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인공심장의 비선형 혈류 역학 변수 예측에 관한 연구

엄경식*·안재목**·최원우***·박성근****·김수정*·조영호****·최재순*·이정훈*·최종훈*·김희찬****·민병구****

*서울대학교 공과대학 의용생체공학 협동과정, **한림대학교 전자공학과,
***바이오메드랩, ****서울대학교 의과대학 의공학교실
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A Study on the Practical Estimation of Nonlinear Hemodynamic Variables for the Moving-Actuator type Total Artificial Heart

K.S. Om*, J.M. Ahn**, W.W. Choi***, S.K. Park****,
S.J. Kim*, Y.H. Jo****, J.S. Choi*, J.H. Lee*,
J.H. Choi*, H.C. Kim****, and B.G. Min****

*Dept. of Biomedical Engineering, College of Engineering, Seoul National University
**Dept. of Electronics Engineering, College of Engineering, Hanlim University, ***Biomedlab
****Dept. of Biomedical Engineering, College of Medicine, Seoul National University
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요 약 : 인공 심장의 연구에 있어서 혈류 역학 변수의 추정은 두말할 필요도 없이 매우 중요하다. 그러나 이 중요도에 견주어 볼지라도 실세계에 적용될 수 있는 연구 결과는 희박하다. 본 논문에서는 이동 작동기형 완전 인공 심장을 위한 혈류 역학 변수 추정 문제가 연구되었다. 추정 방법론으로서 다차원 선형 보간 기법을 이용하였다. 모의 순환 장치의 실험으로 제안된 방법을 검증하였으며 좋은 성능을 보였다.

Abstract : It is needless to say that the nonlinear hemodynamic variables estimation is a very important study for the artificial heart. Even though it is important, there have not been satisfactory results which can be applied to the real world situations. In this paper, the problem of hemodynamic variables estimation for the moving-actuator type total artificial heart(MA-TAH) was studed. Multidimensional linear interpolation(MDI) scheme was used for the estimation. Proposed method was verified by in vitro test and showed good performance.
Key words : MA-TAH, Hemodynamics, Estimation, Interpolation

INTRODUCTION

The natural heart adjusts the stroke volume and heart rate coping with the hemodynamic variables such as LAP (Left Atrial Pressure), RAP(Right Atrial Pressure), AoP (Aortic Pressure), PAP(Pulmonary Artery Pressure), etc, adaptively. The basic control requirements of the artificial heart can be described in terms of three features. First, the heart must respond in a sensitive manner to increases in preload(venous return or atrial flow) by delivering increased cardiac output. second, the artificial heart should be relatively insensitive to the changes of afterload(arterial pressure). Thus, increased artificial resistance should not affect the cardiac output to any significant degree. This is based upon the fact that, for the natural heart, cardiac output is predominantly affected by preload and not by arterial resistance, although resistance to venous return, a preload effect, can have considerable influence on cardiac

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통신저자 : 민병구, (110-744) 서울시 종로구 연건동 28번지 서울대 학병원 의공학과
Tel. (02)760-2509, Fax. (02)745-7870

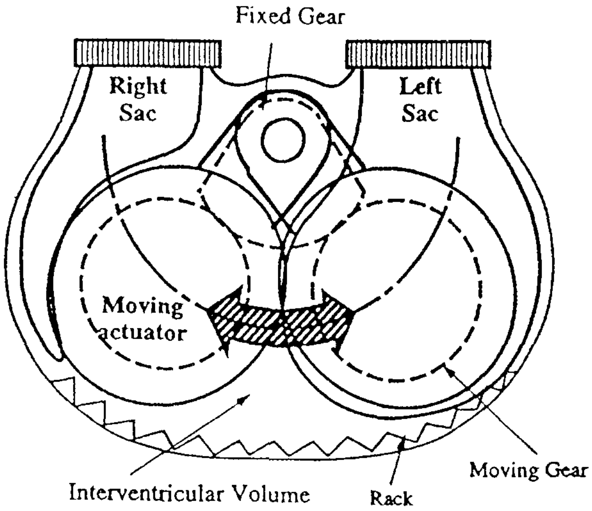

Fig. 1. Schematic diagram of the MA-TAH

output. Finally, in this alternately contracting pump, the outputs of the left and right ventricles must be balanced. With balanced control, we can avoid such a condition as the right ventricle uncontrollably outpumping the left ventricle, which leads to pulmonary edema[1-2].

