

The Sequential Organization of Movement is Critical to the Development of Reaching: A Neural Dynamics Account

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Abstract—We present a neuro-dynamic model of looking, reaching, and grasping movements in infants in three pre-reaching phases. We attribute the evolution from pre-reaches to their suppression and subsequent re-emergence reported in a longitudinal study of von Hofsten [1] to the development of the sequential organization of movements, through which a set of elementary movements (visual fixation, reaching, opening the hand) are coordinated in time. The spatial precision hypothesis, which has emerged from work on spatial, visual, and action working memory, characterizes developmental changes as a change from strongly input-driven to more strongly interaction-dominated neural dynamics. Applying this hypothesis to reaching, we propose that the intention to reach is increasingly able to suppress competing movement behaviors, enabling object-oriented reaches. We evaluate three versions of the model that capture the three phases reported by von Hofsten and illustrate the properties of the movement model in simulations and in demonstration on a NAO robot.

I. INTRODUCTION

In a longitudinal study of the development of infant pre-reaching movements [1], Claes von Hofsten draws several insights from observed infants that reacted to a salient object in their visual array. The object was either stationary (presented for 60 seconds) or moved for a duration of 30 (fast movements) or 60 seconds (slow movements). Visual fixation, arm movements, and hand configurations were recorded and analyzed. Over the examined developmental period, three distinct phases were identified. In a first phase (up to four weeks of age), some arm movements were observed that transported the hand in the forward direction, the general direction of the object. Such arm movement occurred while infants either fixated on the object or not (e.g., because the eyes were closed or the gaze was elsewhere). The hand was more often open than closed into a fist, and grasp posture did not depend on whether the object was fixated. In a second phase (between four and ten weeks of age) infants exhibited a decrease in the number of reaching movements while the time spent fixating the object increased. Pre-reaching movements were often executed with the hand clenched into a fist (a tendency that peaked with $\sim 70\%$ of reaches at week seven). This was again true both whether infants fixated the

object or not. In a third phase (starting around ten weeks of age) pre-reaching movements re-emerged, their frequency increasing. Now these pre-reaches were often combined with object fixation, following the visual fixation of the object with a short delay. The hand now typically was opening during reaching. More reaching was observed for stationary than for moving objects. The faster an object moved, the fewer reaches were observed.

What developmental changes may underlie this pattern of visual and reaching behaviors? In this paper, we consider two main developmental changes that may shape the developmental process. The first change is a progression from movement “babbling” toward intentional and sequentially organized movement. In babbling, movement behaviors such as visually fixating a target, moving the arm, and opening the hand, are activated independently and at random, with little coordination between them. Later in development, the same movement behaviors are activated intentionally and their activation is constrained by their sequential order. That is, behaviors involved in a given task (such as reach to grasp) are not all activated at the same time. Each movement component is activated only if its preconditions are fulfilled.

The second change is a hypothesized developmental change of the neural connectivity that supports the processing pathway from visual input to movement generation. This runs under the label of the “spatial precision hypothesis” [2] and has been used to account for the transition from perseverative to flexible reaching [3] and for the metric sharpening and increasing capacity of spatial [4] and visual working memory [5]. According to the hypothesis, both excitatory and inhibitory recurrent neural connectivity that establishes neural interaction within populations of neurons is strengthened over development more than feed-forward connectivity, leading to a shift from input-dominated toward interaction-dominated neural dynamics. The enhanced capacity to sustain activation without sensory input (the basis for working memory) as well as an enhanced capacity to resist distractor input emerge from that shift. The hypothesis is also broadly consistent with connectionist accounts of the development of recurrent neural networks [6], [7]. This second change supports the first by stabilizing the competitive selection of a movement behavior and enhancing the inhibition of alternative behavior.

We think of the emergence of the sequential organization and coordination of movement behaviors as a developmental milestone, which impacts on movement behavior in a short time frame. The change of connection weights described by the spatial precision hypothesis is a graded process over a

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longer time frame. It continues to strengthen the stability of behavioral organization and coordination, observed as a steady increase in the frequency of reaching movements that are preceded by visual object fixation from week ten onwards.

On this theoretical basis we propose an account for the behavioral signatures of the development of looking, pre-reaching, and grasping movements in infants reported by von Hofsten. In that account, the first phase consists of uncoordinated movement babbling, in which visual processing has little influence on the arm movements. In the second phase reaching emerges as an intentional act that is sequentially organized, so that movement behaviors involved in reaching are initiated dependent on preconditions being met. For instance, the extension movement of the hand in space and the opening of the hand both depend on having attentionally focused on a target. A poor capability to stabilize object fixation together with an increasing capacity to suppress reaches and the opening of the hand without visual fixation leads to a reduction of pre-reaches. With the refinement of the connection weights, phase two transitions into phase three, in which intentional fixation and subsequent reaching attempts with opening hand become increasingly likely. All movements become smoother and the corresponding paths straighter with the graded sharpening of neural interaction (see discussion in [8]).

