Sociedade Brasileira de Automática (SBA)
XXV Congresso Brasileiro de Automática - CBA 2024, 15 a 18 de outubro de 2024

A Recursive Least Squares based Direct Self-Tuning PID for Blood Pressure Control in Hypertensive Emergencies

Gabriel César Silveira * **Alexandro Garro Brito** **

* *Federal University of Santa Catarina, Estr. Dona Francisca 8300, Joinville/SC - Brazil. CEP: 89219-600 (e-mail: gabrielcessil@gmail.com)*
** *Federal University of Santa Catarina, Estr. Dona Francisca 8300, Joinville/SC - Brazil. CEP: 89219-600 (e-mail: alexandro.brito@ufsc.br)*

Abstract: Hypertensive emergencies require extensive medical involvement to prevent adverse health outcomes. Automated systems can streamline procedures and enable professionals to administer seasoned treatments to hypertensive patients. However, utilizing fixed-gain controllers for individuals with unpredictable traits, such as heightened sensitivity, might lead to undesirable responses. This study introduces a Recursive Least Squares-based adaptive PID (Proportional-Integral- Derivative) controller for hypertensive emergencies, comparing three forgetting factors. The goal is to design a controller that adapts to patient profiles using algorithmic learning and clinical guidelines. Finally, the proposed direct adaptive controller with time-varying forgetting factor demonstrated effectiveness in reducing blood pressure across a range of simulated patient profiles.

Keywords: Adaptive Control, Hypertension, Healthcare

1. INTRODUCTION

Hypertensive emergencies severely increase blood pressure with progressive organ damage, posing a risk of death. An immediate intervention with intravenous therapy is normally needed, resulting in several hours of monitoring the pressure level and adjusting the drug delivery (Mancia, 2023; Barroso et al., 2021). However, manual hypertensive case using sodium nitroprusside requires a high level of vigilance due to its swift action and required dosage variations (Westenskow, 1987). Therefore, automated blood pressure control techniques can improve the prioritization and fatigue avoidance of the professionals involved (Baykuziyev et al., 2023). Moreover, some hypertensive patients might have special or unpredictable conditions, such as being excessively sensitive to medication and thus requiring special attention when fixed-gain blood pressure control systems are used (Westenskow, 1987).

The academic community has proposed many intelligent schemes for blood pressure control like Fuzzy (Gao and Er, 2005; Cavalcanti and Maitelli, 2015), Neural-PID (Elamvazuthi et al., 2013), Multiple-Model (Malagutti et al., 2013). There are also works employing self-tuning controllers based on recursive parameter estimators (da Silva et al., 2019; Zhu et al., 2011). Most of these self-tuning methods are found in indirect topologies, i.e., they are calculated using a process model estimation. Meanwhile, Pajunen et al. (1990) applied a stochastic direct self-tuning controller for blood pressure management.

This work addresses blood pressure control using direct adaptive PID controllers. The approach is based on De Keyser (2000), which uses a Recursive Least Squares (RLS) estimator to recursively optimize the PID controller regarding a first-order reference model. Three forgetting factor techniques are assessed to compare their influences on results: no forgetting, a brief time horizon, and a time-varying approach.

To the best of our knowledge, De Keyser's self-tuning controller has not been investigated for blood pressure treatment. As a model-free approach, the studied controller is more consistent when considering the human heterogeneity and blood pressure uncertainties. Hence, the model-free aspect of direct methods has a singular potential to handle hypertensive emergencies. This paper adjust De Keyser's method to ensure proper signal excitement and meaningful PID estimates. Results demonstrate efficacy in managing blood pressure across various patient profiles.

2. HYPERTENSION EMERGENCIES CLINICAL ASPECTS

Hypertensive emergencies can be defined as the severe increase in Systolic Blood Pressure (SBP) above 180 $mmHg$ and/or the Diastolic Blood Pressure (DBP) above 110 $mmHg$ with progressive organ damage. These emergencies pose an imminent risk of death, requiring immediate intervention as intravenous therapy (Mancia, 2023; Barroso et al., 2021). However, identifying the internal status of patients is still a challenging step for the treatment (Mancia, 2023).

