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A Self-Organized Model for the Control, Planning and Learning of Nonlinear Multi-Dimensional Systems Using a Sensory Feedback

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Abstract. A new approach is presented to deal with the problem of modelling and simulating the control mechanisms underlying planned-arm-movements. We adopt a synergetic view in which we assume that the movement patterns are not explicitly programmed but rather are emergent properties of a dynamic system constrained by physical laws in space and time. The model automatically translates a high-level command specification into a complete movement trajectory. This is an inverse problem, since the dynamic variables controlling the current state of the system have to be calculated from movement outcomes such as the position of the arm endpoint. The proposed method is based on an optimization strategy: the dynamic system evolves towards a stable equilibrium position according to the minimization of a potential function. This system, which could well be described as a feedback control loop, obeys a set of non-linear differential equations. The gradient descent provides a solution to the problem which proves to be both numerically stable and computationally efficient. Moreover, the addition into the control loop of elements whose structure and parameters have a pertinent biological meaning allows for the synthesis of gestural signals whose global patterns keep the main invariants of human gestures. The model can be exploited to handle more complex gestures involving planning strategies of movement. Finally, the extension of the approach to the learning and control of non-linear biological systems is discussed.

Keywords: modelling, automatic control, planning, autonomous systems, sensory-motor systems

1. Introduction

This paper describes a method of planning and controlling the motion of an artificial arm with multiple degrees of freedom. Sensory feedback from an observation space is used to update the current state variables controlling each joint movement. This is an inverse problem of finding the appropriate control parameters of a non-linear multi-dimensional system to achieve a desired end-point position. The proposed solution does not try to calculate the inverse transformation analytically. It produces a potential function which characterizes the evolution of the dynamic system in terms of its minimization: when a new target is specified, the system evolves towards a new stable equilibrium state corresponding to the minimization of the potential function. The method is based on a gradient descent minimization of a quadratic function of the error between the desired and the current arm location [1]. We demonstrate in the general case that the equilibrium points of the model correspond effectively to the desired solutions, and that these solutions are asymptotically reached.

Two models of planned arm-movements are presented. The first one describes the multi-joint arm as a geometrical model: this model corresponds to a position-based control scheme. The second includes a mechanical model of the articulated arm in the control loop, each joint being controlled dynamically by driving forces. The second model enables the interaction between biomechanical variables of the arm and environmental variables to be taken into account so that the impact of the arm on a physical object can be simulated. In both cases, the feasibility of the method is demonstrated by simulations for an arm with four degrees of freedom.

Our approach contrasts with previous adaptive control methods in a major way: it is more devoted to explaining physiological aspects of human motor control than to industrial robotics. In particular, the control mechanism does not maintain the dynamic response of a physical device in accordance with some pre-specified desired trajectory. It uses sensory and motor coordinates to adaptively modify the control parameters of the mechanical multi-joint arm.

The originality of our model lies in the introduction into the feedback loop of a nonlinear function which gives rise to natural behaviours. Using psychomotor results, we show indeed that such a model automatically generates gestures which keep the main features of human gestures. Some prospects are then presented which place this modelling within a broader conceptual framework, dealing with multi-dimensional systems for which an analytic function is hard to determine.

2. The Control Model

2.1. Terminology

We adopt as a working basis the Synergetic view: the movement patterns are not explicitly programmed but are rather emergent properties of a dynamic system constrained by physical laws in space and time. The dynamics of the system are determined by a set of non-linear differential equations known as the Langevin equations [2]:

$$\frac{d\mathbf{q}}{dt} = N(\mathbf{a}, \mathbf{a}_t, t) + \eta(t) \tag{1}$$

where N is the deterministic element and η is an internal noise, $\mathbf{q}$ is the state vector of the system, $\mathbf{a}_t$ is the control parameter vector which qualitatively affects the solutions of the differential equations. If a potential function, $V(\mathbf{a}, \mathbf{a}_t)$, depending jointly upon the control parameter vector and the state vector can be extracted from this dynamic system, then the spontaneous trajectory formation can be expressed in terms of potential minimization (if the control parameters are steady) and/or equilibrium phase transition (if the control parameters are variable).

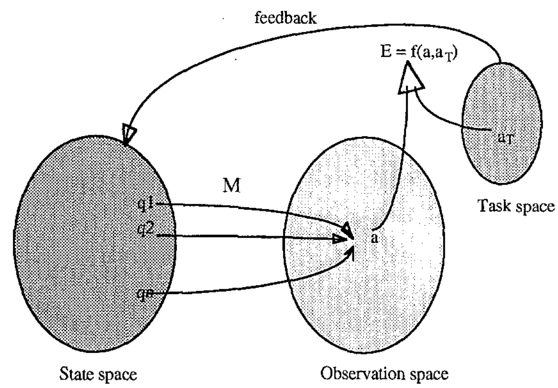

Figure 1. Sensori-motor system.

The state vector $\mathbf{q}$ characterizes the state of the motor system at any time. The observable signals, measured in the observation space, are the movement outputs used as feedback signals to control the movement execution in real time. These signals could be expressed via a variety of modalities, including vision, audition and/or kinaesthesia. The Task space is the vector space in which environmental specifications of tasks are given to the operator: this task vector contains data which evolves more slowly and is used together with the observable data to modify the state of the articulators (Fig. 1). The evolution of this vector with time represents, for instance, a succession of reached targets.

