COMPUTER METHODS AND PROGRAMS IN BIOMEDICINE 128 (2016) 27–39

journal homepage: www.intl.elsevierhealth.com/journals/cmpb

Design of a heart rate controller for treadmill exercise using a recurrent fuzzy neural network

Chun-Hao Lu [a], Wei-Cheng Wang [a], Cheng-Chi Tai [a,*], Tien-Chi Chen [b]

[a] Department of Electrical Engineering, National Cheng Kung University, Tainan, Taiwan
[b] Department of Computer and Communication, Kun Shan University, Tainan, Taiwan

ARTICLE INFO

Article history:
Received 8 August 2015
Received in revised form
1 February 2016
Accepted 16 February 2016

Keywords:
Computer controlled treadmill
Recurrent fuzzy neural network
Heart rate controller
Treadmill speed and incline
Adjustable parameters
On-line learning algorithm

ABSTRACT

Background and objective: In this study, we developed a computer controlled treadmill system using a recurrent fuzzy neural network heart rate controller (RFNNHRC). Treadmill speeds and inclines were controlled by corresponding control servo motors. The RFNNHRC was used to generate the control signals to automatically control treadmill speed and incline to minimize the user heart rate deviations from a preset profile.

Methods: The RFNNHRC combines a fuzzy reasoning capability to accommodate uncertain information and an artificial recurrent neural network learning process that corrects for treadmill system nonlinearities and uncertainties. Treadmill speeds and inclines are controlled by the RFNNHRC to achieve minimal heart rate deviation from a pre-set profile using adjustable parameters and an on-line learning algorithm that provides robust performance against parameter variations. The on-line learning algorithm of RFNNHRC was developed and implemented using a dsPIC 30F4011 DSP.

Results: Application of the proposed control scheme to heart rate responses of runners resulted in smaller fluctuations than those produced by using proportional integra control, and treadmill speeds and inclines were smoother. The present experiments demonstrate improved heart rate tracking performance with the proposed control scheme.

Conclusions: The RFNNHRC scheme with adjustable parameters and an on-line learning algorithm was applied to a computer controlled treadmill system with heart rate control during treadmill exercise. Novel RFNNHRC structure and controller stability analyses were introduced. The RFNNHRC were tuned using a Lyapunov function to ensure system stability. The superior heart rate control with the proposed RFNNHRC scheme was demonstrated with various pre-set heart rates.

1. Introduction

Automated exercise testing systems are increasingly important during exercise training, rehabilitation, and cardio respiratory analyses. However, currently available treadmills that offer heart rate control have poor performance and lack mechanisms for setting desired heart rate profiles. Among heart rate systems for treadmills, proportional–integral (PI) controllers operate on simple algorithms that produce high-stability margins and high reliability when properly designed [1,2]. However, these properties of PI controllers remain

* *Corresponding author*. Tel.: +886 932708277; fax: +886 6 2712818.
E-mail address: astar2.elc@gmail.com (C.-C. Tai).
http://dx.doi.org/10.1016/j.cmpb.2016.02.009

subject to nonlinear speed characteristics of treadmill systems and vary with drive operating conditions, or are too complex to control using traditional strategies [3–10]. Cardiac diseases have a challenging problems with enormous economic impact worldwide [11–13]. A cyber-physical systems approach to pacemaker was designed that exploits the fractal properties of heart rate activity. In order to achieve adaptive tracking performance, an adaptive neural network control scheme is presented to adjust controller parameters based on its on-line learning ability [14].

Recent studies report fuzzy logic controls, adaptive controls, and neural network applications that accommodate control system nonlinearities and uncertainties [15–19]. Although fuzzy logic controls can be manipulated to compensate for system nonlinearities, successful applications are dependent on the experience of the designer. Moreover, fuzzy control rules, rule numbers, and parameter values of membership functions are difficult to select, and parameter values of the membership function cannot be adjusted on-line to provide robust performance against treadmill system nonlinearities and uncertainties. In contrast, adaptive controls automatically adjust system responses in accordance with parameter variations, but generally require reference system models that are impractical for treadmill exercise systems.