Hypertensive emergency management relies on reducing 20-25% of the Mean Arterial Pressure (MAP), so that it falls into normalized safe levels (Mancia, 2023; Reboussin et al., 2018; Barroso et al., 2021). The expected time for the decay is frequently established at 1 hour, but it can vary between half an hour and 2 hours (Reboussin et al., 2018; Barroso et al., 2021; Vidt, 2001; Brathwaite and Reif, 2019). The decay speed must be conservative to avoid renal, cardiac, cerebral, or other damage (Vidt, 2001). There is no common target pressure level or timing for real hypertensive emergency treatment. Instead, these targets are defined according to the specific clinical context (Unger et al., 2020; Mancia, 2023).

3. BLOOD PRESSURE MATHEMATICAL MODEL

Slate (1980) introduced a Single-Input-Single-Output (SISO) mathematical model focusing on control applications that is briefly presented along this section.

The MAP fluctuates around an average value, varying with an amplitude of 2 to 10 $mmHg$ for individuals classified as having low noise. On the other hand, individuals whose pressure varies from 10 to 15 $mmHg$ around the average value are classified as high noise patients. The blood pressure p_a is then modeled as the sum of background activity p_{ba} and the pressure variation caused by medication Δp_d.

The mean pressure $\bar{p_a}$ is monitored by a catheter-transducer instrument subjected to a first-order low-pass filter with a time constant of 2 seconds (Equation 1).

$$S(s) = \frac{1}{2s+1} \tag{1}$$

The Δp_d is linearly related to the Nitroprusside Sodium infusion $I(s)$ as expressed in Equation 2,

$$G_d(s) = \frac{\Delta P_d(s)}{I(s)} = \frac{Ke^{-\tau_i s}(1+\alpha e^{-\tau_c s})}{1+\tau s} \tag{2}$$

where τ_i is the drug transportation time delay after its infusion, τ_c is the time delay caused by fraction α of blood that recirculates, K is the drug sensitivity and τ is the time constant to absorb, distribute and metabolize the delivered drug. The adopted model values are disposed in Table 1, comprising 8 patient profiles.

Table 1. Patient profiles according to the drug absortion (da Silva et al., 2019).

Profile	**Identifier**	K	τ	τ_i	τ_c	α
P.1	Sensitive	0.25	30	20	30	0.4
P.2		0.50	34	25	35	0.2
P.3		0.75	37	30	40	0.4
P.4	Nominal	1.00	40	40	45	0.4
P.5		2.00	45	45	55	0.2
P.6		4.00	55	50	60	0.4
P.7		6.00	65	55	65	0.2
P.8	Hypersensitive	8.00	75	60	75	0.4

The background activity p_{ba} is treated as the sum of four components: the offset value p_o, the stochastic element p_η, the reflex action p_δ, and a sinusoidal component p_s. The p_s term is in phase with respiration, and it can be estimated at 12 breaths per minute, equivalent to 1.2566 rad/s, with amplitude between 2 and 4 $mmHg$. The stochastic element is modeled as white noise filtered by $F_\eta(s)$ (Equation 3) so that p_a varies from 5 to 10 $mmHg$ around the expected mean.

$$F_\eta(s) = \frac{K_\eta}{(30s+1)^2} \tag{3}$$

The reflex activity p_δ reacts to the decrease in p_a below a threshold that typically ranges between 60 and 70 $mmHg$. It is modelled as a unidirectional saturation of 35 $mmHg$ followed by a filter $F_\delta(s)$ (Equation 4). The transport delay τ_δ ranges from 30 to 60 seconds.

$$F_\delta(s) = \frac{e^{-\tau_\delta s}}{240s+1} \tag{4}$$

In this work, a low noise background activity is characterized by a sinusoidal amplitude of 4 $mmHg$, a stochastic gain of 5 $mmHg$, and a reflex threshold of 70 $mmHg$ during the simulations. Notice that the blood pressure is influenced not only by two time delays and other uncertain parameters but also by stochastic components. These characteristics are critical to the safe performance of the control system.

