A developmental approach to sensori-motor coordination in artificial systems.

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ABSTRACT

The aim of the present paper is to propose that the adoption of a framework of biological development is suitable for the construction of artificial systems. We will argue that a developmental approach does provide unique insights on how to build highly complex and adaptable artificial systems. In turn, it might also aid neuroscientists in a better understanding of the human brain functions involved in sensori-motor control. To illustrate our point, we will use as an example the acquisition of goal-directed reaching in human infants, and demonstrate the underlying mechanisms of biological development. In a second part, we will outline a) how mechanisms of biological development can be adapted to the artificial world, and b) how this artificial development differs from traditional engineering approaches to robotics. The experimental part is based on a set-up composed of a monocular robot head with two degrees of freedom and a two degrees of freedom arm. The motor control of both the head and the arm is based on the so-called *force field approach* described in the biological literature as a mechanism implemented at the level of the spinal cord to control ballistic motion of the arm. The visual part is, at this stage, limited to a simple target tracking procedure based on color information. The goal of the system is to reach with the arm the target fixated by the eye. Initially the *new-born* system is capable of performing a limited number of motor actions coded as rough visuo-motor maps and initiated by the appearance of the target in the field of view. During the developmental phase the system, through repetitive reaching of different points in the arm workspace, refines the visuo-motor maps without explicit knowledge of the system's kinematic parameters.

INTRODUCTION

The study of sensori-motor coordination in artificial systems has focused mainly on analyzing and implementing skill levels comparable to those of adult humans. For example, the control of robot heads and visually guided manipulation tasks were studied with reference to psychophysical performance data of adult humans and animals [8], [3], [2], [7], [9], [11].

In spite of the recent advances in this area, the systems implemented are still far from achieving human-like performance levels and task flexibility. More importantly, even for successful implementations the integration of such skills as manipulation and gaze control proved to be more difficult than expected. In our view, this difficulty arises from the traditionally implemented approach of constructing a complex system: to make the problem more tractable, sensori-motor coordination is broken down into a set of sub-problems often defined by a specific sensory modality or specific motor skills.

A different solution is used in humans and many other vertebrates, where flexible and efficient levels of performance are achieved through the simultaneous development of sensory, motor and cognitive abilities. This process is not simply caused by the maturation of single components or by learning a progressively more sophisticated set of skills. Instead it is marked, particularly in the very early stages, by a sequence of changes of the neural circuitry, by a strategic exploitation of the environment with a limited set of motor skills that are present at each developmental stage, and finally, by the ability of biological systems to calibrate themselves in the presence of ongoing environmental and anthropometric changes.

THE EMERGENCE OF REACHING BEHAVIOR IN HUMAN INFANTS

At birth, a human infant can neither reach nor grasp. From a control point of view, the completion of two processes are required to perform successful reaching. First, any neural controller must be capable to interact with its "plant" (i.e., the arm in this example) in such a way that centrally planned, complex actions can be executed. Second, visually specified goals must be linked to appropriate motor acts. These motor acts, in turn, must be suitable to move the arm to the desired goal. There are a number of reasons that seem to explain why newborn infants are not equipped to solve these two tasks:

- they have limited postural control of the trunk, head and arms [16];
- they have limited knowledge about the physical makeup of their bodies (i.e. moments of inertia, viscosity, stiffness of their arm segments);
- they have only a limited movement repertoire consisting of an array of infant reflexes, and basal intra- and interlimb synergies [4];
- they have limited visual capabilities [1];
- they have not established a finite neural control struc-

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ture. Most cortico-spinal projections are not differentiated (for a review, see [18]).

Despite all these limitations, babies as early as one week of age will attempt small arm movements directed towards objects, and are capable of orienting towards and tracking a moving object with coordinated rotations of head and eyes[19]. A few days after birth infants are also able to perform anticipatory arm movements when trying to intercept a moving target [20]. While the arm movements of newborns are characterized by a rather fluid interjoint pattern, reach and grasp motions of two- and three-month old infants reveal either short swiping motions or relatively long lasting jerky movements. These movements appear to be pre-programmed, "ballistic" motions, because trajectory correction is absent [5].

