Minimally invasive estimation of systemic vascular parameters for artificial heart control

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Abstract

Systemic vascular parameters are important indices of heart condition, incorporating these parameters into the control of a ventricular assist device (VAD) would facilitate the implementation of an effective control strategy. In order to minimize the need for indwelling sensors for obtaining these parameters, an estimator was developed to identify the systemic vascular parameters (characteristic resistance, blood inerterance at the aorta, systemic compliance, and systemic resistance) using measurements from the Novacor left ventricular assist system (LVAS) and arterial pressure. Systemic compliance was estimated by the ratio of the LVAS pump stroke volume to the arterial pulse pressure and systemic resistance was calculated by the ratio of mean arterial pressure to LVAS pump output. These two parameters were then used as known parameters in an extended Kalman filter to identify the other unknown parameters using LVAS pump volume and arterial pressure measurements. Performance of the estimator was evaluated using data from a mock circulatory system experiment. The results showed that the estimates converged more accurately in a limited time when arterial pressure was used with the LVAS pump volume as measurements. These parameter estimates can provide diagnostic information for patient and device monitoring and can be used for future VAD control development. © 2002 Elsevier Science Ltd. All rights reserved.

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1. Introduction

Heart disease is a major health problem in the United States and throughout the world. Although heart transplantation is an accepted method to treat severe cases of the disease, the demand for heart transplants exceeds the supply. For many patients, a left ventricular assist device (VAD) could provide a satisfactory alternative to transplantation.

The purpose of ventricular assist devices is to provide sufficient cardiac output to maintain adequate perfusion of the patient’s body. The required cardiac output depends on the patient’s activity level and body demand. The body and the native heart can provide adjustments to adapt the physiological demand. The more blood returns from the venous system to the heart, the stronger the heart muscle contracts (Starling’s law). The body can adjust the blood flow through the vascular system so that more blood returns to the heart when the demand for cardiac output is high. This effect is defined as preload and can be quantified by the left atrial pressure. On the other hand, the cardiac output provided by the heart is not significantly affected by the patient’s systemic vascular impedance (referred to as afterload). The controller of the ventricular assist device should regulate the device to mimic these characteristics of the native heart (Boston, Simaan, Antaki, Yu, & Choi, 1998).

The controls of existing devices, which are either constant stroke volume control of pulsatile devices or constant speed control of nonpulsatile devices, depend
on human operation. This manual approach is effective in a monitored environment but requires continuous engineering and clinical support limiting the patient's activities. For long-term implantation, the need for a human to monitor device operation should be eliminated. The control system for the assist device must be able to respond to changes in the demand for cardiac output. It should monitor the patient's status to recognize a change in the patient's demand for support, and it should have the ability to detect hardware failures of the device.

Hemodynamics of the cardiovascular system reflect the metabolic demand of the body and the pumping capability of the heart (Avanzolini, Barbini, & Cappello, 1992; Sunagawa, Sagawa, & Maughan, 1984). Incorporation of the hemodynamic parameters into the control and monitoring of a VAD would facilitate implementation of an effective control strategy (Kitamura, Matsuda, & Akashi, 1986). These parameters are often difficult to measure directly, particularly in the chronic setting, and indirect estimation techniques will be required for long-term control.