The use of adaptive controls becomes clinically impractical if they are overly aggressive, leading patients to dangerous conditions, such as state of shock (Westenskow, 1987). This underscores the importance of cautious control action, which restricts the infusion rate from 0 to 180 mL/h and limits the rate step from -40 to 3 mL/h (Slate, 1980).

Finally, it's crucial to highlight that the proposed model does not consider other physiological states or outputs in the human body that may lead to side effects, such as the cardiac ones. (Slate, 1980; Baykuziyev et al., 2023). Therefore, parallel treatments may be required.

4. ADAPTIVE CONTROLLERS

Adaptive controllers are classified based on their methods of processing information to modify the controller in order to achieve performance objectives (Landau et al., 2011). Hence, adaptive control comprises systematic techniques for automatically adjusting the controller in real-time to ensure a desired level of performance, even if the plant parameters are initially unknown, become unknown, or change over time.

The logical structures of adaptive controllers are usually categorized as indirect or direct (Landau et al., 2011; Isermann, 1991; Seborg et al., 1986). An adaptive controller is considered "indirect" when it requires the algorithm to estimate the plant, followed by calculating the resulting controller. The direct methods don't refer to a plant model, but apply the estimated parameters as the control law itself. Indirect methods can become ill-conditioned (Åström and Wittenmark, 2013). For this reason, direct approaches often require less design time, because stability consideration is implicitly assumed by relying on the estimator's design.

The well-known Recursive Least Squares can estimate parameters online when the process is linearly parameterizable, as Equation 5

$$\psi(t) = \boldsymbol{\phi}(t)^T \cdot \boldsymbol{\theta}^* \tag{5}$$

where $\boldsymbol{\theta}^* \in \mathbb{R}^{n_\theta}$ represents the vector of unknown parameters, $\psi(t) \in R$ is a known signal, $\boldsymbol{\phi}(t) \in \mathbb{R}^{n_\theta}$ is the regressor vector composed of known signals, and n_θ denotes the dimension of the parametric model, i.e., the number of unknown parameters (Tao, 2003; Landau et al., 2011; Åström and Wittenmark, 2013).

The RLS forgetting factor $\lambda(t)$ weights the past measured data as new ones are collected. Forgetting factors can balance the trade-off between adaptation velocity and noise sensitivity (Hunt, 1986). It can also be related to the time constant T_{ff} as $\lambda = e^{-T/T_{ff}}$, where T is the sampling time (Åström and Wittenmark, 2013). Moreover, it can be designed as a time-varying λ that ensures the algorithm keeps learning with the same confidence on incoming data by keeping the covariance matrix trace value constant (Malik et al., 1991). If $\lambda(t)$ is chosen as unity, there is no forgetting, so no data is neglected as the time progresses.

If the estimated process signals are not well excited, the algorithm may forget the past rich data when using constant forgetting factors. This phenomenon is called *Estimator Wind-up* and has an effect similar to the well-known PID's Integrator Wind-up. Estimator Wind-up can be prevented by methods such as conditional updating, discarding data only during appropriately excited process intervals, or monitoring the covariance-related signal magnitude (Åström and Wittenmark, 2013).

5. DIRECT ADAPTIVE CONTROLLER

The main benefit of direct adaptive strategies is that they do not require the patient model to update the controller gains. Therefore, the model-free aspect of direct methods has singular potential to handle the human heterogeneity and model uncertainty.

The chosen framework to develop the adaptive direct controller is the well known PID Finite-Impulse Response format. A full discussion of this method is presented by De Keyser (2000), which is updated here to ensure the proper signal excitement and meaningful PID estimates in time domain. Furthermore, the simple logical structure of such algorithm is particularly easy to assess, reducing complexity and saving project time.

