A Sensorless Approach to Control of a Turbodynamic Left Ventricular Assist System

Seongjin Choi, James F. Antaki, J. Robert Boston, *Member, IEEE*, and Douglas Thomas

***Abstract*—A fuzzy logic controller for a rotary, turbodynamic left ventricular assist system was developed to optimize the delivery of blood flow without inducing suction in the ventricle. The controller is based on the pulsatility in blood flow through the pump and assumes that the natural heart is still able to produce some pumping action. To avoid the use of flow transducers, which are not reliable for long term use, the controller estimates flow using a model of the assist device. The controller was tested in computer simulation, a mock circulatory system, and in animal experiments. Simulation studies suggest that the fuzzy logic controller is more robust to parameter changes than a traditional proportional-integral (PI) controller. Experimental results in animals showed that the controller is able to provide satisfactory flows at adequate perfusion pressures while avoiding suction in the left ventricle.**

***Index Terms*—Flow estimate, flow pulsatility, fuzzy control, rotary heart pump control, ventricular assist device.**

I. Introduction

CARDIOVASCULAR disease is a major health problem in the United States. Heart transplantation is an accepted method to treat severe cases of the disease [1], but the demand for donor hearts exceeds the supply. Left ventricular assist devices (LVAD) are used to support very sick patients until a donor heart can be found. The purpose of left ventricular assist is to provide sufficient cardiac output at a pressure to maintain adequate perfusion of the patient's body. This paper deals with control of a new generation of assist device, based on turbo-dynamic methods of pumping, that is being evaluated for human use.

The output of a turbo-dynamic blood pump is a steady blood flow instead of a pulsatile flow as is obtained from the natural heart. Although these devices offer several advantages over reciprocating, pulsatile blood pumps currently in use, including small size, efficiency, and reliability, they pose a more difficult control problem because of their relatively poor sensitivity to ventricular preload and high sensitivity to ventricular afterload. The limit appropriate setpoint for the pump rotational speed depends on these loads, which vary with time. The lower pump speed is determined by the requirement to maintain adequate perfusion, avoid regurgitant flow, and avoid unsatisfactory fluid dynamics [2]. The upper pump speed is limited by induction of suction in the left ventricle, which occurs when the LVAD attempts to pump more blood from the ventricle than is available. Suction can be deleterious to the myocardium, blood, and lungs [3].

The objective for control of a rotary LVAD is to provide optimal cardiac output without inducing suction in the ventricle. Control based explicitly on a flow setpoint would require at least two invasive sensors: one for venous flow and one for pump flow. Because of the poor reliability of flow transducers for long-term use, assist device designers have attempted to use pump variables to the greatest extent possible to estimate the hemodynamic state variables needed for control [3]–[5].

In many patients, the native heart continues to provide residual contractility during LVAD support, even though the amount is not sufficient to support the patient. In these cases, hemodynamic signals such as aortic pressure, left ventricle pressure, and aortic blood flow will exhibit varying degrees of pulsatility when the pump is used. Because of the pulsatile load conditions presented to the pump, the pump flow and motor drive current are also pulsatile. We have observed that, as pump speed increases and ventricular unloading occurs, the pulsatility of all these signals decreases. It reaches a minimum as suction is approached. This paper proposes a method to utilize this phenomenon to specify the setpoint for the pump speed using only pump (electrical) input signals, eliminating the need for blood pressure or flow transducers. The speed setpoint is selected so that the pulsatility in these signals is close to a minimum, as defined by a fuzzy logic algorithm.

Fuzzy logic is particularly suited for systems that are complex and show parameter uncertainty [6], [7]. The operating point error, defined as the difference between the desired or reference pulsatility and the actual pulsatility, and the change of error are used as inputs to the fuzzy logic controller. The output of the fuzzy logic controller is the speed change for the pump.

The fuzzy pulsatility controller was tested in computer simulation, using the pump model and a simple biventricular model of the cardiovascular system. The controller was implemented in real-time on a personal computer (PC), tested in-vitro in a mock circulatory system [8], and then evaluated *in vivo* with the Nimbus/UoP axial LVAD (Nimbus Medical, Rancho Cordova, CA) [9]. Section II of the paper describes the models used for the LVAD and for the computer simulation of the cardiovascular system. The fuzzy controller, including the method used to calculate the control index, is described in Section III. Section IV presents results of experiments with the computer simulation,

Manuscript received December 8, 1999; revised August 14, 2000. Manuscript received in final form December 19, 2000. Recommended by Associate Editor F. Ghorbel. This work was supported in part by the McGowan Charitable Fund and by Grant BES-9810162 from the National Science Foundation.

S. Choi and J. R. Boston are with the Department of Electrical Engineering, University of Pittsburgh, Pittsburgh, PA 15261 USA (e-mail: boston@ee.pitt.edu).

J. F. Antaki is with the Department of Surgery, McGowan Artificial Organ Center, University of Pittsburgh, Pittsburgh, PA 15261 USA (e-mail: antakamatics@yahoo.com).

D. Thomas is with Nimbus Medical, Inc., Rancho Cordova, CA 95670-6123 USA (e-mail: nimbus@pacbell.net).

Publisher Item Identifier S 1063-6536(01)03364-4.

1063–6536/01$10.00 © 2001 IEEE

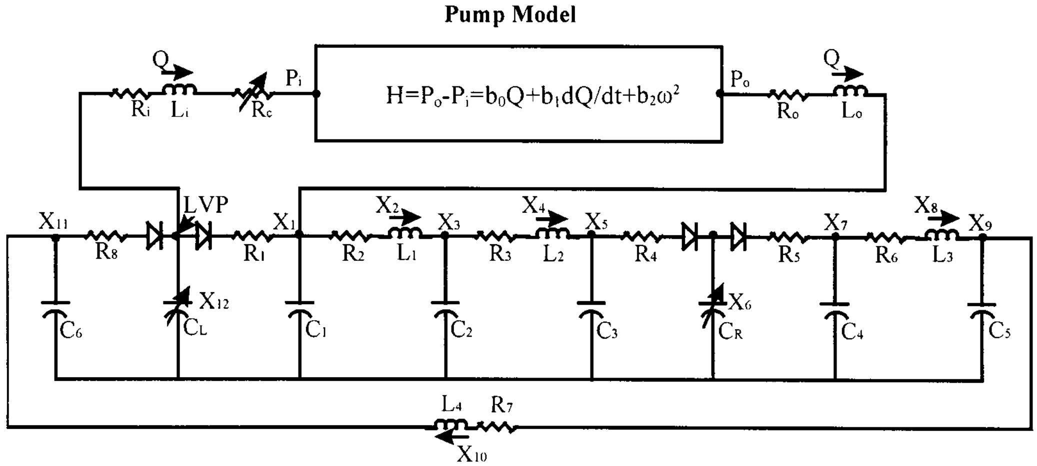


Fig. 1. Equivalent circuit of LVAS, including circulatory system and pump model.

the mock circulatory system and animals. Implications of the results are discussed in Section V.