Procedures to estimate cardiovascular model parameters for an individual patient have been described by several authors (Clark, Ling, Srinivasan, Cole, & Pruett, 1980; Deswysen, 1977; Deswysen, Charlier, & Gevers, 1980). Each of these estimation procedures was designed to utilize specific measurements. Clark et al. (1980) used the aortic pressure, brachial arterial pressure, left ventricular pressure, and left ventricular volume as measurements. Deswysen (1977) and Deswysen et al. (1980) estimated the systemic circulation parameters with the aortic pressure and the aortic flow as measurements. Recursive methods to track parameter values over time have been developed using recursive least squares (Avanzolini et al. 1992; Ruchti, Brown, Jeutter, & Feng, 1993), auto-regressive models (McInnis, Guo, Zu, & Wang, 1985; Shimooka, Mitamura, & Yuhta, 1991), and a Kalman filter (Deswysen, 1977; Yu, Boston, Simaan, & Antaki, 1998). These estimators are also based on specific physiological measurements, for example, aortic pressure and aortic flow. These measurements that are typically available from patients with impaired cardiovascular function change as the clinical environment changes. Extensive pressure and flow measurements can be obtained in the operating room. As the patient is relocated to intensive care unit, then acute care, and finally long-term care facilities, however, measurement possibilities, particularly those based on invasive techniques, are reduced. When a measurement becomes unavailable, the ability to identify a particular circulatory model changes. The estimator may no longer converge for some of the parameters, or parameter accuracy may be decreased. If a mathematical model, including the cardiovascular system and the VAD, is used and the necessary signals to identify cardiovascular parameters can be derived using measurements from the device, on-line parameter estimation techniques can be applied to identify the parameters without the need for invasive sensors in patient's body.

This paper presents a two-stage estimation procedure to identify the systemic vascular parameters using measurements of pump volume from a Novacor left ventricular assist system (LVAS, Novacor Division, World Heart Co., Oakland, CA) and arterial pressure. Systemic resistance was calculated by the ratio of mean arterial pressure to LVAS pump output and systemic compliance was estimated by the ratio of LVAS pump stroke volume to arterial pulse pressure. These two parameters were then used as known parameters in an extended Kalman filter (EKF) to identify the other unknown parameters. The estimator was tested in an experiment using a mock circulatory system. Effects of the arterial pressure measurement on the parameter estimates were also investigated. The parameter estimates can be used to monitor the patient's cardiac function, to detect possible LVAS failure, and to develop a new LVAS controller.

2. System description

The Novacor LVAS is a spring-decoupled dual pusher-plate, sac-type blood pump driven by a pulsed-solenoid energy converter (Portner et al., 1984). During natural cardiac systole, the pump solenoid is unlatched, resulting in a low pump pressure that allows blood from the left ventricle to flow into the pump sac. During cardiac diastole, the solenoid closes rapidly, deflecting the beam springs through the pump pusher plates and exerting a balanced force on the top and bottom surfaces of the blood in the pump sac. This action ejects the blood from the pump sac into the descending thoracic aorta.

An electric analog of the system considered in this paper, including a cardiovascular model (above the dashed line) and the Novacor LVAS (below the dashed line), is shown in Fig. 1. The cardiovascular model consists of a time-varying capacitance as left ventricle (Suga, Sagawa, & Demer, 1980), $C(t)$, ideal diodes with forward resistors as aortic ($D_A$ and $R_A$) and mitral ($D_M$ and $R_M$) valves, a four-element RLC circuit, including characteristic resistance ($R_C$), blood inerance at the aorta ($L_S$), systemic compliance ($C_S$), and systemic resistance ($R_S$), as systemic circulation (Deswysen et al., 1980), and a constant voltage source for the left atrial pressure (Chang, Matson, Kendrick, & Rideout, 1973). This simple cardiovascular model was selected because it can approximate the systemic load adequately and the model parameters can be estimated using a small number of measurements such as aortic pressure and flow (Deswysen et al., 1980).
The model of the LVAS predicts the pump chamber pressure, \( P_{CP} \), for a given instantaneous pump volume, \( V(t) \). The static pressure-volume relationship, \( P(V) \), governed by the stiffness of the springs which couple the solenoid to the pusher plates, was modeled as a nonlinear time-varying capacitance, \( C_{VAD}(t) \). The function \( P(V) \) and its corresponding parameters, represented by

\[
P(V) = \begin{cases} 
202.76 f_{NP} V_N^{1.08 - 0.15 V_N} \\
\text{pump ejection:}
\end{cases}
\]

where \( f_{NP} = 0.43 + 0.57 \cdot V_N \)