In this paper, we validate these hypotheses by formulating a fully embodied neural processing model of looking, reaching, and grasping behavior based on dynamic field theory (DFT). We draw on earlier work that focused separately on looking [9], [10], reaching [8], [11], and the sequential organization of movement [12]. We demonstrate that the model may exhibit the three phases reported by von Hofsten when connection weights of the neural dynamics of sequential movement organization and the visual processing pathway are changed. The resulting neuro-dynamic architecture is simulated, but also implemented on a NAO robot, using both its sensors (front camera) and actuators (arm and hand). We mimic the experimental paradigm of von Hofsten by presenting a colored block to the robot, which may be stationary or move laterally. We record covert attention of the robot within a neural representation of visual attention (since the robot's eyes are fixed inside the head). We register the trajectories of the hand and grasp posture state. We classify the resulting recordings using von Hofsten's categories and evaluate the statistics for the three phases based on exhaustive simulations in the different settings.

II. METHODS

Dynamic field theory is a theoretical framework that uses neural dynamics to model cognitive processes and link these to the sensory and motor surfaces. DFT has been applied in a variety of research areas, from infant development [3], [4], [9] to cognitive robotics [10], [12].

The model architecture we propose makes use of the two core building blocks of DFT — dynamic neural fields (DNFs) and dynamic neural nodes. Fields are populations of

neurons that represent metrical feature spaces (e.g., color or location). Approximated as spatially continuous fields of activation defined along dimensions that span the metric spaces, DNFs represent specific values of the metric features through localized *peaks* of activation that reach above an activation threshold. Neural activation evolves in time according to a neural dynamics,

$$\tau \dot{u}(\mathbf{x}, t) = -u(\mathbf{x}, t) + h + [w_{u,u} * \sigma(u)](\mathbf{x}, t) + \sum_i s_i(\mathbf{x}, t) + \xi(t). \quad (1)$$

Here, $u(\mathbf{x}, t)$ denotes the field's activation defined over feature space, \mathbf{x} , and time, t . Its change on a timescale defined by τ is governed by the resting level, $h < 0$, and the sum of external inputs, s_i , that may originate from sensory surfaces or from other fields. Neural interaction within the field is given by the interaction kernel, $w_{u,u}$, that is convolved with the activation field passed through a sigmoidal threshold function, $\sigma(u)$. Additive noise, ξ , influences the activation pattern in the absence of localized input. The dynamics of a single field may undergo instabilities, which change the attractor landscape. *Detection* decisions describe the change from a sub-threshold state to a localized supra-threshold activation peak. *Selection* decisions pick a single region out of multiple candidates with a stabilized peak, while actively suppressing competing candidates. In the absence of candidates or for low input levels, selection decisions may be shaped by the noise term. Other basic behaviors comprise self-sustained peaks of activation that model *working memory* and *tracking* of input in which a peak moves in response to localized input that moves along the feature dimension.

Rather than spanning continuous feature spaces, dynamic neural nodes represent individual categorical states, but share the same underlying neural dynamics:

$$\tau \dot{u}(t) = -u(t) + h + c_{u,u} \sigma(u(t)) + \sum_i s_i(t) + \xi(t). \quad (2)$$

Neural interactions contract to self-excitation of strength $c_{u,u}$. Inhibitory interactions among different neural nodes arise when other nodes provide inhibitory input. For more details, see [13] (dynamics), [14] (instabilities), and [10] (connectivity).

Particular combinations of fields and nodes with excitatory and inhibitory couplings form units of the sequential organization of behavior. Each such *elementary behavior* (EB) is activated by an *intention* node that drives the execution of a particular motor behavior by being above threshold (e.g., moving the hand to a target). The successful completion of a behavior is monitored by a *condition of satisfaction* node (CoS), which is pre-activated by the intention node and pushed above threshold when matching sensory information is detected. The CoS node inhibits the intention node, so that the EB is deactivated. Sequentiality emerges from coupling through *precondition* nodes that inhibit the intention node of a subsequent EB as long as the CoS node of the previous

EB is not activated. *Suppression* nodes implement mutual exclusiveness between competing EBs by inhibiting the intention node of one EB if the competitor's intention node is active and vice versa. Figure 1 illustrates the inner structure of EBs and possible couplings among EBs (see [12] for more details).

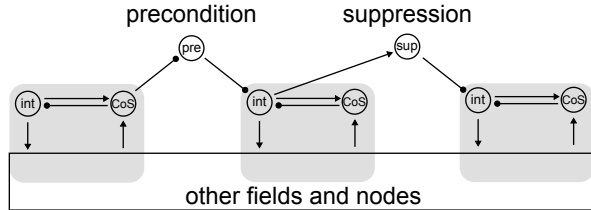


Fig. 1. Each elementary behavior (gray underlay) consists of an intention node, a CoS node, and additional fields and nodes that execute the behavior and detect its completion. Connections between nodes are either excitatory (ending in arrow) or inhibitory (ending in circle). Preconditions are expressed through nodes that inhibit a subsequent intention node as long as the CoS node of a precondition is not active. Suppressions are implemented by an intention node that activates an inhibitory inter-node, which in turn inhibits the intention node of competing behaviors.

A. DFT and Development

DFT has been used to model development in various areas including spatial working memory [4], [15], habituation [9], [16], and the learning of saccadic eye movements [17]. A central concept is the *spatial precision hypothesis* according to which neural interactions within dynamic neural fields are strengthened and sharpened over development [2]. This leads to increased stability of representations, shielding them against fluctuations in the input, while at the same time building the foundation for working memory through self-sustained activation.