II. Models

An empirical model of the Nimbus rotary VAD and its validation have been described previously [10]. This model was developed to estimate the pressure drop H across the pump in terms of the flow Q through the pump and the pump speed ω. The pump flow, in turn, can be estimated from the motor current and the pump speed, using

$$Q = \frac{1}{a_1\omega^2}\left(J\frac{d\omega}{dt} - \frac{3}{2}K_B I + B\omega + a_0\omega^3\right) \tag{1}$$

where

- J inertia of the rotor;
- B motor damping coefficient;
- K_B back EMF constant of the motor;
- a_0 and a_1 empirical constants that are part of the empirical model of the Nimbus rotary VAD.

The pump current and speed are both reliably provided by the Nimbus pump console. A schematic representation of the circulation combined with the model of the pump is shown in Fig. 1. The circulatory model is adapted from a model described by Avanzolini *et al.* [11]. The systemic circulation is modeled by two L-sections, each consisting of a shunt capacitor (C_1 and C_2) followed by a resistor (R_2 and R_3) and inductor (L_1 and L_2) in series. The resistors represent viscous losses in the flow, inductors represent inertance of the blood, and capacitors represent the compliance (elastance) of the blood vessels. The pulmonary circulation is modeled with the same structure (C_4, R_6, L_3, C_5, R_7, and L_4). The pumping functions of the right and left ventricles are represented by time-varying capacitances (C_L and C_R), where the capacitances represent the compliance (elasticity) of the heart chamber [12], [13]. The left and right atria are modeled as constant capacitances (C_3 and C_6), and the valves into and out of the heart are modeled as diodes with finite resistance in the forward direction. Parameter values were taken from Avanzolini *et al.* [11].

The linear elements R_i, L_i, R_o, and L_o represent the inflow and outflow cannulae that connect the VAD to the left ventricle and aorta respectively. To model the suction phenomenon, a pressure dependent resistance was modified from Schima *et al.* [14] as

$$R_c = \begin{cases} 0 & \text{if LVP} > P_{th} \\ -3.5\text{LVP} + 3.5P_{th} & \text{otherwise} \end{cases}$$

where P_{th} was chosen to be 1 mmHg.

The full model represented in Fig. 1 can be described as 13th-order system of differential equations, expressed as

$$\frac{d\mathbf{x}}{dt} = \mathbf{A}(t)\mathbf{x} + \mathbf{B}(t)u \tag{2}$$

where

$$\begin{aligned} \mathbf{x} &= [x_1, \ldots x_{12}Q]'; \\ \mathbf{A}(t) &\in \mathbf{R}_{13\times 13}; \\ \mathbf{B} &\in R_{13\times 1}; \\ u &= \omega^2. \end{aligned}$$

The model was implemented in SIMNON (Mathworks, Natick, MA) and integrated using a Runge–Kutta–Fehlberg 4/5 algorithm.

III. Controller Design

The controller was designed to adjust the pump speed to maintain a specified control index based on the pulsatility of the estimated flow. The controller includes the flow estimator described above, a pulsatility control index extractor algorithm, and a fuzzy inference system to determine the required change in pump speed for a given flow pulsatility. The first part of this section describes the algorithm used to calculate the index of the pulsatility in the flow signal, and the second part presents the structure of the fuzzy logic controller.

A. Pulsatility Control Index

As described above, the pulsatility control index is based on the cyclical variation in the hemodynamic load placed on the LVAD by residual contractility of the native heart. Even though the amount of blood flow produced by the heart is not sufficient to support the patient, it is sufficient to vary the load on the pump, causing the pump flow and motor drive current to

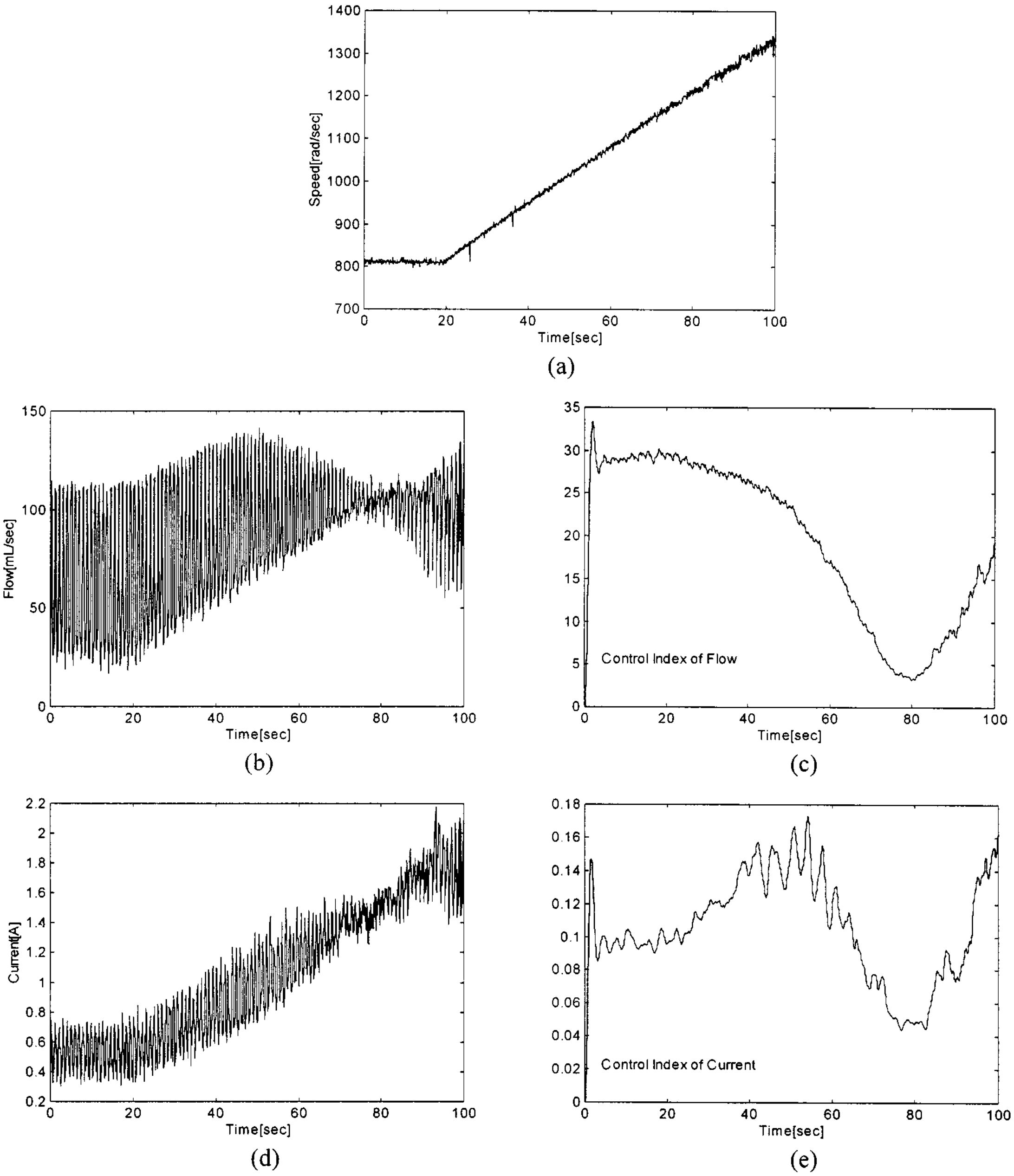


Fig. 2. (a) Pump speed, (b) pump flow, (c) pulsatility control index from pump flow, (d) pump current, (e) pulsatility control index from pump current, obtained using the simulation model in Fig. 1.

also be pulsatile. As pump speed increases and ventricular unloading occurs, the pulsatility of all these signals decreases and reaches a minimum as suction is approached. The speed setpoint is adjusted so that the pulsatility in these signals is close to the minimum.

