Model-Free Predictive Control of Human Heart Rate and Blood Pressure

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***Abstract*—Prolonged bed rest in severely paralyzed or intensive care patients is associated with adverse secondary effects on cardiopulmonary function. To counteract these effects of immobility in bed-ridden patients, we aim at controlling and stabilizing the cardiovascular system via multiple mechanical input variables. A challenge in this control problem is to provide an accurate model of the plant to be controlled. As humans are time variant systems and show individual physiological reactions to external stimuli the identification of such a model appears to be challenging. The current work presents a model-free predictive controller which takes into account these challenges. In this paper we present data concerning the control of heart rate, systolic and diastolic blood pressures, and mean arterial blood pressure via body tilting and leg mobilization. The controller was validated in a simulation study and feasibility was tested on two healthy subjects. The experimental results with healthy subjects show that the mean value differed in average less than 1 beat per minute (bpm) from the desired heart rate values and less than 1 mm Hg from the desired blood pressure values. The long term goal of this project is to control also breathing via body tilting, stepping and electrical muscle stimulation.**

I. Introduction

SEVERELY impaired neurological patients, e.g. stroke, spinal cord and traumatic brain injury or paraplegia patients are often forced to long periods of bed rest. These long periods of bed rest lead to dramatic changes of the cardiopulmonary system that add to the primary disease and often delay recovery [1]. Consequently, mobilization should start as early as possible [2, 3]. At the same time for the safety of the patient, control of cardiovascular parameters within a predefined normal range matters in both severe course of disease and the rehabilitation process [4, 5]. A rehabilitation approach which addresses both perspectives is missing.

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Our overall goal is to develop a novel intelligent rehabilitation bed, which stabilizes and controls the cardiopulmonary system of acute care patients. Biosignals such as heart rate and blood pressure will be controlled in a closed loop control fashion via robotic-induced external mechanical and electrical stimuli. In our previous work, we developed a nonlinear model predictive controller and proved its feasibility in patients [6]. The system required an identification phase of 11 minutes and could not adapt the control strategy to changes in external factors.

To enhance our system, the current study describes an online model-free predictive controller [7] with the goal to keep the heart rate [HR], systolic and diastolic blood pressures [sBP, dBP] as well as mean arterial blood pressure [MAP] in predefined values via body tilting and leg mobilization. We evaluated the performance of the proposed control strategy for different combinations of cardiovascular parameters: i) Multi-input single-output (MISO) control of isolated HR, sBP or dBP, ii) Multi-input multi-output control (MIMO) of HR combined with MAP. The evaluation was done in simulation and on healthy subjects.

II. Materials and Methods

A. Cardiovascular model

To evaluate the designed controller in simulation, a previously validated physiological nonlinear MIMO model of the human body was used. The model includes inclination angle of the tilt table and leg mobilization together with foot loading as inputs, and HR, sBP and dBP as outputs of the system [6]. For the simulation results in this paper, physiological parameters of a typical body were considered.

B. Subjects and study protocol

Subjects: The real-world evaluation of the controller was done on two healthy subjects with no known cardiovascular disorders. Subject 1 is female, 23 years old, weights 55 kg and is 179 cm tall. Subject 2 is male, 24 years old, weights 61 kg and is 170cm tall.

Constraint identification experiment: To demonstrate and evaluate the controller performance, achievable set points had to be considered. To identify the mechanically induced maximum possible changes in the cardiovascular parameters of each subject, an initial constraint identification experiment had to be done. The experiment started with 5 minutes in supine position without stepping; followed by 5 minutes at maximum inclination without stepping, and

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finally 5 minutes at maximum inclination and with maximum stepping frequency. In the last minute of each phase, HR, sBP and dBP values were averaged in order to obtain the steady-state response of the cardiovascular system to the corresponding magnitude and combination of physical stimuli.