Neural networks are classified as feed-forward or recurrent according to structure [20], and it is well known that feed-forward neural networks can closely approximate any continuous function. However, feed-forward neural networks employ static mapping without the aid of delays, and fail to represent dynamic mapping. Although many previously reported feed-forward neural networks have been used to address delays and dynamic problems, these require large numbers of neurons to express dynamic responses [21]. Furthermore, weight calculations do not update quickly and function approximations are dependent on training data.

To overcome these difficulties, we propose the use of a recurrent fuzzy neural network heart rate controller with adjustable parameters and on-line learning algorithms that have potential for wide application in unknown, nonlinear or uncertain dynamic systems such as the fractal characteristics of the heart rate. Recurrent neural networks are dynamic mapping environments that display good control performance in the presence of unknown, nonlinear, uncertain and time-varying model dynamics [22,23]. Moreover, recurrent neurons have internal feedback loops and can capture dynamic system responses without requiring delayed external feedback. Hence, recurrent neural networks are better suited for dynamic systems than feed-forward neural networks [24].

When hidden neurons are too numerous, computation loads can overwhelm systems, which then become unsuitable for practical on-line applications. However, too few chosen hidden neurons lead to insufficient learning performance to achieve adequate control. To overcome this problem, we developed a novel recurrent fuzzy neural network heart rate controller (RFNNHRC) that maintains high accuracy under both of these conditions. In addition, this RFNNHRC employs local modeling and fuzzy input space partition, dynamic fuzzy rule linguistic descriptions, proper learning based structure for training examples, and parsimonious models with reduced

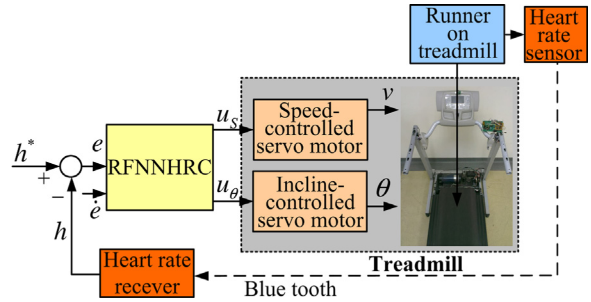

Fig. 1 – The RFNNHRC control scheme.

parametric complexity [25]. This novel combination of fuzzy reasoning capabilities and artificial recurrent neural network learning processes may accommodate information uncertainties and compensate for treadmill system nonlinearities and uncertainties. The present scheme for heart rate control was designed to control heart rate according to a pre-set heart rate profile during treadmill exercise using adjustable parameters and an on-line learning algorithm that overcomes problems of nonlinearity. Moreover, updating of connections weights in the RFNNHRC allows effective computation of variable treadmill characteristics and provides robust performance against parameter variations.

To characterize and validate the present innovation, the proposed RFNNHRC was compared with a conventional PI controller and its utility and validity were verified experimentally. The present analyses demonstrate stable performance of the present RFNNHRC under various exercise conditions.

2. Recurrent fuzzy neural network heart rate control scheme

Fig. 1 shows the RFNNHRC treadmill control scheme. Treadmill speeds and inclines were controlled by corresponding control servo motors, and the RFNNHRC was used to generate the control signals u_S and u_θ, and to automatically control treadmill speed and incline so that the difference between the users heart rate h and the preset heart rate command h^* was minimized.

2.1. *RFNNHRC structure*

As shown in Fig. 2 the RFNNHRC comprises an input layer, a membership layer, a rule layer, and an output layer.

The RFNNHRC mathematical model is summarized as follows:

2.1.1. *Input layer*

RFNNHRC inputs follow the error $e = h^* - h$ and error change $\dot{e}$, and the outputs $x^1_{e,i}$ and $x^1_{\dot{e},i}$ can be expressed as:

$$x^1_{e,i} = e, \quad i = 1, \ldots, 9 \tag{1}$$

$$x^1_{\dot{e},i} = \dot{e}, \quad i = 1, \ldots, 9 \tag{2}$$

Define the fuzzy sets PE, ZE and NE on error e, fuzzy sets PD, ZD and ND on error change $\dot{e}$, fuzzy sets PU, MU, ZU, SU and