The pulsatility control index was derived from the pump flow signal rather than the pump current because pump flow shows a clearer pulsatility minimum than pump current, as discussed below. (See Fig. 2.) The algorithm to extract the control index from the flow signal consists of the following steps. First, the signal is high-pass filtered at 0.5 Hz to eliminate baseline drift. The signal is then converted to absolute value by taking the magnitude and low-pass filtered at 0.25 Hz to estimate the amplitude of the pulsatility. The high-pass and low-pass filters are third-order Butterworth filters implemented in MATLAB (Mathworks, Natick, MA). The pulsatility control index is expressed as units of flow in mL/s. The index extractor algorithm was tested using sinusoidal signals over a range of 1 to 4 Hz and found to be within 1% of the expected value.

The behavior of the control index was studied using the simulation model over a full range of rotational speeds, as illustrated in Fig. 2. When the pump speed was increased from its minimum value of 800 rad/s to 1340 rad/s, the flow pulsatility was observed to first decrease as the speed approached 1200 rad/s and then increase as speed increased further [Fig. 2(b)]. The flow pulsatility control index showed a well-defined minimum and increased at speeds above the speed that caused suction [Fig. 2(c)]. The pulsatility control index based on motor

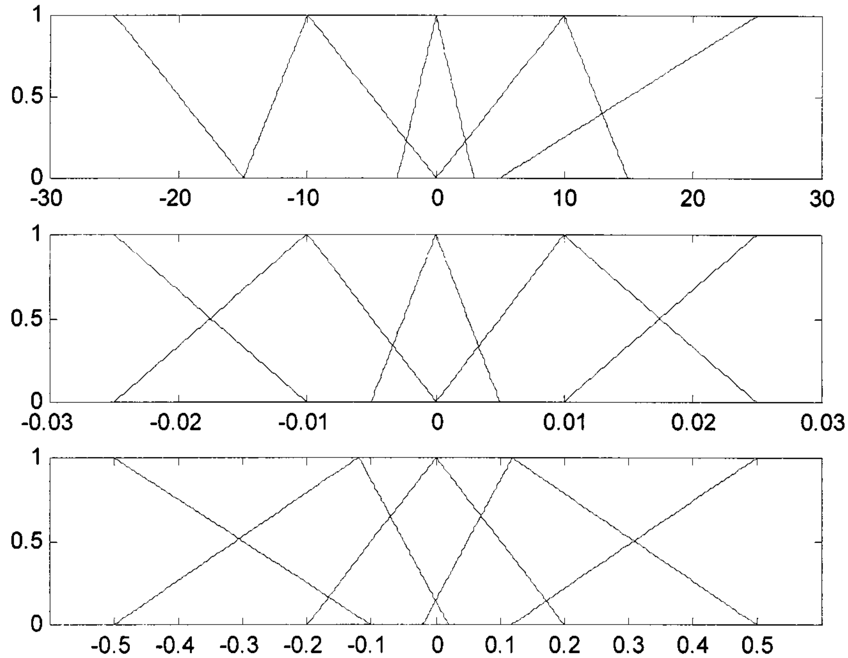


Fig. 3. Membership functions for (top) error e, (middle) change in error δe, and (bottom) speed change $\delta\omega$ used in the fuzzy controller.

current [Fig. 2(e)] is noisy and has a smaller range than the pulsatility index based on pump flow.

B. Proportional Integral-Type Fuzzy Logic Controller

A PI-type fuzzy logic controller with error and change in error as inputs was used to regulate the control index of the pump flow. The control index reference value, which represents the desired pulsatility of the flow, was chosen so that the mitral valve closes during part of the cardiac cycle, allowing the natural heart to produce some stroke volume without introducing suction. The reference pulsatility values used in this study were between 15 and 20 ml/s. The error of the control index at time sample k is defined as $e(k) = c_i(k) - c_{i\_ref}$ where $c_i(k)$ is the actual control index and c_{i_ref} is the control index reference. The change in the error of the control index is $\delta e(k) = e(k) - e(k-1)$. The output of the fuzzy logic controller is a change of speed $\delta\omega$, which is passed to the pump controller and results in an increase of rotor speed to $\omega_{sp}(k+1) = \omega_{sp}(k) + \delta\omega$.

The fuzzy logic controller includes three steps: fuzzification of inputs, fuzzy inference based on control rules, and defuzzification to obtain a crisp value for the control signal. Fuzzy sets for $e(k)$, $\delta e(k)$, and $\delta\omega$ were defined with linguistic labels of "large positive" (LP), "positive" (P), "zero" (Z), "negative" (N), and "large negative" (LN), using triangular membership functions as shown in Fig. 3. The value of each membership function is between zero and one, and input and output variables were not normalized.

The rules of the fuzzy logic controller are shown in Table I. They represent the control law that, when the pulsatility index is higher than the reference, pump speed is increased to reduce the index, and visa versa. The rules are implemented as fuzzy IF–THEN rules. The ith rule can be expressed as

$$\text{IF } e \text{ is } A_i \text{ AND } \delta e \text{ is } B_i \text{ THEN } \delta\omega \text{ is } C_i$$

where

i	ith rule;
A_i and B_i	linguistic labels of the input variables;
C_i	linguistic label of the output.

Nine discrete, uniformly-spaced values of the output (-0.5 to 0.5) were used. Using Mamdani fuzzy implication, the membership in the fuzzy output set R, as a function of speed change $\delta\omega$, is

$$\begin{aligned}\mu_R(\delta\omega) &= \max_i (\mu_{R_i}) \\ &= \max_i (\min(\min(\mu_{A_i}(e), \mu_{B_i}(\delta e)), \mu_{C_i}(\delta\omega)) \\ &= \max_i (\min(\mu_{A_i}(e), \mu_{B_i}(\delta e), \mu_{C_i}(\delta\omega))) \end{aligned} \tag{3}$$

where $i = 1, N$, and the number of rules, $N = 25$. μ_X represents membership in fuzzy set X. The min functions are evaluated for each of the rules and the max function is taken over all 25 rules.

Defuzzification to obtain a crisp change of speed to apply to the pump is implemented by the discrete center of area (COA) method

$$\delta\omega = \frac{\sum_{j=1}^{n} \mu_R(\delta\omega_j)\delta\omega_j}{\sum_{j=1}^{n} \mu_R(\delta\omega_j)}. \tag{4}$$

In (3), i ranges from 1 to 25 (the total number of rules) and in (4), j ranges from 1 to 9 (the number of output values).

IV. Results

Computer simulations were run to demonstrate that the controller responded appropriately to cardiovascular changes. Comparisons with conventional PI control were also obtained.