The maximum possible change in the cardiovascular parameters was calculated using the steady-state values in each phase and the following formula:

$$\Delta y_{max} = \max(y_{max.\ \alpha} - y_{\alpha=0},\ y_{max.\ \alpha\ \&\ f_{Step}} - y_{\alpha=0}) \quad (1)$$

where y is the vector of HR, sBP and dBP steady-state values; α and f_{Step} represent applied inclination angle and stepping frequency, respectively.

Control experiments: Each control experiment took approx. 27 minutes and started with a 5-minute initial measurement in the supine position followed by a learning phase (100 sec) and two 10-minute blocks where the controller tried to match predefined values of HR, sBP, dBP or MAP by changing the inclination angle and stepping frequency provided by the controller. A learning phase was introduced due to the sensitivity of the controller to initial values of the parameters and data model, and to provide further adaptation of the data model in the beginning of the experiment. This phase helps when the outputs show an initial negative relationship with respect to the inputs that leads to the saturation of the control inputs at zero inclination and stepping, and consequently stops the controller from further actions and achieving a better estimation of the plant to be controlled. The learning phase consisted of applying 5 (instead of only 1) predicted sets of control inputs, using the data model initialized before the control phase.

The set points for the first and second 10-minute blocks were set to supine position steady-state values (average of last minute) summed by 60% and 30% of Δy_{max}, respectively. For the evaluation of the controller, the error between the true signal and the desired value during the last 5 minutes of each block was computed. Then the mean and standard deviations of the errors from each experiment was calculated. Mean values represent cardiovascular system long-term dynamics which we aim to control. Standard deviations represent natural short term fluctuations. HR, sBP and dBP were measured directly while MAP was approximated using the well-known formula [8]:

$$MAP = \frac{1}{3}sBP + \frac{2}{3}dBP \quad (2)$$

C. Measurement Equipment and Actuated Tilt Table

Continuous noninvasive measurements of HR, sBP and dBP were done using a CNAP® monitor 500 (CNSystems AG, Austria). The ERIGO tilt table (Hocoma AG, Switzerland) was used as an initial feasible setup for the intelligent bed. It provides continuously adjustable verticalization with a motor-driven stepping module. The inclination angle of the bed (α) can be adjusted between 0 and 75 degrees. The stepping module provides reproducible movements at a constant adjustable speed from 0 to 80 steps per minute (maximum stepping frequency $f_{step,\ max}$ = 1.33 Hz) with equal periods for both extension and flexion phases (Fig. 1).

