journal of Neuroscience*, 18(4), 1583–1594.
- Hogan, N., & Flash, T. (1987). Moving gracefully: Quantitative theories of motor coordination. *Trends in Neuroscience*, 10, 170–174.
- Jobst, U. (1992). *The mapping of movement strategies in posturographic biofeedback training onto a Kohonen neural network*. Paper presented at the International Symposium of the Society for Postural and Gait Research. Graz: Austria.
- Kohonen, T. (1995). *Self organizing maps*. Heidelberg, Germany: Springer.
- Kuperstein, M. (1988). An adaptive neural model for mapping invariant target position. *Behavioral Neuroscience*, 102(1), 148–262.
- Magill, R. A. (1998). Knowledge is more than we can talk about: Implicit learning in motor skill acquisition. *Research Quarterly for Exercise and Sport*, 69, 221–256.
- McNeill, D. K., & Card, H. C. (1999). Competitive learning and its application in adaptive vision for autonomous mobile robots. *Connection Science*, 11(3/4), 345–357.
- Mester, J., & Perl, J. (2000). Grenzen der Anpassungs- und Leistungsfähigkeit des Menschen aus systemischer Sicht – Zeitreihenanalyse und ein informatisches Metamodell zur Untersuchung physiologischer Adaptationsprozesse [Limits of adaption and performance of humans from a system approach – time series analysis and a computer science meta-model for physiological adaptation]. *Leistungssport*, 30(1), 43–51.
- Miall, R. C., & Wolpert, D. M. (1996). Forward models for physiological motor control. *Neural Networks*, 9(8), 1265–1279.
- Neilson, P. D., & Neilson, M. D. (1999). A neuroengineering solution to the optimal tracking problem. *Human Movement Science*, 18, 155–183.
- Neilson, P. D., Neilson, M. D., & O'Dweyer, N. J. (1993). What limits high speed tracking performance? *Human Movement Science*, 12, 85–109.
- Pennartz, C. M. A. (1997). Reinforcement learning by Hebbian synapses with adaptive thresholds. *Neuroscience*, 81(2), 303–319.
- Perl, J. (1998). Aspects and Potentiality of Unconventional Modeling of Processes in Sporting Events. In B. Scholz-Reiter, H.-D. Stahlmann & A. Nethe (Eds.), *Process Modelling*, (S. 74-85). Berlin-Heidelberg: Springer.
- Perl, J. (2002a). Adaptation, Antagonism, and System Dynamics. In G. Ghent, D. Kluka, & D. Jones (Eds.), *Perspectives – The Multidisciplinary Series of Physical Education and Sport Science* 4, (pp. 105-125). Oxford: Meyer & Meyer Sport.
- Perl, J. (2002b). Game analysis and control by means of continuously learning networks. *International Journal of Performance Analysis of Sport* 2, 21-35.
- Perl, J., & Mester, J. (2001). Modellgestützte und statistische Analyse der Wechselwirkung zwischen Belastung und Leistung [Modeling and statistical analysis of interaction between load and performance]. *Leistungssport*, 31(2), 54–62.