TABLE I
REPRESENTATION OF THE FUZZY RULES USED IN THE FUZZY CONTROLLER. SYMBOLS ARE: e—ERROR BETWEEN ACTUAL PULSUALITY VALUE AND REFERENCE VALUE; δe—CHANGE IN ERROR; LP—LARGE POSITIVE; LN—LARGE NEGATIVE; N—NEGATIVE; Z—ZERO; P—POSITIVE

	δe				
e	LP	P	Z	N	LN
LP	LP	LP	LP	P	Z
P	LP	P	P	Z	N
Z	P	P	Z	N	N
N	P	Z	N	N	LN
LN	Z	N	LN	LN	LN

Finally, results with a real-time implementation of the controller were obtained in a mock circulatory system and in animal studies.

A. Results of Simulation Study

Computer simulation studies were performed to evaluate the response of the fuzzy controller algorithm to changes in preload and afterload on the ventricle. Two conditions were simulated by adjusting the values of resistor R_7 (pulmonary vascular resistance, PVR) and resistor R_3 (systemic vascular resistance, SVR) of the model. Condition 1 simulated a change in afterload by increasing SVR from 1.0 mmHg s/mL to 1.2 mmHg s/mL with PVR constant at 0.1 mmHg s/mL. Condition 2 simulated a change in preload by changing PVR from 0.1 mmHg s/mL to 0.02 mmHg s/mL at SVR $= 1.0$ mmHg s/mL. The maximum contractility of the left ventricle (C_L) was set to 0.6 mmHg/mL(1/3 normal) to represent a weak heart.

A pulsatility control index reference of 15 mL/s was used. In the simulations, the pump flow estimated from the pump model is identical to the simulated flow, that is, there is no estimation error. The initial pump speed was set to 838 rad/s, the minimal pump speed used in animal experiments, and maintained for 10 s to allow the control index extractor algorithm to converge. The controller was not allowed to change the pump speed until after the 10 s had elapsed, at which time the simulation was continued 70 s to allow the pump speed and hemodynamic variables to reach steady state. At $t = 80$ s, one of the specified parameter changes was made, and the simulation was continued for another 80 s to allow the system to reach a steady state corresponding to the new parameters values.

Fig. 4 shows simulation results for Condition 1. At 10 s, the control index converged to a value much higher than the setpoint. Closed-loop control was initiated, and the controller began to increase pump speed to reduce the control index. The pump speed settled to approximately 1110 rad/s. Aortic pressure (AoP) was maintained between 90–120 mmHg during this period, and left ventricular pressure (LVP) was maintained below 40 mmHg. After introducing a step increase in SVR from 1.0 mmHg sec/mL to 1.2 mmHg s/mL at 80 s, the controller increased the pump speed from approximately 1110 rad/s to 1190 rad/s to maintain the control index at the reference point. The mean pump flow remained approximately constant at 86 mL/s, while AoP increased from 95 mmHg to 110 mmHg, due to the increase in SVR. As the speed increased, the control index generally decreased.

Since AoP was always larger than LVP during closed-loop control of the pump, the aortic valve was always closed. Consequently, all of the flow from the left ventricle passed through the assist pump. Left atrial pressure (LAP—not shown) was between 6 and 8 mmHg, while LVP varied from approximately 3 mmHg to above 30 mmHg, indicating that the mitral valve was periodically closing during part of the cardiac cycle. The controller reduced LAP from a relatively high value (15 mmHg) to a nominal range (6–8 mmHg), demonstrating that the left ventricle was being properly unloaded.

To observe the response to changes of preload, a simulation of Condition 2 was performed where the SVR was maintained at 1.0 mmHg s/mL and PVR was decreased from 0.1 mmHg s/mL to 0.02 mmHg s/mL. The resulting waveforms were similar to Fig. 4 except that the mean pump flow increased from 86 to 98 mL/sec following the PVR change. AoP increased from 95 mmHg to 105 mmHg and LAP increased by less than 1 mmHg, while LVP was maintained below 40 mmHg. With a decrease in PVR, and attendant increase of venous return flow, the pump provided a greater output at a higher pressure. These two simulation results demonstrate that the controller can maintain pump flow despite an increase in SVR (increased afterload) and can provide increased flow when PVR decreased (increased preload). This response resembles the Starling response of the natural heart [15].

B. Comparison Between a Conventional and Fuzzy PI Type Controller

It has been suggested that fuzzy logic control has an advantage over PI control for systems with time delays and nonlinearities [16], [17]. Since the cardiovascular system involves nonlinear elements and time delays and also shows parameter uncertainty [18], fuzzy logic control may provide better performance than PI control. To investigate this possibility, a comparison between the fuzzy controller and a conventional PI controller was performed. For the PI controller, the change in speed reference point is given by $\delta\omega = g_1 e(k) + g_2 \delta e(k)$, where

$$e(k) = c_i(k) - c_{i\_ref}, \qquad \delta e(k) = e(k) - e(k-1)$$

$g1$ and $g2$ are constant coefficients, and e, δe, c_i, and c_{i_ref} are defined as before.

In order to compare the PI controller to the fuzzy logic controller, the gains of the PI controller were chosen by trial and error to approximate the response of the fuzzy logic controller for simulation Condition 1, resulting in gains g_1 and g_2 of 0.02 and 20, respectively. The two controllers also performed similarly when SVR was increased from 1.0 mmHg s/ml to 1.2 mmHg sec/ml, when PVR was decreased from 0.1 mmHg s/ml to 0.02 mmHg s/mL, or when ventricular contractility was reduced to 0.3 mmHg/ml (not shown). However, when the ventricular contractility was increased to 1.8 mmHg/mL, the response with the PI controller was much less damped than the fuzzy controller. Fig. 5 shows results for simulation Condition 1 with increased contractility and a step change in SVR from 1.0 mmHg s/ml to 1.2 mmHg s/ml at $t = 80$ sec. The response with the PI

