Comments on United States Patent 3,555,252 – "*Learning Control of Actuators in Control Systems*" [1]

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Abstract

This paper discussed in detail the basic ideas behind United States Patent 3,555,252 – "*Learning Control of Actuators in Control Systems*" which was filed in May 11, 1967. It is shown that these ideas are equivalent to Iterative Learning Control (ILC) in general sense. New possible research topics motivated by United States Patent 3,555,252 are briefly discussed.

Key words: Learning control (LC); iterative learning control (ILC); curve identification; rule-based updating law.

1 Introduction

Does every patent contain sufficient technical information to deserve publication at least to the level of a journal article? The answer to this question is "**clearly no**" according to [1]. It was found in [1] that patents are a rich source in technical information of interest to control systems engineers and may suggest new ideas and application possibilities. Nowadays, online information is ubiquitous and pervasive. From many of the web sites suggested in [2], many patents can be searched using the key words "iterative learning control (ILC)". This kind of web searching is not only useful for knowing the already patented techniques so that we would not "re-invent the wheels" but also efficient in obtaining stimulating ideas or motivations for further investigation and more rigor analysis. An initial patent searching effort in "iterative learning control" research [1] shows that there have been a lot of industrial practice in applying "iterative learning control" or the idea very close to it.

It is a common feeling that the academic people are easier to fall into the situation of the "lack of (engineering) motivations". This is due to the so-called "*Theorey/Practice Gap*"[3]. This gap is also embodied in some "control humors" [2] previously published in `IEEE Control Systems Magazine`. Bernstein D. S. presented 18 hints on bridging the theory/practice gap [3]. The 19th hint may be reading the patents which at least could bring in some "(engineering) motivations" to academia. It is true that instead of pushing the industry people to digest and apply the ideas from academia, the academic people should also learn from the industry. At the higher level of abstraction, one of the easier ways is to do patent searching. Based on the above thinking, the major attempt of this paper is trying to discuss in detail the basic ideas behind United States Patent 3,555,252 which was filed in May 11, 1967. It is shown that these ideas are equivalent to Iterative Learning Control (ILC) in general sense. New possible research topics motivated by United States Patent 3,555,252 are briefly discussed. It is stressed that the rule-based learning idea is widely practiced in control systems in industry.

This paper is organized as follows. In Sec. 2, brief descriptions on Iterative Learning Control[4] and United States Patent 3,555,252[5] are presented. Sec. 3 detailizes the rule-based learning law disclosed

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[1] The research work of Professor Kevin L. Moore (E-mail: `moorek@ece.usu.edu`) was conducted in part under the U.S. Army Tank-Automotive and Armaments Command (TACOM) Intelligent Mobility Program (agreement No. DAAE07-98-3-0023). Corresponding author: Dr YangQuan Chen. URL: `http://www.crosswinds.net/~yqchen`

[1] `http://cicserver.ee.nus.edu.sg/~ilc/ILC/ilc_patents/`

[2] `http://cicserver.ee.nus.edu.sg/~ilc/control/humor/`

in [5] with un-addressed issues given in Sec. 4. Sec. 5 concludes this paper with some concluding remarks.

2 Iterative Learning Control and United States Patent 3,555,252

This section presents a brief yet general introduction to ILC and then describes United States Patent 3,555,252 in technically plain language.

2.1 Iterative Learning Control

The term ‘iterative learning control’ (ILC) was coined by Arimoto and his associates [4] for a better control of systems performing repetitive tasks. Intuitively, one can find that learning is a *bridge* between *knowledge* and *experience*. Roughly speaking, the purpose of introducing the ILC method is to utilize the system repetitiveness as *experience* to improve the system control performance even under incomplete *knowledge* of the system to be controlled. Based on Arimoto’s formulation[4], the mathematical description of ILC follows.