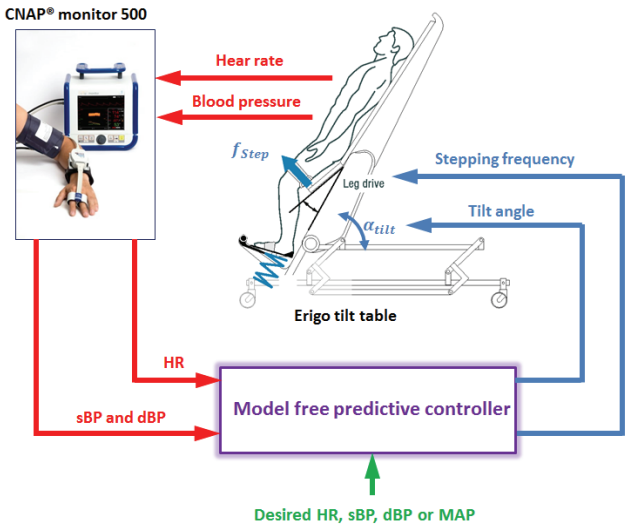

Fig.1. Evaluation of the controller in real world setup

D. Model-free predictive controller

Introduction: generally, an accurate model of the plant is required for the control system design. Since each human body is unique, has a time-dependent nature and shows individual reactions to external stimuli, we propose a model-free predictive controller (MFPC) [7]. MFPC is a data-driven control strategy which directly uses online input-output data of the controlled system and does not need prior knowledge about the system or an identification phase. Similar approaches have been proposed for all kinds of systems, from SISO [9] to MISO [10] and MIMO [11], and are particularly useful when dealing with complex systems with large uncertainties such as the human body. In this work the additional property of a prediction horizon was employed as proposed by Chengli Su [7]. This complementary approach is referred to as model-free predictive control (MFPC) and has several advantages over traditional control approaches. Since it is based on a locally linearized data model, it should be able to better deal with the nonlinearities present in the cardiovascular system. Additionally, no previous knowledge has to be assumed because the response is modeled directly online. This results in improved behavior in the presence of time variance and robustness with respect to subject-specific characteristics such as dead time or physiological oscillations. Finally, the inclusion of a prediction horizon enables more cautious control since the control effort is distributed over more thanone step.

Principle: MFPC employs a dynamic linearization of the partial format and assumes that the one-step-ahead output vector can be expressed as a general nonlinear function of past inputs and outputs:

$$y(k+1) = f(y(k), y(k-1), \dots, y(k-j_y), u(k), u(k-1), \dots, u(k-j_u)) \quad (3)$$

where $f(.)$ is a nonlinear function; $y[n_y \times 1]$ and $u[n_u \times 1]$ are the output and input vectors in different discrete time steps k; n_y and n_u are the numbers of outputs and inputs; j_y and j_u are orders of the system. Consequently, the input and output vectors are defined as:

$$y = (HR, sBP, dBP)^T \quad (4)$$
$$u = (\alpha_{inclination}, f_{step}) \quad (5)$$

and MAP is controlled using equation (2). Assuming that (i) the generalized Lypschitz condition is met and (ii) the partial derivative of $f(.)$ with respect to u(k) is continuous, equation (3) can be linearized as follow:

$$y(k+1) = y(k) + \phi(k)^T \Delta \mathrm{U(k)} \quad (6)$$
$$\Delta y(k+1) = y(k+1) - y(k)$$

where $\Delta y(k+1)[n_y \times 1]$ is the next change in the outputs; $\phi(k)[n_y \times n_u L]$ is the pseudo-jacobian matrix and $\Delta U(k)[n_u L \times 1]$ is the vector of past input changes:

$$\Delta U(k) = \big(\Delta u(k), \Delta u(k-1), \dots, \Delta u(k-L+1)\big)^T$$

$$= \begin{pmatrix} u(k) - u(k-1) \\ u(k-1) - u(k-2) \\ \vdots \\ u(k-L+1) - u(k-L) \end{pmatrix} \quad (7)$$

L is the control input linearization level constant [12] and is the number of past input changes considered in the mapping. The pseudo-jacobian matrix contains the pseudo-partial derivatives describing the mapping from past input changes to the next output changes. It can be subdivided in submatrices of dimensions $[n_y \times n_u]$ as follows:

$$\Phi(k) = (\phi(k)_1, \phi(k)_2, \dots, \phi(k)_L) \quad (8)$$

The predicted outputs for the next P steps can be iteratively calculated, and the resulting vector of predicted outputs is given in [5]:

$$Y_P = Y + \Psi_1 \Delta U_P + \Psi_2 \Delta U_L \quad (9)$$

with P being the prediction horizon; $\mathrm{Y_P} = \big(\mathrm{y(k+1), y(k+2), \dots, y(k+P)}\big)^{\mathrm{T}} \big[\mathrm{n_y P \times 1}\big]$ the predicted output vector; $\mathrm{Y} = \big(\mathrm{y(k), y(k), \dots, y(k)}\big)^{\mathrm{T}} \big[\mathrm{n_y P \times 1}\big]$ an extended current output vector; $\Psi_1\big[\mathrm{n_y P \times n_u P}\big]$ and $\Psi_2\big[\mathrm{n_y P \times n_u (L-1)}\big]$ matrices obtained by a combination of $\Phi_1^{\mathrm{T}}, \Phi_2^{\mathrm{T}}, \dots, \Phi_{\mathrm{L}}^{\mathrm{T}}$ which can be found in [6]; $\mathrm{\Delta U_P} = \big(\mathrm{\Delta u(k), \Delta u(k+1), \dots, \Delta u(k+P-1)}\big)^{\mathrm{T}} \mathrm{[n_u P \times 1]}$; $\mathrm{\Delta U_L} = \big(\mathrm{\Delta u(k-1), \Delta u(k-2), \dots, \Delta u(k-L+1)}\big)^{\mathrm{T}} \mathrm{[n_u (L-1) \times 1]}$ the vector of past control input changes.