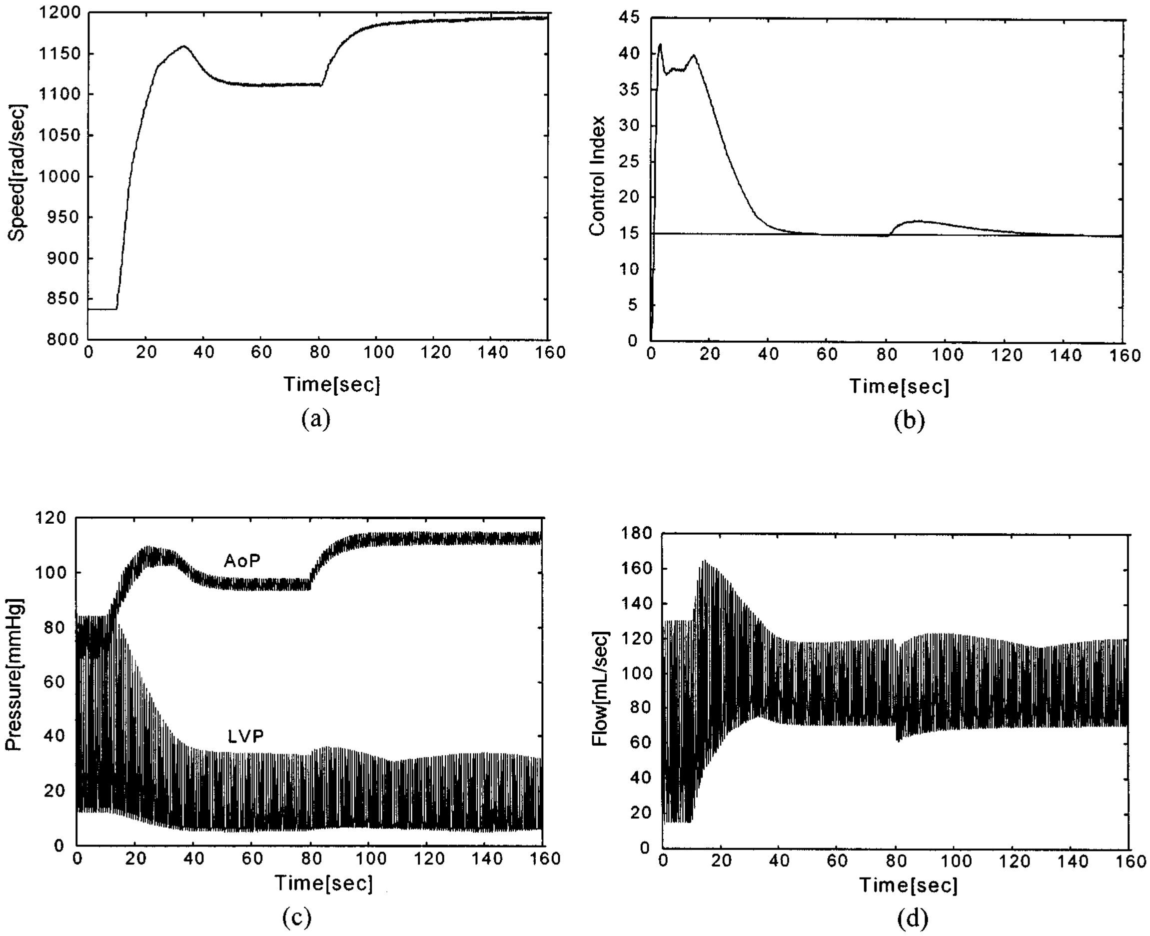


Fig. 4. (a) Pump speed, (b) control index from pump flow, (c) aortic (AoP) and left ventricular (LVP) pressure, (d) pump flow while using the fuzzy controller, obtained by simulation.

controller shows an oscillatory response, while the response of the fuzzy controller is not oscillatory.

Under all conditions, the PI controller demonstrated a slightly faster rise time than the fuzzy controller. It is possible that the relatively high gain ($g_1 = 0.02$) producing this fast rise time might also be responsible for the oscillatory response observed in the case of increased contractility. To test this possibility, simulations of the PI controller were performed with a lower gain ($g_1 = 0.005$). With this low gain, the PI controller showed a noticeably slower response and, even at 80 s, the PI controller did not reach the steady-state pump speed. However, for increased ventricular contractility, the PI controller still showed an oscillatory response. These results suggest that the less oscillatory performance of the fuzzy controller is not just an effect of the gain and that the fuzzy controller is probably more robust to parameter changes than the PI controller.

C. Controller Performance with Mock Circulatory System

The fuzzy logic controller was implemented on a PC equipped with a data acquisition board (Data Translation, Marlboro, MA, DT2821) coupled to the drive circuitry of an investigational axial flow turbodynamic blood pump (Nimbus Medical, Rancho Cordova, CA). The experimental platform included a Donovan-type mock circulatory system which replicates the principal elements of the cardiovascular system [7]. A Jarvik-7 artificial heart (Symbion Inc., Salt Lake City, UT) provided the function of the native left and right ventricle in the mock circulatory system. The system was filled with water. A weakened left ventricle was simulated by adjusting the strength of the driving air pressure to the artificial heart. In this physical implementation, the fuzzy logic controller used the flow estimated from pump current and speed to extract the control index.

The controller was studied under the same conditions as described for the simulation studies above. The reference control index was set to 15 ml/s. The pulsatility extractor was given 10 s to converge, and then the fuzzy logic controller was allowed to provide closed-loop control of the pump speed. A change in SVR was introduced at 80 s by restricting flow through the simulated aorta using a clamp valve.

Results corresponding to Condition 1 are shown Fig. 6. After the 10–s convergence period, the pump speed increased to achieve the reference control index, but the speed oscillated, and the control index oscillated around the reference control index. When the systemic vascular resistance was increased at $t = 80$ s, the control index increased accordingly. The fuzzy logic controller, in turn, increased the pump speed to reduce the control index to the reference control index. AoP was maintained between 80 and 120 mmHg, and the mean pump

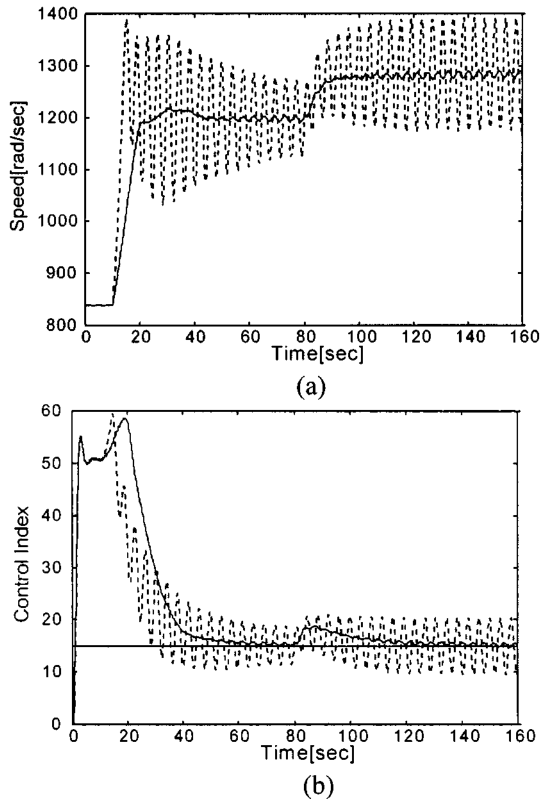


Fig. 5. Comparison of PI controller (dashed line) and fuzzy logic controller (solid line) responding to a change in SVR from 1.0 to 1.2 mmHg sec/mL, obtained by simulation. (a) Pump speed. (b) control index from pump flow.

flow was maintained in the presence of a change in SVR, as desired.

D. In Vivo Results

The controller was also tested in an experiment on a calf. The axial flow blood pump was implanted in the animal with connections between the left ventricle and the aorta. The experimental protocol was based on a previous protocol developed for the Nimbus pump [8], and all experiments were performed under the guidelines of the University of Pittsburgh Institutional Animal Care and Use Committee. To simulate ventricular dysfunction, LV contractility was reduced through a continuous infusion of esmolol.

Fifty minutes after the esmolol injection, with the pump speed set at 830 rad/s and after allowing the pulsatility extractor algorithm to converge, the fuzzy controller was engaged with a control index reference of 17.5 ml/s. The pump speed increased to approximately 1250 rad/s, as shown in Fig. 7, reducing the pulsatility to the reference value within 100 s.

