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An Overview of Learning Control in Robot Applications

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Abstract

This paper presents an overview of research results obtained by the authors in a series of publications. Methods are developed both for time-varying and time-invariant, for linear and nonlinear, for time domain and frequency domain, and for discrete-time and continuous-time systems. Among the topics presented are: 1. Learning control based on integral control concepts applied in the repetition domain. 2. New algorithms that give improved transient response of the learning process. 3. Indirect learning control based on indirect adaptive control ideas. 4. Direct model reference learning control. 5. Learning control based frequency domain. 6. Use of neural networks in learning control. 7. Decentralized learning controllers. These learning algorithms apply to robot control. The decentralized learning control laws are important in such applications because of the usual robot decentralized controller structure.

Introduction

Learning is defined as any relatively permanent change in behavior resulting from past experience, and a learning system is characterized by its ability to improve its behavior with time, in some sense tending towards an ultimate goal. This motivates the development of control strategies that allow the system to improve its performance by proper utilization of past experience in performing the desired task.

Learning control refers to methods of converging to zero tracking error at each time step of a process, including the transient parts and any disturbances that occur each time the process is repeated. This is accomplished with minimal knowledge about the system, by using past experience with the same task in order to improve performance executing the task in the future. As the process is repeated, the input signal is updated based on the data from previous trials, in order to converge to the input signal which produces the desired output.

The origins of the recent research on learning control started around 1984, with papers containing similar ideas appearing on several continents [8, 25-29]. Over the past few years, the field of learning control has grown dramatically [1-24], with numerous experimental works applied to robot manipulators [1-9, 25-29].

There are various methods for the implementation of learning control laws on manipulators. In the sequel, the approaches will be briefly described.

System Models

The learning control theories developed in the references assume a linear system. In many applications, the systems of interest are in fact linear, but the application that originally motivated the work is robotics with its nonlinear dynamic equations. When linearized about the nominal trajectory, these equations generally become linear with time-varying coefficients, and the theory is capable of handling such time-varying models. Linearization can usually be justified by the fact that a feedback controller is assumed to be operating in the system which should keep the trajectories within a linear range about the nominal. It is the job of the learning control to eliminate the errors that remain when the feedback controller executes its command. These errors come from two sources. First, it is only under very special circumstances that a feedback control system given a command will produce zero error in following the command, even when there are no disturbances and the control system operates perfectly. Secondly, when there are disturbances such as gravity torques on a robot link, these disturbances will often be repetitive, appearing every time the robot performs the maneuver. The learning control laws developed here eliminate tracking errors from both sources. In addition, robot controllers are usually decentralized, with independent controllers for each link acting as if no other link exists. The motion of one link can easily produce centrifugal and coriolis effects on other links, and these are nearly repetitive disturbances to the second link. When each link has an independent learning controller operating, one obtains a decentralized learning control situation, and theories are developed in the references that guarantee convergence to zero tracking error in such cases.

Learning Control Concepts

A large number of control systems in use execute repetitive operations, for example controllers for robots in assembling and manufacturing systems. When controllers are given the same command repeatedly, they repeat the same errors in executing the command, except for certain random disturbance effects. In tracking problems these repeating errors can be large. Over the last decade the field of learning control has developed that allows controller designs that learn from previous experience performing a command in order to improve its performance in future repetitions.

There are a number of approaches to producing learning controllers that learn from previous experience executing a command, in order to converge on zero tracking error as the repetitions of the command progress.

1. Integral Control Based Learning Control Algorithms

The simplest form of these algorithms is based on integral control concepts applied in repetition domain [10]. When a feedback controller executes a tracking command it usually produces tracking errors since it is only rarely that the particular solution of a differential equation is equal to the command that determines the forcing function. Integral controllers have the property that they will not tolerate a constant error, because they produce an ever increasing corrective action. Control system errors that repeat every time the same command is given to the system, look like constant errors when viewed at the same time in every repetition, and hence can be eliminated using the equivalent of an integral controller formulated in the repetition domain.

The most basic and predominant form of learning control in the literature is based on integral control concepts. One of the choices corresponds to using a learning control signal analogous to integral control. When one has sufficient information about the system, more sophisticated learning control choices can be made.

2. Adaptive Control Based Learning Control Algorithms

The integral control based learning control algorithms discussed above require that a stability condition be satisfied to ensure that the learning process converges to zero tracking error as the repetitions of the task progress. Knowing that this criterion is satisfied requires some knowledge of the system, i.e. the discrete time input and output matrices. By contrast, adaptive control based algorithms can give guaranteed convergence to zero tracking error.

Adaptive control theory can be divided into direct and indirect adaptive control, depending on whether adaptive control action requires simultaneous identification of the system. By analogy, references [11] and [12] develop direct learning control and indirect learning control algorithms. Reference [11] obtains guaranteed convergence of the learning process by Liapunov methods, developing a theory of model reference learning control based on the discrete-time model reference adaptive control developed in [14]. There is in fact considerable choice in the mathematical model of the system used in the indirect learning control developed in [12], and the range of possibilities treated in detail in [1], giving the advantages and disadvantages of each, and giving a detailed comparison with adaptive control methods.

Because indirect learning control involves identification in the repetition domain, several studies address this identification problem specifically [13, 16, 17].