\[
+1.87 \cdot \frac{V_N - 0.22}{1 + (V_N/0.23)^{15}}
\]

and \( V_N = 7.13 - \sqrt{50.86 - 0.20 \cdot V} \),

\[
\text{pump filling: } -5.98 + 406.01 \times \exp\left\{-\exp\left\{\frac{69.54 - V}{1.95}\right\}\right\},
\]

were obtained by least-squares fit to the experimentally measured quasi-static pump data acquired in-vitro using the Levenburg-Marquardt algorithm (Walter & Pronzato, 1997) in TABLE CURVE (Jandel Scientific, Corte Madera, CA) (Yu, Boston, Simaan, Miller, & Antaki, 2001).

A first-order system, represented by \( R_{SO} \) and \( C_{SO} \), was used to describe the dynamics of solenoid closure. The pressure response for a given \( P(V) \) was represented by the transfer function

\[
P_{\text{inst}}/P(V) = H(s) = 1(s) + 1,
\]

where \( P_{\text{inst}} \) is the pump pressure measurement in the absence of fluid mechanics effects in the pump chamber and \( \tau = R_{SO} C_{SO} \) represents the time constant of the solenoid closure. \( P_{\text{inst}} \) is not measurable in the real situation. However, adding this first-order system to the model significantly improves the accuracy of the pump pressure estimate. The resistance and inductance of blood in the pump chamber were represented by a resistance, \( R_p \), and a flow dependent inductance, \( L_p \), where the pump flow was calculated by the time derivative of the LVAS volume. The conduits connecting the pump to the patient’s cardiovascular system were modeled with the prosthetic heart valves, including an ideal diode for the valve (open or closed), a resistor for the fluid resistance, and an inductance for the fluid inductance. Although the model elements are physically meaningful, the functions of these elements were defined to provide the best fit of the model to the experimental data. The experimental data were obtained from a mock circulatory system experiment where the LVAS was operated in a high preload and low afterload condition. This experimental condition was chosen to provide a wide range of operation of the LVAS in terms of pump inflow, pump outflow, and pump stroke volume. The model parameters estimated from these data cover the entire range of LVAS operation. The values of the LVAS model parameters used in the estimator are listed in Table 1. Determination of the model structure and identification of the model parameters has been described in Yu et al. (2001).

By operating the LVAS in counter-pulsation mode, the pump receives blood from the left ventricle (LV) during LV systole, in which the pump pressure, \( P_{CP} \), is significantly lower than aortic pressure, \( P_A \). Since the patient’s LV contractility, the strength of cardiac contraction, is significantly lower than the normal heart, blood flow through the aortic valve, \( D_A \), is negligible. During LV filling, the LVAS ejects blood from the pump sac to the aorta. Assuming that there is no blood leakage through the aortic valve, \( D_A \), and the pump inlet valve, \( D_I \), while they are closed (represented as open circuits in Fig. 1), the model can be simplified as shown in Fig. 2 during LVAS ejection.
3. Estimation algorithm

The dynamic equations of the model in Fig. 2 can be written as

\[
\begin{align*}
\dot{x}_1 &= -x_2, \\
\dot{x}_2 &= -\frac{R_0(t) + R_C}{L_o + L_s} x_2 - \frac{1}{L_o + L_s} x_3 + \frac{1}{L_o + L_s} P_{CP}, \\
\dot{x}_3 &= \frac{1}{C_s} x_2 - \frac{1}{R_s \cdot C_s} x_1.
\end{align*}
\]

