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Immunological mechanism inspired iterative learning control ☆

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ABSTRACT

In this paper, an iterative learning control method based on the recognition, response, and memory mechanism of immune system (IRRM-ILC) is proposed. According to the immunological recognition, response, and memory processes, several new components are designed and then combined with the conventional ILC. The proposed IRRM-ILC controller can mitigate the disturbances by detecting, identifying, and memorizing them. Thereby, the anti-disturbance ability of the conventional ILC is enhanced. The proposed IRRM-ILC is applied to a temperature control system of wet spinning coagulation process. Simulation results with random and repeated disturbances demonstrate that the IRRM-ILC has a better performance than the conventional ILC in terms of convergence and stability in the presence of disturbances.

1. Introduction

Learning is a process for an intelligent system to acquire knowledge or experience on the basis of its perception and cognition of the environment and then to act on the environment referring the knowledge/experience so as to improve its behavior performance the next time [1]. Iterative learning control (ILC) is a well-known advanced control method which utilizes some basic learning principles to achieve control of the plant. The ILC is a recursive algorithm that utilizes the tracking discrepancy/error of the system output from the desired trajectory and iteratively updates its current control command so as to generate an upgraded control command for the next operation when the system operates repetitively over a fixed finite time interval [2]. It is based on the notion that the performance of a system that executes the same task multiple times can be improved by learning from previous executions (batches, trials, iterations, passes) [3]. It is a data-driven method that uses only the plant's data instead of any knowledge of the plant's model. In many systems such as chemical processes, robot motions, and servo systems, the same tasks are carried out repeatedly over a fixed time interval. The ILC is able to gradually improve its control performance by learning from previous actions [4].

Since introduced by Arimoto et al. in 1984 [2], the ILC has drawn much attention from researchers and has been successfully applied in practices, see [1,3–6] and references therein. It is highly attractive in that the ILC not only requires little prior knowledge of the control system but also controls the plant effectively.

Traditionally, the applications of the ILC have been focusing on those control systems where a single, repeated operation is performed. This focus includes many industrial systems in manufacturing, robotic system, and chemical engineering areas, where mass production on assembly lines entails repetition. The ILC has been successfully applied to industrial robots [7], industrial batch process control [8], injection-molding machines [9,10], aluminum extruders [11], trajectory tracking [12], induction motors [13], chain conveyor systems [14], complex stochastic systems [15], nonlinear system [16], rapid thermal processing [17,18], and semibatch chemical reactors [19].

However, the capacity of resisting disturbance of the ILC needs further improvement [3]. According to [20], the ILC is an integrator along the iterative axis. All the system responses are integrated by the ILC. This means, all the signals including both systems' useful knowledge and disturbing signals are "learned" by the ILC. Thus, a disturbing signal will be continuously amplified along the iterative axis as a snowball effect. Up to present, there are many research findings on improving the ILC's capacity of disturbance resisting. Most solutions propose a similar kind of ways which adds a filter to the ILC, such as second-order Butterworth filter [20], zero-phase filter [21], or more simply, a forgetting factor. However, for these

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filter-adding solutions, the filters would filter away certain signals no matter they are useful or disturbing signals.

The main purpose of this paper is to propose a new method to improve the anti-interference ability of the ILC, which is called the IRRM-ILC. The original idea of this new method is to design an intelligent filter which can filter away disturbing signals while not losing system knowledge. The method is achieved by adopting immunological recognition, response, and memory mechanisms, which can separate the useful signals from the disturbing ones while filtering

When it comes to intelligent system with autonomous recognition and differential reaction, the immune system is one of the most typical and effective systems. The immune system can recognize and distinguish the self and non-self organisms of the body, and then eliminate the non-self part successfully. Furthermore, the immune system is also a learning-type system via generating memory cells. Thus, an intelligent algorithm which imitates the recognition, response, and memory mechanisms of immune system will be a feasible method to improve the anti-interference ability of the ILC. Liu et al. [22] proposed a novel reinforcement learning intelligent controller (RLIC) based on immune system mechanism. The method imitated the primary-secondary response of the immune system, which could be regarded as a process of reinforcement learning with memory. It demonstrated that system response ability and stability of the RLIC are better than those of the conventional PID controller.

The main contributions of this paper are as follows. The proposed IRRM-ILC shares the same immunological mechanism of immune system with the RLIC but with different algorithms. The IRRM-ILC is a complementary algorithm that specifically for the ILC considering its data-driven feature. The proposed IRRM-ILC is applied to a temperature control system of wet spinning coagulation processes with a better performance than the conventional ILC.

The paper is organized as follows. In Section 2, the principle and mathematical model of the ILC and immunological mechanism are introduced in details. In Section 3, the structure and steps of the IRRM-ILC method is presented, together with the algorithms of each component of the IRRM-ILC. In Section 4, an application example is given with its simulation results and analysis. Section 5 concludes the whole paper.

