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Optimal behaviour prediction using a primitive-based data-driven model-free iterative learning control approach

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ABSTRACT

This paper suggests an optimal behaviour prediction mechanism for Multi Input-Multi Output control systems in a hierarchical control system structure, using previously learned solutions to simple tasks called primitives. The optimality of the behaviour is formulated as a reference trajectory tracking problem. The primitives are stored in a library of pairs of reference input/controlled output signals. The reference input primitives are optimized at the higher hierarchical level in a model-free iterative learning control (MFILC) framework without using knowledge of the controlled process. Learning of the reference input primitives is performed in a reduced subspace using radial basis functions for approximations. The convergence of the MFILC learning scheme is achieved via a Virtual Reference Feedback Tuning design of the feedback controllers in the lower level feedback control loops. The new complex trajectories to be tracked are decomposed into the output primitives regarded as basis functions. Next, the optimal reference input fed to the control system in order to track the desired new trajectory is then recomposed from the reference input primitives. The efficiency of this approach is demonstrated on a case study concerning the control of a two-axis positioning mechanism, and the experimental validation is offered.

1. Introduction

As the control systems (CSs) become more and more complex and they need to cope with new situations to which they were not exposed before, the cognitive control capabilities are more and more demanding. The biological systems approach the problem of solving complex tasks not mathematically but by combining the accumulated knowledge stored in memory, called primitives or strategies [1]. Therefore, by combining primitives one living organism is capable of achieving more complex manoeuvres. The living organism next subsequently adds this capability to its current knowledge base, and an extension of the knowledge base is achieved. Several abilities are needed for the brain of biological systems, such as:

- strategy projection to achieve the goal, associated with reasoning and planning,
- decomposition of strategies into other well-known strategies, that also represents a planning ability,
- necessity of storing the learned strategies, associated with the memory,
- feedback in order to improve new strategies by repeated trials, that also represents a learning ability.

In this regard the brain acts as a higher level hierarchical control planner and supervisor that coordinates the lower level feedback control loops.

Several approaches to learning from primitives are presented in the literature. These approaches are grouped in: time-scale transformation approaches, temporal concatenation of primitive-based approaches, and time-based decomposition approaches, briefly discussed next.

Representative time-scale transformation approaches are presented in [2,3]. An iterative learning control (ILC)-based approach is suggested in [2] to improve the manoeuvres of an underwater robotic manipulator. The approach considers a time scale transformation. A demonstration by learning approach using attractor dynamics is proposed in [3].

Temporal concatenations of primitive-based approaches are reported in [4–6]. The feasibility of primitive motion tasks for UAVs is analyzed in [4]. The concept of library of motion primitives is proposed in [5]. An A* search algorithm for the optimal temporal concatenation of primitives is suggested in [6].

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A time-based decomposition approach is given in [7]. The primitives are B-spline functions, considered as elements of the library of primitives. The real-time planning of trajectories is performed using the learned B-spline primitives and combining them in the LTI systems framework.

A comprehensive review of ILC is impossible and in the following only a short review on model-based vs Model-Free Iterative Learning Control (MFILC) approaches is presented. The ILC-based solving of optimal control problems is formulated in [8–11], time and frequency domain convergence analyses are conducted in [8], the stochastic approximation is treated in [12], and the output tracking is discussed in [13]. The affine constraints are handled in [14] by the transformation of ILC problems with quadratic objective function (o.f.s) into convex quadratic programmes. The system impulse response is estimated in [15] using input/output measurements from previous iterations and next used in a norm-optimal ILC structure that accounts for actuator limitations by means of linear inequality constraints. Other model-based approaches for constrained ILC are proposed in [16,17], but they differ from the model-free approach suggested in [18]. A data-driven approach to estimate the Markov matrices from input/output data using MFAC is given in [19] and integrated in a terminal ILC framework. A learning approach that gives the parameters of motion primitives for achieving flips for quadrocopters is proposed in [20], but it makes use of approximate simple models of the process. Similar formulations with reinforcement learning for policy search using approximate models and signed derivative are given in [21]. Neural networks applied to ILC in a model-based approach are also reported in [22]. The ILC-based training of neural networks has been proposed in [23]. Other existing approaches to optimal feed-forward design are presented in [24,25].

