

Data-driven patient-specific fluid resuscitation

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Abstract: Automated fluid resuscitation systems determine fluid infusion rates for patients recovering from, e.g., hemorrhage or dehydration. Instead of relying on models that require patient-specific parameter identification, we present a data-driven patient-specific alternative that bypasses modeling and identification. Specifically, we implement a predictive controller that only uses blood pressure data and manages to regulate the patient's blood pressure to a specified setpoint. We demonstrate the results in a simulation on 100 virtual patients created using a well-established model of cardiovascular hemodynamics.

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I. Introduction

Fluid resuscitation is the process of intravenously infusing fluids to compensate for losses resulting from, e.g., trauma, hemorrhage, or severe dehydration. Clinicians typically determine appropriate bolus infusions based on, e.g., changes in blood volume, pressure, or heart rate [1]. Automated fluid resuscitation systems alternatively employ control algorithms to regulate infusion rates [2], potentially reducing human error, providing optimal dosage strategies, and allowing more patients to simultaneously receive adequate care. Existing fluid resuscitation algorithms rely on parameterized mathematical models for control design, see e.g., [3,4]. Such models may fail to capture patient physiological complexity and variability [5] and typically require invasive Hematocrit measurements to estimate blood volume changes. Hence, there is a need for algorithms that use noninvasive data (e.g., blood pressure) and adapt to intrasubject variability. Recently, direct data-driven analysis and control techniques [6] have gained significant attention. There, input-output data are directly used to study system properties or design controllers without modeling or system identification. For instance, it was shown in [7,8] that all finite-length input-output trajectories of a linear time-invariant (LTI) system are contained in the image of a Hankel matrix of data that satisfies certain rank conditions. This was used for data-driven design of various control strategies for both linear and nonlinear systems, see, e.g., [9-12]. In this work, we leverage recent results on data-driven control to design patient-specific fluid resuscitation algorithms. In particular, we implement a data-driven predictive control (DDPC) scheme to regulate a patient's blood pressure to a desired value. The scheme employs only data measured from the patient (hence, patient-specific) and avoids any modeling or identification steps. We demonstrate the results in a simulation on 100 virtual patients created using a well-established model of cardiovascular hemodynamics [13].

II. Methods

Let G be a discrete-time LTI system of order n , with m inputs and p outputs. For any L satisfying $pL \geq n$, let

$\{u_t, y_t\}_{t=0}^{T-1}$ with $T \geq (m+1)L + n - 1$ be an input-output trajectory of G satisfying $\text{rank} \begin{pmatrix} H_L(u) \\ H_L(y) \end{pmatrix} = mL + n$, where H_L denotes the Hankel matrix of depth L . Then, any $\{\bar{u}_t, \bar{y}_t\}_{t=0}^{L-1}$ is an input-output trajectory of G if and only if there $\exists g \in \mathbb{R}^{T-L+1}$ such that $\begin{bmatrix} H_L(u) \\ H_L(y) \end{bmatrix} g = \begin{bmatrix} \bar{u} \\ \bar{y} \end{bmatrix}$, see [7,8]. Inspired by this, a regularized DDPC algorithm was proposed in [10], which, at each time t , uses past n inputs and outputs $u_{[t-n, t-1]}^{\text{on}}, y_{[t-n, t-1]}^{\text{on}}$, respectively, and solves

$$\begin{aligned} \min_{g, \sigma_y, \bar{u} \in \mathbb{U}, \bar{y} \in \mathbb{Y}} \sum_{k=0}^{N-1} \|\bar{y}_k - y_s\|_Q^2 + \|\bar{u}_k\|_R^2 + \lambda_g \|g\|^2 + \lambda_\sigma \|\sigma_y\|^2 \\ \text{s.t.} \quad \begin{bmatrix} U_f \\ Y_f \end{bmatrix} g = \begin{bmatrix} \bar{u} \\ \bar{y} \end{bmatrix}, \quad \begin{bmatrix} U_p \\ Y_p \end{bmatrix} g = \begin{bmatrix} u_{[t-n, t-1]}^{\text{on}} \\ y_{[t-n, t-1]}^{\text{on}} + \sigma_y \end{bmatrix} \end{aligned}$$

where N is the prediction horizon, \bar{u}, \bar{y} are the concatenated vectors of predicted inputs and outputs, y_s is the desired setpoint, and the (potentially noisy) data matrices are partitioned as follows

$$H_{n+N}(u) = \begin{bmatrix} U_p \\ U_f \end{bmatrix}, \quad H_{n+N}(y) = \begin{bmatrix} Y_p \\ Y_f \end{bmatrix}.$$

Moreover, $Q, R > 0$ are weighting matrices, σ_y is a slack variable, $\lambda_g, \lambda_\sigma$ are tunable regularization parameters, and \mathbb{U}, \mathbb{Y} are input and output constraint sets. Once a solution is found, we apply the first part of the optimal input to the system and repeat the process in a receding horizon manner. Under (relatively mild) assumptions and constraints, DDPC algorithms are shown to be recursively feasible and robustly stabilize the desired setpoint, for linear and classes of nonlinear systems [14]. Despite the fact that much of the underlying theory concerns LTI systems, these approaches can achieve notably good performance when applied to real-world nonlinear systems, see, e.g., [15]. Hence, we study the performance of DDPC algorithms for fluid resuscitation.