- Poizner, H., Fookson, O. I., Berkinblit, M. B., Hening, W., Feldman, G., & Adamovich, S. (1998). Pointing to remembered targets in 3-D space in Parkinson's disease. *Motor Control*, 2, 251–277.
- Polani, D. (2001). Measures for the Organization of Self-Organizing Maps. In L. Jain & U. Seiffert (Eds.), *Self-Organizing Neural Networks. Recent Advances and Applications*. Springer: Heidelberg.
- Pouget, A., & Sejnowski, T. J. (1995). Spatial representations in the parietal cortex may use basis functions. *Advances in Neural Information Processing*, 7, 157–164.
- Prinz, W. (1997). Perception and action planning. *European Journal of Cognitive Psychology*, 9, 129–154.
- Raab, M., Hill, H., Bert, N., Efstathiou, G., Gaßner, K., Neu, E., Schelm, A., Schorer, J., Sessler, M., Thomas, S., & Zechnall, D. (2001). A physiological model of the role of feedback and feedforward processes in visually driven movements. In J. Mester, G. King, H. Strüder, E. Tsollakidis, & A. Osterburg (Eds.), *Perspectives and profiles: ECSS-Congress 2001* (p. 315). Cologne: Sport und Buch Verlag.
- Raab, M., & Schorer, J. (1998). Implicit learning and interference in a tracking paradigm. In A. J. Seargent & H. Siddons (Eds.), *From community health to elite sport* (p. 169). Manchester: University Press.
- Raab, M., Schorer, J., & Magill, R. A. (submitted). *Cue dependent acquisition of strategies in visually driven hand movements when cues are removed or added*.
- Redding, G. M., & Wallace, B. (1996). Adaptive spatial alignment and strategic perceptual-motor control. *Journal of Experimental Psychology: Human perception and Performance*, 22(2), 379–394.
- Ritter, H. (1990). Self-organizing maps for internal representations. *Psychological Research*, 52, 128–136.
- Ritter, H., Martinetz, T. M., & Schulten, K. J. (1989). Topology-conserving maps for learning visuo-motor-coordination. *Neural Networks*, 2, 159–168.
- Rogosky, B. J., & Rosenbaum, D. A. (2000). Frames of reference for human perceptual-motor coordination: Space-based versus joint-based adaptation. *Journal of Motor Behavior*, 32(3), 297–304.
- Rojas, R. (1996). *Theorie der neuronalen Netze – Eine systematische Einführung* [Theory of neuronal nets – a systematic introduction]. Berlin: Springer.
- Rosenbaum, D. A., & Chaiken, S. R. (2001). Frames of reference in perceptual-motor learning: Evidence from a blind manual positioning task. *Psychological Research*, 65, 119–127.
- Rosenbaum, D. A., Loukopoulos, L. D., Meulenbroek, R. G. M., Vaughan, J., & Engelbrecht, S. E. (1995). Planning reaches by evaluating stored postures. *Psychological Review*, 102, 28–67.
- Salinas, E., & Abbott, L. F. (1995). Transfer of coded information from sensory to motor networks. *Journal of Neuroscience*, 15(10), 6461–6474.
- Schöllhorn, W. & Perl, J. (2002). Prozessanalysen in der Bewegungs- und Sportspielforschung [Process analysis in movement science and sport game research]. *Spectrum der Sportwissenschaften* 14, 1, 30-52.
- Schorer, J. & Raab, M. (2000). Effects of different motor control strategies with and without additional information in a pursuit tracking task. *Journal of Sport & Exercise Psychology*, 22 (Suppl.), p. S94-95.
- Soechting, J. F., Buneo, C. A., Herrmann, U., & Flanders, M. (1995). Moving effortlessly in three dimensions: Does Donders' law apply to arm movement? *Journal of Neuroscience*, 15, 6271–6280.
- Spijkers, W. (1993). *Sehen und Handeln: Die Rolle visueller Information bei zielgerichteten Bewegungen* [Visual information in intended movements]. Aachen: Shaker.
- Stanley, M. L., & Franks, I. M. (1990). Learning to organize the frequency components of a perceptual motor skill. *Human Movement Science*, 9, 291–323.
- Szepesvari, C., Cimmer, S., & Lorincz, A. (1997). Neurocontroller using dynamic state feedback for compensatory control. *Neural Networks*, 10(9), 1691–1708.
- Vetter, P., Goodbody, S. J., & Wolpert, D. M. (1999). Evidence for an eye-centered spherical representation of the visuomotor map. *Journal of Neurophysiology*, 81, 935–939.
- Viviani, P., Campadelli, P., & Mounoud, P. (1987). Visuo-manual pursuit tracking of human two-dimensional movements. *Journal of Experimental Psychology: Human*

Performance and Perception, 13(1), 62-78.

Weir, D. J., Stein, J. F., & Miall, R. C. (1989). Cues and control strategies in visually guided tracking. *Journal of Motor Behavior*, 21(3), 185–204.

Wolpert, D. M., & Ghahramani, Z. (2000). Computational principles of movement neuroscience. *Nature Neuroscience*, 3, 1212–1217.

Worringham, C. J. (1991). Variability effects on the internal structure of rapid aiming movements. *Journal of Motor Behavior*, 23(1), 75-85.

Wulf, G., & Schmidt, R. A. (1997). Variability of practice and implicit motor learning. *Journal of Experimental Psychology: Learning, Memory and Cognition*, 7(4), 11–18.