The moving-actuator type total artificial heart(MA-TAH) has two blood sacs, a moving actuator which pushes sacs to pump blood, and a housing which encloses other parts. Internal space of the MA-TAH is divided into two blood sacs, the moving actuator, and the remaining space which is called the interventricular space, some amount of air is filled to compensate the differences between the left and right pump output. The bottom part of the pump housing is made as flexible compliance window to facilitate the compression or expansion of the air in the interventricular space[3]. Well-known pneumatic artificial heart has a subsidiary compliance chamber for preventing suction problem which means the very low atrium pressures. But our developing MA-TAH does not need a compliance chamber, and the air located in the interventricular volume plays its role [1-2]. Not only the suction problem the other hemodynamic variables estimation, e.g., Left Atrial Pressure(LAP), Right Atrial Pressure(RAP), Pulmonary Artery Pressure(PAP), Aortic Pressure(AoP), Cardiac Output(CO), Pulmonary Output(PO), is very important for the physiological control. Especially, the temporary state of a high LAP is related with the sudden death, so the real time supervision of the LAP is required.

The volume of the interventricular space is variable due to the change of ejected and filled blood volume, so that the interventricular pressure(IVP) reflect atrial pressure that act upon the inflow to the sac. Accordingly, it seems reasonable to attempt estimating atrial pressure from IVP [4]. See Fig. 1. for the graphical illustration of the MA-TAH.

But the artificial heart needs extra invasive sensors to find the pressure informations and it is impossible to use in practical point of view and in the perspective of the long-term implantation. In this paper, we showed a methodology which can estimate the full hemodynamic variables with non-invasive methods using the IVP and motor current signals and verified our algorithm by in vitro test.

The modeling techniques can be categorized in Table I. The detailed techniques can be divided into two classes. One is the approach of mathematical modeling[3,5,6], the other is the input-output data approach[8-10]. The general approach is the dynamic state and mathematical model. But in practical point of view, it fails to satisfy the real world situations. So, popular approach is the input/output data approach based model in nowadays.

The desire of adaptation to the real-world situations and practical implementation(microcontroller, e.g., 80C196KD, digital signal processor) can be achieved by the static state based model. Also the mean value of estimated pressure signals rather than dynamic one is much favorable in the perspective of control, display, and database.

Interpolation technique is used in the application of signal processing[11], fuzzy learning[12] and so on. Multidimensional linear interpolation(MDI) is a useful method for nonlinear function problem. Application of this method was the estimation of the pump output of left ventricular assistant device(LVAD), and showed good performance[10]. Recently, Om et al. showed that MDI is a special form of fuzzy reasoning, especially, Tsukamoto's fuzzy reasoning, and also neural network, especially, regularization networks. Even if we can get the same output, the MDI is more efficient than fuzzy reasoning or regularization network in the perspective of operation cost. The detailed reasons are well summarized in[8,9]. Namely, MDI technique is a sufficient and satisfactory method for hemodynamic variables estimation problem.