A time-varying scalar quantity can be defined, $E(\mathbf{a}, \mathbf{a}_t)$, which is a cost function corresponding to some task-level constraints and is dependent simultaneously on the task vector $\mathbf{a}_t$ (target) and on the observation vector $\mathbf{a}$. This quantity is calculated at each step to update the state of the articulatory system through a feedback loop. Let's call M the transformation which links the vector of state coordinates to the vector of observation coordinates: $\mathbf{a} = M(\mathbf{q})M$ is a non-linear and projective function, since the system is a redundant system: "i.e." several possible configurations of the articulators may correspond to a given outcome.

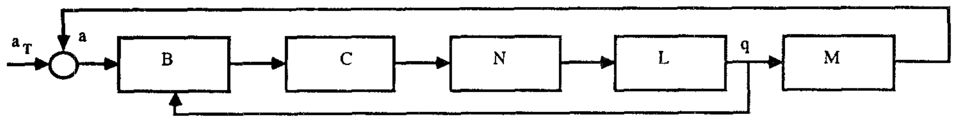

Figure 2. Position-based control scheme.

Systemic considerations lead us to describe the natural evolution of the physical system with a potential function: from an initial equilibrium state, the system goes through a succession of states towards another equilibrium state. The passage from one equilibrium state to another can be determined according to the minimization of the potential function.

2.2. *The Model*

We consider in our model that the observation variables are contained in the space of the plan variables in which the task is assigned. The state coordinates are generated on the basis of the gradient of the cost function. This cost is expressed as a quadratic function of the error between the target vector $\mathbf{a}_t$ and the actual observation vector $M(\mathbf{q})$:

$$E(\mathbf{q}, \mathbf{a}_t) = \tfrac{1}{2} \cdot (M(\mathbf{q}) - \mathbf{a}_t)^T \cdot (M(\mathbf{q}) - \mathbf{a}_t) \quad (2)$$

The behaviour of the whole system can thus be derived from the following set of differential equations:

$$\begin{aligned} \frac{d\mathbf{q}}{dt} &= -g(t) \cdot \mathrm{grad}E(\mathbf{q}, \mathbf{a}_t) \\ &= -g(t) \cdot \left[\frac{\partial M}{\partial \mathbf{q}}\right] \cdot (M(\mathbf{q}) - \mathbf{a}_t) \end{aligned} \quad (3)$$

where $g(t)$ is a non-linear gain function,

$$\left[\frac{\partial M}{\partial \mathbf{q}}\right] = J_{\mathrm{q}} = [b_{ij}] \quad \text{with } b_{ij} = \frac{\partial a_i}{\partial q_j} \quad (4)$$

J_{q} is the Jacobian matrix of the operator M. This matrix relates small changes in the state space to small changes in the observation space results. All of the derivatives in the matrix are forward derivatives and are easily obtained by differentiation if the model M is analytically available. The gradient of the error is then used to adjust the internal state variables of the system.

With such a closed-loop model, the transitions generated can be abrupt and lead to instabilities linked to some intermediate configurations. As a consequence, natural movements are not achieved. As pointed out by Grossberg [3, 4], adding a second order filter and a non-linear function inside the loop (see Fig. 2) ensures the stability of the system and generates smooth transitions. The non-linear gain is a "sigmoïd" function: the gain is low when the error is significant, and it increases as the error goes towards zero. This accelerates the convergence in the vicinity of the minimum. In Figure 2,

$B(\mathbf{a}, \mathbf{a}_t) = -\mathrm{grad}E(\mathbf{q}, \mathbf{a}_t)$

C is a weighting function which permits the addition of articulatory constraints to the system,

E is the error function,

N is a non-linear gain function ("sigmoïd" shape),

L is a second order filter,

M is a kinematics function which calculates the feedback components given the state space components.

The equilibrium point of the system is reached when the current position matches the target position, thereby preventing further changes in the current position and allowing the system to come to rest. Note that using the gradient descent of the error as a strategy to reach the target requires that the optimal solution should correspond to a minimal displacement of the articulators.

2.3. *Equilibrium Points of the Model*

The loop does invert the operator M, as a stable solution is reached when the output $\mathbf{q}$ is equal to the inverse image of the target. This is demonstrated in two steps: first, we show that under appropriate circumstances, the only stable points are such that $M(\mathbf{q}) = \mathbf{a}_t$. Second, we demonstrate that the stable points are indeed reached in an asymptotic way.

(i) We show that the excess of degrees of freedom minimizes the possibility of the system to reach sub-optimal equilibrium points and to stay in such states.