- ***The dynamic system and its control task:*** A general nonlinear dynamic system is considered. The system is controlled to track a given desired output $y_d(t)$ over a fixed time interval. The system is operated repeatedly and the state equation at the k-th repetition is described as follows:

  $$\left\{ \begin{array}{lcl} \dot{x}_k(t) & = & f(x_k(t), u_k(t)) \\ y_k(t) & = & g(x_k(t), u_k(t)) \end{array} \right. \qquad (1)$$

  where $t \in [0, T]$; $x_k(t), y_k(t)$ and $u_k(t)$ are state, output and control variables respectively. Only the output $y_k(t)$ is assumed to be measurable and the tracking error at the k-th iteration is denoted by $e_k(t) \overset{\triangle}{=} y_d(t) - y_k(t)$.

- ***Six Postulates:***
  - **P1**. Every cycle (pass, trial, batch, iteration, repetition) ends in a fixed time of duration $T > 0$.
  - **P2**. A desired output $y_d(t)$ is given *a priori* over $[0, T]$.
  - **P3**. Repetition of the initial setting is satisfied, that is, the initial state $x_k(0)$ of the objective system can be set the same at the beginning of each iteration: $x_k(0) = x^0$, for $k = 1, 2, \cdots$.
  - **P4**. Invariance of the system dynamics is ensured throughout these repeated iterations.
  - **P5**. Every output $y_k(t)$ can be measured and therefore the tracking error signal, $e_k(t) = y_d(t) - y_k(t)$, can be utilized in the construction of the next input $u_{k+1}(t)$.
  - **P6**. The system dynamics are invertible, that is, for a given desired output $y_d(t)$ with a piecewise continuous derivative, there exists a unique input $u_d(t)$ that drives the system to produce the output $y_d(t)$.

- ***Controller design task:*** The controller design task is to find a recursive control law

  $$u_{k+1}(t) = \mathcal{F}(u_k(t), e_k(t)) \qquad (2)$$

  such that $e_k(t)$ vanishes as k tends to infinity.

The simpler the recursive form $\mathcal{F}(\cdot, \cdot)$, the better it is for practical implementation of the iterative learning control law, as long as the convergence is assured and the convergence speed is satisfactory. The above set of postulates reflects the program learning and generation for the acquisition of various kinds of fast but skilled movements. Physiology suggests that ideal or desired pattern of motion must be acquired through a succession of trainings.

In practice, the ILC should be taken as an addition to the existing conventional controller. When analyzing the property of the ILC, considerations should be taken both in the time axis and in the repetition number direction, which is in essence in the category of the 2-D system theory. However, as the repetitive task is to be executed in a fixed finite time interval, more attentions should actually be paid in the repetition axis in the analysis of the iterative learning control property.

Detailed literature reviews on ILC research can be found in [9, 10]. Most of the existing work has focused on the *analysis* issue of ILC schemes. However, the convergence conditions found in the literature are typically not sufficient for actual ILC applications. Therefore, in recent years increasing efforts have been made on the *design* issue of ILC. These can be observed from the latest books [11, 10] and the dedicated ILC web server [12]. A recent survey on ILC *design* issue [13] has documented various practically tested design schemes mainly for robotic manipulators. From the following discussions on the basic ideas behind United States Patent 3,555,252, it is shown that the “iterative learning” idea was effectively practiced in early industry.

2.2 United States Patent 3,555,252

General Information: United States Patent 3,555,252 by Murray Garden was filed in May 11, 1967 and patented in Jan. 12, 1971[5] which had 17 claims and 12 drawing figures. It perhaps is the first patent which explicitly used the word “*learning control*”. In [5], M. Garden disclosed a learning control technique which learns the characteristics of actuators, such as electric drive units, and provides actuator signals based on them. The command signal, which is related to the actuator characteristic, and from which the actuator signal is derived, is stored in the computer memory and is modified by an amount related to a function of the error between the actual movement and the desired movement of the actuator. A specific application of learning control to both electric drive units and pneumatic actuators is described [5]. Two academic journal papers in 1960s, [6] and [7] were cited as background of the invention.