In a model of infant looking behavior [9], Perone and Spencer use a single node neural oscillator based on earlier work by Robertson and colleagues [18]. The oscillatory pattern emerges from lowering the resting level of the node once it goes above threshold, which in turn deactivates the node as soon as the resting level is sufficiently lowered. With the node in its off state, the resting level rises again to its initial value, which concludes one oscillatory cycle. Note that the same behavior can be generated by a two node oscillator based on Amari's work [13] (see Figure 2).

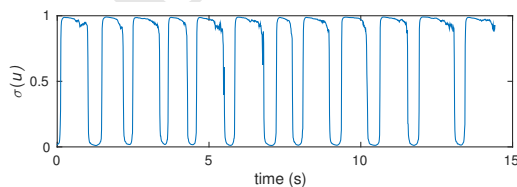


Fig. 2. An exemplary babbling oscillator with an excitatory node u and an inhibitory node v produces oscillatory patterns over time (see [13]). The sigmoided activation of the excitatory node drives the activation of elementary behaviors. During development, excitatory and inhibitory influences on u change the pattern of oscillation, with prolonged periods spent in the on and off states.

Perone and Spencer hypothesized that the characteristic oscillatory dynamics of the single node fixation system may be a general mechanism of exploratory activation of motor behaviors, implementing a form of motor babbling. Here, we combine such neural oscillatory dynamics with the node structure of behavioral organization. The intention node is the excitatory node of the oscillator, with an inhibitory node added to ensure that the intention node is in its inactive state if no further external inputs enter this network. Oscillations are induced by weak excitatory inputs into the intention node, which activate the behavior for a certain amount of time, before inhibition from the second node pushes the intention node back below threshold. During development, the oscillatory pattern is influenced by emerging precondition and suppression couplings, as well as through a rise in self-excitation according to the spatial precision hypothesis and stronger input of top-down intentionality (see Figure 3). All influences affect the statistics of oscillations that arise, with all intention nodes exhibiting a general tendency towards longer periods of being above or below threshold.

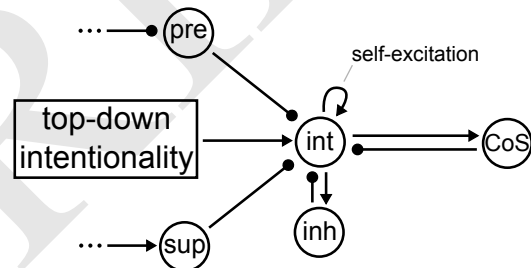


Fig. 3. This figure shows the coupling structure of a single intention node. Initially, the state of the intention node oscillates between the off and on state, driven by weak top-down input and the coupling to the inhibitory node. During development, additional external inputs from preconditions and suppressions, as well as an increase in both top-down intentionality and self-excitation modify the activation pattern of the intention node.

III. MODEL

The model consists of five elementary behaviors (see Figure 4), all of which are implemented using dynamic neural fields and dynamic neural nodes. All EBs start off with their intention nodes driven by oscillatory patterns, which activate the behaviors spontaneously. We call this “babbling”, as movement generation is not coordinated in time, neither with preconditions (e.g., visual selection of a movement target before movement initiation) nor with competing behaviors (e.g., trying to open and close the hand at the same time). During development, preconditions and suppressions between certain EBs are strengthened, based on the experiences gained from randomly activating EBs. We assume that the neural structure that enables establishing these relations is preformed so that every EB has the potential to become a precondition or suppressor of every other EB. More complex behaviors such as reaching for an object emerge from EBs, preconditions, and suppressions. With stronger coupling structure and stabilization of intentional

nodes, the influence of the initial oscillatory patterns involved in babbling decreases.

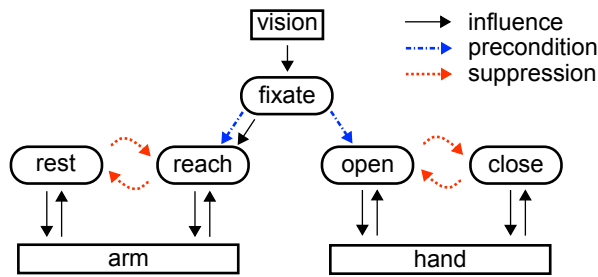


Fig. 4. Overview of elementary behaviors. Potential preconditions and suppressions are highlighted in blue and red, respectively. The internal structure of each behavior follows Figures 1 and 3.

A. Fixation

In the model, the visual pathway consists of a saliency operator applied to the camera image and a DNF defined over retinal coordinates, which selects the most salient region while actively suppressing distractors, thus generating covert attention (see also [10]). This is the attentional front-end of a more elaborate model of infant looking [9], which also accounts for familiarization and habituation effects through a perceptual layer not included here. Development is modeled by strengthening intra-field interactions according to the spatial precision hypothesis, leading to more stable representations and increased capacity to track objects for the “older” model. The activated retinal region projects to a motor field for arm movements (and eye movements in an extended version not described here). This projection requires coordinate transforms from retinal coordinates to motor reference frames, which also evolve over development (see [17] for a DFT model of learning such transforms). Here, we simplify the account by neglecting gaze shifts and modeling the transformation from the retinal to the arm reference frame as a given map with stochastic errors, which decrease over development. The transformation combines an angular estimate of the position of an obstacle obtained from the horizontal retinal location of the object’s projection onto the camera image with a fixed distance of the obstacle from the body whose estimation is not modeled. One-dimensional angle and distance are combined in a two-dimensional DNF over Cartesian movement space, defined as a plane in front of the robot, with peaks arising at intersections of these two ridge-like inputs. These are candidates for reaching targets.

