Proceedings of the 2008 International Conference on Cognitive Systems
University of Karlsruhe, Karlsruhe, Germany, April 2-4, 2008

Multimodal Goal Representations and Feedback in Hierarchical Motor Control

Oliver Herbort, Martin V. Butz and Joachim Hoffmann

Abstract— **The capabilities of human motor behavior build on the integration of multiple sensory modalities in goal representation and feedback processing. Here, we present a hierarchical neural network model of motor control to simulate these capabilities, based on the SURE_REACH model. The model is able to integrate visual and proprioceptive goal representations, but, by now, relies only on proprioceptive feedback to control ongoing movements. Here, we extend the model to a neural network that processes both, proprioceptive and visual feedback. In simulated reaching experiments we demonstrate that visual feedback considerably enhances the accuracy of the original controller. Moreover, the ability to combine visual and proprioceptive goal representations, or to adjust behavior to task-specific constraints is not affected. Finally, we discuss the results, propose further enhancements, and outline the model's relevance for other domains of human cognition.**

I. INTRODUCTION

Human sensorimotor control is truely amazing. An astonishing spectrum of sensory modalities can guide motor behavior and different types of feedback can be processed. Besides proprioception and vision, various other sensations can be organized in motor skills, both to guide behavior and as a goal modality. Furthermore, human behavior is adaptive and flexible to a degree unrivaled by any artificial system. Even the clumsiest among us can readily adjust motor control to novel situations, for example, when moving with heavy winter clothes or when opening a door while balancing a stack of folders and holding a cup of coffee. How these capabilities are achieved by the human brain is not yet well understood. Here, we propose that a hierarchical model may account for the integration of proprioception and vision in goal representations and feedback processing in task-dependent motor control.

A. Behavioral Flexibility and Hierarchical Control

The ability to behave flexible and to adapt movements to different tasks and circumstances depends on the redundancy of the human body. Due to motor redundancy, each possible behavioral goal can be pursued in an infinite number of ways. On the kinematic level, it is possible to grasp a pen while assuming rather different arm postures. Likewise, the transition from an initial posture to a targeted one can follow different trajectories. On the dynamic level, each movement can be carried out with different speeds and varying degrees of muscle stiffness. Of course, at one time, only one of many possible movements can be executed so that an implicit or explicit selection has to be made. In recent years it became apparent that this selection is not based on a single *optimality criterion*, but that it is highly dependent on the current task and situational constraints. For example, the brain takes advantage of postural redundancy to facilitate upcoming tasks [1].

Furthermore, movement goals can be represented in a number of sensory modalities. In most reaching movements, the goal is visually defined. Nevertheless, a goal can also be formulated in proprioceptive terms, for example, when we want to reproduce specific postures during physical exercise or dancing. Moreover, a goal representation might combine multiple sensory modalities. For example, we might want to align forearm and hand (i.e. proprioceptive constraint) when we point at a distant object (visual target). When performing sequential movements, a target may be represented in a vision-based coordinate system but additional proprioceptive information may be integrated in the representation to facilitate subsequent movements [2].

Goal directed human motor behavior is often understood in terms of internal models, which neurally represent how the body moves or can be moved [3]. Whereas *forward models* predict the consequences of motor commands on body posture or sensory input, *inverse models* provide the motor commands necessary to move the body to a desired state. A drawback of models that build upon a simple inverse mapping from goals to actions is that they only account for behavior in very limited contexts, for example, the transformation from target coordinates to abstract movement parameters [4] or the transformation of a desired joint trajectory into motor commands [3]. In these cases, behavior is neither very flexible nor are multiple sources of information integrated to represent goals and guide movements. Hierarchically organized motor control networks might enable these capabilities and, besides, yield other advantages [5], [6]. Different control problems can be tackled independently [7], more degrees of freedom may be controlled [8], or skills of different complexity may be encoded [9]. Here, we show that a hierarchical controller enables the integration of different forms of sensory feedback and multiple goal representation while preserving the flexibility of individual modules to resolve redundancy task-dependently.

This work was supported by the Emmy Noether Program of the German Research Foundation, BU 1335/1.