Technical Summary: This invention is directed to a learning control technique which learns the characteristics of actuators, or of variables which are responsive to actuators, or of composites of actuators and variables responsive to actuators.

Learning control is applicable to actuators that are operated by *discontinuous time duration signals*. The electric drive unit and the solenoid valve-operated pneumatic actuator fall in this category. The former is operated by controlling the closure time of a switch that applies electric power to the motor while the latter is operated by controlling the open time of a valve that applies an air pressure source to or releases air pressure from a pneumatic actuator.

Learning control operates as follows. A demand for valve position correction is received by the learning control system. This system derives from a table of command signals, stored in memory, the time duration that power is to be applied to the actuator to produce the desired travel. The pulse width is applied and, after enough time has elapsed to allow the actuator to come to rest, the resultant travel is compared with the expected travel and the table of command signals, which will be referred to as the learning table, learns the pulse width versus travel characteristic of the actuator and adapts to any changes regardless of their cause, providing automatic compensation for these changing conditions.

A number of separate actuator signals derived from the stored table may be applied to the actuator in sequence to obtain the desired motion. The table from which such a sequence is obtained is corrected by an amount related to the difference between the total travel that results and the expected travel. This procedure may give better performance when hysteresis or backlash is present in the actuator.

Position control of an electric drive unit is difficult because it coasts by a large amount after power is removed. Thus, when the drive unit is placed in a feedback loop, hunting will occur unless an appreciable dead band is provided. This comes about since the feedback loop compares the desired position with actual position and terminates power to the drive unit when the position error is zero while the motor continues to move, resulting in an error of opposite polarity. One simple method to prevent this hunting process is to decrease the sensitivity of the feedback loop so that the error resulting from the coast does not cause power to be re-applied. This result is a deadband which frequently would be greater than tolerable.

Other methods of preventing hunting without causing excessive dead band have in common the need for tuning for the prevailing set of conditions such as load, line voltage, grease viscosity, etc. Learning control provides automatic compensation for changes in these environmental factors.

Learning control can provide a position resolution which is equal to the resolution of the valve position measurement since the entries in the learning table are computed from measurements of valve position. This had been obtained experimentally with a measurement system that had a resolution of 0.02% of full travel. Again, the resolution was maintained despite changing conditions such as changes in load, which have a large effect on coast.

Block Diagram: An block diagram shown in Fig. 1 best illustrates the basic principle of the proposed learning control method. The dashed box **4** is the digital computer. For process **1a**, its process controller **4a** may be a simple `PID` controller. `DCOR`, the output of **4a**, is the *desired correction signal* which is used to select a command signal from the table of command signals **6a**. From the command signal the actuator signal generator **12a** derives an actuator signal which will move the actuator **2a** to its desired position. This actuator signal is a time duration signal specifying the time duration that power is applied to the actuator **2a**.

Learning table correction is by applying the difference of `DCOR` and the actual correction signal `ACOR`. `ACOR` is the output from the difference circuit **7a** which generates the difference between the initial position of the controlled variable at the beginning of a *cycle*, denoted by `IPOS`, and the resultant position of the controlled variable at the end of the cycle. Note that `ACOR` is the actual correction signal obtained in response to a particular actuator signal. The "learner" **9a** modifies the command signals from the table of command signals **6a**. Also noted is that **10a**, the controlled variable may be applied to the "learner" **9a**. The "learner" may update the command signals in the table **6a** in a particular manner depending upon the level of operation of the process. Furthermore, **13a**, allows different tables of command signals depending upon the level of operation of the process. Finally, **11a**, provides a means to update the learning table(s) differently according to the level of the `DCOR`.

