Adaptive combination of motor primitives

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Abstract

Recently there has been a growing interest in modeling motor control systems with modular structures. Such control structures have many interesting properties, which have been described in recent studies. We here focus on some properties which are related to the fact that specific set of contexts can themselves be modeled modularly.

1 Introduction

Humans exhibit a broad repertoire of motor capabilities which can be performed in a wide range of different environments and situations. From the point of view of control theory, the problem of dealing with different environmental situations is nontrivial and requires significant adaptive capabilities. Even the simple movement of lifting up an object, depends on many variables, both *internal and external* to the body. All these variables define what is generally called the context of the movement. As the context of the movement alters the input-output relationship of the controlled system, the motor command must be tailored so as to take into account the current context. In everyday life, humans interact with multiple different environments and their possible combinations. Therefore, a fundamental question in motor control concerns how the control system adapts to a continuously changing operating context.

Recently, there has been a major interest in modeling motor control by means of combinations of a finite number of elementary modules. Within this modular approach, multiple controllers co-exist, with each controller suitable for a specific context. If no controller is available for a given context, the individual controllers can be combined to generate an appropriate motor command. Among the features of this model, two are extremely relevant:

- **Modularity of contexts.** The contexts within which the model operates can be themselves modular. Experiences of past contexts and objects can be meaningfully combined; new situations can be often understood in terms of combinations of previously experienced contexts.

- **Modularity of motor learning.** In a modular structure only a subset of the individual modules cooperate in a specific context. Consequently, only these modules have a part in motor learning, without affecting the motor behaviors already learned by other modules. This situation seems more realistic than a global structure where a unique module is capable of handling all possible contexts. Within such a global framework, motor learning in a new context possibly affects motor behaviors in other (previously experienced) contexts.

Remarkably, Mussa-Ivaldi and Bizzi (2000) have proposed an interesting experimental evidence supporting the idea that biological sensory-motor systems are organized in modular structures. At the same time, Shadmehr and Mussa-Ivaldi (1994) and Brashers-Krug et al. (1996) have shown the extreme adaptability of the human motor control system. So far, adaptation has been proven to depend on performance errors (see Shadmehr and Mussa-Ivaldi (1994)) and context related sensory information (see Shelhamer et al. (1991)).

Based on these findings, there has been recently a growing interest in investigating the potentialities of *adaptive and modular* control schemes (refer to Wolpert and Kawato (1998); Mussa-Ivaldi (1997)). Within these investigations, the modular structure is often formalized in terms of multiple inverse models[1]. Motor commands are usually obtained by combining these elementary inverse models. Given this formalization, two fundamental questions must be faced:

1. Is there a way to choose the elementary inverse

[1] Here an inverse model is considered to be a map from desired movements to motor commands.

models so as to cover all the contexts within a specified set?

2. Given a set of inverse models which appropriately cover the set of contexts which might be experienced, how is the correct subset of inverse models selected for the particular current context?

Both questions have been already investigated in Wolpert and Kawato (1998) and in Mussa-Ivaldi and Giszter (1992) within the function approximation framework. Recently, the same two questions have been considered by Nori and Frezza (2005) within a control theoretical framework. So far this innovative approach has been proven to provide new interesting results in answering the first question (see Nori and Frezza (2004a) and Nori (2005)). In the present paper, we proceed along the same line to answer the second question. Specifically, we propose a strategy to adaptively select a given set of inverse models. The selection process is based on the minimization of performance errors. Context related sensory information (which is related to a different cognitive process) is instead not considered here. The key features of the proposed control scheme are the following:

- **Minimum number of modules.** Previous works Nori (2005) have established the minimum number of modules which are necessary to cover all the contexts in a specified set. The present paper will describe how this minimality result can be fitted in the adaptive selection of the modules.

- **Linear combination of modules.** The theory of adaptive control has been widely studied since the early seventies. Interesting results have been obtained, especially in those situations where some linearity properties can be proven and exploited. In our case, linearity will be a property of the considered set of admissible contexts.

2 Reaching in different contexts

To exemplify the ideas presented in the introduction, we consider a specific action, nominally the action of reaching a target with the hand. In order to immerse the same action into different contexts, we consider the movement of reaching while holding objects with different masses and inertias. Within this framework, a successful execution of the reaching movements requires a control action which should adapt to the current context. Since the controlled system[2] changes its properties with the context, suitable changes should be imposed on the control action.