The authors are with the Department of Psychology, University of Würzburg, Röntgenring 11, 97070 Würzburg, Germany {oliver.herbort,butz,hoffmann}@psychologie.uni-wuerzburg.de

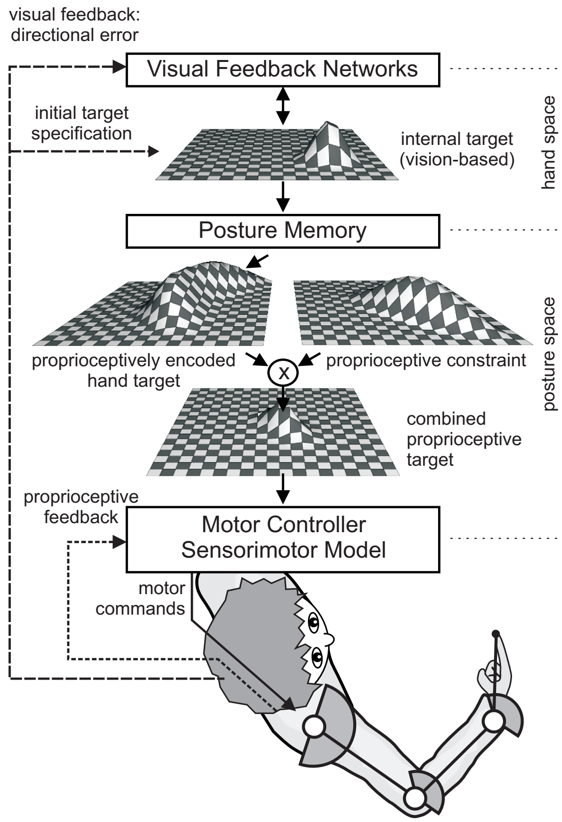

Fig. 1. The hierarchical control networks integrate visual and proprioceptive feedback to pursue a goal representation that is determined by visual representations and proprioceptive constraints.

B. General Approach

In this paper, we extend the SURE_REACH model of motor control [10], [11] by a mechanism for visual feedback processing. SURE_REACH is a physiologically and psychologically plausible neural network model of unsupervised human motor learning and control. It accounts for the task-dependent resolution of motor redundancy to enable flexible behavior in reaching movements to visually encoded targets. Movements may be constrained by additional proprioceptive goals, for example, to reduce the motion of impaired joints, facilitate upcoming movements, or assume a specific angle in a selected joint. However, even if the target is visually encoded and this information is processed during movement preparation, so far movement execution itself was only based on proprioceptive feedback and a proprioceptively encoded movement plan. Thus, it is currently impossible to update motor commands based on a visually perceived discrepancy between hand position and target. However, human goal-directed movements rely heavily on visual feedback [12], [13]. Hence, we extent the proprioceptive SURE_REACH controller to account for visually guided movements.

To preserve the current flexibility of the SURE_REACH model but also enable the integration of visual feedback, we propose a hierarchical modular system that consists of two nested control loops (Fig. 1). The lower level loop, formed by the original SURE_REACH model, proprioceptively controls arm movements. This loop is enclosed by a visual feedback neural network, which minimizes the distance between the exteroceptively perceived hand and target location. This neural network adjusts the lower level goal representation dependent on a visual error signal to acquire the target more accurately but also to preserve the flexibility of the proprioceptive loop.

The next section briefly describes the simulated body, the proprioceptive SURE_REACH controller, the visual feedback mechanism, and the simulated reaching tasks. The results section then shows the enhanced capabilities of the hierarchical system. A discussion of the model, possible extensions, and an outlook on higher cognition concludes the paper.

II. DESCRIPTION OF THE MODEL

In the following section, the original SURE_REACH architecture is briefly outlined. Due to limited space, a full account can only be given elsewhere [10], [11]. Next, the simulated arm and the neural networks for visual feedback processing are described.

A. SURE_REACH

SURE_REACH is a modular hierarchical architecture that solves the inverse problem of generating a sequence of motor commands that move the hand of a redundant arm to a desired location. It is divided into two modules, which are trained with unsupervised associative learning rules.