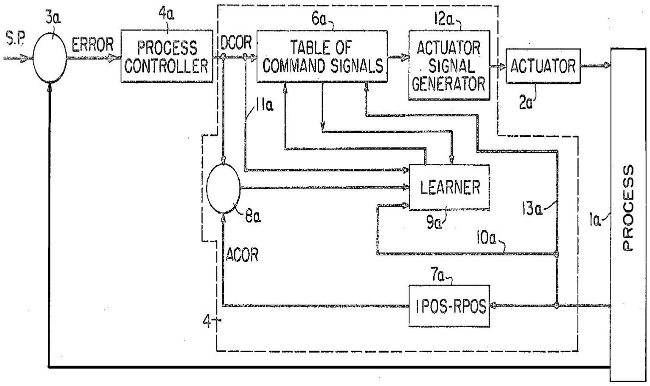

Figure 1: Block Diagram of Learning Control Concept in United States Patent 3,555,252.

3 Mathematical Formulation - Rule-based Learning Updating Law

In plain control language, the control task in this patent [5] is actually an "*aiming control*" problem with a focus on reducing the final positioning error to the sensor resolution. The difficulty here is the control authority which is limited to finite incremental 'pulse width (`PW`)' control. Taking the solenoid valve-operated pneumatic actuator as an example, the valve travel is only one directional. By applying successive finite number of `PW` controls, the valve reaches to its desired travel with very high precision, without any overshoot. The steady state error can be largely reduced by using integral action in the process controller **4a**. When the desired position (`DPOS`) is 50% of the full travel (`FT`), it is easy to achieve 1%-5%`FT` positioning error by the conventional controller **4a** especially when integral action is included in **4a**. However, to further reduce the steady state (positioning) error, the conventional controller **4a** will hit its capability limit. To further reduce the positioning error beyond 1%`FT`, nonlinear effects will dominate. The actuator characteristic curve (`PW` vs. `DPOS` in %`FT`) when `DPOS` $\leq$ 1%`FT` will be highly nonlinear. The curve changes w.r.t. unknown external loads and other uncertain factors like friction etc. Garden proposed a rule based iterative learning feedforward scheme to reduce the error to the sensor resolution [5]. The mathematical description hidden in the lawyer-complicated sentences [5] is explored as presented in the following.

At the $(i+1)$-th cycle, the actual system output is denoted by y_{i+1} (`RPOS`), which is started from y_i ($\texttt{IPOS}_{i+1}$) under `PW` control of $\texttt{PW}_i$. The output of the process controller **4a** ($\texttt{DCOR}_i$) in Fig. 1 is that

$$e_d^i \triangleq C_p(y_d - y_i) \tag{3}$$

where y_d (`DPOS`) is the desired travel to reach and C_p is the (stead-state) transfer function of **4a**. The actual positional error after the i-th cycle is $e_a^i = y_{i-1} - y_i$ ($\texttt{ACOR}_i$). Note $\texttt{IPOS}_i \triangleq \texttt{RPOS}_{i-1}$. Note that the units here are all in percent full travel (%`FT`). The iterative learning updating law for $\texttt{PW}_{i+1}$ is given by

$$\texttt{PW}_{i+1} = \texttt{PW}_i + \mathcal{L}(\texttt{DCOR}_i, \texttt{ACOR}_i) \tag{4}$$

where $\mathcal{L}$ is a learning operator which may be discontinuous. Denote e_{ad}^i the difference between the actual correction error ($\texttt{ACOR}_i$) and the desired correction error ($\texttt{DCOR}_i$) at the i-th cycle. According to [5], the updating law is rule-based, i.e.,

$$\texttt{PW}_{i+1} = \begin{cases} \texttt{PW}_i + \alpha e_{ad}^i, & \text{if } e_d^i > 1\%; \\ \texttt{PW}_i + \alpha e_{ad}^i, & \text{if } e_d^i \leq 1\% \text{ and if } e_a^i > 1\%; \\ \beta \frac{(e_d^i)^2}{e_a^i}, & \text{if } e_d^i \leq 1\% \text{ and if } e_a^i \leq 1\%; \end{cases} \tag{5}$$

where α is a learning gain known as a "constant corrective step" (`CS`) [5]; β is a proportional factor known as `PF` with `PW=PF`$\times$`DCOR`[5].

