SPRINGER BRIEFS IN ELECTRICAL AND COMPUTER ENGINEERING · CONTROL, AUTOMATION AND ROBOTICS

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Springer

SpringerBriefs in Electrical and Computer Engineering

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ISSN 2191-8112 ISSN 2191-8120 (electronic)
SpringerBriefs in Electrical and Computer Engineering
ISSN 2192-6786 ISSN 2192-6794 (electronic)
SpringerBriefs in Control, Automation and Robotics
ISBN 978-1-4471-6725-9 ISBN 978-1-4471-6726-6 (eBook)
DOI 10.1007/978-1-4471-6726-6

Library of Congress Control Number: 2015941126

Springer London Heidelberg New York Dordrecht

Printed on acid-free paper

Springer-Verlag London Ltd. is part of Springer Science+Business Media (www.springer.com)

Contents

Chapter 1
Introduction

Stroke is the largest cause of disability in developed countries. One cause of a stroke is a blood clot that blocks a vessel in the brain and stops blood reaching the regions downstream. As a result some of the connecting nerve cells die and the person commonly suffers partial paralysis on one side of the body, termed hemiplegia. In the United Kingdom, as one example, approximately 50 % of people who survive a stroke require some form of rehabilitation to reduce impairment and assist with activities of daily living. Upper limb function is particularly important in regaining independence following stroke as impairments impact on daily living and well-being.

Research on rehabilitation following a stroke has consistently identified treatment intensity and goal oriented strategies as critical for successful therapeutic outcomes. The current prognosis for upper limb recovery following stroke is poor, with the literature reporting that complete recovery occurs in less than 15 % of patients with initial paralysis. Stroke is also an age-related disease, placing an increasing burden on long-term health and related resources unless improvements are made in achieving independence. Consequently there is a pressing need to improve the effectiveness of treatments.

To further maximize rehabilitation after stroke, novel therapeutic and cost-effective rehabilitation methods, or interventions, are required, which may combine different methodologies. For example, one possibility is to combine the application of assistive stimulation with robot-aided therapy and virtual reality. The premise is that this approach, supported by mobile technology, could be a major step towards enabling rehabilitation outside the hospital, where two of the major objectives are increased intensity of therapy and reduced cost.

To be accepted for use by health professionals any new method requires development of technology and clinical trials to establish feasibility. This monograph is based on a research programme that aims to combine the use of electrical stimulation, virtual reality and iterative learning control for upper-limb stroke rehabilitation. Iterative learning control was especially developed for systems, such as a gantry robot executing pick and place of objects, which repeat the same finite time task over and over again. Once each task is complete, the system resets and information generated

C.T. Freeman et al., *Iterative Learning Control for Electrical Stimulation and Stroke Rehabilitation*, SpringerBriefs in Control, Automation and Robotics, DOI 10.1007/978-1-4471-6726-6_1

during its completion is available for use in updating the control action to be applied during the next execution of the task.

The transfer of iterative learning control to rehabilitation is based on the patient making repeated attempts to complete a task, such as reaching out over a table top to an object, with electrical stimulation applied to the relevant muscle(s). As the patient attempts the task, performance is measured and the error between the supplied reference trajectory and that produced by the patient is calculated. The limb is then reset to the starting point and during this time an iterative learning control law, which makes explicit use of the error on the previous attempt, is used to adjust the level of electrical stimulation to be applied on the next attempt, where the use of previous trial error is unique to iterative learning control. If the patient is improving with each successive attempt, the level of stimulation should be reducing and the patient's voluntary effort increasing.

This monograph begins in the next chapter with a review of iterative learning control with emphasis on the particular laws used in stroke rehabilitation and pointers to the general literature. The following chapter then describes in general terms how iterative learning control can be transferred to the stroke rehabilitation domain and summarizes how health professionals assess the performance of a patient undergoing a rehabilitation programme based on repeated attempts at completion of a specified task. These assessment measures are used in the small-scale clinical trials that have supported the engineering developments.