2.1 Model of the arm

We model the dynamics of the arm as a fully actuated kinematic chain with n degrees of freedom corresponding to n revolute joints. It is well known in literature that such model can be expressed as follows:

$$M(\mathbf{q})\ddot{\mathbf{q}} + C(\mathbf{q}, \dot{\mathbf{q}})\dot{\mathbf{q}} + g(\mathbf{q}) = \mathbf{u}, \tag{1}$$

where $\mathbf{q}$ are the generalized coordinates which describe the pose of the kinematic chain, $\mathbf{u}$ are the control variables (nominally the forces applied at the joints) and the quantities M, C and g are the inertia, Coriolis and gravitational components.

2.2 Model of the contexts

In this paper, we consider the problem of controlling (1) within different contexts. The different contexts affect the arm in terms of modifying its dynamical parameters. The considered parameters are the mass, the inertia and the center of mass position of each of the n links which compose the controlled arm. The vector with components represented by these parameters is:

$$\mathbf{p} = \begin{bmatrix} m_i & I_1^i & \dots & I_6^i & {\mathbf{c}^i}^\top \end{bmatrix}^\top_{i=1\dots n}, \tag{2}$$

where m_i is the mass of the i^{th} link, $I_1^i, \dots, I_6^i$ represent the entries of the symmetric inertia tensor, and $\mathbf{c}^i = \left[c_x^i, c_y^i, c_z^i\right]^\top$ is the center of mass position. The system to be controlled is therefore:

$$M_{\mathbf{p}}(\mathbf{q})\ddot{\mathbf{q}} + C_{\mathbf{p}}(\mathbf{q}, \dot{\mathbf{q}})\dot{\mathbf{q}} + g_{\mathbf{p}}(\mathbf{q}) = \mathbf{u}, \tag{3}$$

where $\mathbf{p}$ identifies by the specific context. Note that the considered class of contexts is suitable for modeling an arm which holds objects with different masses and inertias. Therefore, the model is appropriate for the proposed reaching scenario.

Note: the proposed set of contexts is itself modular. It can indeed be proven that (see Kozlowski (1998)):

$$M_{\mathbf{p}}(\mathbf{q})\ddot{\mathbf{q}} + C_{\mathbf{p}}(\mathbf{q}, \dot{\mathbf{q}})\dot{\mathbf{q}} + g_{\mathbf{p}}(\mathbf{q}) = \mathbf{u}, \tag{4}$$

can be rewritten as:

$$\sum_{j=1}^{J} \Psi_j(\mathbf{p}) Y^j(\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}}) = \mathbf{u}. \tag{5}$$

[2] composed of the arm *and* the held object.

This is a crucial property which is fundamental to prove the results which will be claimed in the rest of this paper.

3 Modular control action

In this section we formalize our concept of modular control action. The proposed formalization is biologically inspired and has been originally proposed by Mussa-Ivaldi and Bizzi (2000). Specifically, experiments on frogs and rats have shown that their motor systems is organized into a *finite number of modules*. Each module has been described in terms of the muscular synergy evoked by the microstimulation of specific interneurons in the spinal cord. These modules can be *linearly combined* to achieve a wide repertoire of different movements. A mathematical model of these findings has been proposed again by Mussa-Ivaldi and Bizzi (2000):

$$\mathbf{u} = \sum_{k=1}^{K} \lambda_k \Phi^k(\mathbf{q}, \dot{\mathbf{q}}). \tag{6}$$

Practically, the system (1) is controlled by means of a linear combination of a finite number of modules $\Phi^k(\mathbf{q}, \dot{\mathbf{q}})$, which can be seen as elementary control actions. The control signals are no longer the forces $\mathbf{u}$ but the vector $[\lambda_1, \ldots, \lambda_K]^\top = \lambda$ used to combine the modules.

3.1 Modules synthesis problem

Remarkably, a modular structure requires a major attention in selecting the modules themselves. In this section it is pointed out that only a suitable choice of the modules allow to generate a wide repertoire of movements (Section 3.1.1) while handling different contexts (Section 3.1.2).