MATERIALS AND METHODS

In this research, we adopted the static state input/output

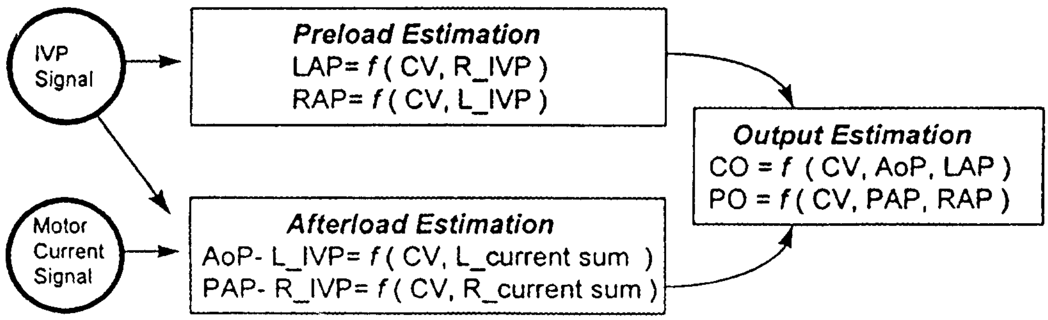

Fig. 2. Overall structure of estimation flow and relationships

Table 1. Categorization of modeling technique

Approach \ State	Dynamic (If the system uses previous state, it is called a dynamic system.)	Static (If the system does not use previous state, it is called a static system.)
Mathematical Model	Electric Components Modeling[4,5]	Geometric modeling[2] Energy based modeling[16]
Input/Output Data	ARMA modeling[17] Kalman Filtering[19] Fuzzy Reasoning Neural Network	Interpolation Fuzzy Reasoning Neural Network[8-10]

data based model for the estimation of the hemodybamic variables. The estimated hemodynamic variables are also the mean value and we adopted the MDI technique.

1. Relationships between the hemodynamic variables and other non-invasive signals

Fig. 2 shows the overall structure of estimation flow and relationships between the hemodynamic variables and other non-invasive signals.

The control algorithm of the MA-TAH has six control variables(CV), i.e., left velocity(L_Vel, [degree/sec]), right velocity(R_Vel, [degree/sec]), left stroke length(L_SL, [1 L_SL = 0.5 degree length]), right stroke length(R_SL, [1 L_SL = 0.5 degree length]), left break time(L_BT, [msec]), right break time(R_BT [msec]).

1) Preload

The right and left atrial pressures are important parameters in automatic control of an MA-TAH. During the operation of the MA-TAH, the interventricular space's volume is changed dynamically by the difference between the ejection volume of ventricle and the inflow volume of the other. Therefore, the changes in pressure of the interventricular space is related to the both atrial pressures. We can measure the IVP using a pressure sensor and attempt to indirectly estimate the changes of atrial pressure[6]. Especially, *Jo* has studied the relations deeply[7]. The simple relation can be given by Eq.(1). Namely, IVP can attribute to the estimation of preload(atrial pressures : LAP, RAP)

$$\text{LAP, RAP} \propto -K \times (\text{Negative Peak to Peak Value of IVP}) \quad (1)$$

where K is a proportional coefficient.

This simple relation is correct for the whole operational range. But experimental results have shown that it is very nonlinear depending on the operational range of control.

2) Afterload

One stroke work from a motor point of view is

$$\text{Work} = (\text{Current}) \times (\text{Voltage}) \times (\text{Time}) \quad (2)$$

One stroke work from a hemodynamics point of view is

$$\begin{aligned} \text{Work\&} &= (\text{Flow Rate})(\text{Pressure}) \times (\text{Time}) \\ &= f(\text{CV, Pressure}) \quad (3) \\ &= f(\text{CV, AoP-IVP}) \end{aligned}$$

From Eq.(2) and(3)

$$\mathrm{AoP} = f(K_1 \sum_{i=1}^{n} \mathrm{I}_i, \mathrm{CV}) + \mathrm{IVP} \tag{4}$$

The motor current data are not continuous but sampled ones, and they depend on the communication transmission rate. So, the coefficient K_1 was introdunced in Eq.(4). Similarly,

$$\mathrm{PAP} = f(K_1 \sum_{i=1}^{n} \mathrm{I}_i, \mathrm{CV}) + \mathrm{IVP} \tag{5}$$

We can estimate the AoP and PAP using the relations of Eq.(4) and(5). Namely, motor current has relations with afterload(AoP, PAP). But experimental results have shown that it is very nonlinear depending on the operational range of control.

3) Output

Finally, when we know the AoP and LAP, we can attempt to find the relation between output and other variables in Eq.(6) and Eq.(7). Here, AoP and LAP reflect the affections of regurgitation and inflow, respectively.

$$\begin{aligned} \mathrm{CO} &= \mathrm{SV} \times \mathrm{HR} \\ &= f(\mathrm{CV}, \mathrm{AoP}, \mathrm{LAP}) \end{aligned} \tag{6}$$

$$\begin{aligned} \mathrm{PO} &= \mathrm{SV} \times \mathrm{HR} \\ &= f(\mathrm{CV}, \mathrm{PAP}, \mathrm{RAP}) \end{aligned} \tag{7}$$

Where SV and HR are stroke volume and heart rate, respectively.