B. Reaching and Resting

Movement generation depends on two inputs that use the same neural substrate to move the hand to a desired target (see Figure 5). One input sets the attentional foreground of the visual pathway as the target of the movement, the other defines a resting (or default) position for the arm. Target positions for the hand are defined in Cartesian coordinates along the two-dimensional movement space.

Both inputs project to a DFT model of arm movement generation [8]. In that model, the representation of the target

position is convolved with an internal representation of initial hand position to form a hand-centered motor plan. A two-layer neural oscillator transforms this motor plan into a velocity profile, which shifts an internal representation of the currently desired hand position generating a virtual hand trajectory. A virtual hand velocity vector is computed by weighting each activated location in the two-dimensional neural oscillator field and integrating across these weighted locations. The resulting velocity vector typically exhibits a Gaussian-shaped trajectory of acceleration and deceleration over one oscillatory cycle. The virtual hand velocity is transformed into a velocity in joint space through an approximate inverse kinematic map. That joint velocity vector is path-integrated to generate a virtual joint configuration vector, $\lambda(t)$, that drives a muscle model whose outputs generate movement of the robot’s arm. The muscle model is a second order linear oscillator whose resting position is set by the descending virtual joint angle. The virtual joint trajectory is further transformed through a forward kinematic model to predict the current hand position which is represented in a dynamic neural field. This is a form of corollary discharge. At the end of each oscillation, the then current virtual hand position updates the initial hand position. Behavioral organization in the form of dynamic neural nodes takes care of the switching between the phases of movement and postural control. As shown in [8], movement generation successfully reaches targets iteratively even if the model is put into an ‘infant’ stage, in which parts (connection weights, lateral interactions, transformations onto muscle/joint space) are decalibrated. In this impaired state, the model exhibits multiple distinct movement units and less straight trajectories, as is found in infant reaching [19].

Since there is no coordination between the different components of movement in the early phase of reaching development, reaching is likely to be activated even while input to the target representation is insufficient to bias target selection toward the true location of the object. Through intra-field interaction, noise, and a sufficiently strong boost input originating in the intention node of the reaching behavior, the field representing the reaching target may form a peak at a random position. With the emergence of behavioral organization and improvements along the visual pathway (e.g., less error in the transformation between retinal and hand coordinates) the reaching target selected in the target field becomes an increasingly accurate representation of the fixated object.

C. Opening and Closing the Hand

The generation of hand movements uses a network of fields and nodes similar to the model of arm movement generation. The behaviors *open* and *close* set targets for an open and a closed hand state at fixed positions along a one-dimensional representation of hand states. We leave out the internal representation of initial hand configuration to simplify movement generation.