The *posture memory* (Fig. 1) transforms a population encoded hand location into a likewise encoded set of all those arm postures that realize the respective hand location. It thus transforms the goal from a visual into a posture-based, proprioceptive frame of reference. Based on this representation, the *motor controller* generates motor commands that move the arm toward the closest goal posture. This is realized in two steps. First, the *motor controller* prepares a sensory-to-motor mapping based on learned *sensorimotor body models*. This mapping provides suitable motor commands to move the simulated arm from each possible posture toward the desired hand location. It can be considered an online generated inverse model. Next, the sensory-to-motor mapping is used as a proprioceptive closed-loop feedback controller that moves the hand to the target.

The emphasis of the adaptive movement preparation is also one of the key differences to previous neural network models. Whereas other models encode a single or only few inverse models during motor learning, which are used for all reaching movements later on, SURE_REACH generates an individual inverse model for each newly presented target. This enables the flexible incorporation of task-dependent constraints and optimality criteria by adjusting the sensory-to-motor mapping to the current task demands. In this paper, we used the same configuration as in [11] to setup the components of the SURE_REACH controller.

B. Arm Model and Hand Space Representation

We simulate reaching experiments with a kinematic model of a three joint planar arm moving in the transverse plane. The lengths of the upper arm, forearm, and hand are

$32cm$, $25cm$ and $18cm$, respectively. The shoulder, elbow and wrist joints are restricted to move within $[-60°, 120°]$, $[-160°, 0°]$, and $[-80°, 60°]$, respectively (see gray angles in Fig. 1). The proprioceptive controller moves the arm by activating a pair of antagonistic muscles for each joint. As this paper mainly addresses the direction of corrective movements and not their dynamics, muscle activations are normalized, resulting in a constant arm velocity of $0.57°$ in each time step.

In the SURE_REACH controller, hand targets are represented by a population code of neurons $\vec{h}$. A neuron h^i of $\vec{h}$ fires, if the target coordinates (x, y) are close enough to the neuron's preferred location (h^i_x,h^i_y):

$$h^i = \max(1.0 - \frac{|x - h^i_x|}{3.0cm}; 0) \cdot \max(1.0 - \frac{|y - h^i_y|}{3.0cm}; 0) \quad (1)$$

The preferred hand locations are arranged in a $h = 51 \times 26 = 1326$ grid with $3cm$ distance, covering a $150cm \times 75cm$ rectangle, which surrounds the frontal part of the arm's work space.

C. Visual Feedback Controller

In the original SURE_REACH model, the hand target representation $\vec{h}$ would be directly computed from the location of a visually presented target. To enable visually guided movements, this representation is now detached from the physical target stimulus. It is mediated by an internal representation of the target (the *internal target*, as in contrast to the *external target*, which finally should be touched by the hand). Thus, small but systematic errors, which might arise due to the inaccuracy of necessary coordinate transformations or novel visual distortions, can be corrected by altering the goal representation of the proprioceptive loop.

Initially, the internal target may be identical to the external target representation but it changes as soon as a discrepancy between the external target and the hand position is perceived. Thus, it is not necessarily identical to the external target but helps the underlying control structures to acquire the external target more accurately. The internal target is continuously forwarded to SURE_REACH's posture memory and results in an adjustment of its control behavior. If an error is perceived, the internal target is shifted in the direction opposite to that of the error, as proposed in [8]. For example, if the hand is to the left of the external target, the internal target is shifted slowly to the right, resulting in a rightward hand movement.

The internal target representation has to meet three requirements. First, the internal target representation has to be detached from the external target representation to enable arbitrary adjustments. Second, despite this detachment, a neural activity distribution that accurately encodes the internal target has to be maintained throughout the movement. Third, the neural activity has to be controllable in order to induce corrective movements. A lateral inhibition neural field with gated lateral connections fulfills these requirements [14]. Due to excitatory lateral connections between spatially associated neurons and inhibitory connections between distant neurons,