2. Multidimensional Linear Interpolation

Before we proceed, it is necessary to comprehend that what we mean the multidimensional linear interpolation (MDI) is the problem of interpolating on a mesh that is Cartesian, i.e., has not tabulated functional values at 'random' points in n-dimensional space rather than at the vertices of a rectangular array. This rectangular data array will be called a look-up table(LUT) from now. For simplicity, we consider only the case of three dimensions, the cases of two and four or more dimensions being analogous in every way. If the input variable arrays are $x_{1a}[\ ]$, $x_{2a}[\ ]$, and $x_{3a}[\ ]$, the output $y(x_1, x_2, x_3)$ has following relation[13].

$$y_a[m][n][r] = y(x_{1a}[m], x_{2a}[n], x_{3a}[r]). \tag{8}$$

The aim is to estimate, by interpolation, the function y at some untabulated point(x_1, x_2, x_3). If x_1, x_2, x_3 satisfy

$$\begin{cases} x_{1a}[\,m\,] \le x_1 \le x_{1a}[\,m\,] \\ x_{2a}[\,n\,] \le x_2 \le x_{2a}[\,n\,] \\ x_{3a}[\,r\,] \le x_3 \le x_{3a}[\,r\,], \end{cases} \tag{9}$$

the grid points are

$$\begin{aligned} y_1 &= y_a[\,m\,][\,n\,][\,r\,], \\ y_2 &= y_a[\,m\,][\,n\,][\,r+1\,], \\ y_3 &= y_a[\,m\,][\,n+1\,][\,r\,], \\ y_4 &= y_a[\,m\,][\,n+1\,][\,r+1\,], \\ y_5 &= y_a[\,m+1\,][\,n\,][\,r\,], \\ y_6 &= y_a[\,m+1\,][\,n\,][\,r+1\,], \\ y_7 &= y_a[\,m+1\,][\,n+1\,][\,r\,], \\ y_8 &= y_a[\,m+1\,][\,n+1\,][\,r+1\,]. \end{aligned} \tag{10}$$

The final 3-dimensional linear interpolation is

$$\begin{aligned} y(x_1, x_2, x_3) = \ & (1-u)(1-v)(1-w)y_1 \\ &+ (1-u)(1-v)(w)y_2 \\ &+ (1-u)(v)(1-w)y_3 \\ &+ (1-u)(v)(w)y_4 \\ &+ (u)(1-v)(1-w)y_5 \\ &+ (u)(1-v)(w)y_6 \\ &+ (u)(v)(1-w)y_7 \\ &+ (u)(v)(w)y_8, \end{aligned} \tag{11}$$

where

$$\begin{aligned} u &= \frac{x_1 - x_{1a}[m]}{x_{1a}[m+1] - x_{1a}[m]}, \\ v &= \frac{x_2 - x_{2a}[n]}{x_{2a}[n+1] - x_{2a}[n]}, \\ w &= \frac{x_3 - x_{3a}[r]}{x_{3a}[r+1] - x_{3a}[r]}. \end{aligned} \tag{12}$$

(u, v, and w each lie between 0 and 1.)

We can see the estimated y uses 2^n table terms if n-dimensions.

3. Prerequisite Studies

Before estimation of hemodynamic variables from the IVP and motor current signals, prerequisite studies were summarized as follows.

(1) The air volume in the interventricular space : This has influence upon all hemodynamic variables. See [14] for deep relations.

(2) The control algorithm

- PI gain : Heart rate and cardiac output are influenced by the P(Proportional) and I(Integral) gain in the PI control.
- Correct center position : We can say that the reliable center position is an important factor because of its possibility of affecting other variables related with stroke length. So reliable positioning is also important for setting a reliable estimation of hemo-

dynamic variables.

- The range of operational control variables must be settled reasonably. In this research, we used(20, 65) for SL,(200, 600) for Vel, and(0, 990) for BT.

(3) IVP sensor position: This has influence upon the IVP signal.

