In vitro Estimation of Cardiac Output for the TAH using an Adaptive Fuzzy Identifier

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ABSTRACT

An estimation algorithm based on training of fuzzy logic system using back-propagation is proposed, in this paper, for determining cardiac output in the TAH. The proposed estimation utilizes only a motor current waveform generated from the moving actuator of the electromechanical TAH without using any extra transducers as an information source for estimation. In in vitro tests, the resultant estimation performance was acceptable to alppy the proposed algorithm to animal experiments and further clinical applications.

I. INTRODUCTION

Since the major objective of the TAH replacement is to provide sufficient cardiac output in response to the changes of the physiological demand, successive measurements of cardiac output is an important issue in long-term use artificial heart implantation. However, owing to many problems associated with implanted transducers, chronic measurements of cardiac output in TAH implants are difficult to acquire by conventional methods. Therefore, an indirect method to estimate cardiac output from other information sources is indispensable.

Considering the reliability of transducers and the fact that circulatory systemic modeling including the TAH is fairly intricate due to the system's nonlinearity and time varying characteristics, a new method based on training of fuzzy logic system using back-propagation is proposed, in this paper, for determining cardiac output in the long-term use TAH. The proposed estimation utilizes only a motor current waveform generated from the moving actuator of the electromechanical TAH without using any extra transducers as an information source for estimation. Further, a sophisticated mathematical model of the circulatory system and the TAH is not necessary for determining cardiac output of the TAH. Based on the fuzzy logic system[7] as a universal approximator of nonlinear systems, the proposed algorithm is an on-line adaptive identifier of the circulatory system with the TAH and the adaptation procedure includes adjustments of parameters of the fuzzy logic system using a back-propagation training algorithm.

II. MATERIAL and METHODS

A. Adaptive Fuzzy Logic System for Estimation of Cardiac Output

Let the circulatory system with the TAH be the following discrete nonlinear system:

$$y(t+1)= f(y(t),\dots,y(t-n+1);u(t),\dots,u(t-m+1)) \tag{1}$$

where f is an unknown function, u and y are the input and output of the system, respectively, and n and m are arbitrary positive integers.

Control parameters of the TAH and motor current of the moving actuator consist the input vector $\underline{u}$ and cardiac output of the TAH is adopted as the output disturbed by hemodynamic variables such as atrial and arterial pressures. The objective is to identify this unknown function f and in turn to estimate cardiac output of the TAH.

A fundamental fuzzy logic system[4] as a universal approximator used in this paper is of the following form:

$$f(\underline{u})= \frac{\sum_{j=1}^{k} \omega^{j} \{\Pi_{i=1}^{n} \exp(-(\frac{u_i - c_i^j}{\sigma_i^j})^2)\}}{\sum_{j=1}^{k} \{\Pi_{i=1}^{n} \exp(-(\frac{u_i - c_i^j}{\sigma_i^j})^2)\}} \tag{2}$$

where input vector $\underline{u} = \left(u_1(t),\dots,u_n(t)\right)^T$ is a crisp point in U.

This fuzzy logic system is composed of center average defuzzifier, product-inference rule, singleton fuzzifier, and Gaussian membership function. The adjustable parameters of the above fuzzy logic system are ω_j, c_i^j, and σ_i^j. Because the back-propagation training algorithm is able to be applied to any feedforward networks and this fuzzy logic system can be represented as a feedforward network, the back-propagation method was utilized for the on-line adaptation which tunes the parameters of the fuzzy logic system, $\hat{f}$, such that the error e between the system output y and the identified output $\hat{y}$ is minimized. The adaptation algorithm is to train the parameters, ω_j, c_i^j, and σ_i^j such that the error in the following equation is minimized.

$$e = \frac{1}{2}\{f(\underline{u}) - y\}^2 \qquad (3)$$

Wang et al.[4] derived the following equations for adaptation of the parameters through an error back propagation procedure.

Let

$$G(t) = \prod_{i=1}^{n} \exp\left(-\left(\frac{u_i(t) - c_i^j(t)}{\sigma_i^j(t)}\right)^2\right) \qquad (4)$$

Then first, in order to adapt the weight of the defuzzification or ω^j,

$$\omega^j(t+1) = \omega^j(t) - \alpha\frac{f(\underline{u}) - y(t)}{\sum_{j=1}^{k} G(t)} G(t) \qquad (5)$$

where α is a constant adaptation gain.

The normalized error term, $(f(\underline{u}) - y(t)) / \sum_{j=1}^{k} G(t)$, is back-propagated to the layer of ω^j and then it is updated by eq.(5).