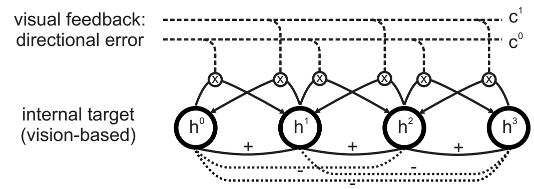

Fig. 2. A population of neurons (h^i) represents the hand target. The lateral inhibition type connectivity below the nodes keeps the representation stable (black: excitatory, dotted: inhibitory). Drawn above the nodes, biased lateral connections (black arrows), which are gated by the error signals c^k (dashed lines), enable controlled shifts of neural activity between neurons.

neural activity can be preserved over a longer period of time without external input. Furthermore, multiple layers of gated lateral connections may induce shifts in the neural activity distribution if they are activated by an external control signal.

In the following, the neural network model of the visual feedback controller is formulated (Fig. 2 depicts a simplified and one-dimensional version). The internal target representation is implemented by a vector $\vec{h}_{int}$ encoded like the hand space representation $\vec{h}$. If a visual target is presented, the hand target representation $\vec{h}$ is not directly forwarded to the posture memory as in previous versions of the model but defines the initial state of the internal target representation. The activity distribution of the internal target representation is then continuously forwarded to the proprioceptive SURE_REACH controller. The internal target representation is updated each time step according to the equation:

$$\begin{aligned}\frac{\Delta h^i_{int}}{\theta} =& -\alpha h^i_{int} - \beta \sum_{j=0}^{h-1} f(h^j_{int}) + \gamma \sum_{j=0}^{h-1} f(h^j_{int}) d(i,j) \\ &+ \delta \sum_{j=0}^{h-1} \sum_{k=0}^{3} f(h^j_{int}) c^k g(i,j,k), \end{aligned} \quad (2)$$

where Δh^i_{int} is the change in the i-th component of $\vec{h}_{int}$, θ is a scaling factor, α reduces the activity of the neuron proportional to its activity, β weighs a general inhibitory term that scales down overall network activity, γ weighs the influence of the lateral inhibitory and excitatory connections, δ weighs the influence of the gated connections, and c^k is the k-th component of the visual error signal, which gates the layers of lateral connections. Table I lists the values of the parameters. The activity of a single neuron is restricted to the range from 0.0 to 2.0. The steep nonlinear sigmoidal function $f(t)$ bounds the propagated neural network activity:

$$f(t) = \frac{1}{1 + e^{-20(t-0.8)}}. \quad (3)$$

The weight of lateral connections is determined by the function $d(i, j)$:

$$d'(i,j) = \frac{\pi}{2d_{inh}} \sqrt{(h^i_x - h^j_x)^2 + (h^i_y - h^j_y)^2} \quad (4)$$

$$d(i,j) = \begin{cases} \cos(d'(i,j)) & d'(i,j) < \pi \\ -1 & d'(i,j) \geq \pi, \end{cases} \quad (5)$$

TABLE I

PARAMETERS

parameter	value	description
α	0.2	activity leak
β	0.01	weight of general inhibitory term
γ	0.1	weight of lateral connections
δ	1.0	weight of adaptive connections
θ	0.01	scaling coefficient
d_{inh}	11.25	distance of zero lateral inhibition / excitation

where d_{inh} is the distances for which neuron neither excite nor inhibit each other and h_x^i, h_y^i, h_x^j, and h_y^j are the preferred values of the i-th and j-th neuron, respectively.

Finally, shifts of the internal target may be induced by the four different layers of gated lateral connections. If a layer is activated, it propagates neural activation in a specific preferred direction. The preferred directions of the four layers $(l_x^i, l_y^i), i = 0 \ldots 3$ are $(1,0)$, $(0,1)$, $(-1,0)$, and $(0,-1)$. The gated lateral connections excite or inhibit other neurons according to the equation:

$$g(i,j,k) = \frac{(h_x^j - h_x^i)l_x^k + (h_y^j - h_y^i)l_y^k}{\sqrt{(h_x^i - h_x^j)^2 + (h_y^i - h_y^j)^2}}. \qquad (6)$$

During an ongoing movement, the visual error signal $\vec{c}$ is computed from the directional error ϕ_e between the location of the hand and the external target:

$$c^k = \frac{1}{1 + e^{2(l_x^k \cos\phi_e + l_y^k \sin\phi_e)}}. \qquad (7)$$

The closer the direction from hand to target matches the preferred direction of the k-th layer of gated connections, the higher is the excitation of the k-th component of the error signal, normalized by a sigmoidal term. Potential learning mechanisms and advanced error representations are discussed in Section IV.