Taking $E(\mathbf{q}, \mathbf{q}_t)$ expressed in (2), we have, for each $i (i = 1 \dots N)$:

$$\frac{\partial E}{\partial q_i} = \sum_{j=1}^{N} (M(\mathbf{q})_j - a_{j_t}) \cdot \frac{\partial M(\mathbf{q})_j}{\partial q_i} \tag{5}$$

The stable points satisfy:

$$\frac{\partial \mathbf{q}}{\partial t} = 0 \tag{6}$$

This is equivalent to saying:

$$E(\mathbf{q}, \mathbf{a}_t) = 0 \text{ or } \frac{\partial E}{\partial q_i} = 0 \qquad \text{for each } i \tag{7}$$

The first equality means: $M(\mathbf{q}) = \mathbf{a}_t$, which is the desired solution. The second equality leads to the cancellation of the scalar product:

$$\left\langle M(\mathbf{q}) - \mathbf{a}_t, \frac{\partial M(\mathbf{q})}{\partial q_i} \right\rangle \tag{8}$$

which is the condition for a local minimum. This means that the set of vectors $\frac{\partial M(\mathbf{q})}{\partial_{q_i}}$ is in the hyper-space orthogonal to $(M(\mathbf{q}) - \mathbf{a}_t)$.

At this point it should be noted that the previous condition becomes harder to satisfy as the number of independent degrees of freedom increases. In our application, we assume that the system verifies: for all $\mathbf{q}$ there is at least i such that

$$\left(\frac{\partial M(\mathbf{q})}{\partial q_i} \neq 0\right) \text{ and } \left(\frac{\partial M(\mathbf{q})}{\partial q_i}\right)$$

is not orthogonal to $(M(\mathbf{q}) - \mathbf{a}_t)$ for any reachable target $\mathbf{a}_t$.

(ii) Moreover, these steady states can be reached in an asymptotic way. The method of Lyapounov [5] is used to demonstrate this: it states that a system is asymptotically stable if one can exhibit a potential function with a defined sign whose temporal derivative exists and is of opposite sign. We consider the potential function defined as $V(\mathbf{q}) = E(\mathbf{q}, \mathbf{a}_t)$. We have $V \geq 0$ for each $\mathbf{q}$.

According to the difference equation extrapolated from (1) (in which we neglect the noisy part $\eta(t)$), we may write:

$$\mathbf{q}_{n+1} = \mathbf{q}_n + N(\mathbf{q}_n, \mathbf{a}_t) \tag{9}$$

An approximation of the first order gives:

$$V(\mathbf{q}_{n+1}) = V(\mathbf{q}_n) + \left(\frac{\partial V}{\partial \mathbf{q}}\right)^T_{\mathbf{q}_n} \cdot N(\mathbf{q}_n, \mathbf{a}_t) \tag{10}$$

Therefore, if we replace the derivative by:

$$\left[\frac{\partial V}{\partial \mathbf{q}}\right]_{\mathbf{q}_n} = \left[\frac{\partial M}{\partial \mathbf{q}}\right]_{\mathbf{q}_n} \cdot (M(\mathbf{q}_n) - \mathbf{a}_t) \tag{11}$$

and the function $N(t)$ by the expression given in (3) we obtain:

$$V(\mathbf{q}_{n+1}) = V(\mathbf{q}_n) + (M(\mathbf{q}_n) - \mathbf{a}_t)^T \cdot \left[\frac{\partial M}{\partial \mathbf{q}}\right]^T_{\mathbf{q}_n} \cdot \left(-g(t) \cdot \left[\frac{\partial M}{\partial \mathbf{q}}\right]_{\mathbf{q}_n} \cdot (M(\mathbf{q}_n) - \mathbf{a}_t) \right) \tag{12}$$

and thus:

$$V(\mathbf{q}_{n+1}) - V(\mathbf{q}_n) = -g(t) \cdot \left\| \left[\frac{\partial M}{\partial \mathbf{q}}\right]_{\mathbf{q}_n} \cdot (M(\mathbf{q}_n) - \mathbf{a}_t) \right\|^2 \leq 0 \tag{13}$$

which shows that V is a positive potential function, always decreasing with time. As a consequence, the arm endpoint is asymptotically approaching the target $\mathbf{a}_t$.

It should be pointed out that:

(i) If $N(\mathbf{q}, \mathbf{a}_t) = R \cdot [-g(t) \cdot \text{grad} E(\mathbf{q}, \mathbf{a})]$ where R is a square matrix, definite and positive, then:

$$\Delta V_n = -g \cdot U^T R U \leq 0$$

with

$$U = \left[\frac{\partial M}{\partial \mathbf{q}}\right]_{\mathbf{q}_n} \cdot (M(\mathbf{q}_n) - \mathbf{a}_t)$$

and $U^T R U$ is a quadratic form both positive and definite.

(ii) In the same way, if we introduce a filtering on the g function of the form:

$$N(\mathbf{q}, \mathbf{a}_t) = -\left(\frac{\partial g}{\partial t} + \alpha \cdot g(t)\right) \cdot \text{grad } E$$

with $\alpha > 0, g(t) \geq 0$ and $\frac{\partial g}{\partial t} > 0$, we still have $\Delta V_n \leq 0$.

For instance g can be a "sigmoïd" function of the form: $g_0 \cdot (\frac{e^t - 1}{e^t})$ with g_0 small.

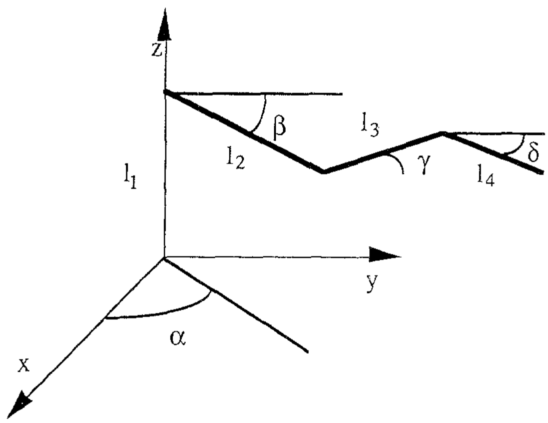

Figure 3. Articulated arm with four degrees of freedom.