2. Theoretical Foundations

2.1. The classical iterative learning control algorithm

In this section, the classical ILC algorithm under the continuous time is briefly summarized. The algorithm block diagram is shown in Fig. 1.

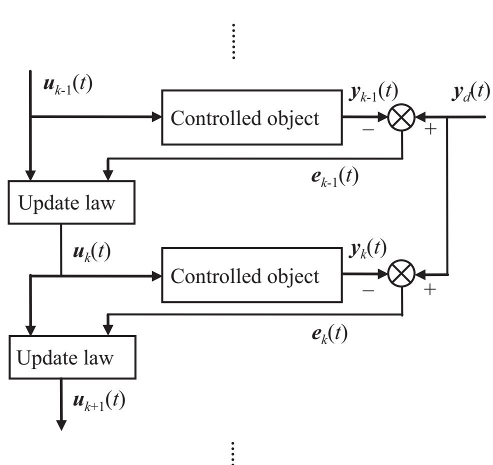

Fig. 1. Block diagram of the basic ILC algorithm.

The ILC aims at perfectly tracking the desired output of the system without using any information of the state space. Consider the following linear continuous-time system:

$$\dot{\boldsymbol{x}}_k(t) = \boldsymbol{f}(\boldsymbol{x}_k(t), \boldsymbol{u}_k(t), t),$$

$$\boldsymbol{y}_k(t) = \boldsymbol{g}(\boldsymbol{x}_k(t), \boldsymbol{u}_k(t), t),$$

where $\boldsymbol{x} \in \boldsymbol{R}^{n\times 1}, \boldsymbol{y} \in \boldsymbol{R}^{m\times 1}, \boldsymbol{u} \in \boldsymbol{R}^{r\times 1}$. $\boldsymbol{f}, \boldsymbol{g}$ are the continuous functions with respect to the state variable $\boldsymbol{x}$, control input $\boldsymbol{u}$, and time variable $\boldsymbol{t}$, whose structure and parameters are unknown. The subscript k indicates the k-th iteration.

The control error is

$$\boldsymbol{e}_k(t) = \boldsymbol{y}_d(t) - \boldsymbol{y}_k(t),$$

where $\boldsymbol{y}_d$ is the desired output. The control task is to servo $\boldsymbol{y}_k$ to track $\boldsymbol{y}_d$, and make $\boldsymbol{e}_k(t) \to 0$ on a fixed interval $t \in [0, T]$ along with the iteration k increasing.

For the classical ILC, the following basic postulates are required, although in recent researches some of these postulations have been relaxed [23].

1) Every trial (pass, cycle, batch, iteration, repetition) ends in a fixed time of duration.
2) Repetition of the initial setting is satisfied. That is, the initial state $\boldsymbol{x}_k(0)$ of the objective system can be set to the same point at the beginning of each iteration.
3) Invariance of the system dynamics is ensured throughout the repetition.
4) Output $\boldsymbol{y}_k(t)$ is measured in a deterministic way.
5) The system dynamics are deterministic.

Under these assumptions, the classical ILC with open-loop learning method is given by:

$$\boldsymbol{u}_{k+1}(t) = \boldsymbol{L}(\boldsymbol{u}_k(t), \boldsymbol{e}_k(t)), \tag{1}$$

where $\boldsymbol{L}$ is a linear or nonlinear operator. This is the core idea of the ILC. The control input of the $(k+1)-$th iteration is calculated by the control input of the k-th iteration and its control error.

Based on this open-loop learning method, considering the closed-loop control error, a more robust learning method is given by:

$$\boldsymbol{u}_{k+1}(t) = \boldsymbol{L}(\boldsymbol{u}_k(t), \boldsymbol{e}_k(t), \boldsymbol{e}_{k+1}(t)), \tag{2}$$

where, $\boldsymbol{L}$ is the update law of the learning process. There are varieties of different research on this update law. The most original and typical one is called "Arimoto-type" update law [2], which is given by:

$$\boldsymbol{u}_{k+1} = \boldsymbol{u}_k + \Gamma \dot{\boldsymbol{e}}_k, \tag{3}$$

where Γ is a diagonal learning gain matrix.

Starting from this classical Arimoto-type ILC algorithm, a number of more general expressions have been developed. For instance, in [24], a "PID-like" update law was given as:

$$\boldsymbol{u}_{k+1} = \boldsymbol{u}_k + \Phi \boldsymbol{e}_k + \Psi \int \boldsymbol{e}_k dt + \Gamma \dot{\boldsymbol{e}}_k, \tag{4}$$

where Φ,Ψ, and Γ are learning gain matrices.

These algorithms highlighted the perspective that the ILC is a kind of control law which utilized all available past information for the control of a periodic system. The next trial's control input is calculated from the previous trial's control input and transient errors.

2.2. Adaptive immune system mechanism

The immune system is a system of biological structures and processes within an organism that protects against disease.

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