D. Simulated Reaching Task

To evaluate the performance of the model, we demonstrate that the additional visual feedback enhances the accuracy of simulated movements, without impairing SURE_REACH's original capability to adhere to task-dependent constraints. Hence, the performance of the model was tested in three different tasks. First, as a baseline, the neural network had to move the hand to visually presented targets without the possibility to correct errors with visual feedback ("proprioception only"). To simulate this task, the target position was determined according to (1) and directly forwarded to SURE_REACH's posture memory. Second, the same movements were repeated with the help of the visual feedback networks as described above ("visual feedback"). Third, again the same hand targets had to be approached, but this time also a specific shoulder, elbow, or wrist angle had to be assumed ("visual feedback (... constrained)"). For example, the task could be to move the hand to a specific point and also flex the elbow to 30°. The proprioceptive controller is well able to fulfill such constraints [10]. The joint angle constraint is imposed on the network by inhibiting all neurons in SURE_REACH's redundant goal posture representation that do not match the specified constraint (Fig. 1). In the constraint task, each movement had to be performed under three conditions, in which either the shoulder, elbow, or wrist joint was required to assume a randomly selected angle[1].

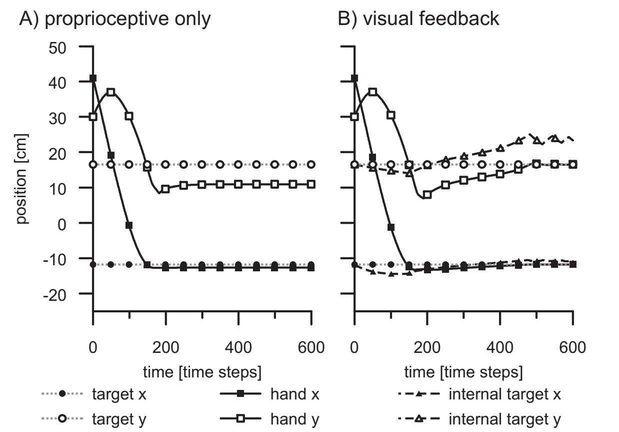

Fig. 3. The charts show the trajectories of the x- and y-coordinate of the hand (squares) of two exemplar movements. The target is indicated by circles. A) If the controller is only guided by proprioception, a small error remains. B) The error can be compensated by shifting the internal target (triangles) if visual feedback is used.

Before these tests were performed, 10 individual controllers were independently trained as in [11]. Then, each controller had to make 20 movements from randomly chosen goal postures to randomly chosen hand targets in each task. A single movement lasted for 600 time steps.

III. RESULTS

A quick glance at the exerted movements reveals that the controller benefits considerably from visual feedback. Fig. 3 displays the trajectories of an "proprioception only" movement and a movement in the "visual feedback" task. In the former, the hand approaches the target but the controller is unable to detect the remaining difference between hand position and target. Initially, the latter movement resembles the former. However, the controller detects the discrepancy between hand position and target and adjusts the internal target accordingly. The internal target is shifted in the direction opposite to the error between target and hand, thus reducing the hand position error.

To evaluate the accuracy of the controller and the different tasks systematically, we computed the average hand position and arm posture of the last 10 time steps of a movement. The averaged hand position was then compared to the target location to compute the final hand position error. Table II reports average error values for the different tasks. In the visual feedback tasks, the movement accuracies surpass that of the proprioceptive controller by far, even if additional constraints are imposed. The histograms in Fig. 4 show, that exclusively proprioceptively controlled movements usually terminate at least $0.5cm$ away from the target (95.0% of

[1]It was assured, that the hand target and proprioceptive constraint were not exclusive.