3. Geometric Model of the Arm and Planned Movements

3.1. Description of the Control Model

We limit the problem to the task which consists of positioning a multi-joint arm to reach a sequence of static targets or a moving target. There are two ways of assigning a desired position to the arm:

a) through the state coordinates given by the joints angles denoted by q_i. The vector of state coordinates of a n-joints arm is $\mathbf{q} = (q_1, q_2, \ldots, q_n)^T$.
b) through the observation coordinates of the arm with respect to the absolute coordinate frame: $\mathbf{a} = (x_1, x_2, \ldots, x_m)^T$. The correspondence between the state coordinates $\mathbf{q}$ and the observation vector $\mathbf{a}$ can be written: $\mathbf{a} = M(\mathbf{q})$.

The function M expresses the transformation law between the joint angles and the position of the extremity of the arm. In our simulations we considered a three-segment arm with four degrees-of-freedom (Fig. 3).

3.2. Simulations: The Model Satisfies Natural Rules of Movement

Appropriate filters have been calculated, such that several general human rules involved in planned-arm movements are respected. These rules express invariant characteristics of the motor performance, "i.e." movement properties which are independent of the execution conditions. The invariants thus reveal general laws underlying spatio-temporal organization of motricity. We essentially retained two types of invariants [6]:

— a temporal invariant, which constitutes the "isochrony" principle: this relates to the fact that the action of the different muscles and articulators involved in a synergy occurs synchronously through time; in other words, this means that the duration of the movement to be performed is independent of the amplitude of this movement. When no constraint is imposed on the average velocity of the gesture, there is a spontaneous tendency to increase this velocity with the distance to perform.

— a spatial invariant characterized by the velocity profile: studies of the kinematics of planned-arm movements have shown that the simultaneous action of many skeleto-motor units produces velocity profiles whose global shape is approximately bell-shaped for simple movements. Moreover, this shape presents an asymmetry which depends on the speed of the movement. As the speed increases the curve becomes more symmetrical until the direction of the asymmetry is reversed.

Simulations of the geometrical arm which demonstrate these natural laws of movement have been carried out. This is illustrated by the velocity profiles (Fig. 4).

Furthermore, the "isochrony" property is imposed by adjusting parameters of the nonlinear gain function (Fig. 5): these parameters determine the duration of the transition which constitutes a temporal invariant. The end-point trajectories (Fig. 6) show the influence of the "sigmoïd" function on the quality of the transition (more or less abrupt).

3.3. Planning Gestures

The organization of more complex motor sequences requires the structural and parametric characterization of the system and the characterization of the coupling of the adaptive control loop to a higher level symbolic command. In most human skilled motor tasks, in particular those requiring phonetic code (spoken

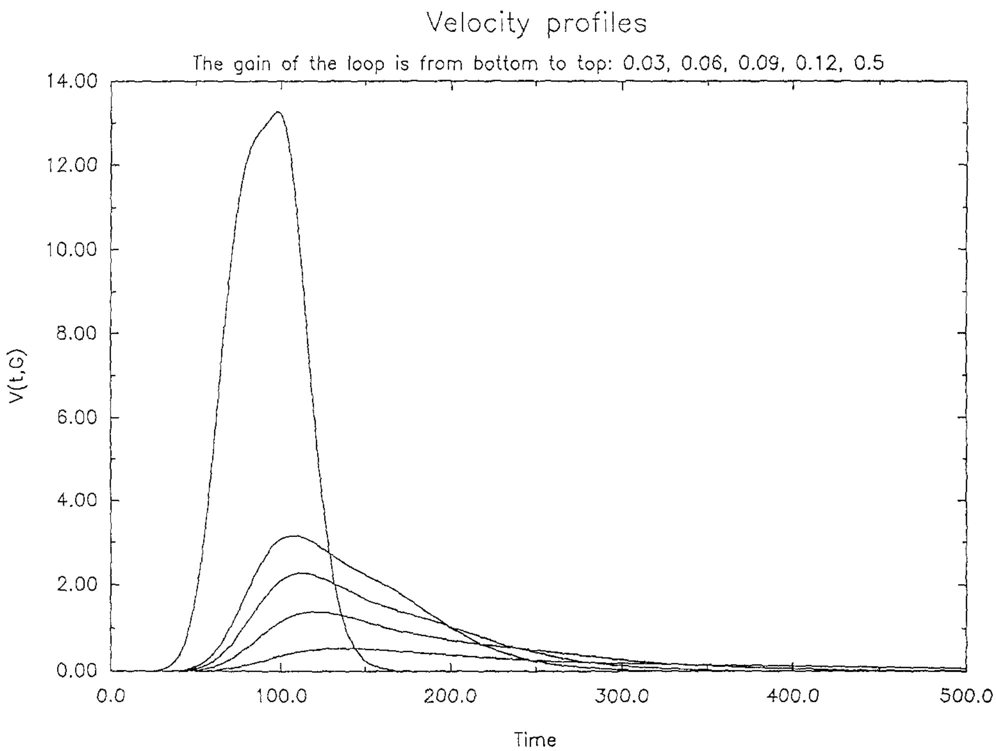

Figure 4. Velocities profiles.