The PID Finite-Impulse Response is given by Eq. 6

$$C(q^{-1}) = \frac{\Delta u(t)}{e(t)} = c_0 + c_1 q^{-1} + c_2 q^{-2} \tag{6}$$

where c_0, c_1, and c_2 are the specified coefficients of the controller $C(q^{-1})$ and $\Delta u(t)$ is the incremental command.

From PID rectangular discretization, parameters c_0, c_1, and c_2 can be interpreted as follows:

$$\begin{cases} c_0 = K_c\left(1 + \frac{T_s}{T_i} + \frac{T_d}{T_s}\right) \\ c_1 = -K_c\left(1 + 2\frac{T_d}{T_s}\right) \\ c_2 = K_c\frac{T_d}{T_s} \end{cases} \tag{7}$$

where K_c, T_i, and Td represents the proportional gain, integral and derivative time constant. This information can be used to suggest initial estimates to the adaptive algorithm, utilizing the techniques previously discussed.

On the other hand, Equation 8 is then used to validate the temporal form of the estimated controller.

$$\begin{cases} K_c = -(c_1 + 2c_2) \\ T_i = -T_s\frac{c_1+2c_2}{c_0+c_1+c_2} \\ T_d = -\frac{T_s c_2}{c_1+2c_2} \end{cases} \tag{8}$$

To formulate the controller estimation, De Keyser (2000) introduces a signal filtering based on assumption of $y(t)$ and $u(t)$, as shown in Equation 9:

$$\begin{cases} u_f(t) = U_f(q^{-1})u(t) \\ y_f(t) = Y_f(q^{-1})y(t) \end{cases} \tag{9}$$

where the discrete causal filters $U_f(q^{-1}) = (1-q^{-1})R(q^{-1})$, $Y_f(q^{-1}) = (1 - R(q^{-1}))$, and $R(q^{-1})$ is the designed reference model. Finally, thanks to the filtered form of the signals (Equation 9), the linear parameterization is defined as Equation 10, compensating the approximations and truncated Finite-Impulse Response (FIR) model with a residual error $\varepsilon(t)$:

$$u_f(t) = C(q^{-1})y_f(t) + \varepsilon(t) \tag{10}$$

Thus, Equation 10 formulates an optimization problem to estimate $C(q^{-1})$ by minimizing the prediction error of $u_f(t)$ based on $y_f(t)$, i.e, computationally solves the controller determination problem.

In order to assist the design based on such algorithm, De Keyser (2000) describes guidelines to define $R(q^{-1})$ rooted to guarantee its null steady state error, overestimate dead-times and include non-minimum zeros. In this context $R(q^{-1})$ can be defined as below:

$$R(q^{-1}) = \frac{y(t)}{w(t)} = q^{-d_r}\frac{1-a_r}{1-a_r q^{-1}} \tag{11}$$

Here, d_r represents the temporal reference delay, and a_r is associated with the system's response time. This reference model considers that its transfer function is similar to the open loop arterial pressure response model, then easily seen as an ideal response.

6. DESIGN CONSIDERATIONS

The practical medical procedure strongly depends on the clinical context. Thus, the designed approach aligns with the standards in medical guidelines (Mancia, 2023; Reboussin et al., 2018; Unger et al., 2020; Barroso et al., 2021).

A hypertensive emergency scenario of 200 $mmHg$ SBD and 120 $mmHg$ DBP was represented by a MAP of 146 $mmHg$[1]. The desired MAP decay of 20 % from the initial value leads to a control setpoint of 116 $mmHg$ that should be achieved during the first hour. The following requirements were used in order to better assess the results

[1] MAP is estimated as DBP+1/3 (SBP–DBP) (Sainas et al., 2016).

and track in a control perspective the clinical objectives previously discussed. [2]