The progress reported in this monograph is the outcome of three main research programs, which are described in successive chapters. To establish proof of concept, the first program considered movement in one plane and stimulated one muscle group (triceps) to control movement around the elbow joint. Patients tracked a moving trajectory with their hand whilst electrical stimulation was applied to assist with the movement. Following each trial, iterative learning control was used to update the electrical stimulation applied on the next trial. Results showed improvements in tracking accuracy during the sessions.

Following the successful proof of concept, the system was extended to movements in 3D space using a virtual reality tracking task. In this research, each patient's arm was supported by a robot that compensates for the effects of gravity, with electrical stimulation applied to the triceps and anterior deltoid muscle groups to control movement around elbow and shoulder joints. A clinical trial demonstrated the system's effectiveness, with improvements shown in tracking accuracy and in clinical assessment scores. The final program extended the research to include control of the hand and wrist during functional tasks. Iterative learning controlled electrical stimulation in this case is also applied to the extensors of the wrist and hand to assist with picking up and manipulating real world objects. Minimal robotic support is provided by a spring system and patient tracking is achieved using a Microsoft Kinect. The results of a clinical trial are also given.

The final chapter of this monograph gives critical overview of the results obtained and briefly discusses possible areas for future research. Other possible roles for iterative learning control in rehabilitation are also briefly discussed, e.g., the suppression of intention tremor in patients with Parkinsons disease.

Chapter 2
Iterative Learning Control—An Overview

This chapter gives the required background on iterative learning control. After introducing the defining characteristic of this form of control, attention is restricted to the laws used in the stroke rehabilitation research.

2.1 Introduction

The development of iterative learning control (ILC) emerged from industrial applications where the system involved executes the same operation many times over a fixed finite time interval. When each operation is complete, resetting to the starting location takes place and the next operation can commence immediately, or after a stoppage time. A common example is a gantry robot undertaking a pick and place operation in synchronization with a moving conveyor or assembly line. The sequence of operations is: (a) the robot collects a payload from a fixed location, (b) transfers it over a finite duration, (c) places it on the moving conveyor, (d) returns to the original location for the next payload and then (e) repeats the previous four steps for as many payloads as is required or can be transferred before it is required to stop.

To operate in pick and place mode it is necessary to supply the robot with a trajectory to follow and the task for a control law is to ensure that the robot follows the prescribed trajectory exactly or, more realistically, to within a specified tolerance. In addition to controlling its own movement and that of the payload, the control law must prevent other effects, such as disturbances and signal noise, from degrading tracking and thereby forcing it outside of the tolerance bound. If the robot begins to operate outside permissible limits, the control task is to bring it back within the specified limits as quickly as required or is physically possible. This task must be achieved without causing damage to, e.g., the sensing and actuating technologies used.

C.T. Freeman et al., *Iterative Learning Control for Electrical Stimulation and Stroke Rehabilitation*, SpringerBriefs in Control, Automation and Robotics, DOI 10.1007/978-1-4471-6726-6_2

In the ILC literature, each completion or execution of the task is described as a pass, iteration or trial, but in this monograph the latter term is exclusively used. Similarly, the finite time each trial takes to complete will be referred to as the trial length. Once a trial is finished, all data used and generated during its completion is available for use in computing the control action to be applied on the next trial. The use of such data is a form of learning and is the essence of ILC, embedding the mechanism through which performance may be improved by past experience.

The ILC mode of operation outlined above is the most common, i.e., complete a trial, reset and then repeat. This is different from repetitive control where the system continuously executes over the period of the reference signal, i.e., with no stoppage time between trials.

This chapter gives an overview of ILC, where the focus is on the algorithms that have been used to date in the technology transfer to next generation healthcare, with pointers to the literature for other design algorithms and applications. The particular area of next generation healthcare addressed is robotic-assisted upper limb stroke rehabilitation. In this context ILC is used to adjust the level of assistive stimulation applied during a treatment session where the patient attempts to re-learn a daily living task, such as reaching out to an object with the affected limb, by repeated attempts guided by a robot.