In practice, the actuator characteristic curve, $\texttt{PW}(e_a)$, is divided by a number of parts in 0%-1%, say, n parts. Then, $\texttt{PW}_{i+1}$ obtained in (5) is to be stored in the table of length n at the cell number determined by $\texttt{DCOR}_i$ (e_d^i). Similarly, if the process controller is applied alone and the positional error may be as high as 10%, segmentation in 1%-10% is also needed. Suppose there are m segments. So, the total table length is $n + m$.

Note that α and β may be segment-dependent. Choosing a set of suitable α's and β's is based on the operational experience and prior knowledge about the plant to be control. Note, however, up to now, any prior knowledge about the plant, the load and the environment was not assumed explicitly.

When the positional error is reduced to about 0.1% or less, the hysteresis will be an important nonlinear player. The learning procedure for handling hysteresis includes the following rules:

- If there is no motion resulting from a command for motion, update the learning table;
- if there is motion, but it is incorrect, update the learning table only if there has been a previous motion in response to a command for motion;

- The correction is made to the learning table representing the actuator characteristic without hysteresis if the `PW` had been formed without adding hysteresis. The correction is made to the hysteresis entry if hysteresis was added in forming the `PW`.

4 Comparisons and New Research Opportunities

4.1 Comparisons

The difference between the iterative learning method in [5] and ILC [4] lies in their control objectives. The former is for *terminal positioning with a higher accuracy from cycle to cycle* while ILC is for *asymptotic point-wise trajectory tracking control from iteration to iteration in an equal-length time interval*. However, in general, the ideas on *"iterative learning"* are similar as listed below. It is worth to note that the "*Terminal Iterative Learning Control*" proposed in [16] is actually a mix of ILC and the control task of [5].

By comparing to **P1-P6** of ILC in Sec. 2.1, we can see the following similarities between ILC and [5]: 1) The desired output is given *a priori*; 2) The plant is operated cycle after cycle; 3) The control function is to be stored in a table; 4) The output error is measurable (**P4**); and 5) The control function, or profile stored in the table is to be updated according to the above output error in last cycle.

4.2 New research opportunities

The unaddressed issues in a patent are actually a source of motivations for further investigation and rigor analysis. In [5], we found the following new opportunities:

- **Convergence analysis**. For the terminal pointing control problem, the iterative scheme (5) is very effective. However, if the learning gains (α, β) were not determined properly, the iterative process may diverge. A convergence analysis is required to find out the convergence conditions for the learning gain as well as the possible constraints on the plant and its process controller(s).
- **Using fuzzy membership function**. The possible segment-dependent learning gains (α, β) can be fuzzy membership functions.
- **Minimal number of cycles**. This is a very practical concern. How to pre-tell an estimate of the minimal number of cycles required to achieve the pre-defined accuracy?
- **Application possibilities**. Reaching control of slender flexible space manipulators with minimal vibration via iterative attempts; pH neutralization by iterative blending; iterative goal achieving of an autonomous mobile robot in a slowly changing environment $\cdots$
- **New opportunities for ODV navigation**. ODV (omni-directional vehicles) [17, 18, 19] uses multiple "smart wheels" whose speed and direction can be independently controlled through dedicated processors for each wheel. For the Utah State University (USU) Omni-Directional Vehicle (ODV) [17, 18], a novel robotic platform, the guidaance and navigation (G&N) is a challegence which inherently requires a hybrid "learning" goal-achieving strategy. The idea in US Patent 3,555,252 can be applied in the decision and control tasks of ODVs.

5 Concluding Remarks

By taking a closer look of US Patent 3,555,252 – "*Learning Control of Actuators in Control Systems*", which was filed in May 11, 1967, this paper shows that the basic ideas are equivalent to Iterative Learning Control (ILC) in general sense. New possible research topics motivated by United States Patent 3,555,252 are briefly discussed. Rule-based learning updating law calls more rigor theoretical analysis.

Acknowledgment

The authors are grateful to Dr Dou, Huifang for getting references [6] and [7] from Great Britain Library.

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