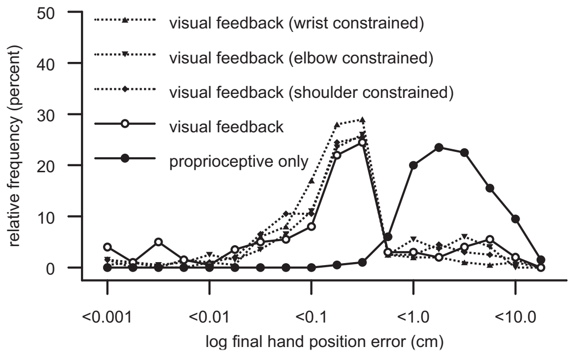

Fig. 4. The chart shows the distribution of the final hand position error for the different tasks.

movements). In contrast, if visual feedback is used the hand position error only seldom exceeds $0.5cm$ (14.5% of movements). T-tests of the mean hand position errors of the ten controllers reveal that movements in all visual feedback tasks are more accurate than in the proprioceptive task (table II). However, there is no significant difference between the various conditions with visual feedback.

Finally, we verified if the SURE_REACH controller is still able to adhere to the proprioceptively defined joint angle constraint. Therefore, we computed the absolute difference between the to be acquired joint angle and the actual resulting joint angle for the constrained joint at the end of each movement. The histograms in Fig. 5 reveal that the constraint is met with high accuracy, deviating only a few degrees from the targeted angle ($m = 2.50°,\ sd = 2.44°$).

The results confirm two important claims. First, the hierarchical network model is able to integrate vision and proprioception in feedback processing. The SURE_REACH

TABLE II

MEAN HAND POSITION ERROR AND STANDARD DEVIATIONS

task	m (cm)	sd (cm)	$t(18)$	p
proprioceptive only	2.55	0.554		
visual feedback	0.617	0.343	9.39	< 0.01
visual feedback and ...				
... wrist constrained	0.291	0.165	12.4	< 0.01
... elbow constrained	0.513	0.231	10.7	< 0.01
... shoulder constrained	0.469	0.280	10.6	< 0.01

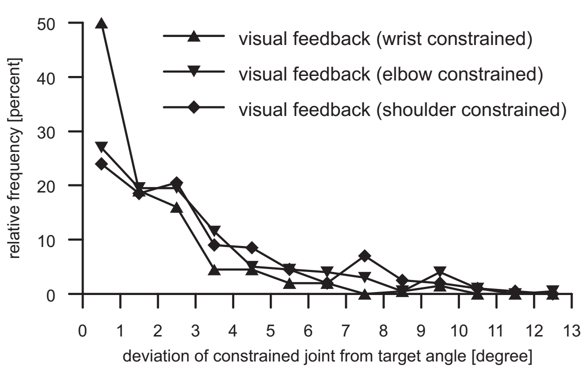

Fig. 5. The chart shows the distribution of the deviation of the final angle of the constrained joint from the intended angle.

controller uses proprioceptive feedback of the current joint posture to quickly move the hand to the target. Additionally, visual feedback is used to reach the target location with high accuracy. Second, the integration of visual feedback does not impair the flexibility of the original proprioceptive controller, but it is possible to combine a visually presented target and visually perceived deviations from the target with proprioceptively encoded constraints. Thus, the presented neural network model accounts for flexible, task-dependent behavior and for the integration of multiple sensory modalities

IV. DISCUSSION

We presented a hierarchical neural network model of motor control. This model combines high behavioral flexibility with the capability to integrate multiple sensory modalities in goal representation and to adjust behavior with feedback from different information sources. We simulated reaching experiments in which the visual feedback considerably enhanced the movement accuracy. Visual feedback did not interfere with the proprioceptive controller's capability of integrating task-specific visual and postural constraints.