3. Robustness Learning Control Algorithms

Sometimes it is unreasonable to ask for zero tracking error. The desired trajectory may not be feasible because:

1) Sometimes the only thing you know to ask for is something that cannot be done physically, e.g. having zero vibrations in a flexible robot during a maneuver.
2) The desired trajectory may require control actions larger than the saturation limits of the actuators.
3) In digital control, controllability only guarantees that you can go wherever you want in the state space after n steps, where n is the order of the system.

Specifying a desired trajectory at all steps will in general result in infeasibility. To address these issues, [21] develops methods that are more robust. In addition, reference [4] shows the benefits of using anti-reset windup(ARW) ideas for the following purposes in learning control:

1) Limiting poor transient behavior during learning, particularly when the gain is poorly set.
2) Learning control assumes that the initial condition is on the desired trajectory. In some cases, such as robots under gravity, one does not know how to obtain the desired initial condition, and may start with whatever initial condition the robot supplies given the desired position as command to the robot. ARW may help under these conditions.
3) When the desired trajectory is executable without saturation, but the transients induce saturation, ARW may speed the recovery following a time interval of saturation.
4) Sometimes the desired trajectory is not physically executable, such as a unit step command, because it requires control actions that go beyond the saturation

limit. This reference discusses the robustness of learning controllers to system uncertainties in the disturbances and determine methods of obtaining zero tracking error in systems.

4. Frequency Based Learning Control Algorithms

Learning controllers are developed here for linear systems using a frequency domain formulation, which provides simplicity and additional insight compared to time domain methods. The development is in the discrete frequency domain as opposed to prior frequency based learning controller designs that have been in the continuous frequency domain. The discrete formulation avoids approximations involved in applying a continuous time theory to digital systems. A unifying mathematical formulation is developed that gives the true condition required for convergence of the learning process. This condition and the design methods are extended to the use of zero-phase filters that limit learning to a certain bandwidth of interest.

Reference [7] demonstrates how very simple learning controllers that are easy to implement can be used to improve robot tracking accuracy by more than two orders of magnitude in a few repetitions. These experiments show the effectiveness of learning control concepts for improving high speed tracking accuracy by a large margin, and doing so with minimal knowledge about the system dynamics, and doing so very quickly and easily. Reference [5] investigates several issues in the application of the learning or repetitive control concepts to belt drive systems which is a color copy machine in Xerox. This class of problems include: studying the ability of the method to address a large portion of the error frequencies present by using a properly chosen learning period; the influence of the learning process on frequency components in the error at frequencies other than those being addressed; and the practical issues of using noncausal zero-phase low-pass filtering in the repetitive control problem in order to aid in insuring stability of the learning process. These experiments indicate that a proper implementation of learning control could very significantly improve the velocity error in rolling operations, using the simple learning control approach.

5. Use of Neural Networks in Learning Control

A neural network is an information processing system that is non-algorithmic, non-digital, and intensely parallel. It is a system with inputs and outputs and is composed of many simple and similar processing elements. The processing elements each have a number of internal parameters called weights. Changing the weights of an element will alter the behavior of the element and therefore, will also alter the behavior of the whole network. The goal here is to choose the weights of the network, self-learning process. The use of neural networks to control unknown non-linear systems has been motivated by their capability of very complex mapping between their outputs and inputs and their potentially high speed in computing this mapping due to their massive parallelism. The neural network is a natural candidate in the area of identification and control of both linear and non-linear systems. The neural networks are typically implemented in the adaptive form, and thus possess similar attributes of adaptive control as in [6].

6. Decentralized Learning Control

As discussed above, the usual robot feedback controllers operate in a decentralized manner in which each link is controlled without knowledge of the actions performed by other links. When each of these decentralized controllers employs an independent learning controller, one obtains a decentralized learning control system. Reference [22] studies the conditions for convergence of the decentralized learning control system to zero tracking error when integral control based learning is used in each of the decentralized systems. A surprisingly strong result is obtained saying that, the decentralized learning control applied to the coupled dynamic system is stable and converges to zero tracking error for sufficiently small sample time, provided that learning controls for each subsystem with all dynamic coupling removed are stable for all sufficiently small sample time. For linear systems, this result applies no matter how large the dynamic coupling is between the systems.

Reference [23] presents a number of algorithms for indirect decentralized learning control, related to the indirect learning control of [12]. Guaranteed convergence can be obtained for sufficiently small sample time. In addition, it is shown that in a noise free environment, if the maximum number of repetitions needed for any subsystem to obtain zero tracking error, then the decentralized indirect learning control can accomplish zero tracking error in this same number of repetitions.

Conclusions

In this paper an overview is presented of a rather comprehensive mathematical theory of learning control that has been developed by the authors [1-24]. The field of learning control has been developed to formulate controllers that achieve zero-tracking error at each time step of a process including transients parts and the presence of disturbances, with a minimal knowledge about the system involved. This might seem to much to ask for, but the goal is attained by using past experiences to improve performance. This is the key property that distinguishes learning control from conventional controllers. The same process is repeated continuously and each time the input signal is updated based on the feedback information of previous trials. Eventually, the input signal is modified to the point that when applied to the system it produces the desired output. A learning control law has been presented that is well-behaved and converges fast, producing a monotonic and geometric reduction in error including transients.

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