Wünstel, M., Boll, M., Polani, D., Uthmann, T., & Perl, J. (1999). Trajectory clustering using self-organizing maps. In S. Sablatnög & S. Enderle (Eds.), *Workshop RoboCup at KI '99 in Bremen, Germany* (pp. 41–46). Ulm: (University of Bremen report 1999/2).

Young, R. P., & Zelaznik, H. N. (1992). The visual control of aimed hand movements to stationary and moving targets. *Acta Psychologica*, 79, 59–78.

Zechall, D. (2001). *Simulation of eye-hand coordination with a neuronal network using a Kohonen network*. Unpublished master's thesis, University of Heidelberg.

Appendix

PerPot-driven DyCoN

The particular DYCoN type presented here is dynamically controlled using the performance-potential control system (PERPOT), which originally had been developed for the analysis and control of physiological adaptation processes (Mester & Perl, 2000; Perl & Mester, 2001). In this approach, each neuron controls its individual learning rate by its learning progress, and the neuron's individual radius of activation is controlled by its performance potential. Because of the properties of PERPOT, such a "PERPOT-driven" DYCoN is able to learn continuously and concurrently, to forget and to collapse, and, therefore, it can be used to model the basic learning processes underlying the tracking behavior (see a discussion in Perl, 2002a, for an overview).

DYCoN considers a grid of neurons \underline{N} containing weight vectors that are situated to represent stimuli or input space. Each input \underline{I} is mapped to the neuron with weights nearest to \underline{I} . Learning is accomplished by updating the weight vectors using a learning rate \underline{LR} , which describes the "amount of learning," and a radius of activation \underline{RA} , which represents the "region of influence."

The concept of the DYCoN approach, in general, is that of having the \underline{LR} and the \underline{RA} dynamically controlled by the developing situation of the network. In particular, in the case of the PERPOT-driven DYCoN, the basic concept is to combine each neuron \underline{N} of the network with a specific PERPOT model, which assists the self-control of its radius of activation $\underline{RA}[\underline{N}]$. The method $\underline{RA}[\underline{N}]$ is a function of the current performance potential $\underline{PP}[\underline{N}]$ and, hence, implicitly depends also on the values of training intensity \underline{TI} (i.e., the PERPOT "load rate"). The self-control of the learning rate \underline{LR} is managed by strongly coupling it to the current learning situation -- that is, by means of the distance $\underline{d}[\underline{N}]$ between the weight vector of the neuron \underline{N} and the current learning impulse \underline{I} .

The advantage of the DYCoN concept is that a once-trained network can be used as a platform for further learning steps, requiring only very little additional information for adjustment, which is needed when comparing intrinsic and extrinsic information acquisition. Input vectors represent different types of time series, the items of which are, in the presented simulation, motion coordinates or visual space information in visuo-motor mapping. The aim is to recognize the specific and distinctive aspects of the pattern of simulation results to understand the assumed visuo-motor control strategies.

To accomplish this, a time series is cut continuously into pieces of length \underline{n} , which are called the processes of length or dimension \underline{n} :

(4,4,3,2,1,4, ...) \rightarrow <4,4,3,2> ; <4,3,2,1> ; <3,2,1,4> ; <2,1,4,...>; ...

A set of these \underline{n} -dimensional processes is then called a pattern of the regarding behavior. A pattern characterizes the individual behavior for each trial of the tracking data. Two properties are essential in DyCoN:

Atrophy (modeled). Atrophy plays an important role in physiological adaptation processes, in general, and in learning processes in particular. Atrophy describes the

dynamic process of losing information in the case of extremely low or missing learning stimuli. To model atrophy is useful in learning strategies in the context of the continuous learning of changing and concurrent patterns. In our case, the omitted distance information in the vector of target-trained networks will be modeled by atrophy.

Entropy is used to measure, quantitatively, the learning success by the amount of information already stored: Testing a pattern \underline{P} with a number of \underline{P} -specific inputs results in an acceptance frequency distribution over the total number of neurons \underline{N} of the network. Using $p(\underline{n})$ as the probability of \underline{n} to accept \underline{P} , the \underline{P} -specific total entropy $h(\underline{P}, \underline{N})$ of the network is given by $h(\underline{P}, \underline{N}) = -\sum_{\underline{n}} p(\underline{n}) \times \log_2 p(\underline{n})$.