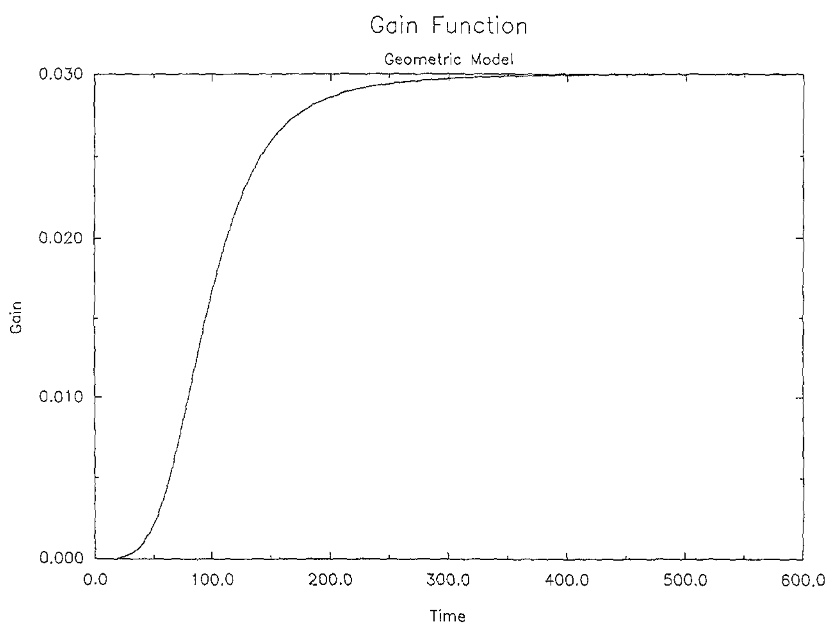

Figure 5. Gain function.

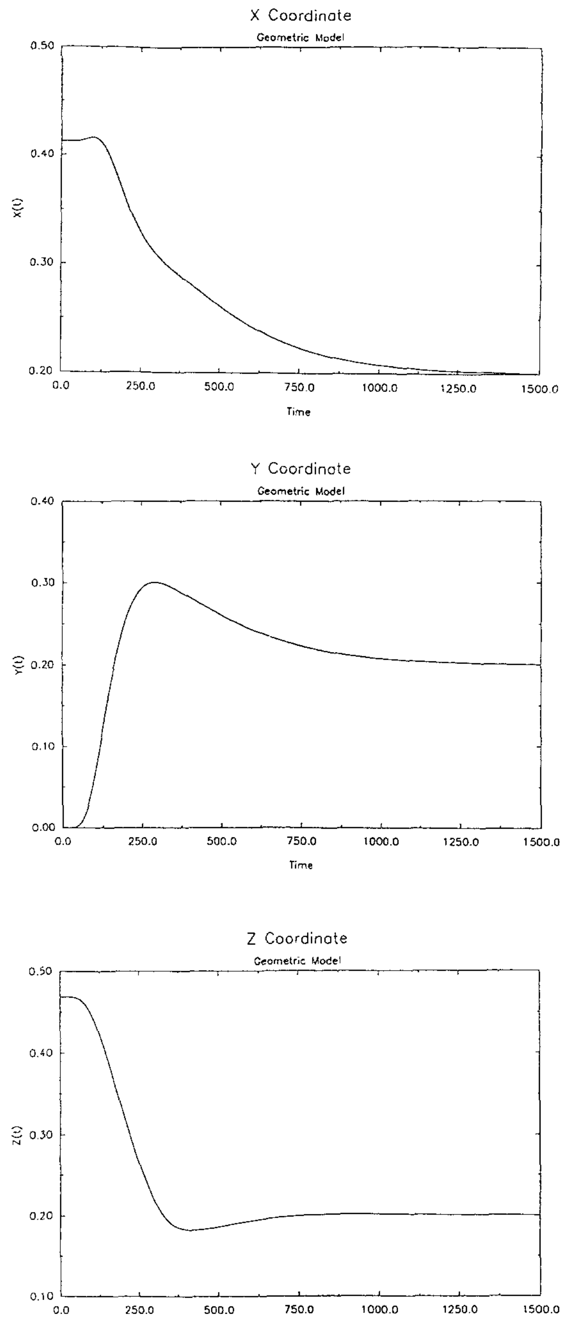

Figure 6. X, Y, Z trajectory coordinates.

language) or graphemic code (hand writing), this command necessitates learning and planning strategies.

In our current framework, the element relevant to the motor device is represented by the adaptive control loop. The link with the higher levels of planning is realized by opening the model to a reference command, which evolves more slowly through time than the physical signals in the control loop.