Building upon recent results given in [18], this paper's main contributions with respect to the state-of-the-art are:

- The concept of primitive-based ILC is proposed. This concept aims the improvement of the execution of different tasks in terms of the time-based decomposition of complex tasks in simpler tasks.
- The concept of primitives is embedded into an original experiment-based iterative reference input tuning algorithm, formulated as an MFILC algorithm for Multi Input-Multi Output (MIMO) reference trajectory tracking problem.
- The guaranteed convergence of the MFILC scheme by using the closed-loop transfer functions (t.f.s) imposed via a Virtual Reference Feedback Tuning (VRFT) model-free design of the feedback controllers.
- The reduction of the dimension of the optimized reference inputs in the ILC learning scheme is achieved using radial basis functions (RBFs) for approximation purposes.

The combination of these two contributions leads to a novel control approach referred to as model-free primitive-based approach to trajectory tracking which uses very little information about the controlled process. Our approach allows for the near-optimal solutions that correspond to the new trajectories to be tracked can be obtained on the basis of the composition of already learned/optimized motions. In addition, our approach imitates the behaviour of biological systems.

This paper uses the previously developed tools for the MFILC-based reference input signal optimization to propose a new concept that improves the execution of different tasks on the basis of previous experience in executing simpler tasks called primitives. An optimal execution is a priori inferred for the new task, without executing the task and without the need to learn from multiple runs/trials/iterations/passes. The merge of MFILC and primitive learning leads to a new control approach referred to as model-free primitive-based approach to trajectory tracking.

Our approach consists of two steps. In the first one, primitive pairs consisting of sets of reference input primitives and controlled output primitives are optimized with respect to a trajectory tracking criterion in an MFILC fashion. In the second step, the new trajectory to be tracked is decomposed in terms of the output primitives. The optimal reference inputs are recomposed from the reference input primitives, they are thus straightforward computed without learning from repeated trials of the tracking task. The CSs become endowed with planning, reasoning and learning capabilities.

The approach suggested in this paper leads to hierarchical CS structures, with MFILC at the higher hierarchical level and VRFT at the lower hierarchical level. This structure carries out a synergy of artificial intelligence, computers and control, with promising industrial implementations, exemplified here in a representative 3D crane system application.

This paper is organized as follows: Section 2 gives the process model specific to the MIMO position control of a 2D system that belongs to a 3D crane. The reference trajectory tracking problem is largely discussed in Section 3, where the convergence analysis is performed and the reduction of the dimension of the optimized reference inputs is also introduced. The MFILC primitive-based solution to a novel trajectory tracking problem is offered in Section 4. The approximation of the output primitives is treated in Section 5 using Gaussian kernels as universal function approximators. The proposed approach is validated by experimental results in Section 6. The conclusions are highlighted in Section 7.

2. The controlled process

The simplified linear model of the process in the MIMO 3D crane system concerning only the XY-plane positioning of the cart [26] consists of the following t.f.s:

$$\begin{aligned} H_x(s) &= \frac{Y_1(s)}{U_1(s)} = \frac{0.173}{s(1+0.0743s)}, \\ H_y(s) &= \frac{Y_2(s)}{U_2(s)} = \frac{0.172}{s(1+0.129s)}, \end{aligned} \tag{1}$$

where: $U_1(s)$ is the Laplace transform of the first control input $u_1(t)$ [%], i.e., the PWM duty cycle driving the X-axis DC motor, $U_2(s)$ is the Laplace transform of the second control input $u_2(t)$ [%], i.e., the PWM duty cycle driving the Y-axis DC motor, $Y_1(s)$ is the Laplace transform of y_1 [rad] – the first process output, i.e., the X-axis position of the cart, and $Y_2(s)$ is the Laplace transform of y_2 [rad] – the second process output, i.e., the Y-axis position of the cart. The values of all parameters of the model (1) reflect the electro-mechanical behaviour of the process illustrated in Fig. 1.

The DC motors being used to generate motion on both axes are driven by a voltage in the interval $-12\,\text{V} \ldots 12\,\text{V}$. The optical encoders used to measure the position on each axis are high resolution capable of generating 4096 pulses per rotation. The computer communicates with a power interface board via USB connection. The Xilinx® chip in the board contains the PWM logic to operate the DC motors and the activation and read logic of the encoders. The power interface board is then connected with the rig through a power interface unit which also operates both ways and on one hand it amplifies the PWM signal while on the other hand it converts the pulse signals from the encoders to 16-bit digital numbers.

As observed in Fig. 1, a rail which contains the cart is moved on the X-axis using one DC motor and on this moving rail the Y-axis motion is achieved using the other DC motor. For the purpose of the following case study, no payload is attached to the cart. Several