Fig. 7 shows aortic pressure [Fig. 7(c) AoP], pump flow [Fig. 7(d)], mean aortic pressure [Fig. 7(e) mAoP], and mean pump flow [Fig. 7(f)] over the 120 s interval during which the controller converged. While there was a noticeable change of mean pump flow, mAoP did not show a large variation. At the final converged value of speed, the pump provided a flow of approximately 6 L/Min without introducing suction.

The esmolol infusion was continued for an additional 56 min, continuing to reduce the contractility of the left ventricle. At 106 mins after the initiation of esmolol injection, another experiment was performed, again with a reference control index of 17.5 mL/s. The resulting pump speed was 1050 rad/s, lower than in the previous experiment (1250 rad/s). AoP, mAoP, and mean pump flow were lower than the values seen earlier, but the patterns were similar. At the final pump speed of 1050 rad/s, the pump flow was 4.75 L/Min, and suction was avoided.

V. DISCUSSION

This paper presents a control strategy for an axial flow rotary ventricular assist pump. The strategy utilizes pulsatility introduced into the pump flow by residual function of the natural heart. The goal is to regulate the LVAD pump to a flow close to the maximum possible flow without introducing suction into the ventricle. Suction occurs when the pump attempts to draw more blood from the ventricle than is available. We have observed that the pulsatility of the pump flow decreases as the pump speed increases to the point of introducing suction, and this phenomenon was used to regulate the pump speed.

Currently available pressure and flow sensors are not reliable for long-term implantation, and it is desirable to implement the control strategy without them, using instead information that can be reliably obtained from the pump itself. The current drawn by the axial flow pump considered here reflects the load on the pump and, together with models of the pump dynamics, can be used to estimate the pump flow. Although the current signal itself is also pulsatile, with pulsatility decreasing as suction is approached, the current is not as useful as the flow signal for control because of noise. The pump model effectively acts as a filter on the current signal. The estimated flow is smoother than the current signal, and the pulsatility is larger and can be more reliably calculated.

A method to calculate a pulsatility control index to use as a control signal was developed, and it was shown to be accurate over the frequency range relevant to the cardiovascular system (1–3 Hz). A PI-type fuzzy logic system was implemented to determine the change in the pump speed required to drive the pulsatility index to a desired reference point. Simulation studies showed that the controller could maintain a pulsatility index reference point with changes in preload and afterload. The simulation studies also suggested that the fuzzy controller is more robust to changes in model parameters than a traditional PI controller. With an increase in heart contractility in the simulation model, the traditional PI controller showed an underdamped response to changes in systemic parameters, while the fuzzy PI controller showed an almost critically damped response. The fact that the control index is a nonlinear function of the system state may contribute to this behavior in the traditional PI controller.

The controller was implemented in real-time and tested in a mock circulation system and in an animal. In the mock circulation system, the controller maintained approximately constant flow when systemic vascular resistance (afterload) was increased and increased flow when pulmonary vascular resistance was decreased (simulating preload increase). These changes are consistent with the changes that would be expected in the cardiovascular system of an artificial heart patient. The responses

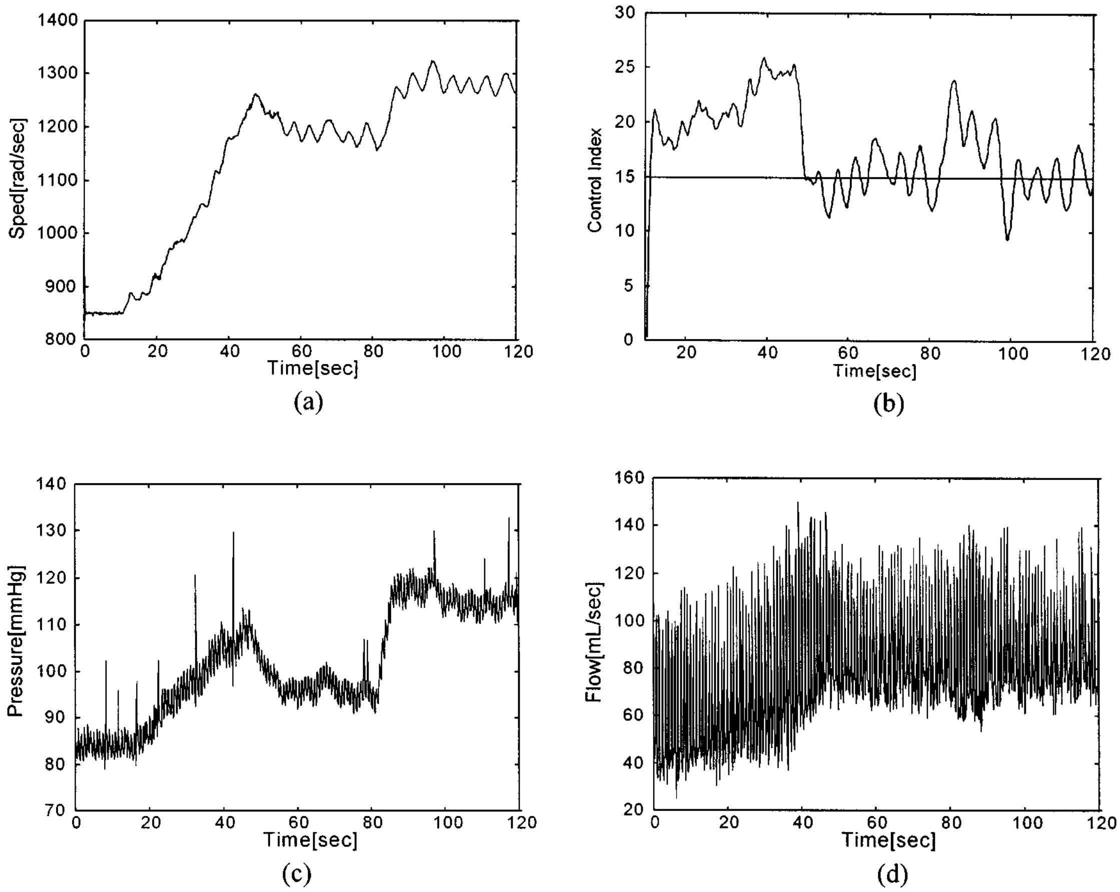


Fig. 6. (a) Pump speed, (b) control index from pump flow, (c) aortic (AoP) pressure, (d) pump flow while using the fuzzy controller, obtained using the mock circulatory system.

to disturbances in the mock loop studies were similar to those seen in the simulation study except that, in the mock loop, the response was slower and the speed and control index showed oscillations around the final values. (Compare Fig. 6 with Fig. 4.)

One contributor to the performance differences between the simulations and the mock loop studies may be due to the flow estimator. There was no estimation error in the simulation studies, but errors would be expected in the mock loop studies. Another contributor to these differences may be the relative simplicity of the cardiovascular model that was employed. This model was designed to describe the pressure and flow at the aorta, and it may not adequately represent the inertance of the blood. Deswysen *et al.* observed that the values of inertance that provided a good description of the input impedance of the human arterial circulation was much less than would be expected from the volume of blood in the body [19]. The inertance of water in the mock loop may contribute to the observed oscillations. The increased viscosity of blood may damp these oscillations *in vivo*.