The first successful goal-directed reaches of human infants appear around the age of 4 to 5 months after birth ([21],[13]). Within the first 4 to 8 weeks after the onset of goal-directed reaching kinematic improvements are dramatic (figure 1). At the onset of reaching, their hand trajectories consist of about 5 segments. Two months later, the number of movement units of the hand is halved. By the age of 7 months, a typical reach consists of one large transport segment and one or two additional units in the approach phase. In order to achieve this goal, they have to embed basal muscular synergies that are present at birth, into functional, task-adequate multi-joint movements. That is, during early reaching emphasis is put on refining the transport, not the approach phase, nor on skillful handling of the grasped object.

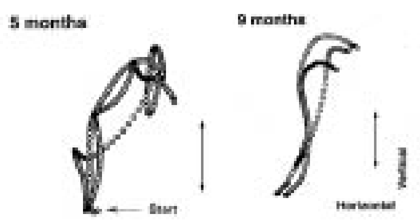

Fig. 1. Exemplar saggital hand paths of one infant at two different developmental times illustrating the progression toward the "smoothing" of endpoint motion. Time interval between successive data points is 10ms (from: [14]).

About 3 months after the onset of reaching, infants reach consistently for objects in their surround and rarely miss their target. However, an adult-like skill economy will not develop before 24-36 months of age ([14]).

WHAT DOES AN INFANT HAVE TO LEARN IN ORDER TO ACQUIRE LIMB CONTROL?

A second step is necessary in order to understand how physiological mechanisms of development are helpful for building complex artificial systems. This step is to outline the control problems that have to be solved by human infants when trying to reach for objects in their immediate workspace.
The first question to ask in the context of motor control is: what physiological or movement parameters does the system actually have to control to achieve its goal of reaching for a target in extrapersonal space? To answer this question, consider that each limb segment of the human arm is moved by a set of actuators with spring-like properties. To move such "plant" appropriately, any controller needs to have at least reasonable approximations of the parameters involved (inertia, viscosity, stiffness as well as links length and centers of mass). That is, a first step for a control system must be the identification of the plant's parameters. A second step before goal-directed reaches are possible is the mapping of sensory maps onto available motor maps. In a traditional learning paradigm, these two processes of calibration have to be completed before the system can begin to work on control. From an engineering perspective this implies that calibration and control are separated. Consequently, many neural network models of arm control follow a learning paradigm where the first step is the calibration of the system. Subsequently it learns to "control" the arm [15]. Such a separation of calibration and control is not observed in the development of biological systems. Here calibration and control are not two distinct and sequential phases of development, but are rather intertwined, proceeding in parallel, and build upon each other.
Today this view of a parallel development of calibration and control processes seems widely accepted by researchers working on neural modeling of adaptive eye-hand coordination. Yet, most researchers model this process as a learning and not as a developmental operation [15]. Implicit to such an approach of artificial sensorimotor coordination is the premise that all behaviors of the system have to be learned. However, this assumption is not necessarily true for biological systems. One major difference between biological and artificial systems is that a biological system does not come as a "blank slate". In a wide variety of different species one can observe stereotyped inborn movement sequences that are clearly unlearned [10]. Newborn human infants already possess a repertoire of coordinated movements. For example, they can perform a series of complex multi-joint bilateral movements (i.e. kicking) and have available a set of so-called primitive reflexes. These motor primitives may also serve a second function. They help to build up a relationship between vision and proprioception. For example, dur-

ing pre-reaching the presence of the Asymmetric Tonic Neck Reflex (ATNR) plays a crucial role in allowing babies to see their hand and in increasing visual fixation of the hands [6] providing an effective mean for linking visual and proprioceptive maps.

RELEVANT ISSUES FOR ARTIFICIAL DEVELOPMENT

Based upon the description of human development of goal-directed reaching the aspects that we see as most relevant for artificial systems are presented in this section.

The first, and perhaps the major, observation relates to the fact that the newborn is, in a systemic way, a complete system in the sense that major sensory and motor components are present and functional. Motor reflexes and sensory-triggered motions are present at birth, exploiting the still limited sensory and motor abilities. This allows the infant to start some form of interaction with the external environment and the acquisition of first sensori-motor experiences. The control structure changes with age starting from an almost purely reflexive system at birth, passing through phases where basal muscular synergies are formed, towards a state where stable kinematic patterns are expressed.