When the heart failure patient is completely supported by the LVAS, the patient's ventricular stroke volume (SV) and cardiac output (CO) can be approximated by pump stroke volume and pump output (PO). If pump volume and mean arterial pressure (PS) are measurable, the systemic resistance can be estimated by (Deswensen, 1977)

\[ R_s = \frac{MAP \cdot CO}{(V_{max} - V_{min}) \cdot PR / 60} \]

where MAP is the mean arterial pressure, \( V_{max} \) and \( V_{min} \) are the maximum and minimum pump volume in one pumping cycle, and PR is the pump rate in beats per minute. The systemic compliance, \( C_s \), can be approximated by (Segers et al., 1999)

\[ C_s \approx \frac{SV}{AP_{max} - AP_{min}} \approx \frac{V_{max} - V_{min}}{AP_{max} - AP_{min}}, \]

where \( AP_{max} \) and \( AP_{min} \) are systolic (maximum) and diastolic (minimum) arterial pressure in one cardiac cycle. The estimates of \( R_s \) and \( C_s \) from (4) and (5) can then be used as known parameters in the estimator to identify the other unknown parameters, \( L_s \) and \( R_C \).

Including the unknown parameters in (3) as states of the model with zero time derivatives and substituting the known outflow conduit resistance, \( R_0(t) = R_{00} + R_{01} \cdot x_2 + R_{02} \cdot x_2^2 \) into (3) leads to

\[ \dot{X} = F_{VAD}(X), \]

where \( X = [x_1, x_2, x_3, x_4, x_5]^T, x_1 = V, x_2 = f_0, x_3 = P_s, x_4 = 1/(L_o + L_s), x_5 = R_C, \) and \( F_{VAD}(X) = [-x_2, x_4 \cdot P_{CP} - (R_{00} + R_{01} \cdot x_2 + R_{02} \cdot x_2^2) \cdot x_3 + x_5], \)

\( (x_3 - x_1/R_s)^T \cdot C_s, 0, 0)^T \). A noise term representing model uncertainty, assumed to be a zero mean white Gaussian process, \( W_{VAD}(t) \sim N(0, Q_{VAD}(t)) \), was also included in the state equations. \( Q_{VAD}(t) \) describes the level of confidence in the estimates of the state variables (Siouris, 1996). When elements in \( Q_{VAD}(t) \) have large values, the confidence in the corresponding state estimates is lower. Here \( Q_{VAD}(t) \) was assumed to be constant over time. The system dynamic equations can then be expressed as

\[ \dot{X} = F_{VAD}(X) + W_{VAD}, \]

where \( W_{VAD} = [w_{VAD_1}, w_{VAD_2}, w_{VAD_3}, 0, 0]^T \). The measurement vector, \( Y_{VAD}(X) \), was

\[ Y_{VAD}(X) = h_{VAD}(X(t_k)) + v_{VAD}(t_k), \]

where \( h_{VAD} = [x_1, x_2]^T \) if \( V \) and the pump outflow rate, \( f_0 \), are measurable and \( h_{VAD} = [x_1, x_2, x_3]^T \) if arterial pressure (PS) is measurable as well. The measurement noise term, \( v_{VAD}(t_k) \), was also assumed to be a white Gaussian process with \( v_{VAD}(t_k) \sim N(0, R_{VAD}(t_k)) \).

The outflow conduit resistance, \( R_0(t) \), creates a nonlinearity in the estimator. In order to prevent the divergence of the estimator due to inappropriate approximation of the nonlinearity in the system, a second-order EKF (Gelb, 1974) was used. The estimator predicts the state vector, \( X(t_k) \), and the estimation error covariance matrix, \( P_{EKF}(t_k) \), for given \( X(t_{k-1}) \) and \( P_{EKF}(t_{k-1}) \) by integrating

\[ \dot{\hat{X}}(t) = F_{VAD}(\hat{X}(t), t) + \frac{1}{2} [0 \quad 0 \quad 0 \quad 0]^T \]

and

\[ \dot{P}_{EKF}(t) = \frac{\partial}{\partial X} \left[ F_{VAD}(\hat{X}(t), t) \right] \cdot P_{EKF}(t) + P_{EKF}(t) \cdot \frac{\partial}{\partial X} \left[ F_{VAD}(\hat{X}(t), t) \right]^T + Q_{VAD}(t), \]

where \( \partial \) is the partial derivative of the state vector \( Y_{VAD}(t_k) \) as