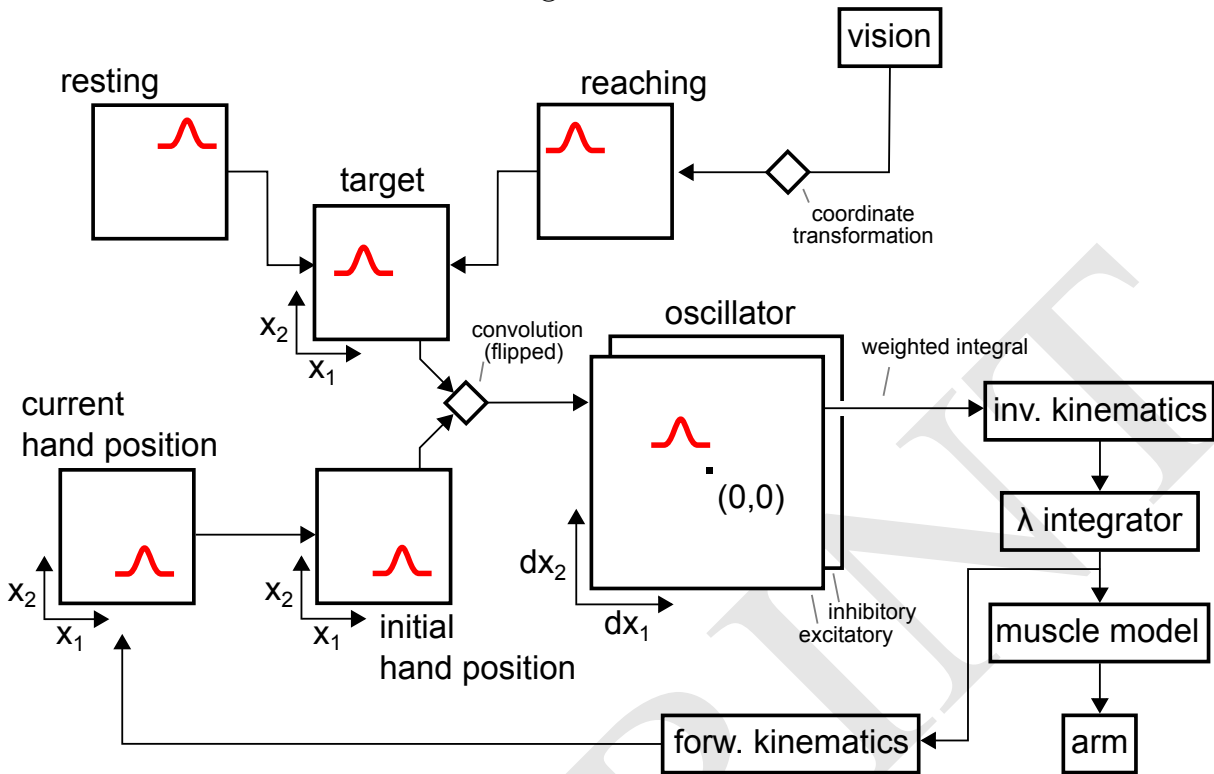


Fig. 5. This figure shows a schematic overview of how the two elementary behaviors ‘reach’ and ‘rest’ couple into movement generation. Squares with red activation peaks denote fields. Diamonds along connections are indicators of reference frame transformations. Nodes and connections realizing behavioral organization, both within each EB and between them, are not shown in this figure. For more details, please refer to [8]. Note that a similar network of fields translates the targets of the elementary behaviors ‘open’ and ‘close’ into movements of the hand.

D. Three Developmental Phases of Reaching

With the five behaviors described above and emerging preconditions and suppressions between them, we define a developmental process that exhibits similar properties to the three phases found by von Hofsten. The starting point is an uncoordinated, spontaneous activation of all five behaviors. Arm movements are not coordinated with the selection of a visually perceived target, which leads to a low frequency of reaches towards the target object and reaches happening while the object is not fixated at all (covering the *intermediate gaze*, *non-fixated*, and *eyes closed* reaches). Since the hand’s state is not coordinated with arm movements either, there is no significant association between hand state and reaches towards the object. This babbling phase is replaced by emerging intentional reaching, which requires the coordination of a subset of behaviors in time (i.e., ‘first bring a target into the attentional foreground, then move the hand towards it and open the hand’) and the stabilization of behavior activation for prolonged time intervals (e.g., “keep an object in the attentional foreground until a reaching movement is executed”). Preconditions are established between the fixation behavior and the movement generation (see Figure 4, blue arrows). A parallel developmental change strengthens the suppression relations between the behaviors using the same actuators (see Figure 4, red arrows). A third developmental change increases lateral

interactions in the fixation behavior, which improves the stability of selection decisions and also allows tracking of moving objects. These three factors produce the second and third phases of von Hofsten’s study. First, the introduction of preconditions makes spontaneous activations of reaches and the opening of the hand less likely, resulting in fewer reaches, mostly executed with a closed or closing hand. Along with increased stability of visual fixation, object-oriented reaches become more and more likely, with the hand opening during arm movement. The third phase is the foundation for further refinements of all involved processes, leading up to more complex behaviors such as grasping, which adds the closing of the hand on arrival at the object and potential transport movements (see [11] for an exemplary DFT architecture) and the improvement of arm trajectories in general (see [8]). Both trends are supported by the exponential increase in reaching movements made possible by behavioral organization.

IV. EXPERIMENTS

The target platform of our model is the NAO robot. We use simulations of the kinematics of the right arm and hand, as well as simulated visual input in our experiments. Motor output is sent to kinematic simulations of both the five degrees-of-freedom (DoF) arm and the one DoF hand. We record the Cartesian position of the hand in the movement plane, its hand state as floating point interval $[0.0, 1.0]$ from closed to open, and the states of intention nodes over

simulated trials. Due to kinematic constraints of the NAO arm, we chose the experimental setup shown in Figure 6. The resting position of the hand is in the top right corner of a plane covered by the movement generation of our model. The object is moved in front of the head, with object-oriented reaches moving left and down from the resting position.

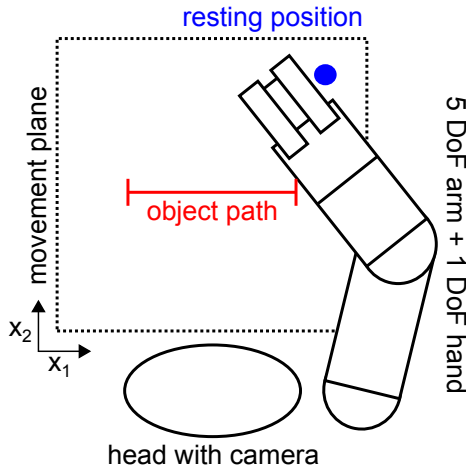


Fig. 6. This sketch depicts the experimental setup, showing the area of reaching, the object path, and the resting position of the NAO arm.

We run simulations of each phase for five million iterations of 1 ms length, accumulating an overall simulated time of 83 minutes and 20 seconds per phase. We then identify forward extensions directed towards the object by extracting single movements that cover at least a minimal distance of 20 mm and are directed away from the resting position. A movement is considered fixated if the CoS node of *fixate* is above threshold at the beginning of the arm movement and non-fixated in any other case. For each matching reaching trajectory, we determine the hand states during movement and the target fixation state. Each trajectory is classified into categories defined by von Hofsten’s study (‘fixated’, ‘non-fixated’ and ‘closed/fisted’, ‘open before’, ‘opening during’)

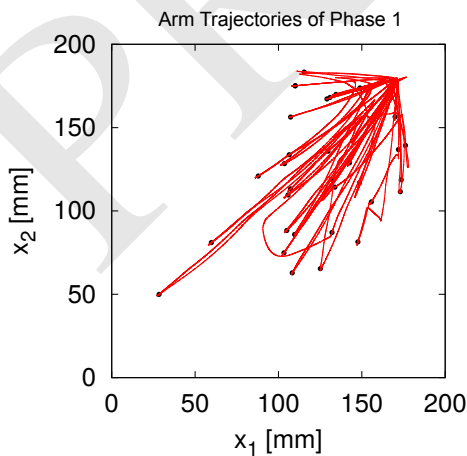


Fig. 7. This plot shows a selection of object-oriented trajectories of the simulations of phase 1. Black dots denote end points of movements.