The control strategy also allows a reference trajectory to be introduced from the current operating point to the setpoints and defines how the outputs should reach the setpoints. For the controller, a commonly used exponential reference trajectory was defined:

$$y_{ref}(k+i) = y(k) + (y(k+1)^* - y(k))(1 - e^{-\frac{iT}{\tau}}) \quad (10)$$

with $i = 1, \dots, P$; $y(k+1)^*$ being the vector of the next desired setpoints, T the sampling period of the controller (20 sec) and τ the time constant of the reference trajectory. In the following, $\frac{iT}{\tau}$ will be referred to as β, decrement of the exponential function. The reference trajectory can be expressed as a vector of size $[n_y P \times 1]$:

$$Y_{ref} = (y_{ref}(k+1), y_{ref}(k+2), \dots, y_{ref}(k+P))^T \quad (11)$$

Having a predicted trajectory and a reference trajectory for the outputs, the goal is to optimize the first one to be as close as possible to the second one. This can be achieved by minimization of the following cost function:

$$J(\Delta U_P) = (Y_P - Y_{ref})^T Q\ (Y_P - Y_{ref}) + \lambda \Delta U_P{}^T R \Delta U_P \quad (12)$$

where Q is a diagonal matrix of output error weights; R is a diagonal matrix of input change weights and λ is the penalty on the input changes. The cost function consists of two parts: the first part represents the error of the prediction with respect to the reference trajectory; the second part is a term to minimize the change in the inputs. The relative importance of these two terms can be tuned with the parameterλ. Taking the first derivative of the cost function with respect to ΔU_P and setting it to zero gives:

$$\Delta U_P = \big(\Psi_1{}^T Q \Psi_1 + \lambda R\big)^{-1} \Psi_1{}^T Q (Y_{ref} - Y - \Psi_2 \Delta U_L) \quad (13)$$

Similarly to receding horizon concept in model predictive control, only the first term in ΔU_P is applied, and in the next step the whole procedure of the prediction and the minimization of the cost function is performed again. This allows avoiding too much confidence in the prediction made on the base of the current data model.

To obtain the pseudo-jacobian matrix$\Phi(k)$, another cost function has to be minimized:

$$J(\Phi(k)) = \left(y(k) - y(k)_{exp}\right)^T \left(y(k) - y(k)_{exp}\right) \quad (14)$$
$$+\mu(\Phi(k) - \Phi(k-1))^T(\Phi(k) - \Phi(k-1))$$

where μ is the penalty on the change of $\Phi(k)$ (a sort of learning rate) and $y(k)_{exp}$ is the expected output which is equal to $y(k)_{exp} = y(k-1) + \Phi(k-1)^T \Delta U(k-1)$. Taking the first derivative of the cost function with respect to $\Phi(k)$ and setting it to zero gives:

$$\Phi(k) = \Phi(k-1) + \left(\mu I + \Delta U(k-1)^T \Delta U(k-1)\right)^{-1} \times$$
$$\Delta U(k-1)(\Delta y(k)^T - \Delta U(k-1)^T \Phi(k-1)) \quad (15)$$

where I is the identity matrix. For the simulation results of the cardiovascular system control, $\lambda = 1$; $\mu = 10^{-5}$; $L = P = 30$; $\beta = 0.37$ were considered. For the experiments on healthy subjects similar values were used except in some cases where instead of $\lambda = 1$, $\lambda = 0.1$ was used due to difficulties of controller tuning.