(4) Noise filtering for IVP and motor current signals : In this research, we used the center weighted median (CWM) filter(side length=4, weight=1)[15].

(5) IVP sensor gain.

(6) Type of valve(e.g., mechanical valve or polymer valve) : This has influence upon the output(CO, PO)

(7) Communication speed(In this research, we used the high speed serial communication, 38400 [bps, bits per second]) : This has influence upon the motor current summation data.

(8) The reproducibility of TAH(sac, housing,…) : This has influence upon all hemodynamic variables, and the estimation scheme does not fit well if the reproducibility is not guaranteed.

(9) Step number of peak to peak IVP and motor current summation values : In this research, we used the mean of present value and the five previous values for the final present value, and the motor current value is divided by 100 for the prevention of overflow of value(range of integer value(2 byte)=-32767 ~32767).

(10) Data acquisition(mechanical flow meter or ultrasound flow meter, mechanical pressure gauge or polygraph pressure value) : In this research, we used the mechanical flow meter. It is known that the ultrasound flow meter has a high possibility of deviation from the correct value(about 10 [%]).

RESULTS

In vitro experiments were carried out for the performance evaluation of the proposed estimation scheme. The brushless DC servo motor uses 20 [V] for power source. In an MDI, as the gird points increase, the accuracy increases also. Whereas the cells of LUT increase also. So the trade-off between the estimation accuracy and LUT size is necessary. In this research, we considered the simplest LUT - each variables consists of low and high in each range. In this case, the LUT for CO need $2^8=256$ cells(number of(L_SL, R_SL, L_Vel, R_Vel, L_BT, R_BT, AoP, LAP)=8). This is somewhat tremendous data. For the simplicity of the LUT of preload(LAP), we assumed the LAP is not influenced by break time. For the simplicity of the LUT of afterload (AoP), we assumed the AoP is not influenced by break time and the reverse velocity(R_Vel). R_Vel was set to be the middle value in the operation range. The cell number for the cases of LAP and AoP vary highly depending on the grid points between the motor current summation value and IVP peak to peak value. The final LUT protocol are listed in Table II, III, and IV.

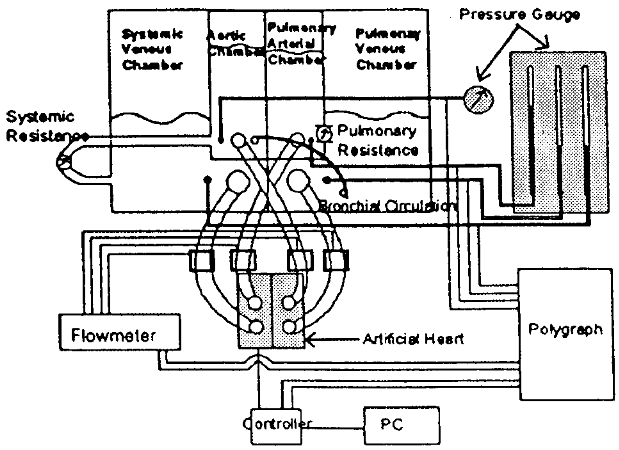

Fig. 3. Diagram of the mock circulatory system

Table V, VI, and VII are the *in vitro* experiment results. Fig. 3 is the diagram of the mock circulatory system. The mean error of the estimated CO, AoP, and LAP are 0.3[l/min], 8[mmHg], and 3.4[mmHg], respectively[14]. uses the fuzzy logic method for CO estimation. Results of [14] showed maximum estimation error is about 0.9 [l/min], but proposed one has the 0.8 [l/min]. Like other cases[14], was testified in a local operational range of control, but proposed one was testified in the overall operational range of control. This means proprosed one has the stable estimation capability. Also learning methods[14,19] - fuzzy logic, neural network - have the shortcoming of failure of generalization capability when the training is not fully carried out and the training data are not gathered in the overall operational range. Furthermore, proposed one is the static value - mean one for the one stroke - while others are dynamic one. This means that our methods have less operational cost than others and many merits, e.g., control of TAH, database of hemodynamic variables[18]. showed the estimator of AoP has the maximum estimation error is

Table 2. Cardiac output(CO) estimation protocols, AoP=(50, 150), LAP=(2, 20), RAP=fix to mean pressure 4 mmHg, L_BT =(0, 990), R_BT=(0, 990), L : Low, H : High