- The algorithm shall provide a MAP decrease within less than 10 $mmHg$ of maximum undershoot, so that the patient does not suffer hypotension damages.
- The algorithm shall provide a MAP decrease within less than 10 $mmHg$ of maximum overshoot, so that the patient does not return to hypertensive emergency stages.
- The algorithm shall provide a MAP decrease within maximum rising time lower than two hours (7200 seconds), but ideally 1 $hour$ (3600 seconds), so that the treatment follows the timely expected manner.
- The algorithm shall provide a MAP decrease within minimum rising time higher than half an hour (1800 seconds), so that the treatment is not excessively rapid causing damages to the patient.
- The algorithm shall provide a MAP around the set-point within 5 $mmHg$ of absolute maximum steady-state error.

One can notice that the resulting requirements have similarities to those originally defined by Slate (1980), differing by using more conservative time metrics in this work.

Regarding the algorithm design, $R(q^{-1})$ is defined considering the suggested first-order discrete transfer function form and $\tau_r = 4\tau_{max}$ and $a_r = e^{-\frac{T_s}{\tau_r}}$, where τ_{max} is the maximum plant time constant expected in the model. The system sampling time T_s is set to the model's original value of 15 seconds, ensuring non-aggressive monitoring of blood pressure.

The maximum time constant τ_{max} is adopted because some latency is desirable, taking into account the need to provide a reasonable amount of samples for the estimator algorithm to learn. Also, this slow decay contributes to the assumption made by De Keyser (2000) that the reference model is close to the plant output during initial instants. Moreover, the temporal delay of the reference model d_r is established as 5, which overestimates by one unit the longest delay within the process discrete model, as suggested by De Keyser (2000).

Adaptive controllers can be initialized by taking advantage of the process dynamics knowledge and performing low proportional integrative action (Åström and Wittenmark, 2013). The estimate $\hat{\boldsymbol{\theta}}(0)$ is chosen to provide a PI controller with low proportional action, prioritizing the avoidance of overshoot effects that could lead the patient into a state of shock. For this, the Lambda tuning method for PID controllers from Åström and Hägglund (2006) was chosen, then the proportional gain K_c was gradually reduced while keeping the resulting integral gain $\frac{K_c}{T_i}$. Finally, the initial PI controller adjusted as in Eq. (12).

$$K_c(0) = \frac{\tau_{max}}{1000K_{max}}(\tau_{i_{max}} + \tau_r), \quad T_i(0) = \frac{\tau_{max}}{1000} \tag{12}$$

From SBD model: $K_{max} = 9$, $\tau_{max} = 75$, and $\tau_{i_{max}} = 60$.

[2] Rising time was defined as the moment when the MAP error first reached 2% to the final setpoint, while overshoot and undershoot referred to the maximum and minimum MAP errors recorded thereafter. Steady-state error was considered the standard deviation of the MAP error after achieving the final setpoint

Table 2. Estimator derivatives comparison

Identifier	Concept	Definition
Estimator I	Influenced by all collected information	$\lambda = 1$
Estimator II	Influenced only by the necessary data obtained in certain time horizon	$\lambda = e^{-\frac{T_s}{T_{ff}}}$; $T_{ff} = 4\tau_r$
Estimator III	Update λ to maintain constant confidence on incoming data	$\lambda(t+1) = \frac{tr\{F(t)\}}{tr\{F(0)\}}$

This work investigates the usage of three distint concepts of forgetting factor due its relevance to the RLS algorithm operation as previously discussed. In this context, Table 2 outlines the main differences in the approaches of the RLS previously discussed and tested in this study.

The initial covariance matrix $F(0)$ was set with a maximum component value of 1, since the magnitudes are arbitrary by definition. Specifically, $F_{3,3}(0) = 1$ because of straightforward influence on c_2 undefined in the initial PI format. Meanwhile, $F_{1,1}(0) = 0.01$, $F_{2,2}(0) = 0.001$ were assigned to the main diagonal to match the initial c_0 and c_1 gains scale. All others componentes of $F(0)$ were initialized as zero.