Another issue worth stressing is the role of the infant's own body in development. In biological systems, development is very much dependent on the ability of the system to interact with the external world. Many early sensori-motor experiences are stimulated by the newborn's own body motions which becomes an essential tool to establish a coupling between perception and action. Self-generated motor commands elicit sensory feedback that not only give the newborn a motivation to repeat or to avoid a specific action, but also serve to adjust and refine the voluntary motor commands.

The final remark we would like to make is related to the role of reflexes in the development of sensori-motor coordination. One potential role of the early motor repertoires is to give the newborn a way of starting to interact with the world, even if the fine control of the muscles is still not present. More strongly, such interactions with the environment are the necessary condition to calibrate the physics of the system (the "plant"), and to establish functional motor synergies that can be used in voluntary goal-directed behavior.

DEVELOPMENTAL ENGINEERING

If we consider an artificial system engaged in a reaching task, the number of motor degrees of freedom (d.o.f.) that have to be controlled in parallel can be as high as 10 or more. A fairly standard approach to this kind of problem is to characterize the plant as much as possible. After the identification procedure a general purpose or a customized control law is applied [22]. In this case the problem is simplified by an accurate design but it might require a substantial effort during the design phase in order to be applied.

An alternative solution, which we believe is more suited to a developmental approach, is based on direct motor primitives representing multi-joint synergies. In this case a single command may produce complex multi-joint coordinated movements without the voluntary control of each individual d.o.f. In order for this approach to be feasible and effective, the crucial points are:

- how to represent the motor primitives;
- the mechanism of sensori-motor mapping;
- its developmental rules.

Motor primitives

As far as the coding of motor primitives is concerned, one possible procedure is the so-called force fields approach originally proposed by Mussa-Ivaldi and Bizzi [17]. According to this theory the neuro-muscular control of a limb can be mathematically described considering that each joint is controlled by a set of actuators with spring-like properties. Each actuator is fully modeled by a torque field, such as:

$$\boldsymbol{\tau}(\mathbf{q}, a) \tag{1}$$

where $\mathbf{q}$ is the vector of generalized coordinate, a is the activation value and $\boldsymbol{\tau}$ is the generalized torque field. Actuators, as used in our experiments, are described by the following equation:

$$\tau = -a\kappa(q - q_0) \tag{2}$$

where a is the activation value (which modulates the overall stiffness κ) and q_0 the resting configuration. From the mechanical point of view a multi-joints structure controlled by a set of spring-like actuators (as in equation 2) is a passive system. As a consequence it has a stable Equilibrium Point (EP) in its state space. The EP can be thought of as the point toward which the system is moving at each instant of time and a limb trajectory can be represented by a sequence of EPs.

Concerning the motor primitives, each of them can be represented by a structure which activates a single or a group of actuators. Thus, each primitive can be described by the following torque field:

$$\mathbf{T}_j = C_j \sum_i I_{ji} \boldsymbol{\tau}_i \tag{3}$$

where $\boldsymbol{\tau}_i$ is the i^{th} actuator field, C_j the activation value and:

$$I_{ij} = \begin{cases} 1 & \text{if the } j^{th} \text{ controller activates the } i^{th} \\ & \text{actuator} \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

The feasibility of this schema comes from the fact that any position of the arm can be obtained by combining linearly a small number of primitives represented through torque fields (which are called *basis fields*). The task of the controller is thus that of generating the activation values C_j. Specification of C_j determines consequently a new EP for the system. Following this model the total torque applied to the system is: $\mathbf{T} = \sum_j C_j \mathbf{T}_j$. It is worth noting that if the torques corresponding to the previous equation were applied to the arm it would eventually move to the respective EP (at equilibrium).

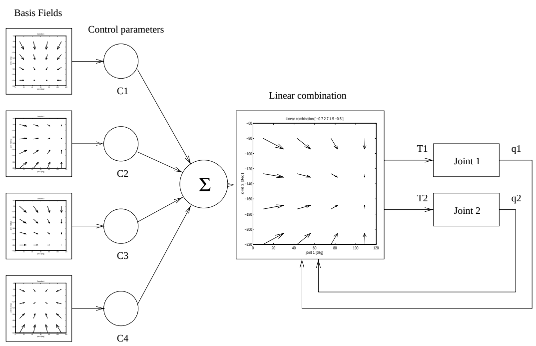

Fig. 2. Controller structure: motor primitives, represented by torque fields are combined (weighted by C_1, C_2, C_3 and C_4). The overall field "guides" the arm end-point toward its EP.