\[ \dot{\hat{X}}(t_{k+}) = \hat{X}(t_{k-}) + K_t \cdot [Y_{VAD}(t_k - h_{VAD}(\hat{X}(t_{k-}))], \]

and

\[ \dot{P}_{EKF}(t_{k+}) = [I - K_t \cdot H_t(\hat{X}(t_{k-}))] \cdot P_{EKF}(t_{k-}), \]

where \( K_t = P_{EKF}(t_{k-}) \cdot H_t(\hat{X}(t_{k-})) \cdot P_{EKF}(t_{k-}) \cdot H_t(\hat{X}(t_{k-}))^T + R_{VAD}(t_{k-})^{-1} \) and \( H_t = \begin{bmatrix} 0.352 & 2.053 \end{bmatrix} \).
if \( x_1 \) and \( x_2 \) are measurable and \( \mathbf{H}_k = [I_{353} \ 0_{352}] \) if \( x_1, x_2, \) and \( x_3 \) are measurable.

The pump chamber pressure in the estimation algorithm was estimated by

\[
P_{\text{CP}} = P_{\text{tct}} + (L_{P0} + L_{P1} \cdot \dot{V}) \cdot \ddot{V} + R_p \cdot \dot{V}.
\]

(13)

\( P_{\text{tct}} \) was obtained by integrating (2) for a given quasi-static pump pressure, \( P(V) \), from (1) with the initial state \( P_{\text{tct}}(0) = 40 \text{ mmHg} \). \( P(V) \) was calculated from the given pump volume signal and the pump operation mode, ejection or filling. \( P_{\text{tct}}(0) \) was chosen by assuming that the pump had been full-filled in the filling phase so that the pump pressure had reached a steady-state condition at the beginning of integration. The pump operation mode (ejection or filling) was determined based on the calculated flow rate and the pump control variable settings: end-of-ejection (EOE), end-of-filling (EOF), and ejection delay (LaForge & Portrar, 1976). The pump flow rate and the flow acceleration were calculated by a five point Lagrange approximation (Marble, McIntyre, Hastings-James, & Hor, 1981).

\[
\ddot{V}(t_k) = [V(t_{k-2}) - 8 \cdot V(t_{k-1}) + 8 \cdot V(t_{k+1}) - V(t_{k+2})] \cdot (f_s/12),
\]

(14)

where \( V(t_k) \) is the \( k \)th volume measurement and \( f_s \) is the sampling frequency. A 3rd-order Butterworth lowpass filter with a forward-backward filtering technique (Stephan, Boolson, & Chiasson, 1994) was used to smooth the estimates of \( \dot{V}(t_k) \) and \( \ddot{V}(t_k) \). The block diagram for \( P_{\text{CP}} \) estimation is shown above the dashed line in Fig. 3. When the LVAS was in the ejection mode, \( P_{\text{CP}}, \) pump volume, estimated pump flow, and arterial pressure were used in the estimator to identify the systemic vascular parameters below the dashed line in Fig. 3.

4. Evaluation of estimator

The estimator was evaluated using data from a mock circulatory system, which mimics the systemic circulation of the human body. The configuration of the mock loop setup is shown in Fig. 4. This setup contained venous compliance and atrial compliance which were not included in the estimator model. This difference provided a test of robustness of the estimator to model structure change as well. The positive displacement pump, mimicking the natural LV, was operated at the rate of 100 beats per minute with stroke volume of 64 ml per beat. Mean arterial pressure was set to 90 mmHg and the reservoir pressure was 4 mmHg. Data were collected using a data acquisition system (Dataq Instruments, Akron, OH) with 1000 Hz sampling rate. The pump volume, \( V \), and arterial pressure, \( P_s \), obtained from the mock loop experiment were used to evaluate the estimator, while the pump outflow was calculated from the time derivative of the pump volume.