III. Results

Simulations showed that MISO control of HR, sBP and dBP as well as MIMO control of HR together with MAP is possible by changing inclination angle and stepping frequency (Fig. 2). The desired values can be reached without any errors. The experiments on one healthy subject are shown in Fig. 3 and the result of all experiments are summarized in TABLE I. Average absolute mean errors from desired heart rates and blood pressures are 0.59 bpm (SD: ± 3.51 bpm) and 0.87 mm Hg (SD: ± 2.02 mm Hg), respectively. This corresponds to average absolute errors of 0.79 mm Hg, 0.43 mm Hg and 0.46 mm Hg for sBP, dBP and MAP, respectively.

TABLE I
CONTROLLER PERFORMANCE ON HEALTHY SUBJECTS
(M IS THE MEAN ERROR AND Σ THE STANDARD DEVIATION)

Experiment	Setpoint 1		Setpoint 2		Total (abs. mean)	
	μ	σ	μ	σ	μ	σ
Subject1- HR	-0.44	3.2	0.39	2.81	0.41	3.01
Subject1-sBP	-0.18	3.1	1.39	1.91	0.79	2.52
Subject1-dBP	0.51	2.4	0.35	1.35	0.43	1.89
Subject1-HR/MAP (HR)	-0.65	4	0.1	3.18	0.38	3.59
Subject1-HR/MAP (MAP)	-2.53	2.2	-1.26	1.87	1.89	2.03
Subject2-HR	0.79	5.2	0.72	2.91	0.76	4.01
Subject2-dBP	-0.72	4	-0.24	3.39	0.48	3.68

IV. LIMITATIONS

The tuning of the controller parameters is challenging as the parameters optimized by simulation studies appeared to be not optimal for the real application of the controller.

The other issues are robustness and adaptability during the initial phase of the control experiment. The initial I/O relationships which are recorded and used by the controller determine the success of the controller. If, for example, in the beginning of the experiment, the outputs show that increasing the inputs will decrease them and introduces a bigger deviation from desired values, the controller will decrease the inputs. If the control inputs fall into the saturation, they will remain in the saturated minimum, since the possibility of further exploration by the controller and consequently, adaptation of the data model even when the response is changed and the performance can be improved, is strongly prevented. To solve for this sensitivity to the initial conditions and parameters, an initial phase called "Learning Phase" was introduced.

A prolonged saturation of control inputs can negatively affect the data model. In such a case, the inputs change would remain constant at zero, while outputs would vary due to the time-variance of the human body. Therefore, the data model would integrate wrong I/O relations in the partial derivatives and furthermore, would have limited information about the global response of the human body.

The initial constraint identification experiment was an appropriate way to identify the mechanically induced maximum possible changes in the cardiovascular parameters of each subject and accordingly, choice of setpoints for the evaluation of the controller in MISO case. However, in MIMO control of HR/MAP due to the underlying nonlinearity and coupling, which are neglected in this procedure, it is not an optimal way. In this case it is possible that the chosen setpoints can be reached alone but reaching them simultaneously will not be possible due to the coupling of the cardiovascular parameters.

Finally, in addition to stepping and tilting, other important aspects, e.g. psychological factors, might also influence the cardiorespiratory system.

V. Conclusion and Outlook

We were able to control human cardiovascular parameters in simulation as well as on healthy subjects with only mechanical stimuli. The applied model free predictive controller had no prior knowledge on the human body. In simulation desired values were reached without any deviations. The experimental results with healthy subjects show that the mean values differed on average less than 1 bpm/mm Hg from the desired values of HR and BP (sBP, dBP, MAP). According to daily clinical practice, HR deviations of less than 2.5 bpm and BP deviations of less than 5 mm Hg can be neglected. The results of this feasibility study are very promising and will be expanded on more physiological parameters (e.g. Control of respiration) in more individuals, as well as bed-ridden patients.