In the animal experiments, the controller was seen to provide satisfactory regulation of the pump speed when the heart was weakened by an esmolol infusion. These results also showed the slow response and oscillations in speed and control index that were observed in the mock loop, further suggesting that these effects are due to flow estimation errors and limitations in the linear models used in the simulation. Additional animal data are not presently available, and it will be necessary to conduct more experiments to evaluate the robustness of the controller over a range of cardiac conditions.

The controller described in this paper considered only initial pump speeds below the speed that produces suction, and the controller was able to increase the speed to a point safely below suction. However, as shown in Fig. 2, flow pulsatility increases with speed when suction exists. If the pump is operating at a speed that produces suction, the controller would try to reduce pulsatility by increasing the speed further, leading to greater suction. To avoid this problem, the control strategy requires an additional mechanism to detect when suction is occurring in order to reduce speed immediately to a level that does not produce suction [20].

The pulsatility index reference should be selected to operate as close as possible to its minimum value, so that it will produce the largest possible cardiac output without suction. If the reference is too high, the pump may operate at a low speed that does not provide sufficient cardiac output. If the reference is too low, the pump may operate too close to suction for safety. In both the mock loop and in vivo studies, a control index reference of 15–17.5 mL/s provided an appropriate operating speed for the pump. This value was in the range that was effective in the simulation studies. However, all of these tests were conducted with one pump (or model of that pump). Since this control index reference is based on empirical observations, it may not be appro-

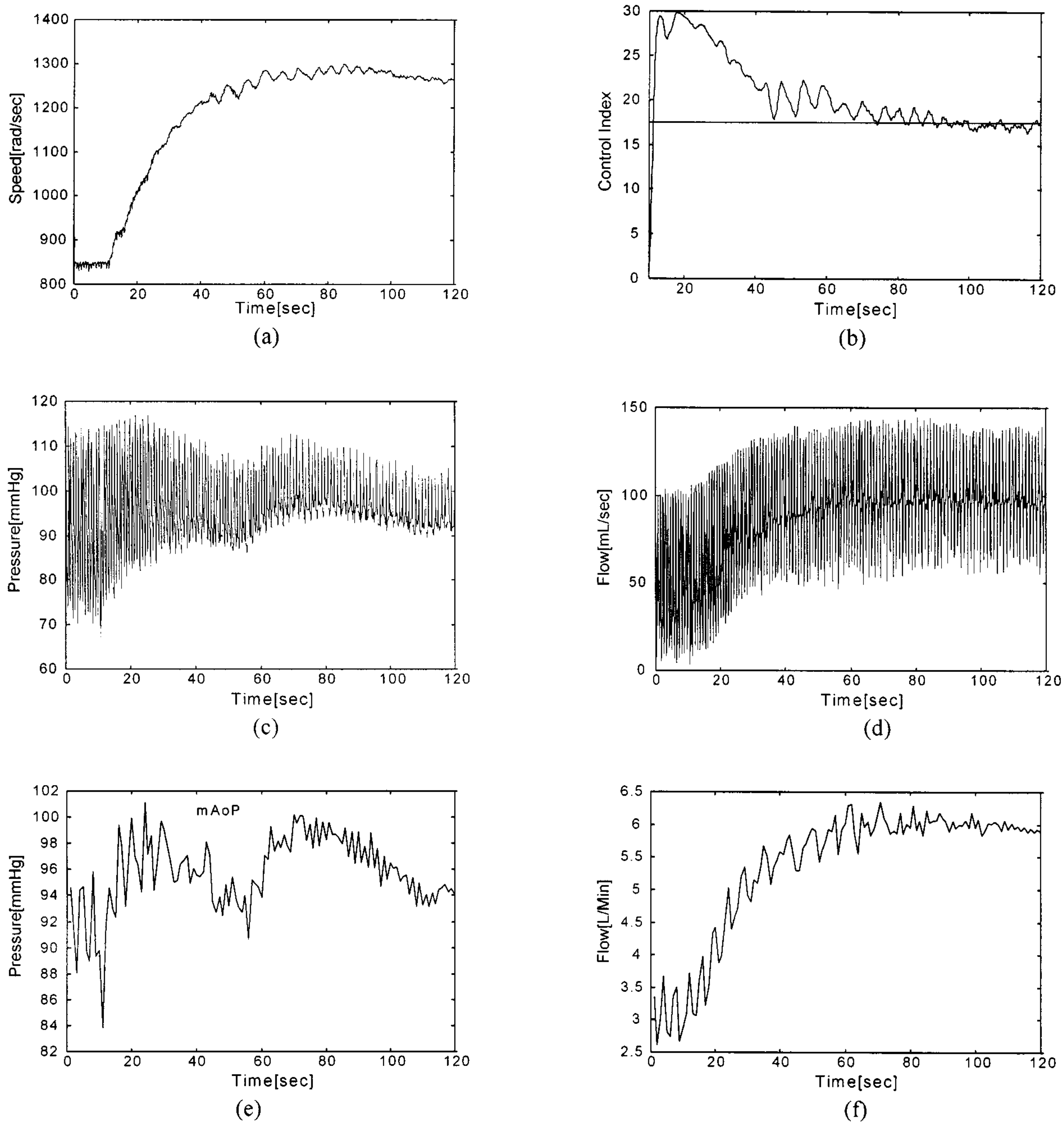


Fig. 7. (a) Pump speed, (b) control index from pump flow, (c) aortic (AoP) pressure, (d) pump flow, (e) mean AoP, (f) mean pump flow while using the fuzzy controller, obtained during an animal experiment.

priate for other pumps, even of the same type. Additional studies with several pumps and several animals will be required to determine whether a universally appropriate pulsatility reference value can be identified or whether the reference must be adapted to each patient.

The pulsatility approach requires that the natural heart retain enough contractility to be able to maintain a pulsatile load on the pump, creating a pulsatile pump flow and pump current. This approach would not be useful if the heart is not able provide some output, as, for example, during ventricular fibrillation. However, this situation would be considered an alarm condition that would require immediate medical attention, and supplemental circuitry will be required to detect it.

We have proposed incorporating the pulsatility control approach as one component in a hierarchical control structure [21]. In the proposed system, the residual pulsatility and adequacy of the index reference would be evaluated using system identification techniques, and other control strategies would be used when suitable conditions for pulsatility control are not present. These alternative strategies include a multiobjective optimization approach, other approaches based on empirical indices derived from the pump current waveform, and a preset constant speed. The hierarchical controller would switch to these mechanisms when necessary, although they may not provide as much cardiac output as pulsatility control.

REFERENCES

[1] J. R. Hogness and M. V. Antwerp, Eds., *The Artificial Heart: Prototypes, Polices, and Patients, Committee to Evaluate the Artificial Heart Program of the National Heart, Lung, and Blood Institute*. Washington, DC: Division of Health Care Services, Institute of Medicine, National Academy Press, 1991.

