A self-calibrating and learning control system for non-invasive continuous perioperative blood pressure measurement

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Abstract: State-of-the-art non-invasive blood pressure measurement devices according to Riva-Rocci only allow for non-continuous measurements every few minutes. This paper presents a non-invasive system that can measure the blood pressure continuously. The system contains a pressure control loop as well as an Iterative Learning Control loop. The pressure controller initially performs a calibration procedure to adapt itself to different pressure dynamics. Furthermore, time-scale transformation is applied for the Iterative Learning Control to enable the system to deal with varying heart rates. The mentioned system properties render it well suited for blood pressure monitoring during surgery.

I. Introduction

The instantaneous detection of hypotensive events during surgery is crucial [1]. Hypotensive events are e.g. defined in [1] as mean arterial pressure lower than 65 mmHg or lower than 20 mmHg from the baseline. The duration of those events is associated with the risk of mortality, longer hospitalization, acute kidney injury, myocardial injury or stroke [1]. Nowadays, clinically applied devices for non-invasive blood pressure measurement during surgery utilize the principle of Riva-Rocci. However, those devices cannot measure blood pressure continuously and therefore, hypotensive events are only detected with a delay or not even recognized at all. The alternative solution of invasive (intra-arterial) blood pressure measurement is likewise disadvantageous, since it is associated with the risk of infection, bleeding, hematoma, sepsis and several further complications [2].

In [3] a blood pressure measurement system for continuous and non-invasive blood pressure measurement has been introduced. However, so far, this system can only operate under ideal and fixed conditions and it only estimates the blood pressure during periodic trials. Therefore, the present article proposes an improved control system that renders the measurement system more suitable for clinical practice. First, we propose a pressure controller that adapts to different pressure dynamics. Second, we address the problem of varying heart rates, which physiologically occur in humans. Furthermore, a correction algorithm for the determined blood pressure as well as an estimation algorithm for the blood pressure during inactive learning control system are introduced.

II. Material and methods

II.I. Measurement setup and methodology

The measurement setup and methodology are depicted in Figure 1 and further detailed in [3]. The blood pressure inside the arteria radialis, referred to as artery pressure P_{artery}, is determined.

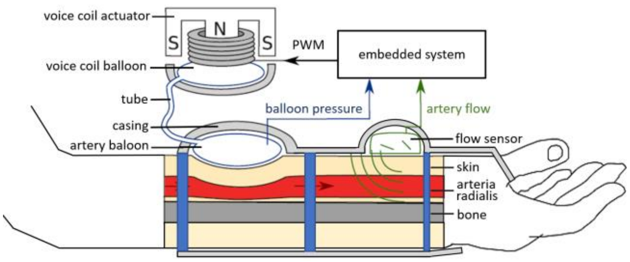

Figure 1 Measurement setup of the self-calibrating and learning blood pressure measurement system (based on [3])

A flow sensor exploits the Doppler effect to measure the artery flow Q_{artery} through the arteria radialis. Due to pulsatile heart activity, Q_{artery} and P_{artery} exhibit physiological pulses. The balloon pressure $P_{balloon}$ is adjusted by the PWM signal applied to a voice coil actuator such that Q_{artery} is controlled to a low and constant value. $P_{balloon}$ to reach this goal is assumed to be equal to the actual artery pressure, except for a small offset error.

II.II Control System

The structure of the control system is illustrated in Figure 2. It consists of a pressure control loop and an Iterative Learning Control (ILC) loop.

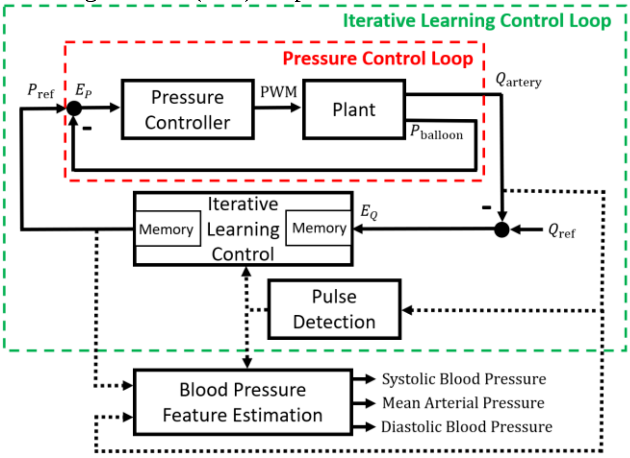

Figure 2 Control loops of the self-calibrating and learning blood pressure measurement system