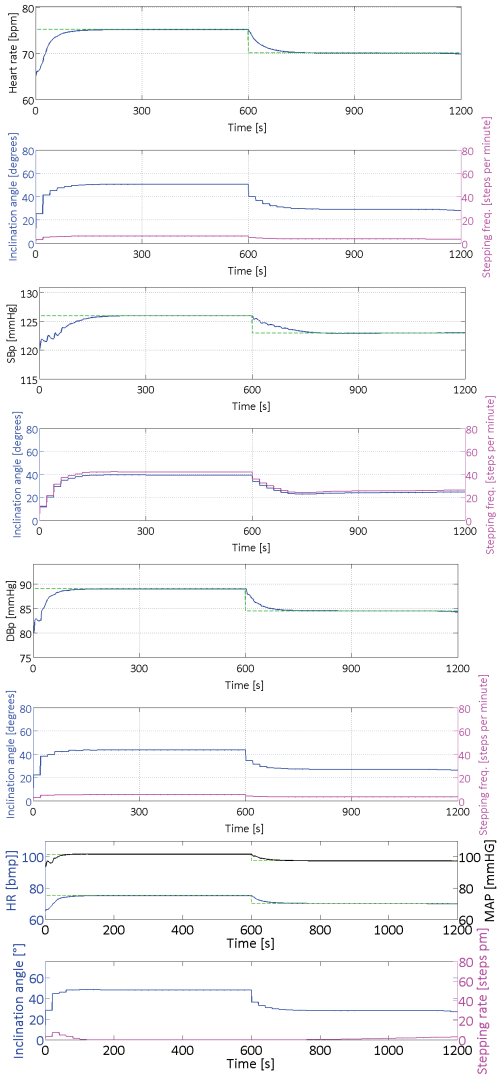

Fig.2. Evaluation of the controller in simulation; MISO control of HR,sBP and dBP; MIMO control of HR and MAP together

VI. Acknowledgment

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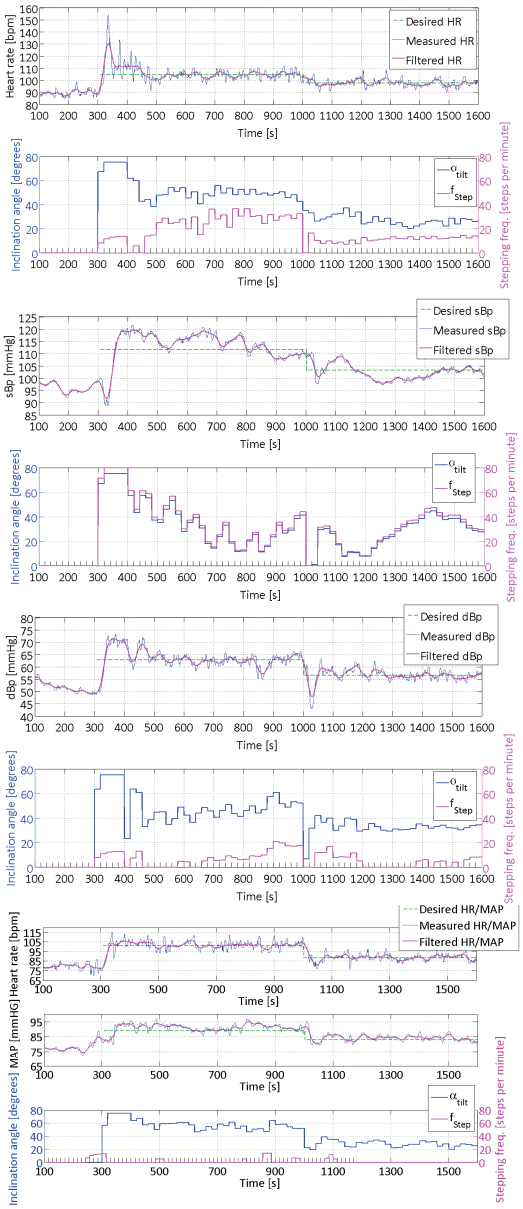

Fig.3. Evaluation of the controller on subject 1; MISO control of HR,sBP and dBP; MIMO control of HR and MAP together

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