[2] Z. Wu, J. F. Antaki, G. W. Burgreen, K. C. Butler, D. C. Thomas, and B. P. Griffith, "Fluid dynamic characterization of operating conditions for continuous flow blood pumps," *ASAIO J.*, vol. 45, pp. 429–442, 1999.

[3] H. Schima, W. Trubel, A. Moritz, G. Wieselthaler, H. G. Stöhr, H. Thoma, U. Losert, and E. Wolner, "Noninvasive monitoring of rotary blood pumps: Necessity, possibilities, and limitations," *Artificial Organs*, vol. 16, pp. 195–202, 1992.

[4] U. Tasch, J. W. Koontz, M. A. Ignatoski, and D. B. Geselowitz, "An adaptive aortic observer for the Penn State electric ventricular assist device," *IEEE Trans. Biomed. Eng.*, vol. BME-37, pp. 374–383, 1990.

[5] Y.-C. Yu, J. R. Boston, M. Simaan, and J. F. Antaki, "Estimation of systemic vascular bed parameters for artificial heart control," *IEEE Trans. Automat. Contr.*, vol. AC 42, pp. 765–778, 1998.

[6] R. R. Yager and D. P. Filev, *Essentials of Fuzzy Modeling and Control*. New York: Wiley, 1994.

[7] M. J. Patyra and D. M. Mlynek, *Fuzzy Logic—Implementation and Application*. New York: Wiley, 1996.

[8] F. M. Donovan, "Design of a hydraulic analog of the circulatory system for evaluating artificial hearts," *Biomat., Med. Dev., Art. Org.*, vol. 3, pp. 439–449, 1975.

[9] K. C. Butler, "Development of an innovative ventricular assist system," Nimbus Inc., Rancho Cordova, CA, Tech. Rep., 1994.

[10] S. Choi, J. R. Boston, D. Thomas, and J. F. Antaki, "Modeling and identification of an axial flow blood pump," in *Proc. Amer. Contr. Conf.*, Albuquerque, NM, June 4–6, 1997, pp. 3709–3713.

[11] G. Avanzolini, P. Barbini, A. Cappello, and G. Cevenini, "CADCS simulation of the closed-loop cardiovascular system," *Int. J. Biomed. Comput.*, vol. 22, pp. 39–49, 1988.

[12] K. Sunagawa, D. Burkhoff, K. Lim, and K. Sagawa, "Impedance loading servo pump system for exercised canine ventricle," *Am. J. Physio.*, vol. 243, pp. H346–H350, 1982.

[13] K. Sagawa, L. Maughan, H. Suga, and K. Sunagawa, *Cardiac Contraction and the Pressure–Volume Relation*: Oxford Univ. Press, 1988.

[14] H. Schima, J. Honigschnabel, W. Trubel, and H. Thoma, "Computer simulation for the circulatory system during support with a rotary blood pump," *Trans. Amer. Soc. Artif. Intern. Org.*, vol. 36, pp. 128–137, 1990.

[15] A. G. Guyton, *Textbook of Medical Physiology*. Philadelphia, PA: Saunders, 1976, pp. 168–170.

[16] J. J. Buckley and H. Ying, "Fuzzy controller theory: Limit theorems for linear fuzzy control rules," *Automatica*, vol. 25, pp. 469–472, 1989.

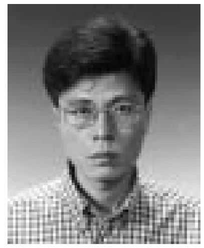
[17] H. Ying, W. Siler, and J. J. Buckley, "Fuzzy control theory: A nonlinear case," *Automatica*, vol. 26, pp. 513–520, 1990.

[18] E. A. Woodruff, J. F. Martin, and M. Omens, "A model for the design and evaluation of algorithms for closed-loop cardiovascular therapy," *IEEE Trans. Biomed. Eng.*, vol. 44, pp. 694–705, 1997.

[19] B. Deswysen, A. A. Charlier, and M. Gevers, "Quantitative evaluation of the systemic arterial bed by parameter estimation of a simple model," *Med. Biol. Eng. Comput.*, vol. 18, pp. 153–166, 1980.

[20] D. Liu, J. R. Boston, H.-H. Lin, J. F. Antaki, M. A. Simaan, and J. Wu, "Monitoring development of suction in an LVAD," in *Proc. BMES-EMBS 1st Joint Conf.*, Atlanta, GA, Oct. 13–16, 1999, p. 240.

[21] J. R. Boston, M. A. Simaan, J. F. Antaki, Y.-C. Yu, and S. Choi, "Intelligent control design for heart assist devices," in *Proc. 1998 ISIC/CIRA/ISAS Joint Conf.*, Gaithersburg, MD, Sept. 14–17, 1998, pp. 497–502.



Seongjin Choi received the B.S. and M.S. degrees in electrical engineering from Korea University, Korea, in 1984 and 1986, respectively. He received the Ph.D. degree in electrical engineering from the University of Pittsburgh, Pittsburgh, PA, in 1998.

In 1986, he joined LG Electronics Inc. as a Research Engineer. His research interests concern the area of modeling and control of a left ventricular assistance system, especially using a nonpulsatile axial blood pump. He is also interested in fuzzy systems for modeling and control and applications of this theory to biomedical systems.

James F. Antaki received the B.S. degree in mechanical and electrical engineering from Rensselaer Polytechnic Institute, Troy, NY, in 1985 and the Ph.D. degree in mechanical engineering from the University of Pittsburgh, Pittsburgh, PA, in 1991.

He is an Associate Professor of Surgery and Bioengineering at the University of Pittsburgh. Over the past ten years, he has been leading the Artificial Heart R&D team at the McGowan Center for Organ Engineering of the University of Pittsburgh. In 1997, his team completed the development of a novel magnetically levitated turbodynamic blood pump, the *Streamliner*, which recorded the world's first *in-vivo* implant of such a device. His current interests relate to computational design optimization and optimal control of artificial organs. He holds five patents related to artificial organs and two related to the harmonica.

J. Robert Boston (M'72) received the B.S. and M.S. degrees in electrical engineering from Stanford University, Stanford, CA, in 1964 and 1966, respectively, and the Ph.D. degree from Northwestern University, Evanston, IL, in 1971.

Dr. Boston has held faculty appointments at the University of Maryland, Carnegie Mellon University, and the University of Pittsburgh School of Medicine. He is currently Professor and Undergraduate Coordinator in the Department of Electrical Engineering at the University of Pittsburgh. His research interests include knowledge-based signal processing, representation of uncertainty using fuzzy set and Dempster–Shafer theory, and biomedical control systems. His current research projects include the application of motion analysis techniques to study patients with chronic pain, signal detection methods using fuzzy logic, and development of control systems for cardiovascular assist devices.

Douglas Thomas received the B.S. degree in biological sciences from the University of California, Davis, the B.S. degree in electrical engineering, and the M.S. degree in biomedical engineering from California State University, Sacramento.

He is one of the Founders of Nimbus Inc., now a subsidiary of ThermoCardiosystems Inc. He has been involved in the development of NIH supported research of total artificial hearts and left ventricular assist devices for over 15 years. His work has focused on embedded brushless motor control and power systems design.