III. Results and discussion

To evaluate the proposed closed-loop hemorrhage resuscitation algorithm, we use a well-established model of

cardiovascular hemodynamics in humans (Guyton’s model, see [13]). This highly nonlinear computer model includes over 40 parameters, the 9 most sensitive of which were varied to generate 100 virtual patients, yielding patients with blood volumes of 4.5–5.5 L and pressures of 70–100 mm Hg. The model takes the infusion rate as an input ($m=1$), and can be disturbed by hemorrhage. We assume that only mean arterial blood pressure (MAP) can be measured, hence $p=1$. The order of the system is unknown, but is needed for successful implementation of the DDPC algorithm. This is because, for LTI systems, the most recent n input-output measurements are used to fix some internal state of the system at time t . Here, we heuristically set $n=6$, as it was observed to perform favorably on an average patient. We consider a standard hemorrhage resuscitation scenario from the literature [4,5], wherein a virtual patient is subject to major hemorrhage (2.5 L in 120 min). The hemorrhage is then stopped during the next 120 min. Afterwards, several bolus infusions are administered for a duration of 40 min (0.15 L for 15min, 0.1 L for 15min, then 0.02L for 10min) and the corresponding blood pressure data is measured and used to set up the Hankel matrices in the DDPC algorithm. Then, closed-loop control is activated at $t=280$ min and lasts for 120 min, with the goal to bring back the patient’s blood pressure to 100mmHg, i.e., $y_s=100$. Furthermore, we set $N=15$ min, $Q=10^3$, $R=0.1$, and fix the choice of regularization parameters for all 100 virtual patients to $\lambda_g = 10$, $\lambda_\sigma = 10^3$. Lastly, we set $\mathbb{U} = \{u \in \mathbb{R}: 0 \leq u \leq 0.1\}$ and $\mathbb{Y} = \{y \in \mathbb{R}: y \leq 140\}$ to adhere to safe infusion rates and avoid over-resuscitation, respectively. This scenario was repeated for all 100 virtual patients and compared to an expert’s rule-based algorithm, see [3,4]. Fig. 1 shows the simulation results for all patients using DDPC, while Fig. 2 shows the results using the rule-based controller.

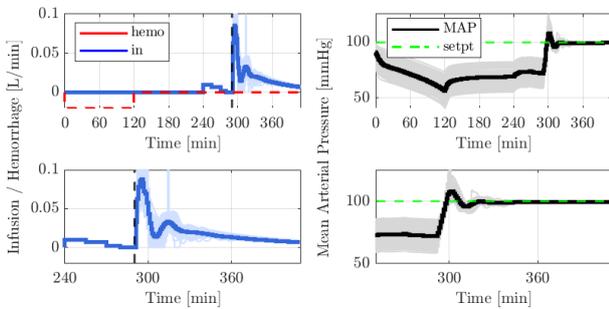


Fig. 1: Simulation results using DDPC. Top panel: full scenario; bottom panel: bolus and closed-loop control ($t \geq 240$ min). Light colors show individual patients; solid colors show the average.

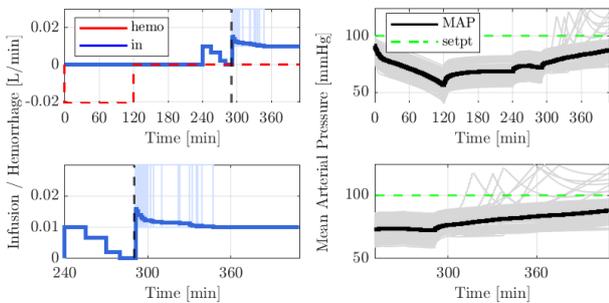


Fig. 2: Simulation results using a rule-based controller.

To further compare the two algorithms, we calculate the following performance indices (which are standard when comparing fluid resuscitation algorithms, see [3-5]): the median performance error (MDPE), median absolute

performance error (MDAPE), and root mean square error (RMSE). The results, reported in Table 1, show that the proposed algorithm significantly outperforms the experts’ rule-based (RB) controller. We note that the average computation time of the optimization problem (0.115 sec) is significantly smaller than the sampling time (1 min), thus making our scheme amenable to real-time implementation.

Table 1: Performance metrics comparison

	MDPE (%)	MDAPE (%)	RMSE
DDPC	-0.49 ± 0.29	0.60 ± 0.25	48.93 ± 11.5
RB	-17.84 ± 8.2	18.65 ± 6.7	52.42 ± 12.4

IV. Conclusions

We presented a patient-specific fluid resuscitation algorithm based on recently developed data-driven predictive control schemes. The algorithm uses only blood pressure data and can be implemented in (almost) real time. Extensive simulations on a well-established cardiovascular model suggest that such schemes can significantly outperform expert rule-based strategies. Future work will focus on patient-specific hyperparameter tuning and comparisons with other fluid resuscitation algorithms from the literature.

AUTHOR’S STATEMENT

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