And secondly, for update of the center of each membership function or c_i^j,

$$c_i^j(t+1) = c_i^j(t) - \alpha\frac{f(\underline{u}) - y(t)}{\sum_{j=1}^{k} G(t)}(\omega^j(t) - f(\underline{u}))G(t)\frac{2(u_i(t) - c_i^j(t))}{\sigma_i^j(t)^2} \qquad (6)$$

Finally, to train the standard deviation of the gaussian function or σ_i^j in each membership function,

$$\sigma_i^j(t+1) = \sigma_i^j(t) - \alpha\frac{f(\underline{u}) - y(t)}{\sum_{j=1}^{k} G(t)}(\omega^j(t) - f(\underline{u}))G(t)\frac{2(u_i(t) - c_i^j(t))^2}{\sigma_i^j(t)^3} \qquad (7)$$

To apply this fuzzy logic system with parameters adaptation procedure to estimate cardiac output of the TAH, we build a difference equation for the circulatory system with the TAH to be identified. Cardiac output is changed by control parameters of the moving actuator in the TAH and affected by hemodynamic conditions, especially by changes of the aortic pressure and the inflow to the left ventricle. With the assumption that motor current reflects dominantly hemodynamic conditions and we can get a linear relationship between cardiac output and motor control parameters through mock circulatory experiments, we build a mathematical equation governing cardiac output as follows.

CO = g(linear combination of motor control parameters)
+ h(motor current) (8)

Then the problem is to identify the unknown nonlinear function *h* with the given linearized function *g* for estimating cardiac output as follows.

$\hat{CO}$ = *g(linear combination of motor control parameters)*
+ $\hat{h}$ *(motor current)* (9)

where the function $\hat{h}$ is of the form eq.(2) with k=40 and α =15.5 in the back propagation training algorithm at eqs.(5)-(7).

Initial values of the parameters ω_j, c_i^j, and σ_i^j were chosen by two or three steps trial and error through mock circulatory experiments. Training of these parameters is performed through wide range of cardiac output variation by adjustment of control variables and hemodynamic conditions, and stopped when the estimate error sum is less than an arbitrary level ε, 1% of real cardiac output in this paper. Cardiac output estimation procedure mentioned above is summarized in the following algorithm.

CARDIAC OUTPUT ESTIMATION ALGORITHM

Step 1: **Calculate the estimate error,**

$$e = CO - \hat{CO} = h - \hat{h}$$

Step 2: Calculate sum of the estimate error and check it is less than ε. If true, stop training the parameters of the fuzzy logic system. Otherwise, go to next step.

Step 3: Adjust parameters ω_j, c_i^j, and σ_i^j using eqs.(5)-(7) and calculate the estimate of cardiac output.

Before applying the on-line adaptive fuzzy identifier to estimate cardiac output of the TAH on in-vitro tests, to verify the performance of the identifier as a universal approximator, we performed numerical simulations for an arbitrary nonlinear function.

B. Numerical Simulations

In these computer simulations, we considered an arbitrary nonlinear system to be identified. The plant equation is governed by the following equations.

$$u(t) = 1.5\cos(2\pi t/110)\sin(2\pi t/25)$$

$$y(t+1) = -0.5 + \frac{y(t)y(t-1)\{y(t)+2.5\}}{1+y^2(t)+y^2(t-1)} + u(t) \tag{10}$$

We identify the nonlinear part of the plant using a series-parallel identifier modeled by the following equation.

$$\hat{y}(t+1) = \hat{f}(y(t), y(t-1)) + u(t) \tag{11}$$

where $\hat{f}(y(t), y(t-1))$ is in the form of eq.(2) with k=40.

The fuzzy logic system $\hat{f}$ with k=40 has 40x3=120 adjustable parameters, in other words, corresponding to each rule there are three adjustable parameters: ω_j, c_i^j, and σ_i^j. We simulated the fuzzy identifier in the case of α =0.5 in the back propagation algorithm. Result of the simulation is depicted in Fig. 1. The estimate of the nonlinear system output keeps track of the plant output after over 2000 steps back propagation training to the same plant input as the case of training period. Using the resultant characteristics of the fuzzy identifier on simulations, we estimated cardiac output of the TAH in in vitro mock circulatory experiments.