Considering writing gestures, the quantitative features of the movement reveal two kinds of invariants: a motor invariant characterized by the underlying mechanical system, and an invariant depending on the spatio-temporal properties of the command. The most immediate approach is to specify directly at the command level a sequence of targets in the tri-dimensional Cartesian space. These targets can be pre-determined by a segmentation of the written trace [7]. The potential function is modified so that it becomes a weighted sum of elementary costs, each cost being activated at each target occurrence in the sequence:

$$E(\mathbf{a}, \mathbf{a}_t) = \sum_{i=1}^{n} \lambda_i(t) \cdot \|\mathbf{a} - \mathbf{a}_t^i\|^2 \tag{14}$$

where $\lambda_i(t)$ is a bell-shaped function.

This modified cost function allows the model to take into account the contextual effects in the time structure of the motor sequence. This means that the articulatory configuration may change according to the temporal context. In particular, an anticipatory behaviour is observed in real performances: some articulators are pre-positioned in order to reach their subsequent target(s).

By simulating a sequence of repetitive signs ("*lll*" or "*nnn*"), we verify the linear relationship between the instantaneous velocity of the endpoint movement and the radius of curvature (two-third law highlighted by Viviani [6]).

4. Mechanical Model of the Arm and Planned Movements

4.1. *Mechanical Model of the Arm*

The arm is modelled as a triple pendulum composed of three weightless links connected to each

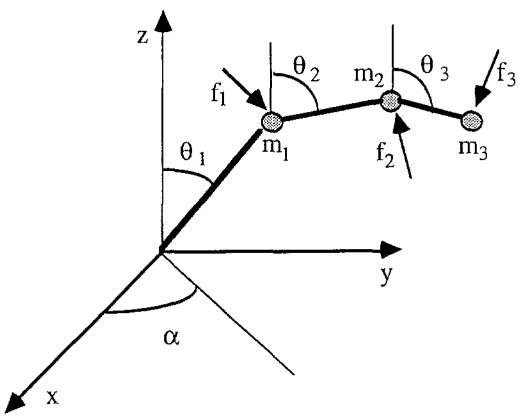

Figure 7. Mechanical model of the arm.

other by inertial links (Fig. 7). The movement of the i-th joint is described by the corresponding internal joint coordinate q_i which represents the angle between the two neighbouring links. The i-th joint movement is also described by joint velocity and acceleration. Each joint is submitted to driving forces as well as gravitational moments. The movement of each joint is strongly interconnected with the movement of all the other joints and the driving forces affect all the joints in the mechanism.

A convenient method to determine the motion of this complex non-linear system with four degrees-of-freedom is derived from the Lagrangian multiplier method [8].

The Lagrangian equations of motion of the whole mechanical system follow from Hamilton's principle. The Lagrange factor L expresses the difference between the kinetic energy T and the potential energy V of the system. Q_i is the torque exerted by gravity on the i-th articulated variable, and Γ_i is the torque exerted by the outside forces (drive control forces). $\{q_i\}$ represents a set of independent variables (or generalized coordinates).

The Lagrangian-multiplier method provides a means of avoiding the elimination of variables. A new Lagrangian function is thus defined in terms of the Cartesian non-independent coordinates $(x_1, x_2, \ldots, x_n)$, including auxiliary constraints which can be put in the form: $g_i(x_1, x_2, \ldots, x_n) = 0$.

If we consider:

$$L' = L + \sum_{i=1}^{p} \lambda_i \cdot g_i \tag{15}$$

the equations of motion can be expressed as:

$$\frac{d}{dt}\left(\frac{\partial L}{\partial \dot{x}_i}\right) - \frac{\partial L}{\partial x_i} = \sum_{i=1}^{p} \lambda_i \cdot \frac{\partial g_i}{\partial x_i} + Q_i + \Gamma_i \tag{16}$$

assuming that the (λ_i) satisfy the equations of constraints.

In our implementation of the model we use an alternative formulation, the Legendre transformation, introducing the moments p_i:

$$p_i = \frac{\partial L}{\partial \dot{x}_i}$$

and thus changing the basis from the $(x, \dot{x}, t)$ set to the (x, p, t) set.

The canonical equations of Hamilton follow from this transformation: they constitute a new set of first order differential equations:

$$H = \sum_i p_i \cdot \frac{dx_i}{dt} - L \qquad \text{with}$$

$$\frac{dp_i}{dt} = -\frac{\partial H}{\partial x_i} \quad \text{and} \quad \frac{dx_i}{dt} = \frac{\partial H}{\partial p_i} \tag{17}$$

4.2. *Force Control Adaptive Loop*

The adaptive loop in the case of the geometrical model of the arm is modified such that the small displacements of the arm result from the application of forces or torque's applied on each joint. The same error between the extremity of the arm and the target is used to calculate the forces (moments) which are applied on each joint to minimize the potential function. The drive forces are automatically computed by the retroactive adaptive loop, through the application of a non-linear function of the successive derivatives of the angle variables: $F = \Psi(\delta q, \dot{q}, \ddot{q})$.

This is shown on figure 8.