3.1.1 Modules for reaching admissible configurations

Obviously, the individual modules Φ^k need to be carefully chosen in order to preserve the capability of reaching any admissible configuration[3]. Simple examples can demonstrate that, in general, this capability may be easily lost. As to this concern, the following problem has been formulated:

Problem 1: *find a set of modules* $\{\Phi^1, \ldots, \Phi^K\}$ *and a continuously differentiable function* $\lambda(\cdot)$*, such that for every desired final state* $\mathbf{q}_f$ *the input:*

$$\mathbf{u} = \sum_{k=1}^{K} \lambda_k(\mathbf{q}_f) \Phi^k(\mathbf{q}, \dot{\mathbf{q}}) \tag{7}$$

steers the system (1) to the configuration $\mathbf{q}_f$*.*

Nori and Frezza (2004b) have proposed a solution to the problem above with the use of $n + 1$ modules. This solution was proven to be composed by a minimum number of modules (see Nori (2005)).

3.1.2 Modules for handling admissible contexts

In this paper, we consider the problem of solving problem 1 in different contexts. Practically, we face the following problem where instead of controlling (1) we want to control (3) which is context dependent.

Problem 2: *find a set of modules* $\{\Phi^1, \ldots, \Phi^K\}$ *and a continuously differentiable function* $\lambda(\cdot, \cdot)$*, such that for every desired final state* $\mathbf{q}_f$ *and for every possible context* $\mathbf{p}$ *the input:*

$$\mathbf{u} = \sum_{k=1}^{K} \lambda_k(\mathbf{q}_f, \mathbf{p}) \Phi^k(\mathbf{q}, \dot{\mathbf{q}}) \tag{8}$$

steers the system (3) to the configuration $\mathbf{q}_f$*.*

Obviously the proposed problem is related to the question posed in the introduction: is there a way to choose the elementary (inverse) models so as to cover all the contexts within a specified set? The answer turns out to be 'yes'. Specifically, a complete procedure for constructing a solution of problem 2 has been proposed in Nori (2005). The solution turns out to have the following structure:

$$\mathbf{u} = \sum_{i}^{I} \sum_{j}^{J} \lambda_i(\mathbf{q}_f) \mu_j(\mathbf{p}) \Phi^{i,j}(\mathbf{q}, \dot{\mathbf{q}}), \tag{9}$$

where $\{\Phi^{1,j}, \ldots, \Phi^{I,j}\}$ is a solution to problem 1 for a specific context $\mathbf{p}^j$.

3.2 Adaptive modules combination

In many situations, the context of the movement is not known *a priori*. Within our formulation, if the context $\mathbf{p}$ is unknown, we cannot compute the way the modules have to be combined. This is a consequence of the fact that the way modules are combined depends not only on the desired final position $\mathbf{q}_f$ but

[3] in control theory the capability of the system of reaching any admissible configuration is called *controllability* (see Nori and Frezza (2005)).

also on the current context $\mathbf{p}$. A possible solution consists in adaptively choosing μ_j (which are context dependent) on the basis of available data. When the only information available is the performance error[4], we can reformulate the estimation problem in terms of an adaptive control problem. It can be proven that a way to successfully reach the desired final position $\mathbf{q}_f$ consists in adaptively adjusting μ_j according to the following differential law:

$$\frac{d}{dt}\mu_j = -\mathbf{s}^\top \left[\sum_i^I \lambda_i(\mathbf{q}_f)\Phi^{i,j}(\mathbf{q}, \dot{\mathbf{q}}) \right], \qquad (10)$$

where $\mathbf{s}$ is the performance error (see Kozlowski (1998) for details). A mathematical proof of the system stability properties is out of the scope of the present paper and is therefore omitted. It suffices to say that, in fact, it can be proven that (10) leads to a stable system.

4 Future works

In the framework of motor control, this paper proposes a method for performing on-line learning of reaching movements. The proposed control structure is not only biologically compatible, but turns out to be very useful when dealing with modular contexts. A crucial step in our future work will be the implementation of the system in a robot capable of adapting itself to different contexts determined, for instance, by manipulating/holding different objects. The underlying idea is that a modular control structure should reveal useful for handling objects which are themselves modular.

5 Conclusions

Modular control structures are appealing since there exist contexts which can be modular as well. In the present paper we have considered a simple movement (moving the arm towards a target) within different contexts (handling different objects). Intuitively, a modular control structure is best suited to operate within modular contexts. In the specific problem of moving the arm while holding different objects, we have shown that the system dynamics are modular themselves. Taking advantage of this property we have shown that a modular control structure is capable of handling multiple contexts. Finally, a way to adaptively combine the modules has been proposed.

[4]The performance error $\mathbf{s}$ measures the difference between the desired reaching trajectory $\mathbf{q}^d$ and the actual trajectory q. Further details can be found in Kozlowski (1998)

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