A. Phase 1: Babbling

For simulations of the babbling phase, all precondition and suppression weights are set to zero. The intention of all five elementary behaviors receive weak excitatory input to push them slightly above threshold, which drives the inhibitory nodes connected to them, bringing them back below threshold. The input level for *open* is slightly higher than for *close* to reflect the bias for hand openings found in von Hofsten’s data. Self-excitation of nodes and fields is weak. The behavior *reach* is mostly driven by noise, as input from visual fixation is not coordinated and, if present, weak. Elementary behaviors that project their targets to the same movement generation system may become active at the same time, resulting in corrupted targets, as movement generation synthesizes a combination of both target influences.

B. Phase 2: Emergence of Behavioral Organization

The second phase is simulated with developing preconditions from *fixate* to *reach* and *open*. We change the weights projecting the activation of precondition nodes between the CoS node of *fixate* and the intention nodes of *reach* and *open*. These nodes now inhibit the intention nodes of *reach* and *open* and push both behaviors in a regime, where oscillations are still possible, but occur less frequently. The behaviors *rest* and *close* do not depend on any preconditions. Suppressions between mutually exclusive behaviors (*reach* and *rest*; *open* and *close*) are established as well. A sharpening of lateral interactions along the visual pathway increases fixation time.

C. Phase 3: Re-emergence of Reaching Movements

The third phase is characterized by the monotonous increase of fixation through the continuous sharpening of lateral interactions in associated fields and intention nodes. In addition, inhibition through the precondition from *fixate* to *reach* and *open* is further increased, decreasing the likelihood of spontaneous activation of *reach* and *open* in the absence of fixation. The top-down intention input is increased to turn on the *reach* and *open* behavior once the precondition is fulfilled. The increased inhibition and excitation through precondition and intentional task input, as well as stronger lateral interactions stabilize the behavior against fluctuations. The behaviors *rest* and *close* remain unchanged.

An additional increase in fixation alone does not yield an increase in forward extensions, because the arm remains extended until the target becomes non-fixated and the *rest* behavior is activated. We define a later state of phase 3, which we call phase 3+. We endow this later phase with additional behavioral organization, in our case a CoS node that states whether the fixated target is reached and a similar CoS node for successful opening of the hand. These nodes inhibit *fixate*, removing the mutual inhibition on *rest* and *close*, thus making a contraction to the resting position and closing of the hand after a forward extension more likely.

D. Results

For the simulations of the three phases of development, we find the following statistics of reaching movements (see

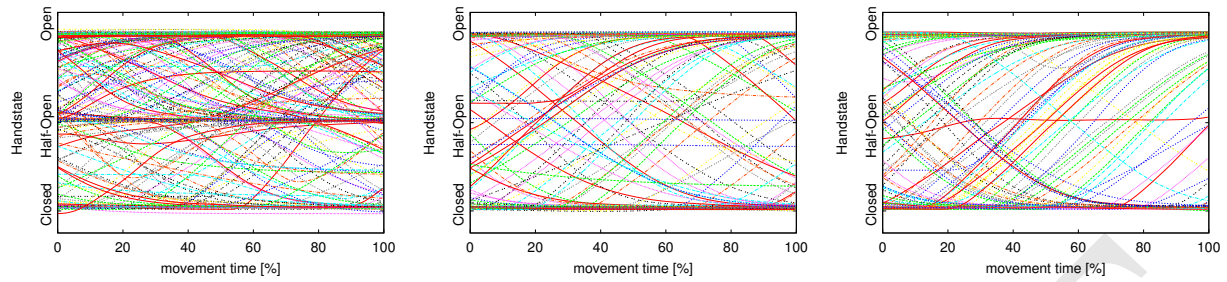


Fig. 8. This figure shows hand state trajectories for all forward extensions observed in the three phases of development. On the left, the babbling phase exhibits every conceivable combination of state changes during reaching. In the middle, the emergence of behavioral organization in the second phase affects the occurrence of overall reaching behaviors. Spontaneous reaches are often executed with clenched fist. On the right, reaches profit from the evolving visual fixation behavior of phase three. The hand frequently opens during reaches or stays open.

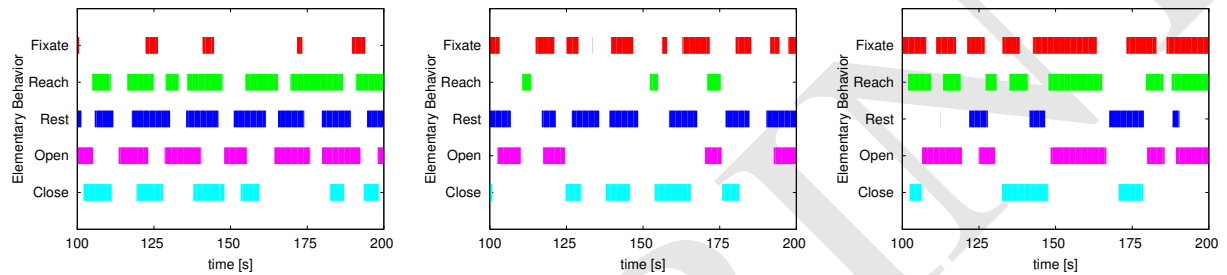


Fig. 9. This figure shows an extract of the activation patterns of all EBs' intention nodes for all three phases, with color marking the 'on' state of the nodes. From left to right, the transition can be observed from the uncoordinated babbling phase, on to the intermediate suppression of reaches, ending in fully coordinated, frequent reaches following fixation.