A schematic diagram of the controller is shown in figure 2 in the case of four basis fields and two joints.

Motor-motor map

The situation, however, becomes more complicated when goal directed movements (such as reaching a point in space) are considered. In this case the trajectory of the arm has to be controlled (or initiated) on the basis of visual information. The solution we propose is based on the use of a direct mapping between the eye-head motor plant and the arm motor plant. One premise we make is that the position of the fixation point coincides (at least at some stage of the control process) with the object to be reached. In other words, the reaching of an object starts by looking at it. Under this assumption, the fixation point can be seen as the "end effector" of the eye-head system and its position in space with respect to the shoulder is uniquely determined by the motor commands controlling the position of the head with respect to the torso and that of the eyes with respect to the head. Assuming the eye-head plant is controlled using force fields, the position in space of the fixation point can be coded using motor commands and, at least in principle, the arm's force-fields can be obtained by a transformation of the eye-head's force fields. We call this approach *motor-motor coordination*, because the coordinated action is obtained by mapping motor commands onto motor commands.

Development of a motor-motor map

The goal, therefore, is to learn the motor-motor mapping while executing visually guided reaching. Formally, the motor-motor map can be seen as a function $\mathbf{C} = f(\mathbf{q})$ which converts values from head position to arm activation. Under these hypothesis, each time step i of the proposed learning algorithm can be described as:

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1. A proper stimulus appears in the field of view;
2. By fixating the visual target the robot also initiates arm motion by computing the arm activation vector $\mathbf{C}$ in the following way:

$$\hat{f}_i(\mathbf{q}) + \mathbf{n} \tag{5}$$

The term $\mathbf{n}$ describes a zero-mean uniform noise component introduced to simulate errors in the arm control. $\hat{f}_i$ is the estimate of f at the i^{th} iteration.
3. The vector $\mathbf{C}$ is used by the arm controller which moves the arm toward the new EP.
4. At this point the arm is as close as possible to the target so that the system can re-direct the gaze to its own hand.
5. As a result of the previous step a new pair $(\mathbf{q}, \mathbf{C})$ is available which is used to update the map by computing the value $\hat{f}_{i+1}(\mathbf{q})$ in the following way:

$$\hat{f}_{i+1}(\mathbf{q}) = \hat{f}_i(\mathbf{q})\frac{n_v - 1}{n_v} + \frac{\mathbf{C}}{n_v} \tag{6}$$

where n_v is the number of visits of the cell corresponding to $\mathbf{q}$.
6. The arm then returns to a fixed resting position.

It is worth mentioning that the map must be initialized in a meaningful way in order to allow the initiation of movements. In our experiment the robot utilizes three initial reflexes (simulating the ATNR) which are manually tuned and stored into the map from the beginning. Figure 3 shows the equilibrium arm positions corresponding to the three reflexes (lower row) and the corresponding torque fields.

By means of these initial reflexes the system can fixate a target and keep the arm in the field of view thus eliminating the need to search for the arm end-point. It is important to note that if the controller were not noisy the system would be bound to whatever is initially stored into the map (i.e. exploration would be absent).

THE EXPERIMENT

Based upon the algorithm and control scheme presented in the previous section we designed an experiment to show how the reaching behavior can be acquired by building the motor-motor map. We used an experimental set-up composed of a two d.o.f. head (controlling the orientation

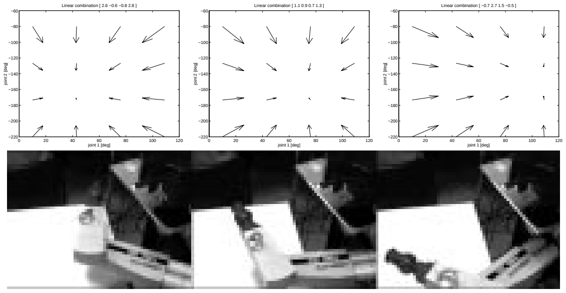

Fig. 3. Equilibrium arm position (lower row) and torque fields corresponding to the three initial reflexes. Abscissa and ordinate (upper row) show arm joint position (joint 1 and 2 respectively). Arrows point to the common equilibrium position of the two joints. The three equilibrium positions have been preset by the experimenter.

of a color camera) and a planar two d.o.f. arm. Visual location of the arm end-point and targets is based on a simple color segmentation algorithm.