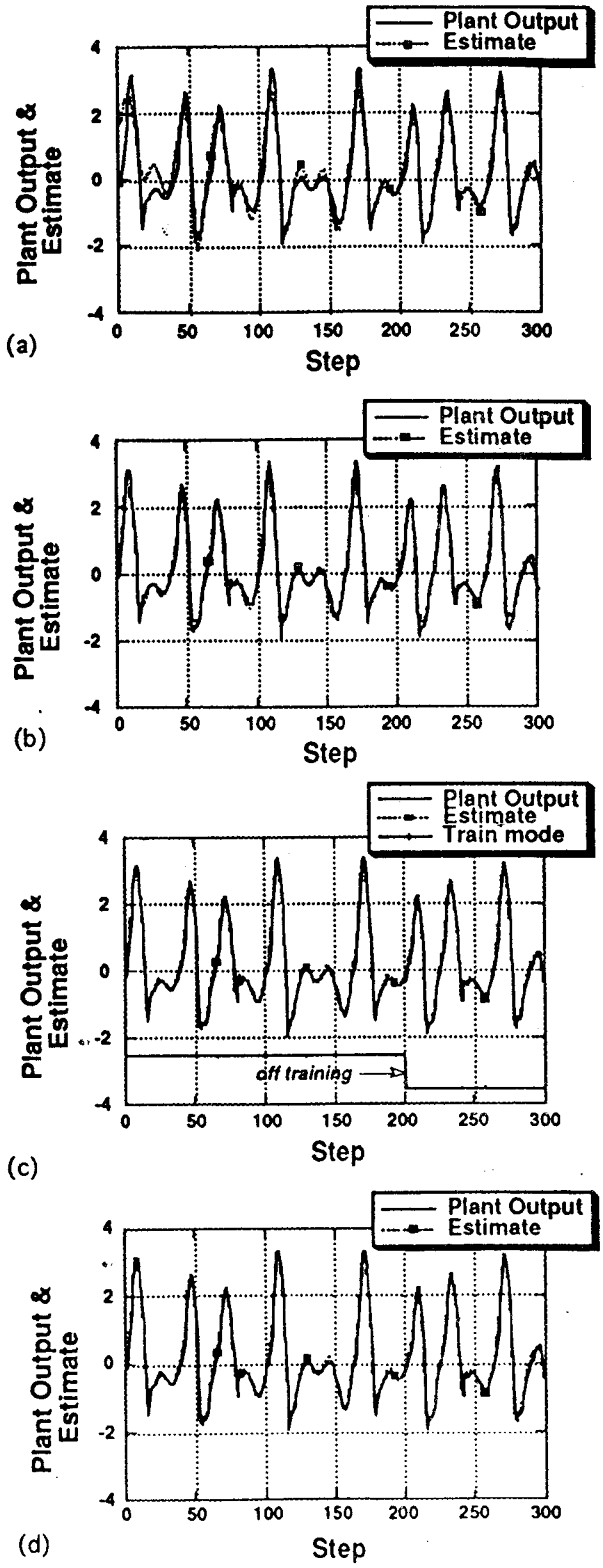

Fig. 1 Numerical Simulation Results
(a) on training, 1st section
(b) on training, 2nd section
(c) off training, after 7th section
(d) off training, off training, 10th section

C. In Vitro Experiments

A Donovan type mock circulatory system, which simulate the circulatory system of the human body, is used to evaluate the cardiac output estimation performance of the fuzzy identifer. Four chamber pressures corresponding to the aortic pressure (AoP), pulmonary arterial pressure (PAP), left (LAP) and right atrial pressure (RAP) are monitored by pressure transducers (COBE, USA). And also, the systemic flow rate, which is estimated by the fuzzy identifier, is measured by ultrasonic flowmeter (TRANSONIC T-201) at the aortic port of the TAH and converted to a digital data by an A/D converter(AD7870, Analog Device, USA). The impulsive noise of this converted digital data from the measured systemic flow is removed by a so-called order statistic filter, a kind of weighted median filter [5]. The median filter uses only rank-order information of the input data within the filter window, and discards its original temporal-order information.

In order to simulate a limited volume of atrial reservoir, 150 cc flexible polymer chambers are connected between the inflow ports of the blood pump and the circulatory system. Also, in order to simulate a bronchial circulation of human circulatory system, left atrial chamber is bypassed through a variable resistance to the aortic chamber.

III. RESULTS AND DISCUSSION

Prior to in vivo applications, the performance of the cardiac output estimation was assessed by a number of mock circulatory experiments. Through adjustments of pump rate and stroke volume of the TAH, we varied cardiac output of the TAH and trained the fuzzy identifier for about 30 minutes to estimate cardiac output under wide range of hemodynamic changes in the mock circulatory experiments. Aortic pressure varied from 60 to 150mmHg , right atrial pressure(RAP) from 0 to 15mmHg, and left atrial pressure(LAP) from 3 to 20mmHg. Fig. 2 gives real-time estimates according to wide range fluctuations of cardiac output of the TAH in the mock circulatory experiments after training the fuzzy identifier.