To achieve more accurately targeted responses, and to ensure a stable behaviour of the loop, one has to apply rapid force impulses to each joint. The current driving forces depend at each step on the relative directions of the movement and on the gradient of the error signal. As the extremity of the hand approaches the tar-

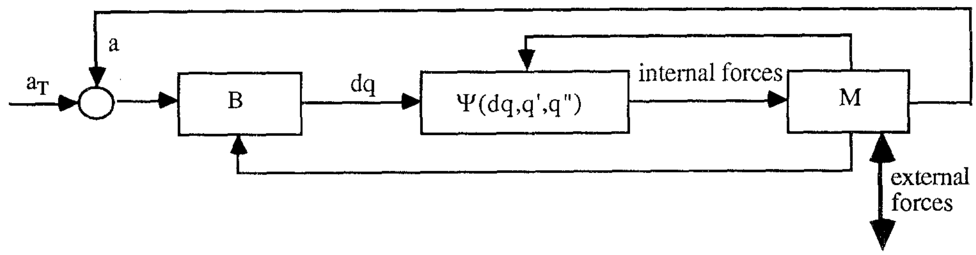

Figure 8. Force-based control scheme.

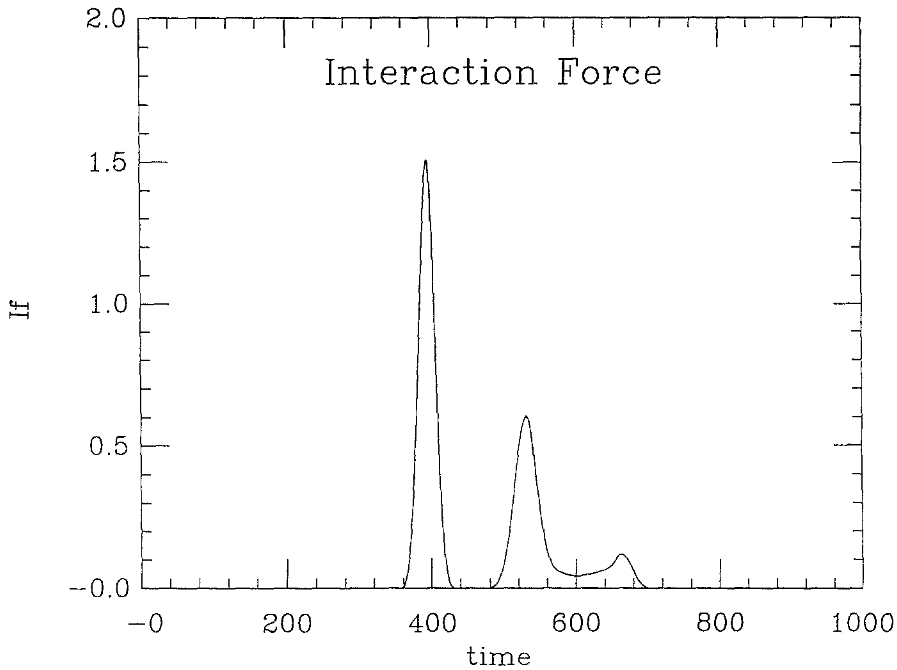

Figure 9. Interaction force.

get, both the angular increments and the angular velocities decrease, allowing the forces to reach asymptotically constant values which compensate for gravitational forces. The main advantages of this control structure lie in its ability to take into account the dynamics of the arm system, and its interaction with the environment. If the hand-arm system hits an obstacle for example, the dynamics of the impact can be described by an additional interaction force acting simultaneously on the last inertia of the hand and on the obstacle.

This interactive phenomenon is illustrated by an original application. A multi-joint dynamic arm is simulated, and hits a vibrating membrane [9]. We see in Fig. 9 the interaction force: it presents several peaks corresponding to the instants of the rebounds of the hand on the drum.

It should be pointed out that:

- The principles developed for the geometrical model are still a powerful way to solve this non-linear inverse problem. The difficulties are overcome by the gradient descent strategy and the introduction of a second fast feedback loop acting directly on the force variables.
- The analysis of stability is difficult in such a force-based control, because of the non-linearities of the different elements of the system, and also because of the strong coupling between the forces

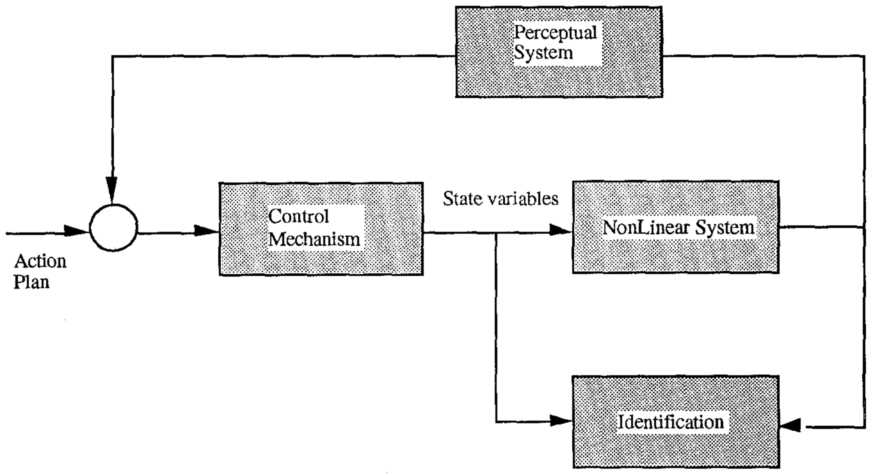

Figure 10. Identification principle.

applied on the different joints. In order to ensure the stability of the whole system, it is necessary to adjust the frequency ratio of the feedback correction, while maintaining a quasi-constant loop gain.