L_Vel	R_Vel \ L_SL	L 20		H 65	
	R_SL	L 20	H 65	L 20	H 65
L 200	L 200	CO			
	H 600				
H 600	L 200				
	H 600				

Table 3. Preload(LAP) estimation protocols, AoP=about 100, RAP=fix to mean pressure 4mmHg, IVP value=(small to large), L : Low, H : High

L_Vel	R_Vel \ L_SL	L 20		H 65	
	R_SL	L 20	H 65	L 20	H 65
L 200	L 200	LAP			
	H 600				
H 600	L 200				
	H 600				

Table 4. Afterload(AoP) estimation protocols, RAP=fix to mean pressure 4mmHg, LAP=about 10, motor current value=(small to large), L : Low, H : High

L_Vel	R_Vel \ L_SL	L 20		H 65	
	R_SL	L 20	H 65	L 20	H 65
L 200	M400	AoP / IVP			
H 600					

about 30[mmHg], whereas ours is 17[mmHg]. It must be reminded that the performance evaluations are carried out in the worst cases of possibility of high deviation of estimation value from the real one. And the LUT is the simplest form as was stated before. These mean that the proposed estimation scheme can be enhanced by magnifying the LUT. Considering these points, we can see the proposed estimation scheme has a very high ability to estimate the hemodynamic variables.

The only worrisome estimation is the preload estimation with very very small SL and one of Vel is small, e.g., L_SL=20[low], R_SL=20[low], L_Vel=400[middle], R_Vel=200[low] and L_SL=20[low], R_SL=20[low], L_Vel=200[low], R_Vel=400[middle]. We presume this results came from the fact that IVP usually generated when the stroke length and velocity are not very small.

Finally, the pulmonary output(PO) can be easily obtained by symmetric form compared with the CO, i.e., when we exchange the left and right control variables and setting AoP to PAP and LAP to RAP, we get the PO. Similarly, we can get the PAP and RAP. For PAP, we modified the

Table 5. *In vitro* experiments for the performance evaluations of cardiac output(CO) estimation [l/min], L : Low, M : Middle, H : High, AoP=100, LAP=10 mmHg

SL	M 40	L 20	L 20	M 40	M 40	L 20	M 40	M 40	H 65	H 65
Vel	L 200	M 400	L 200	M 400	L 200	M 400	M 400	H 600	M 400	H 600
BT	L 0	L 0	M 500	L 0	M 500	M 500	M 500	H 990	H 990	M 500
Real Value	2.3	2.6	1.5	4.4	1.9	1.8	3.7	3.8	4.2	6.6
Estimated Value	2.7	2.4	1.6	3.8	2.2	1.9	3.3	4.2	3.9	6.4
Error	0.4	0.2	0.1	0.6	0.3	0.1	0.4	0.4	0.3	0.2

SL	M 40	M 40	H 65	M 40	H 65	H 65	M 40	L 20	L 20	
Vel	M 400	H 600	M 400	H 600	M 400	L 200	L 200	M 400	H 600	
BT	H 990	M 500	M 500	L 0	L 0	M 500	H 990	H 990	M 500	
Estimated Value	3.0	5.0	5.0	6.0	5.4	2.9	2.1	1.8	3.1	
Real Value	2.9	4.7	4.3	5.6	4.8	2.8	2.0	1.7	2.3	
Error	0.1	0.3	0.7	0.4	0.6	0.1	0.1	0.1	0.8	

Table 6. *In vitro* experiments for the performance evaluations of afterload(AoP) estimation[mmHg], L : Low, M : Middle, H : High, R_Vel : 400, AoP=100, LAP=10, RAP=4mmHg