Using entropy as a quantitative measure enables the detection and analyses of the time-dependent behavior of a network. If entropy is maximal, then

$p(i) = \frac{1}{N}$ for all $i \in I$ yields entropy by Equation 1:

$$-N \cdot \left(\frac{1}{N} \cdot \log_2 \left(\frac{1}{N} \right) \right) = -\log_2 \left(\frac{1}{N} \right) = \log_2(N). \quad (1)$$

For a 20×20 matrix of neurons ($\underline{N} = 400$), this equation results in a maximal value of 8.64 total entropy. The maximal entropy value will be used as a criterion benchmark for the acquisition by the four different models of visuo-motor mapping.

Superposed and Concurrent Learning

Figure 1 shows the scenario of superposed learning. The values of the respective training intensities are indicated by \underline{u} and \underline{l} (upper and lower patterns, respectively). Figure 1a shows a situation with constant \underline{u} values, resulting in a temporal coexistence of the concurrent patterns. Using too high \underline{u} values for the superposing process, as shown in Figure 1b, causes low entropy for both patterns, indicating low grades of representation. If, however, superposing starts with a high \underline{u} value and is then continued using a decreasing \underline{u} , (Fig. 1c), there is again a bad effect for the superposed pattern -- but this effect offers the best support for the pattern carrying out the superposing.

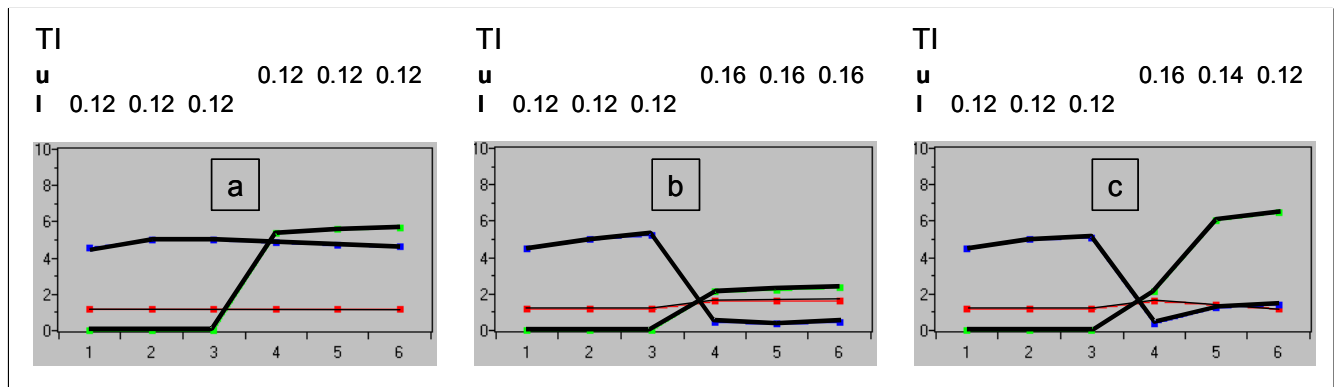


Fig. 1. Entropy, in the case of concurrent learning, depending on training intensities (\underline{I}); each training was carried out in two series of three episodes of 1,000 steps each. Abbreviations: \underline{u} = amount of training, \underline{I} = intensity, and the interaction of \underline{u} and \underline{I} when changing the amount of training from 0.12 (a) or 0.14 (c) to 0.16 (b).

The role of atrophy in the case of concurrent learning is shown in Figure 2. In the first phase the lower pattern is trained, which also influences the upper pattern due to common inputs. In the second phase the upper pattern is trained, affecting the atrophy of the lower one. To clarify what this means for the qualitative behavior, the acceptance frequencies of the neurons in Figure 2 are represented by their diameters. This shows that atrophy reduces the grade of representation of a pattern with respect to the number of involved neurons, as well as with respect to their acceptance frequencies. However, the sensitivity of all aforementioned parameters change only the total amount of activation and duration of learning, but not the relative amount of activation and learning between the different nets (Zechnall, 2001).