Before starting the actual blood pressure measurement, the pressure controller performs auto-calibration. For that, the pressure dynamics are initially determined using an automatic system identification procedure based on a recursive least squares algorithm. The pressure dynamics are modeled as a second order transfer function with dead time. The identified model is used to automatically calculate the parameters of the PI pressure controller using the digital magnitude optimum method [4]. After controller parameterization, the pressure controller is executed with 1000 Hz to rapidly adjust the balloon pressure P_{balloon} to the reference pressure pattern P_{ref}. P_{ref} is learned via ILC over several iterations to control the Q_{artery} to a low and constant value. The P-type ILC algorithm with fixed learning rate and Butterworth robustness lowpass filter is executed with 100 Hz. ILC requires pulse detection to determine the iterations. A new iteration always starts 150 ms after a peak in Q_{artery} is detected. Furthermore, time-scale transformation according to [5] is used to deal with physiological varying heart rates. To ensure sufficient blood perfusion of the hand, ILC alternates between two active iterations followed by three inactive iterations. During active ILC, the estimated blood pressure is corrected based on the remaining flow deviation. During inactive ILC, P_{artery} is estimated based on P_{artery} of the previous iteration and the currently measured Q_{artery}.

III. Results and discussion

The blood pressure measurement system was tested with a cardiovascular simulator, developed by the Biofluid Mechanics Lab at Charité Berlin. The software is implemented in Matlab/Simulink (version R2017b) and executed on a Raspberry Pi 3 Model B V1.2.

III.I. Self-calibrating pressure controller

Figure 3 demonstrates the ability of the self-calibrating pressure controller to adapt to different pressure dynamics. Pressure dynamics are varied by inserting extra tubes of different lengths between the artery balloon and the voice coil balloon. Although no extra tube shows dominating PT1 pressure dynamics whereas 25 cm or 150 cm extra tube length show dominating PT2 pressure dynamics, the performance is similar for all three cases.

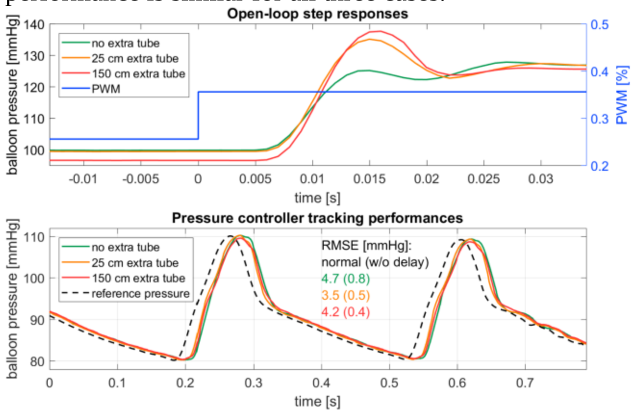

Figure 3 Open-loop step responses and pressure controller tracking performances for different extra tube lengths

III.II Adaption to varying heart rates

Figure 4 demonstrates that the system can deal with varying heart rates. If a constant heart rate of 60 bpm is used, time-scale transformation does not have an impact on the RMSE. However, if a variable heart rate occurs, time-scale transformation is required to maintain ILC performance.

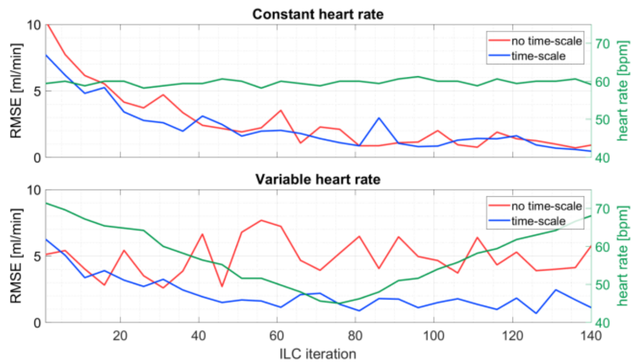

Figure 4 Performance of time-scale transformation with constant heart rate (upper plot) and with varying heart rate (lower plot)

IV. Conclusions

The proposed blood pressure measurement system seems well suited for blood pressure monitoring during surgery because it self-calibrates, tolerates heart rate variability and provides continuous measurements. These properties allow for studies of the blood pressure measurement system with human subjects in the near future.

AUTHOR'S STATEMENT

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