L_SL	M 40	L 20	L 20	M 40	M 40	L 20	M 40	M 40	H 65	H 65	M 40	M 40	H 65
R_SL	L 20	M 40	L 20	M 40	L 20	M 40	M 40	H 65	M 40	H 65	M 40	H 65	M 40
L_Vel	L 200	L 200	M 400	L 200	M 400	M 400	M 400	H 600	H 600	M 400	H 600	M 400	M 400
Current summation corresponding to the AoP of 100	91	78	48	78	100	85	135	150	200	235	136	145	194
IVP corresponding to the LAP of 10	126	91	10	95	65	36	168	190	133	172	105	198	154
Real negative peak to peak IVP Pressure [mmHg]	4	3	0	3	2	1	6	6	4	6	3	7	5
AoP-IVP	104	103	100	103	102	101	106	106	104	106	103	107	105
Estimated	108	112	117	87	107	113	103	108	93	92	102	102	92
Error	4	9	17	16	5	12	3	2	11	14	1	5	13

range of LUT from(50, 150) to(0, 50, 150).

DISCUSSION

It is needless to say that the nonlinear hemodynamic variables estimation is a very important study for the artificial heart. Even though it is important, there have not been satisfactory results which can be applied to the real world situations. In this paper, the problem of hemodynamic variables estimation for the MA-TAH was studed. MDI scheme was used for the estimation. Proposed method was verified by in vitro test and showed good performance.

Most TAHs use the microcontroller for the central processing unit(CPU), so the dynamic models cannnt be applied to it satisfactorily. And as we know the human system is the well-known nonlinear system, the mathematical model has a difference from the real-world situations, so most researches are based on the simulation stage. If the reproducibility is guaranteed, our method has the potentials of estimation of all hemodynamic variables(AoP, PAP, RAP, LAP, CO, PO). Moreover proposed scheme has the merits of the covering of full operational range of control and low operational cost from the static state value(mean value, current sum, mean IVP, peak to peak IVP).

The characteristics of proposed estimation scheme is that it is based on the non-invasive measurement and practical algorithm for real world situations. Our method can be applied to the similar application, e.g., flow estimation of LVAD(Left Ventricular Assistance Device)[10]. We showed the minimum data acquisition protocol for LUT construction which is needed as a database for MDI. Further researches are necessary to find the static state mathematical estimation model[16].

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Table 7. *In vitro* experiments for the performance evaluations of preload(LAP) estimation[mmHg], L : Low, M : Middle, H : High, AoP= 100, LAP=10 mmHg

L_SL	M 40	L 20	L 20	L 20	M 40	M 40	M 40	L 20	L 20	L 20	M 40	M 40	L 20	M 40
R_SL	L 20	M 40	L 20	L 20	M 40	L 20	L 20	M 40M	L 20	M 40	M 40	M 40	M 40	
L_Vel	L 200	L 200	M 400	L 200	L 200	M 400	L 200	M 400	L 200	M 400	M 400	L 200	M 400	M 400
R_Vel	L 200	L 300	L 200	M 400	L 200	L 200	M 400	L 200	M 400	M 400	L 200	M 400	M 400	M 400
IVP corresponding to the LAP of 10	122	120	20	27	80	26	140	45	140	100	90	250	170	220
Real negative peak to peak IVP Pressure [mmHg]	4	4	1	1	3	1	5	2	5	4	3	9	6	8
Estimated LAP	8	9	21	17	15	14	9	12	8	7	13	4	9	11
Error = | 10 - Estimated LAP |	2	1	11	7	5	4	1	2	2	3	3	6	1	1

R_SL	M 40	H 65	H 65	H 65	M 40	M 40	M 65	H 65	H 65	H 65	M 40	M 65	H 65	
L_SL	H 65	M 40	H 65	H 65	M 40	H 65	H 65	M 40	M 40	H 65	M 40	M 40	M 40	
R_Vel	H 600	H 600	M 400	H 600	H 600	M 400	H 600	M 400	H 600	M 400	M 400	H 600	M 400	
L_Vel	H 600	H 600	H 600	M 400	H 600	H 600	M 400	H 600	M 400	M 400	H 600	M 400	M 400	
IVP corresponding to the LAP of 10	540	470	650	630	560	630	390	500	400	580	470	490	530	
Real negative peak to peak IVP Pressure [mmHg]	20	17	24	23	20	23	14	18	14	21	17	18	19	
Estimated LAP	9	16	4	16	13	6	11	8	15	9	8	12	6	
Error = | 10 - Estimated LAP |	1	6	6	6	3	4	1	2	5	1	2	2	4	

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