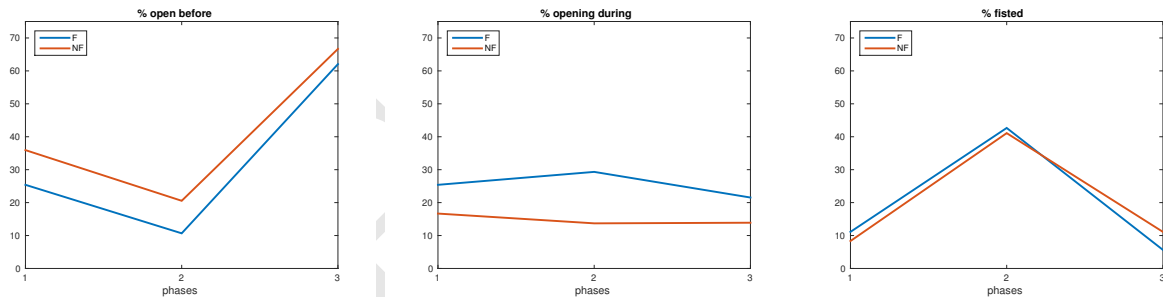


Fig. 10. From left to right, fixated (F) and non-fixated (NF) movements of our model are plotted separately for the three categories of von Hofsten's study and the three developmental phases.

TABLE I

AMOUNT OF FORWARD EXTENSIONS, DIVIDED INTO HAND STATE CATEGORIES

Phases	Total	Percent Fixated	Opened Before	Opening During	Closed	Other
1	255	24.71%	33.33%	18.82%	9.02%	38.82%
2	148	50.68%	15.54%	21.62%	41.89%	20.95%
3	231	84.42%	62.77%	20.35%	6.49%	10.39%
3+	264	93.62%	23.76%	29.08%	15.25%	31.91%

Table I and Figure 7 for examples). We see a drop in overall forward extensions between phases 1 and 2, with an absolute and percental increase in reaching movements executed with a clenched fist. The transition from phase 2 to 3 shows an increase in executed reaching movements. 83.12% of

movements are executed with the hand already opened or opening during movement. Movements with clenched fist go down to 6.49%. Continued improvements in connection weights (called phase 3+ in Table I) exhibit further growth in fixated reaches. Figure 8 plots the evolution of the hand state over normalized movement time for all three phases, showing the decrease in overall movements of phase 2 and the increase of reaches with opened or opening hand in phase 3. The development of coordination between elementary behaviors is exemplified in Figure 9, showing a snapshot of activation patterns of all intention nodes for the three phases. The random babbling of phase 1 is replaced by sequences of activations in phase 2 and 3, with an overall increase in fixation followed by reaching and opening of the hand over development. Figure 10 shows the percentage of fixated and non-fixated movements for the three dominant hand

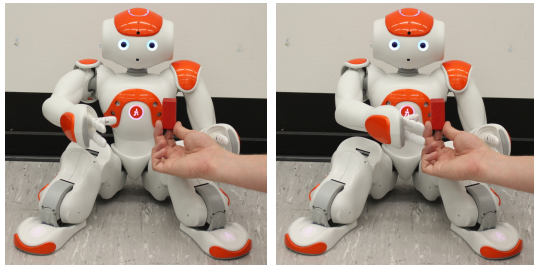


Fig. 11. Two snapshots of our model running on NAO show a typical object-oriented reaching movement. The red object is perceived with the camera mounted in the head. The hand is already open at the beginning of the movement.

configurations. The amount of fixated movements increases in phase 2. Movements with opening hand have a higher percental occurrence for fixated movements than for non-fixated movements in phases 2 and 3. All phases were tested on the NAO robot as proof of concept, without statistical analysis in this paper. Figure 11 shows a snapshot of NAO running phase 3+ of our model.

V. DISCUSSION AND CONCLUSION

We have developed a neuro-dynamic process model of the development of infant pre-reaching that covers the complete pathway from visual input to generating hand movement. By increasing the strength of coordination among elementary behaviors and by strengthening overall neural interaction consistent with the spatial precision hypothesis, we accounted for the developmental progression through the three phases of pre-reaching reported by Claes von Hofsten [1]. Based on the model, we propose that there is only one developmental milestone, the emergence of intentional reaches that are coordinated through the sequential organization of component processes. Phases 2 and 3 are, in the model, different snapshots of the same underlying developmental transient obtained as the model continuously improves the coordination of object selection and movement initiation.

Not contained in our account is a process model of the actual learning process. The reported account provides constraints for a model of autonomous learning, however. Preliminary unpublished work suggests that the autonomous learning of chunks of elementary movement behaviors is possible based on a simple form of memory formation together with a reinforcement signal that rewards sequences of elementary behaviors that bring the hand toward the target.