In the test, the pump chamber pressure, \( P_{\text{CP}} \), was estimated using the pump volume data with the pump operation mode (ejection or filling) determined based on the pump flow rate (\( \dot{V} \)) as described in Section 3. The estimated \( P_{\text{CP}} \) and pump outflow from pump volume data are close to the signals measured from the experiment as shown in Fig. 5. Pump outflow estimate, obtained as the time derivative of pump volume measurement and assuming an ideal valve, was less accurate at the beginning and end of pump ejection due to un-modeled fluid turbulence causing by the prosthetic valves. These turbulent effects were filtered in the pump chamber pressure estimate due to the inclusion of pump chamber resistance and inductance, \( R_p \) and \( L_p \), in the model. The estimated \( P_{\text{CP}} \) and pump outflow along with the measurements \( V \) and \( P_s \) were used to test the systemic parameter estimator.

Convergence of the estimator to different values of model parameters and measurement noise levels was
when arterial pressure was not measurable. $R_{VAD}$ was obtained by calculating the covariance of the error between the measurement vector and the signal vector. $Q_{VAD}$ and $P_{EKF}(0)$ were adjusted to ensure that 63% or more of the estimation error values of the state variables were bounded by the standard deviations predicted by the estimator with these values (Siouris, 1996). The matrices $Q_{VAD}$ and $P_{EKF}(0)$ were set as

$$Q_{VAD} = \begin{bmatrix} 4100 & 0 & 0 \\ 0 & 62500 & 0 \\ 0 & 0 & 250 \end{bmatrix},$$

and $P_{EKF}(0) = 100 \cdot I_{n \times n}$, where $I$ is an identity matrix.

The estimators used multiple cardiac cycles because the estimator required more than one pumping cycle to converge. At the start of each pump ejection, the state variables, $x_1$, $x_2$, and $x_3$, were reset to the values of $x_1 = 70$, $x_2 = 0$, and $x_3 = $diastolic pressure, which implies that the pump reaches full-fill with no outflow before the start of pump ejection. The first 3 by 3 submatrix in the covariance matrix, $P_{EKF}(t)$, related to the state estimates, was reset to $10 \cdot I_{3 \times 3}$. Since the estimator only identifies the unknown parameters during pump ejection, this re-initialization reduces the error from the discontinuity, allowing the estimates to converge more quickly. The estimator was stopped when $L_S$ and $R_C$ estimates changed by less than 2% in a complete cardiac cycle. The sequence of data were reused if the estimator could not converge after using all the data points in essence, by assuming the data were periodic. The final estimates were used for the parameter values. The total number of cardiac cycles to reach the steady state was used as an index of convergence speed.

The estimates of $R_S$ and $C_S$ from (4) and (5) using $V$ and $P_S$ measurements were $R_S = 0.75 \text{ mmHg s/ml}$ and $C_S = 1.75 \text{ ml/mmHg}$, which were 5.06% and 1.88% less than their expected values, 0.79 mmHg s/ml and 1.78 ml/mmHg. The expected value of $R_S$ was calculated as the ratio of the mean arterial pressure to the mean aortic flow (the clinical definition of $R_S$). The expected value of $C_S$ was obtained by least-squares fit of the ratios of accumulated fluid volumes to the resulting pressures in the systemic compliance chamber. The pump rate was obtained from the LVAS control console.

The estimated $R_S$ and $C_S$ were then used in the estimator to identify $R_C$ and $L_S$. When $P_S$ was included in the measurement vector for estimating $L_S$ and $R_C$ in EKF, the estimates converged in 132 cardiac cycles (less than 1.5 min) as shown in Fig. 6(a). The converged estimates, $L_S = 1.88 \times 10^{-3} \text{ mmHg s^2/ml}$ and $R_C = 9.66 \times$
10^{-3}\text{mmHg s}^{-2}/\text{ml}, were small because the LVAS pump outflow conduit was connected directly to the systemic compliance in the experiment setup.