Besides, root mean squared error and percent error between the real value and estimate of each cardiac output are represented in Fig. 3.

As compared with computer simulational results, in vitro estimate error is relatively serious. This is because the mean value of cardiac output of the TAH is affected by not only hemodynamic changes which are partially reflected in the motor current as an input to the fuzzy identifier, but also other dynamics such as artificial valve pressure drop, compliance of the blood pump housing, various folding pattern of the blood sacs and so on. Thus other information sources as inputs to the fuzzy identifier is necessary so as to estimate more accurate cardiac output.

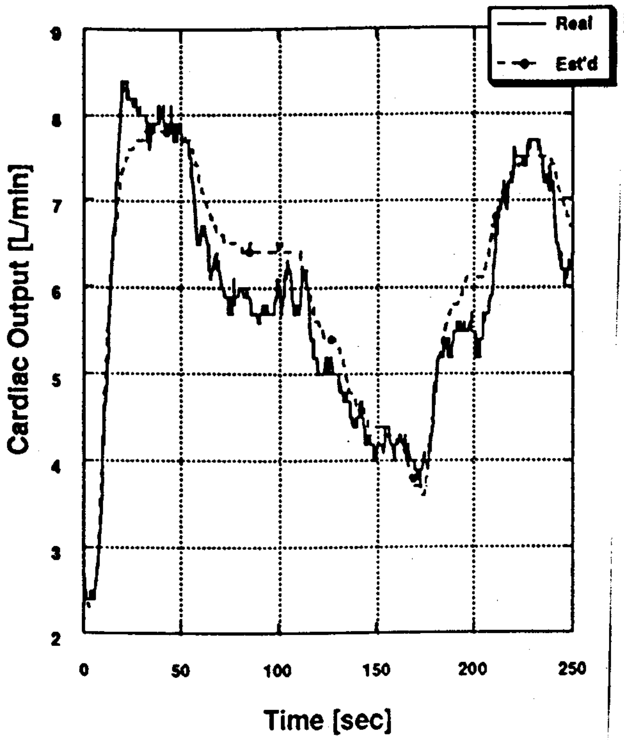

Fig. 2 Experimental Result of Cardiac Output Estimation

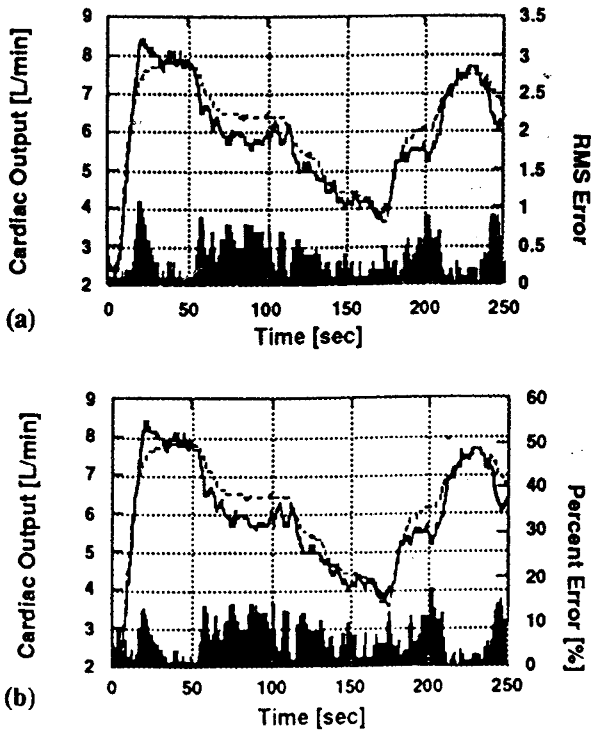

Fig. 3 Root Mean Squared(a) and Percent(b) Error of the Estimation

However, goal of the proposed estimation is to use a simple, reliable information source as the motor current. Further, generally speaking, the performance criteria for estimation of cardiac output can be set below 10 percent of estimate error. Therefore, the proposed identification algorithm is acceptable to be used in the estimation of cardiac output of the TAH and further can be applied to in vivo test.

On the other hand, while performances of the adaptive fuzzy identifier proposed by Wang et al. have been evaluated on computer simulations only, this paper gives one experimental application of the fuzzy identifier to some practical problems.

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