Why does the model (and, perhaps the infant) start out with a phase of motor babbling? For one, autonomously learning to sequentially organize movement components requires a form of exploration in which various combinations of elementary behaviors are tried out. Moreover, early in development, a number of different mappings between reference frames have to be established that require the continuous activation of movement generation. While we did not address the autonomous learning of the mappings themselves in this paper, doing so is possible within the neural dynamics framework [17].

REFERENCES

- [1] C. von Hofsten, "Developmental changes in the organization of prereaching movements.," *Developmental Psychology*, vol. 20, no. 3, pp. 378–388, 1984.
- [2] A. R. Schutte, J. P. Spencer, and G. Schöner, "Testing the Dynamic Field Theory: Working Memory for Locations Becomes More Spatially Precise Over Development," *Child Development*, vol. 74, no. 5, pp. 1393–1417, 2003.
- [3] E. Thelen, G. Schöner, C. Scheier, and L. B. Smith, "The dynamics of embodiment: A field theory of infant perseverative reaching.," *Brain and Behavioral Sciences*, vol. 24, pp. 1–34, 2001.
- [4] A. R. Schutte and J. P. Spencer, "Tests of the dynamic field theory and the spatial precision hypothesis: capturing a qualitative developmental transition in spatial working memory.," *Journal of experimental psychology: Human perception and performance*, vol. 35, pp. 1698–725, Dec. 2009.
- [5] S. Perone, V. R. Simmering, and J. P. Spencer, "Stronger neural dynamics capture changes in infants' visual working memory capacity over development.," *Developmental science*, vol. 14, pp. 1379–92, Nov. 2011.
- [6] Y. Munakata, J. L. McClelland, M. H. Johnson, and R. S. Siegler, "Rethinking infant knowledge: Toward an adaptive process account of successes and failures in object permanence tasks," *Psychological Review*, vol. 104, pp. 686–719, 1997.
- [7] J. B. Morton and Y. Munakata, "Active versus latent representations: A neural network model of perseveration, dissociation, and decalage.," *Developmental Psychobiology*, vol. 40, pp. 255–265, Apr. 2002.
- [8] S. K. U. Zibner, J. Tekülve, and G. Schöner, "The neural dynamics of goal-directed arm movements: a developmental perspective," in *Development and Learning and Epigenetic Robotics (ICDL-Epirob), 2015 Joint IEEE International Conferences on*, 2015.
- [9] S. Perone and J. P. Spencer, "Autonomy in action: linking the act of looking to memory formation in infancy via dynamic neural fields," *Cognitive science*, vol. 37, no. 1, pp. 1–60, 2013.
- [10] S. K. U. Zibner, C. Faubel, I. Iossifidis, and G. Schöner, "Dynamic neural fields as building blocks of a cortex-inspired architecture for robotic scene representation," *Autonomous Mental Development, IEEE Transactions on*, vol. 3, no. 1, pp. 74–91, 2011.
- [11] G. Knips, S. K. U. Zibner, H. Reimann, I. Popova, and G. Schöner, "Reaching and grasping novel objects: Using neural dynamics to integrate and organize scene and object perception with movement generation," in *Development and Learning and Epigenetic Robotics (ICDL-Epirob), 2014 Joint IEEE International Conferences on*, pp. 311–318, 2014.
- [12] M. Richter, Y. Sandamirskaya, and G. Schöner, "A robotic architecture for action selection and behavioral organization inspired by human cognition," in *IEEE/RSS International Conference on Intelligent Robots and Systems (IROS)*, pp. 2457–2464, 2012.
- [13] S.-i. Amari, "Dynamics of pattern formation in lateral-inhibition type neural fields," *Biological cybernetics*, vol. 27, no. 2, pp. 77–87, 1977.
- [14] G. Schöner, "Dynamical systems approaches to cognition," in *Cambridge Handbook of Computational Cognitive Modeling* (R. Sun, ed.), (Cambridge, UK), pp. 101–126, Cambridge University Press, 2008.
- [15] V. R. Simmering and S. Perone, "Working memory capacity as a dynamic process.," *Frontiers in psychology*, vol. 3, p. 567, Jan. 2012.
- [16] G. Schöner and E. Thelen, "Using Dynamic Field Theory to Rethink Infant Habituation," *Psychological Review*, vol. 113, no. 2, pp. 273–299, 2006.
- [17] Y. Sandamirskaya and T. Storck, "Learning to Look and Looking to Remember: A Neural-Dynamic Embodied Model for Generation of Saccadic Gaze Shifts and Memory Formation," in *Artificial Neural Networks SE - 9* (P. Koprinkova-Hristova, V. Mladenov, and N. K. Kasabov, eds.), vol. 4 of *Springer Series in Bio-Neuroinformatics*, pp. 175–200, Springer International Publishing, 2015.
- [18] S. S. Robertson, J. Guckenheimer, A. M. Masnick, and L. F. Bacher, "The dynamics of infant visual foraging," *Developmental science*, vol. 7, no. 2, pp. 194–200, 2004.
- [19] E. Thelen, D. Corbetta, and J. P. Spencer, "Development of reaching during the first year: role of movement speed.," *Journal of Experimental Psychology: Human Perception and Performance*, vol. 22, no. 5, pp. 1059–1076, 1996.