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Flow profile generation for a left ventricular assist device using iterative learning control

Abstract: Nowadays, rotary blood pumps for the treatment of end-stage heart failure patients are usually fixed-speed controlled. Therefore, without sufficient heart activity, patients may reveal reduced blood flow pulsatility. However, there is evidence that pulsatile flow reduces adverse events. Furthermore, optimized pump flow profiles could be used to achieve certain control objectives. Therefore, a pump flow model is identified and subsequently used to design a control system with an iterative learning controller to generate desired pump flow patterns. Either a flow sensor is required for direct measurement or the flow can be estimated from pressure sensor readings using the proposed pump flow model. For comparison, a PID controller with disturbance feedforward control is also designed. Furthermore, the robustness against respiratory sinus arrhythmia is analyzed.

Keywords: Ventricular assists device, Mock circulatory loop, PID control, Iterative learning control

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1 Introduction

Heart failure is a global pandemic affecting around 26 million people around the world and is increasing in prevalence [1]. Heart failure describes a complex clinical syndrome characterized by a reduced ability of the heart to pump blood and/or fill with blood [2]. In the case of acute heart failure, rotary blood pumps (RBPs), which are a subclass of left ventricular assist devices, are frequently implanted due to donor heart scarcity [3]. RBPs support the patient's failing

heart by pumping an additional amount of blood from the left ventricle to the aorta.

Nowadays, RBPs are usually fixed-speed controlled [4]. Therefore, without sufficient remaining heart activity, patients may reveal reduced blood flow pulsatility. However, there is evidence that pulsatile flow reduces the risk for gastrointestinal bleeding, pump thrombosis, stroke, and aortic valve insufficiency, as well as increases the rate of heart recovery [5, 6]. Furthermore, optimized pump flow profiles could be utilized to optimize for control objectives such as minimizing left ventricular stroke work (c. f. [7]), maximizing pump washout, or minimizing pump-induced hemolysis.

Iterative learning control (ILC) is a promising approach to optimize reference tracking or disturbance rejection of cyclic repetitive processes. The remaining heart activity of heart failure patients can be regarded as a cyclic disturbance on the RBP. Respiratory sinus arrhythmia (RSA) describes the cyclic increase of the heart rate during inspiration and decrease during expiration. The level of heart rate variability depends on the breathing frequency [11]. Varying iteration lengths complicate the control task for ILC algorithms.

2 Measurement setup

The Sputnik RBP, introduced in [8], is an axial flow pump, which has been implanted in 49 patients by the beginning of 2020 in Russia [9]. The RBP is connected to the hybrid mock circulatory loop (MCL) described in [10] (c. f. Figure 1).

Figure 1: Sputnik RBP connected to the MCL.

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The MCL allows to generate any pressure set values at the pump inlet and pump outlet. A numerical model of the cardiovascular system (CVS) generates physiological pressure curves at the pump inlet and outlet by measuring the pump flow through the RBP. The CVS model is executed on a dSpace DS1103 real-time computer, which is also utilized to execute the pump control system. The pump flow is measured by a Transonic HT-110 clamp-on flow Sensor and the pressure is measured by Codan Xtrans DPT-9300 pressure sensors. The MCL is filled with distilled water.

3 Pump flow model

Figure 2 shows the proposed pump flow model and the corresponding parameters that have been determined using the MCL. The model consists of a static map, that describes the static relationship between pressure head P_{head} , rotational pump speed v_{ref} , and pump flow Q_{RBP} . Furthermore, the dynamics from pressure head to pump flow and from pump speed to pump flow are modeled by individual PT1 dynamics with dead time. The rise time of both PT1 dynamics is determined by the average value of corresponding step response experiments at different relevant operating points. The dead times are calculated by minimization of the root mean squared error (RMSE) between estimated flow curves $\hat{Q}_{\text{RBP}}$ and measured flow curves Q_{RBP} .

Figure 2: Pump flow model consisting of a static map and PT1 dynamics with dead time.

4 Control system

The pump flow control system with direct flow measurement is depicted in Figure 3. However, pump flow can also be estimated by pressure measurements using the pump flow model. The control system consists of an inner pump speed control loop as well as a feedback flow controller in parallel to an iterative learning controller (ILC). The remaining heart activity of patients can be regarded as a disturbance.

The speed of the Sputnik pump is controlled by an Escon 50/4 motor controller, which allows for closed-loop speed control

of sensorless brushless DC motors. The corresponding PI speed controller parameters are manually tuned using the Escon Studio Software.