• Replacing the mechanical model of the arm by a robot commanded at each joint by a rapid regulation loop may avoid the above problems. We would then have an inverse problem expressed in the geometrical space, the transformation of the angular displacements into external torque's being directly achieved through the force-based adaptive loop.

5. Identification by Supervised Learning

Most of the time, the analytic equations of the dynamics of the system are difficult to derive, or hard to compute. In such cases we may use the external behaviour of the system, "i.e." the observations upon the inputs and outputs of the system to extract a mathematical model that could yield the observed data. This can be viewed as an identification problem [10] as illustrated in figure 10.

We aim to generalize the previous control concepts to non-linear systems in which the relationship between state variables (motor coordinates) and output variables (sensory coordinates) is not known a priori. In such cases, a neuromimetic approach can be considered to learn the non-linear dynamics. More precisely, as some functions in our model are projective (gradient function and forward model), they can be learned by simple "feedforward" neural networks. They achieve an internal mapping between the sensory data of the environment and the state variables of the system.

We can consider a network to be composed of a set of connections that implement the transformation of internal state units (articulatory variables) into observable units. It includes intermediate hidden units so that non-linear functions can be learned.

The learning procedure is viewed as a straightforward application of supervised learning techniques [11]. The algorithm is a steepest descent algorithm in the error measure expressed as the quadratic function of the difference between the actual output of the network $\mathbf{a}^p$ and the desired output $\mathbf{a}_t^p$ for one pair p:

$$E^p = \frac{1}{2} \cdot \left(\mathbf{a}_t^p - \mathbf{a}^p\right)^T \cdot \left(\mathbf{a}_t^p - \mathbf{a}^p\right) \tag{18}$$

The back-propagation algorithm is used to compute the incremental changes to the weights according to the gradient of the error measure E^p. For n input-output pairs, the descent rule changes the parameter values ω as follows:

$$\Delta\omega = \alpha \cdot \sum_{p=1}^{n} \left(\frac{\partial \mathbf{a}_t^p}{\partial \omega}\right) \cdot \left(\mathbf{a}_t^p - \mathbf{a}^p\right) \tag{19}$$

where α is a learning rate.

The control procedure differs from classical approaches in the way that the gradient of the error function is found with respect to the inputs **q** and not with respect to the weights as during the learning procedure. This leads to an updated process that computes the appropriate changes to the internal state inputs **q**:

$$\Delta \mathbf{q} = -\beta \cdot \left(\frac{\partial \mathbf{a}}{\partial \mathbf{q}}\right)^T \cdot (\mathbf{a}_t - \mathbf{a}) \tag{20}$$

where β represents a gain function. Thus, for a fixed set of weights, the back-propagation algorithm is able to propagate the error backwards from the observable units to the state units.

Several approaches have already been considered that use different kinds of networks [13–20] A survey *"Neural Networks in Robotics"* [21] provides an overview of the research tackled in neural networks applied to robotics and presents its limitations and current trends. Our approach differs from other classical control models in several ways: first of all, it does not require an a priori knowledge of a desired trajectory nor of the qualitative structure of the inverse dynamics. Moreover, it achieves an adaptive mapping between sensory and motor coordinates through the learning of both the gradient and the non-linear mechanical model.

6. Conclusion

The work presented here puts forward a new approach to adaptive sensory-motor control. We have presented a control model of planned-arm movements which aims to solve the inverse problem. From current sensory information measured in the observation space, it calculates the current state variables controlling the multi-effector system. We know that there are an infinite number of solutions to this problem, involving various combinations of values for the degrees of freedom. However, we think that some solutions are better than others, in terms of the smoothness of the articulatory transition between the actions. Our model is a biologically-inspired model which provides a functional understanding of the sensory-motor system involved in simple hand-arm movements, in the scope of control theories and dynamic process theories.

This model is composed of an adaptive loop dedicated to the command of a muti-joint articulated system. It can automatically translate a visual target specification into a complete movement trajectory via a mechanism of continuous vector updating and integration. Therefore this autonomous and adaptive model provides a means of spontaneous trajectory formation, from targets specified in a perceptual representation space. This model has several interesting features, which might help us to understand quantitatively how the arm system achieves its flexibility and versatility:

- It provides an economical control mode: the motions of the different articulators as well as the time-sequencing are not explicitly programmed. They are emergent properties of a dynamic system, constrained in space and time.
- An important characteristic is the low information flow at the command level; this permits an interface with higher planning levels in which symbols are more relevant than physical signals.
- The generated movements present some "natural" features, since properties characterizing the kinematics of human gestures have been highlighted: this has been shown through the "isochrony" principle and the invariance of the velocity profiles.

The same principles have been applied to two models of the articulated arm:

– a geometric model in which the angular variables characterizing each articulation are directly controlled by the adaptive loop, according to a gradient descent strategy.
– a dynamic model in which the drive forces are calculated from a similar error signal and according to the same strategy.

The relative independence of the control principles with respect to the application models shows the generality of the mechanisms considered above.

Moreover, this approach suggests how functional and mechanical devices could be involved in the neural systems governing arm movements. It can be extended to more complex non-linear systems for which the transformation from an internal configuration to an observable output is not known a priori. In such cases, it would be possible to replace the forward system and the gradient function by "feedforward" neural networks.

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