The estimation verification step is performed at each iteration to aid in the algorithm's convergence and keep its control within a familiar operating range. Specific conditions are established about $\hat{\boldsymbol{\theta}}(t+1)$ to ensure the PID typical characteristics in time domain $\hat{\boldsymbol{\theta}}(t+1)$: $K_c < 0$, $T_i > 0$ and $T_d \geq 0$. The concept of Conditional Update is applied by blocking adaptation during low excitation periods. The lack of excitation is assumed when the output signal first rises to the final setpoint and is inside the accommodation zone of 10 $mmHg$.

To avoid overly agressive results, this work utilized a incremental referece signal with two transient periods. The premise is that the signal may become more excited and yield better results and, additionally, restricts the initial decay. The initial step was configured to be 150 $mmHg$ and the second step is set to the main setpoint after 30 minutes, ensuring the reference model accommodation and minimum rising time achievement.

7. RESULTS

The simulation environment was built in MATLAB Simulink (MathWorks, 2018) and its defined setup result in time responses as those shown in Figure 1, illustrating examples of patients with minimum, nominal and maximum sensitivity gain to the drug.

The Figure 1 visually exemplify how the controlled MAP converges to the designed reference signal and highlights how sensitivity affects the rise time, with less sensitive patients experiencing a longer rise time.

Furthermore, the quantitative analyses are present in Tables 3-7, which investigate the dynamic response regarding the profiles of Table 1, running 1000 simulations for each profile and collecting the performance indicators over 6 hours of treatment [3].

[3] The maximum value for a certain indicator was considered as the average of its results summed with the double of the standard

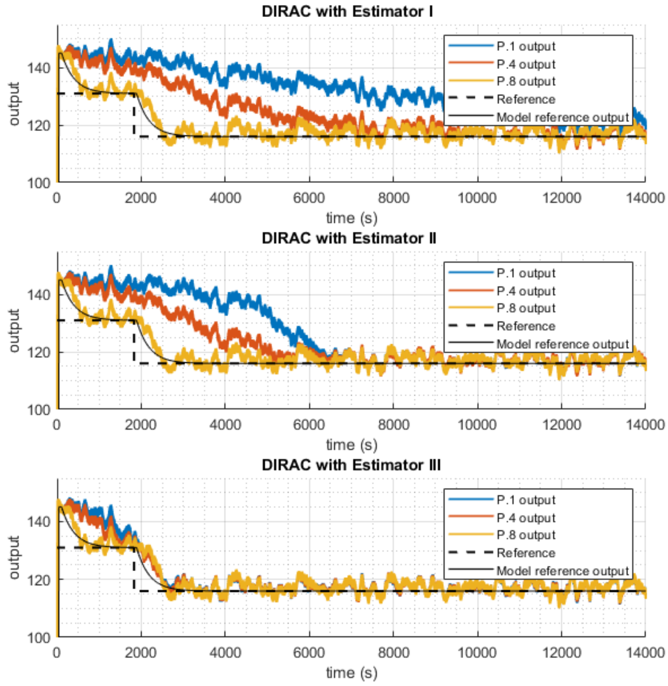

Figure 1. Example of time responses for sensitive, nominal and hypersensitive patients.

Table 3. Maximum Overshoot ($mmHg$).

Profiles	Estimator I	Estimator II	Estimator III
P.1	13.301	10.164	9.763
P.2	12.854	10.232	9.816
P.3	12.406	10.809	9.792
P.4	12.151	10.926	9.786
P.5	11.008	10.853	9.719
P.6	10.089	10.068	9.753
P.7	9.644	9.646	9.693
P.8	9.814	9.810	9.664

Table 4. Maximum Undershoot ($mmHg$).

Profiles	Estimator I	Estimator II	Estimator III
P.1	4.727	6.494	6.444
P.2	5.294	6.130	6.471
P.3	5.576	6.027	6.525
P.4	5.626	6.006	6.565
P.5	5.901	6.002	6.627
P.6	6.202	6.233	6.649
P.7	6.667	6.673	6.758
P.8	6.842	6.842	6.795

Table 5. Maximum Rising Time (s).