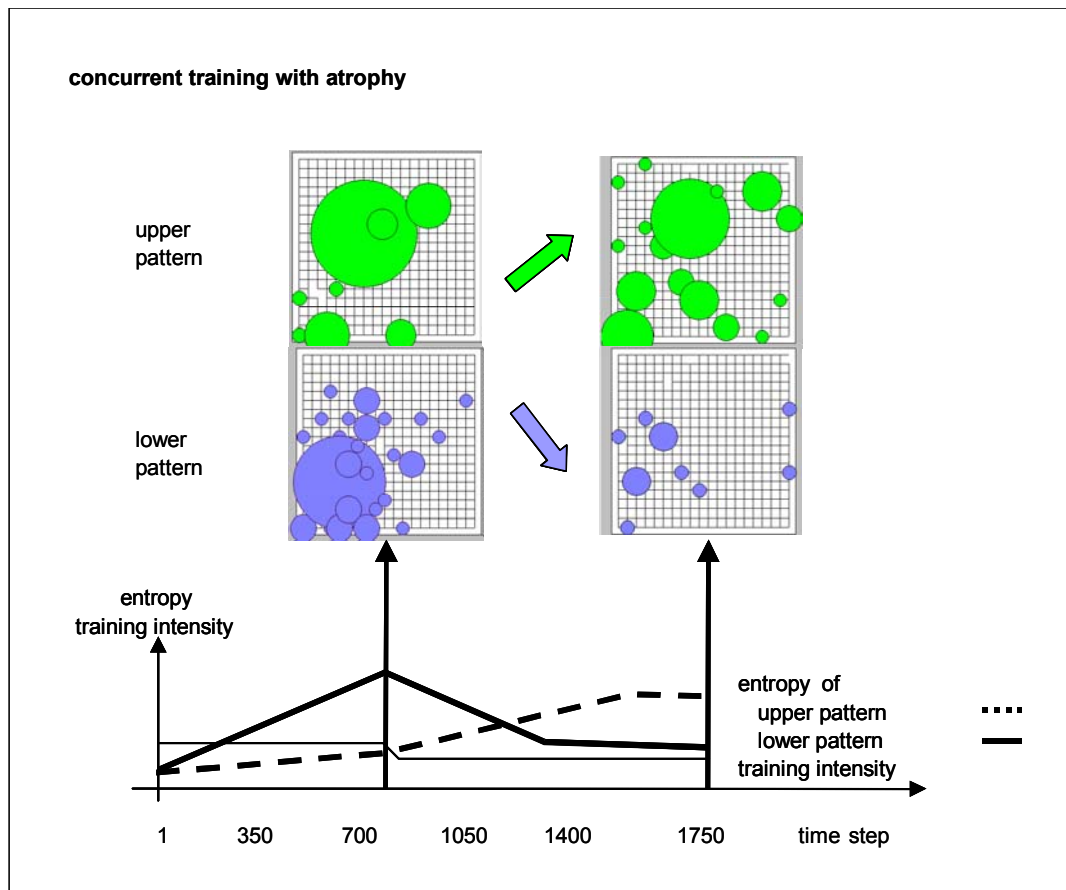


Fig. 2. Concurrent training with atrophy. The upper pattern shows the increase of entropy and the lower pattern shows the decrease of entropy in the long run, in relation to training intensity over time.

MARKUS RAAB^{6,7}, JÜRGEN PERL⁸ AND DIRK ZECHNALL⁹

The Mapping of Intrinsic and Extrinsic Information in Continuous Visuo-Motor Control

Contact :

AUTHOR(S): Markus Raab, Jürgen Perl & Dirk Zechall

ADDRESS: Max Planck Institute for Human Development
Adaptive Center for Behavior and Cognition
Lentzealle 94
D-14195 Berlin

EMAIL: raab@mpib-berlin.mpg.de

COPYRIGHT : © Markus Raab, Jürgen Perl & Dirk Zechall, 2003, All Rights reserved

⁶ Center for Adaptive Behavior and Cognition, Max Planck Institute for Human Development, Berlin, Germany

⁷ Institute for Human Movement and Sport, University of Flensburg, Germany

⁸ Institute for Computer Science, University of Mainz, Germany

⁹ Institute for Sport and Sport Sciences, University of Heidelberg, Germany