When \(V\) and the calculated \(f_0\) but not \(P_S\) were used as measurements in the estimator, the parameter estimates converged in 147 cycles (about 1.5 min) with the steady state estimates \(L_S = 5.71 \times 10^{-4}\text{mmHg s}^{-2}/\text{ml}\) and \(R_C = 5.33 \times 10^{-2}\text{mmHg s}/\text{ml}\), shown in Fig. 6(b). The estimate of \(L_S\) was small as expected. However, the \(R_C\) estimate was 5.5 times greater than the estimate obtained by including \(P_S\) in the measurements. Table 2 shows the final parameter values obtained by the estimator with and without \(P_S\) as measurement. The estimation results in Yu, Boston, Simaan, & Antaki (1999) using \(V, \dot{V}\) and \(P_S\) as measurements with \(R_S\) from (4) as a known parameter are also listed for comparison. The estimate of \(C_S\) provided by (5) was more accurate than the result in Yu et al. (1999), in which the \(C_S\) estimate was identified by the EKF.

5. Discussion

An estimator to identify the systemic vascular parameters was developed. This estimator used LVAS volume and arterial pressure measurements to identify the systemic vascular parameters (characteristic resistance, blood inertance at the aorta, systemic compliance, and systemic resistance) using measurements from the Novacor LVAS and arterial pressure, minimizing the need for indwelling sensors. Systemic compliance was estimated by the ratio of the LVAS pump stroke volume to the arterial pulse pressure, and systemic resistance was calculated by the ratio of mean arterial pressure to LVAS pump output. These two parameters were then used as known parameters in an EKF to identify the other unknown parameters using LVAS pump volume and arterial pressure measurements.

Evaluation of the estimator was performed using data from a mock circulatory experiment. The estimates of
$R_S$ and $C_S$ were close to their expected values with errors below 5%. The parameters of $R_S$ and $C_S$ were provided by an EKF, and they converged in a reasonable time. The $R_C$ estimate was more accurate if $P_S$ was included in the measurement vector of the EKF. The value of $R_C$ is usually close to zero. As long as it is small, its exact value is not clinically important. If the accuracy of the $R_C$ estimate is not a concern, the estimator can be implemented without an indwelling pressure sensor because the mean, systolic and diastolic arterial pressure can be measured noninvasively. The estimator was insensitive to the difference between the experiment setup, which included a representation of venous compliance, and the model used for estimation, which did not explicitly include venous compliance.

This parameter estimator can be integrated with an intelligent controller (Boston et al., 1998) to monitor the patient’s left ventricular (LV) contractility and detect possible pump failure. Improving LV function would cause part of the blood volume from the LV to pass through the aortic valve. This would cause the pump output to be lower than total cardiac output, resulting in a long-term increase in the estimated value of $R_S$. Therefore, by monitoring the long-term trend of $R_S$, a noninvasive index of recovering LV function may be obtained. This estimate of LV function could be distinguished from possible chronic hypertension by routine (for example, daily) modulation of the LVAS synchronization (through end-of-ejection, end-of-filling, and ejection delay). This could be used to gradually wean the patient from dependence on the assist device.

The estimate of $R_C$, the characteristic resistance of the aorta, is also important regarding diagnosis of the operation of the LVAS. $R_C$ is usually small, and its exact value is not clinically essential. Because aortic characteristic resistance is unlikely to change significantly throughout the course of LVAD support, a significant change in the estimate of $R_C$ most likely indicates a malfunction or obstruction of the outlet tract of the device. For example, outlet valve stenosis or outflow cannula kinking can cause the estimate of $R_C$ to rise above its baseline value.

A ventricular assist device should be able to provide adequate cardiac output for a patient. It should be insensitive to changes in systemic vascular variables, and it should respond to patient’s physiologic demand changes properly. In addition, the use of invasive sensors for VAD control should be minimized since most physiologic sensors are not for long-term use. The estimator described herein provides a method to deal with varying availability of information concerning the patient’s cardiovascular status and assist device operation. Further work would involve integrating this estimator with the VAD control scheme proposed in Boston et al. (1998) to control the long-term use of heart assist devices.

References