Due to the cyclic nature of heart activity, ILC is a meaningful approach to generate desired pump flow profiles. A P-ILC algorithm updates the reference speed pattern for the next iteration $v_{\text{ref},j+1}$ based on the flow deviation vector e_j (stored during the previous iteration) and the previous reference speed pattern $v_{\text{ref},j}$ at the end of each iteration:

$$v_{\text{ref},j+1}(k) = Q[v_{\text{ref},j}(k+d) + L \cdot e_j(k+d)] \quad (1)$$

The parameter j is the iteration domain index, k is the discrete-time domain index (sample time = 1000 Hz), d is a non-causal shift, L is a constant learning rate, and Q is a robustness filter. The learning rate L is chosen as the inverse of the mean amplification A_{mean} , which has been determined from the step response experiments:

$$L = \frac{1}{A_{\text{mean}}} = 339 \quad (2)$$

Minimization of the RMSE of the 200's ILC iteration e_{200} (without Q and RSA) results in an optimal shift d of 30 samples. To avoid overshoot and noise affecting the manipulating variable, Q was selected to be a first-order Butterworth lowpass filter with a cutoff frequency of 40 Hz. A zero-phase filter for Q and the non-causal shift d can be used because the vectors e_j and $v_{\text{ref},j}$ have already been stored before Equation 1 is applied.

Furthermore, a slow and robust PI controller in parallel to the ILC counteracts non-repeating disturbances and reduces the settling time of the ILC. The sum of ILC and flow controller output is bounded between 4000 rpm and 9500 rpm.

a PI flow controller in parallel to an ILC (direct flow measurement).

For comparison, a PID controller with disturbance feedforward control (referred to as reference controller) was designed as well. The PID controller was tuned using the PID tuner app in Matlab/Simulink (v2020a). The disturbance feedforward control was calculated by inversion of the PT1 dynamic from pressure head to pump flow and searching for an optimal gain factor.

5 Results

Pump flow estimation

Figure 4 indicates the ability of the pump flow model with the determined parameters to estimate the pump flow in real-time. The mean RMSE under several relevant operation conditions of RBP support is lower than 0.4 L/min.

Figure 4: Estimated and measured flow curves for excitation by remaining heart activity or pulsatile pump speed.

ILC with pump flow measurement versus estimation

The reference flow pattern is a rectangular signal, filtered at 20 Hz. It alternates between 3 L/min and 6 L/min with a duty cycle of 50 % (independent of the heart rate). The high flow region is synchronized to the remaining heart contraction.

Figure 5 compares the performance of the ILC using direct flow measurement and the ILC using flow estimation by the proposed model (no RSA). Both approaches yield a high and comparable tracking performance after few ILC iterations and the ILC performance exceeds that of the reference controller.

Figure 5: Comparison of ILC tracking behaviour for estimated and measured pump flow after 1, 4 and 100 iterations (no RSA, 60 bpm). The tracking behaviour of the reference controller is also shown.

Robustness to varying heart rates

To simulate RSA, the heart rate is modulated with a sinusoidal signal with different amplitudes and frequencies according to Table 1, which has been determined from [11]. Furthermore, some uniform distributed random noise with amplitudes between -0.5 and 0.5 accounts for the random nature of heart rate variability.

Table 1: RSA frequencies and amplitudes determined from [11].

	Breathing frequency	RSA amplitude
Slow	0.1 Hz ($\triangleq$ 6 bpm)	16 bpm
Typical (rest)	0.25 Hz ($\triangleq$ 15 bpm)	7 bpm
Fast (exercise)	0.5 Hz ($\triangleq$ 30 bpm)	4 bpm

Figure 6 depicts the ILC performance over several iterations for the simulation of RSA according to Table 1. Furthermore, the performance of the reference controller is shown for comparison. The reference controller performance barely depends on the simulated RSA conditions. Fast RSA with low amplitudes only has little influence on the ILC performance, whereas slow RSA with high amplitudes strongly degrades the ILC performance. However, after a few iterations, the ILC outperforms the reference controller for all simulated RSA conditions.

Figure 6: ILC and reference controller performance for different heart rate variabilities simulated by RSA parameters according to Table 1.

6 Conclusion

The described ILC algorithm can be successfully applied to blood pumps with either a flow sensor or pressure sensors at the pump input and output. For a pump with pressure sensors, the pump flow can be estimated by the proposed pump flow model. Furthermore, there is some robustness against heart

rate variations. However, further optimization needs to be considered. So far, the heart cycles are assumed to be known. However, in practice, the iterations need to be determined from signals like pump speed, pressure head, pump flow, or an additional ECG measurement. Furthermore, to imitate blood viscosity, the MCL could be filled with a mixture of glycerin and distilled water. However, the ILC algorithm is assumed to be robust against changes in blood viscosity.

In future investigations, the proposed ILC algorithm can be used as an inner control loop to optimize for certain control objectives.

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