A. Hierarchical Motor Control

Motor control is generally understood as a hierarchy or cascade of nested control processes [3], [5], [15]. In such a hierarchy, a rather abstract goal — such as wanting to have the hand at a certain location — is decoded into more concrete representations, for example, in proprioceptive terms, until motor commands are finally generated. Thereby, intermediate representations are not only the byproduct of a stepwise transformation process but are actively controlled to enhance movement accuracy and stability. SURE_REACH and the presented visual feedback neural network fit well into this framework. They form two nested control loops. The proprioceptive, lower level loop controls the arm posture, striving to match actual and desired posture. This loop is enclosed by the visual feedback loop, which minimizes the distance between the exteroceptively perceived hand and target location. The model differs from approaches that map rather higher level goals, for example, visually encoded errors, directly to motor commands or movement based representations [16]. These models lack intermediate representations and thus, on their own, can hardly integrate goal representations of multiple sensory modalities. In order to account for the flexibility and complexity of human sensory control, it seems necessary to integrate multiple control modules, which process different sensory modalities, in a hierarchy or cascade of feedback loops.

B. Learning and Error Representation

In the current implementation, the representation of the error signal is yet very simple and the neural networks for visual guidance are not shaped by sensorimotor learning. Hence, in the future we want to extend the model in different ways. First, by now the representation of the error only encodes the directional discrepancy between hand and target.

However, for a more realistic account of human reaching movements, the amplitude of the error should be encoded as well. A retina-like representation, centered on the target, may be able to encode both. Additionally, this would enable the encoding of subtle differences in the target region while allowing a sparse coverage of more remote areas. Second, the connectivity between the error representation and the activation of the gated connections should be learned. A reinforcement learning architecture should be readily able to acquire such a mapping [17]. The distance between hand and target might serve as a psychologically plausible and easily available reward signal. Here, a retina-like error representation may enable the adjustment of the rate of the internal target shift to the amplitude of the error. Also, currently the internal target is initially set to the location of the external target. A related learning mechanism might learn to place the internal target between the hand and external target to avoid overshoots. Such a bias toward undershoots is also found in human movements [18]. In future work, the error signal might not depend on the actual hand location but on a prediction of the final hand location to avoid adjusting motor commands based on a not yet finished movement [19]. Third, the gated lateral connections could develop in initial learning phases [14]. Information to distinguish between different movement directions could be extracted from proprioceptive or motor codes of saccades following the hand during early sensorimotor development.

C. Outlook on Higher Cognition

Recently, it has been suggested that the complex representations necessary to control the human body with its many redundant degrees of freedom may lay the foundation for higher cognitive functions [20]. Furthermore, modular internal models appear to be involved in the formation of abstract representations and even language [21]. SURE_REACH may provide a suitable framework for the generation of higher level cognition, possibly combining and integrating multiple representations. Moreover, higher-level cognitive functions are deeply interwoven with anticipatory, goal-directed behavior [22], as modeled within the SURE_REACH framework.

Besides the possibility to develop higher-level cognitive representations based on likewise hierarchical models, it seems also easy to integrate the internal generation of goals based on motivational modules. Recently, adaptive motivational systems have been successfully integrated into robot platforms [23]. Due to the high modularity and flexibility of the SURE_REACH model, goal activations that originate from the motivational system may flexibly invoke the goals and constraints necessary to solve self-induced tasks optimally, given current environmental circumstances and internal motivations. Future research awaits the creation of such highly flexible, motivational, cognitive control architectures. To conclude, hierarchically structured architectures, as presented herein, seem the key to understand the interplay of the many different feedback sources and goal modalities that ground the unmatched sophistication of human behavior and maybe even human cognition.

References

[1] M. Weigelt, W. Kunde, and W. Prinz, "End-state comfort in bimanual object manipulation," *Experimental Psychology*, vol. 53, no. 2, pp. 143–148, 2006.

[2] M. H. Fischer, D. A. Rosenbau, and J. Vaughan, "Speed and sequential effects in reaching," *Journal of Experimental Psychology: Human Perception and Performance*, vol. 23, no. 2, pp. 404–428, 1997.

[3] D. M. Wolpert, K. Doya, and M. Kawato, "A unifying computational framework for motor control and social interaction," *Philosophical Transactions of the Royal Society of London*, vol. 358, pp. 593–602, 2003.

[4] A. Karniel and G. F. Inbar, "A model for learning human reaching movements," *Biological Cybernetics*, vol. 77, pp. 173–183, 1997.