Profiles	Estimator I	Estimator II	Estimator III
P.1	16578.610	7290.665	3354.349
P.2	10802.199	6196.542	2971.140
P.3	7219.309	5687.218	2715.598
P.4	6608.300	5487.627	2673.890
P.5	3830.808	3747.356	2711.783
P.6	3011.257	3006.672	2782.003
P.7	2524.670	2525.507	2903.956
P.8	2447.461	2448.129	2916.692

deviation across the profile samples, while the minimum value was considered as the double deviation discounted from the average. The assumption is that a normal distribution due to the stochastic nature of the plant leads to probabilistic confidence of approximately 97.8 % over the population.

Table 6. Minimum Rising Time ($mmHg$).

Profiles	Estimator I	Estimator II	Estimator III
P.1	9900.161	4180.396	1971.049
P.2	7419.508	4330.255	2051.632
P.3	5180.707	3921.869	2150.113
P.4	4703.958	3809.629	2168.853
P.5	2912.997	2863.375	2195.036
P.6	2402.806	2400.762	2221.270
P.7	2185.287	2185.546	2216.218
P.8	2166.410	2166.320	2215.970

Table 7. Maximum Steady State Error ($mmHg$).

Profiles	Estimator I	Estimator II	Estimator III
P.1	2.534	1.682	1.609
P.2	2.446	1.677	1.614
P.3	2.154	1.739	1.616
P.4	2.074	1.761	1.618
P.5	1.739	1.717	1.622
P.6	1.643	1.641	1.626
P.7	1.616	1.617	1.626
P.8	1.626	1.626	1.627

Estimator III has demonstrated the best performance, while Estimator I has shown the worst, in terms of Maximum Overshoot, Maximum Rising Time, and Maximum Steady State Error, considering both average and variance magnitudes across profiles. For Maximum Undershoot and Minimum Rising Time, Estimator I has better average values than Estimator III across profiles, but with significantly higher variance. At the same time, Estimator II consistently exhibits medium performance in terms of average and variance values for all measured parameters.

Moreover, the results indicate that the designed direct adaptive PID with Estimator III is capable of decreasing the SBP following medical guidelines successfully, overcoming the uncertain model. Meanwhile, Estimator I and II failed to achieve overshoot requirements in non-hypersensitive profiles. Estimator I also failed to achieve the maximum rising time requirement in less sensitive profiles P.1, P.2 and P.3.

8. CONCLUSION

To enhance the performance of control systems, the academy investigates adaptive methods that learn and adjust the controller recursively based on the observed system behavior. This study aimed to develop a direct self-tuning controller applied to hypertensive emergency scenarios, while contextualizing topics such as estimation algorithms, problem modeling, and clinical implications.

The applied direct PID has a model-free nature, providing potential to handle human heterogeneity and uncertain dynamics. The controller was initiated as a PI tuned by the Lambda method. It was then recursively optimized by the Recursive Least Squares algorithm concerning the behavior of a first-order reference model. Additionally, this paper brings modifications to the original method proposed by De Keyser (2000), so that it can ensure the proper signal excitement and meaningful PID estimates in the time domain. Moreover, the three direct adaptive controllers compared in this work differ in their forgetting factor concepts: no forgetting, a brief time horizon, and time-varying thzat root the confidence of incoming data.

The time-varying option has shown the best performance among the verified forgetting factors.

The employed direct adaptive controller performance was assessed through simulations, demonstrating its ability to reduce mean blood pressure effectively for hypertensive emergency scenarios regarding clinical guidelines in uncertain patients. However, this work investigated exclusively low noise patients with static parameters, thus recommendations for future researches include exploring robustness under different conditions like noisier patients, disturbances in offset or drifting parameters values. In this context, other reference models and estimation algorithms could lead to improved results.

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