2.2 The Origins of ILC

The widely recognized starting point for ILC is Arimoto et al. (1984), which considered a simple first order linear servomechanism system for a voltage-controlled dc-servomotor. As in other areas, there is debate on the origins of ILC, for which the survey papers (Ahn et al. 2007; Bristow et al. 2006) and, in particular, Ahn et al. (2007) give coverage and relevant references. In the opening paragraphs of Arimoto et al. (1984) the analogy between ILC and human learning is drawn in the text: 'It is human to make mistakes, but it also human to learn from such experience. Is it possible to think of a way to implement such a learning ability in the automatic operation of dynamic systems?'.

The analysis in Arimoto et al. (1984) developed, using the servomotor example as a particular example, a control law applicable to systems required to track a desired reference trajectory **of a fixed trial length** T and **specified a priori**. On completion of each trial, **the system states reset** and during time taken to complete this task the **measured output** is used in the construction the next control output. The system dynamics were assumed to be **trial-invariant** and **invertible**. These distinguishing features led to the establishment of ILC as a major and ongoing area of control systems research and applications. Several of these assumptions, e.g., trial-invariant dynamics, have been relaxed in recent years but the concept of learning from experience gained over repeated trials of a task is retained.

Since it was first introduced ILC has broadened in breadth and depth, including links with established fields such as robust, adaptive and optimal control. Application areas have also expanded beyond industrial robotics and process control. In the latter area, one starting point for the literature is the survey paper Wang et al. (2009), which also considers the connections with repetitive control and run-to-run control. This chapter now proceeds to consider the ILC theory and algorithms that have found novel application in stroke rehabilitation. For consistency, discrete descriptions of the dynamics are used.

2.3 ILC for Linear Systems

When ILC is applied to discrete dynamics the notation used for a scalar or vector valued variable in this monograph is $y_k(p),\ p = 0, 1, \dots, T$. Here the nonnegative integer k is the trial number and $T \in \mathbb{N}$ denotes the number of samples on each trial, with the assumption of a constant sampling period. Suppose also that the dynamics of the system or process considered can be adequately modeled as linear and time-invariant. Then the state-space model of such a system in the ILC setting is

$$\begin{aligned} x_k(p+1) &= Ax_k(p) + Bu_k(p) \\ y_k(p) &= Cx_k(p),\ \ x_k(0) = x_0 \end{aligned} \tag{2.1}$$

where on trial k, $x_k(p) \in \mathbb{R}^n$ is the state vector, $y_k(p) \in \mathbb{R}^m$ is the output vector and $u_k(p) \in \mathbb{R}^l$ is the control input vector.

In this model it is assumed that the initial state vector does not change from trial-to-trial. The case when this assumption is not valid has also been considered in the literature. The dynamics are assumed to be disturbance-free but again this assumption can be relaxed. It also possible to write the dynamics in input-output form involving the convolution operator or take the one-sided z transform and hence analysis and design in the frequency domain is possible. To apply the z transform it is necessary to assume $T = \infty$ but in most cases the consequences of this requirement have no detrimental effects. For a more detailed analysis of cases where there are unwanted effects arising from this assumption, see the relevant references in Ahn et al. (2007), Bristow et al. (2006) and more recent work in Wallen et al. (2013).

Let $r(p) \in \mathbb{R}^m$ denote the supplied reference vector. Then the error on trial k is $e_k(p) = r(p) - y_k(p)$ and the core requirement in ILC is to construct a sequence of input functions $u_{k+1}(p),\ k \geq 0$, such that the performance achieved is gradually improved with each successive trial and after a 'sufficient' number of these the current trial error is zero or within an acceptable tolerance. Mathematically this can be stated as a convergence condition on the input and error of the form

$$\lim_{k\to\infty} ||e_k|| = 0,\ \lim_{k\to\infty} ||u_k - u_\infty|| = 0 \tag{2.2}$$

where u_∞ is termed the learned control and $||\cdot||$ denotes an appropriate norm on the underlying function space. As one possibility, let $||\cdot||_2$ denote the Euclidean norm of its argument and set $||e|| = \max_{p\in[0,T]} ||e(p)||_2$. The reason for including the requirement on the control vector is to ensure that strong emphasis on reducing