In order to test the performance of the system at different learning stages the position in the arm's workspace of three targets was calibrated beforehand. During the training phase the target of the reaching task was manually moved by the experimenter over the arm's workspace while the reaching behavior was continuously activated. From time to time training was suspended and the performance evaluated.

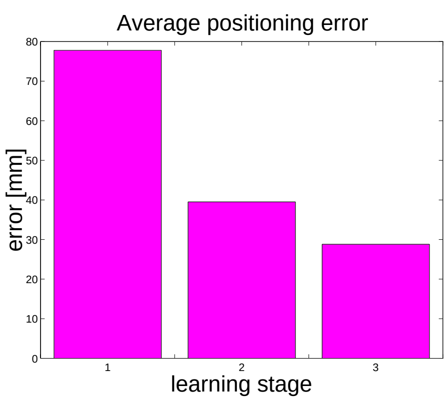

Fig. 4. Endpoint positioning error at three different learning stages. The first bar shows the initial error before learning, the second and the third bars correspond to the map after about 51 and 134 practice trials, respectively. The maximal achievable precision of the arm was 30mm.

During the evaluation phase the three targets in the calibrated positions were activated one at a time and the trajectory of the arm stored. The reaching error was measured by computing the cartesian distance between the pre-calibrated target positions and the position of end-effector at the end of the reaching movement. The error in the initial condition and in two successive stages of the learning phase is shown in Figure 4. The first point in the plot refers to the initial error. The second and third point, plot the error after 51 and 134 reaching movements. A typical arm trajectory, after training, is shown in figure

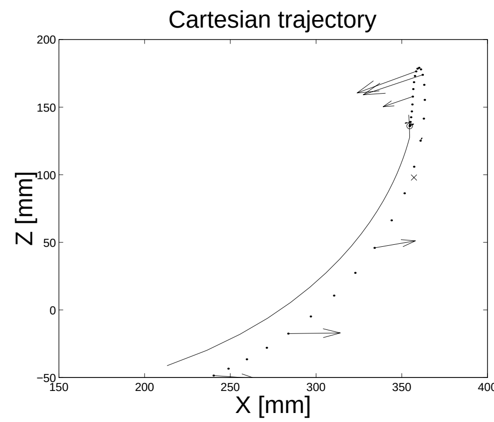

Fig. 5. Typical arm end-point trajectory. The dotted line represents the real arm trajectory and the continuous line plots the EP trajectory. $\circ$ is the final end-point position and $\times$ is the actual position of the target. The vectors plotted every 5 data points are the applied forces.

5. The plot shows the trajectory of the EP (solid line), the actual trajectory (dotted line), "$\times$" represents the position of the target while "$\circ$" the final position of the end-effector. The superimposed vectors are the applied forces. It is clear the presence of an overshooting which is the combined effect of the unknown arm dynamic and reduction gears friction.

CONCLUSION

Engineering a developmental process means being able to define a sequence of events that cause the system to become incrementally more skilled. One way of looking at it is to model a developmental stage as a set of control variables (in our case motor but, in general, also sensory and cognitive) and to model the process of development as a progressive, dynamic selection of the variables under voluntary control. This developmental process can be characterized as adaptive change towards competence [12]. Adaptive change is not the same as learning. In distinguishing between learning and development, we view learning as a function of development rather than development being the overall summation of a series of learnings.

Consider the developmental state of an human infant at birth. That state is characterized by an incomplete visuomotor map, by imprecise knowledge of the plant, by the availability of basal intra- and interlimb synergies and a set of primitive reflexes. This setup allows the infant to *explore* and to *exploit* the environment at the same time even at that early age. For example, 20 day-old infants will try to reach for objects although their reaches will be not very consistent and jerky. As a result infants will often misreach the target. However these reaching errors are beneficial from a control point of view because they drive the system to visit new states. These newly visited states will enhance the visuo-motor map but are also important for the issue of system calibration (i.e. gravity compensation), meaning effectively that the system is working on calibration and control at the same time.

With our robot setup we attempted to follow a similar line of developmental events. We equipped our robot with a set of three "artificial reflexes" that allowed the system to start exploring and exploiting the environment.

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