[5] J. Hoffmann, M. Berner, M. V. Butz, O. Herbort, A. Kiesel, W. Kunde, and A. Lenhard, "Explorations of anticipatory behavioral control (abc): a report from the cognitive psychology unit of the Univerisity of Würzburg," *Cognitive Processing*, vol. 8, pp. 133–142, 2007.

[6] T. Poggio and E. Bizzi, "Generalization in vision and motor control," *Nature*, vol. 431, pp. 768–774, 2004.

[7] G. E. Loeb, I. Brown, and E. Cheng, "A hierarchical foundation for models of sensorimotor control," *Experimental Brain Research*, vol. 126, pp. 1–18, 1999.

[8] D. A. Rosenbaum, L. D. Loukopoulos, R. G. J. Meulenbroek, J. Vaughan, and S. E. Engelbrecht, "Planning reaches by evaluating stored postures," *Psychological Review*, vol. 102, no. 1, pp. 28–67, 1995.

[9] F. A. Mussa-Ivaldi and E. Bizzi, "Motor learning through the combination of primitives." *Philosophical Transactions of the Royal Society: Biological Sciences*, vol. 355, pp. 1755–1769, 2000.

[10] M. V. Butz, O. Herbort, and J. Hoffmann, "Exploiting redundancy for flexible behavior: Unsupervised learning in a modular sensorimotor control architecture," *Psychological Review*, vol. 114, no. 4, pp. 1015–1046, 2007.

[11] O. Herbort and M. V. Butz, "Encoding complete body models enables task dependent optimal control," *Proceedings of the International Joint Conference on Neural Networks*, vol. 20, pp. 1639–1644, 2007.

[12] W. Spijkers and S. Spellerberg, "On-line visual control of aiming movements?" *Acta Psychologica*, vol. 90, no. 1-3, pp. 333–348, 1995.

[13] A. Ma-Wyatt and S. P. McKee, "Visual information throughout a reach determines endpoint precision," *Experimental Brain Research*, vol. 179, no. 1, pp. 55–64, 2007.

[14] S. M. Stringer, E. Rolls, and P. Taylor, "Learning movement sequences with a delayed reward signal in a hierarchical model of motor function," *Neural Networks*, vol. 20, no. 2, pp. 172–181, 2007.

[15] P. Cisek, "Integrated neural processes for defining potential actions and deciding between them: A computational model," *Journal of Neuroscience*, vol. 26, no. 38, pp. 9761–9770, 2006.

[16] N. Srinivasa and S. Grossberg, "A self-organizing neural model for fault-tolerant control of redundant robots," *Proceedings of the International Joint Conference on Neural Networks*, vol. 20, pp. 483–488, 2007.

[17] J. Peters, S. Schaal, and B. Schölkopf, "Towards machine learning of motor skills," in *Proceedings of Autonome Mobile Systeme (ams)*, 2007.

[18] C. Prablanc, J. F. Echallier, E. Komilis, and M. Jeannerod, "Optimal response of eye and hand motor systems in pointing at a visual target I. spatio-temporal characteristics of eye and hand movements and their relationships when varying the amount of visual information," *Biological Cybernetics*, vol. 35, no. 2, pp. 113–124, 1979.

[19] M. Desmurget and S. Grafton, "Forward modeling allows feedback control for fast reaching movements," *Trends in Cognitive Sciences*, vol. 4, no. 11, pp. 423–431, November 2000.

[20] H. Cruse, "The evolution of cognition - a hypothesis," *Cognitve Science*, vol. 27, pp. 135–155, 2003.

[21] R. Grush, "The emulation theory of representation: Motor control, imagery, and perception," *Behavioral and Brain Sciences*, vol. 27, pp. 377–396, 2004.

[22] M. V. Butz, O. Sigaud, G. Pezzulo, and G. Baldassarre, Eds., *Anticipatory Behavior in Adaptive Learning Systems: From Brains to Individual and Social Behavior*, Berlin Heidelberg, 2007.

[23] G. Konidaris and A. Barto, "An adaptive robot motivational system," *From Animals to Animats*, vol. 9, pp. 346–356, 2006.