A RISE-based Controller Fine-tuned by an Improved Genetic Algorithm for Human Lower Limb Rehabilitation via Neuromuscular Electrical Stimulation

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Abstract— **In the last few years, several studies have been carried out showing that functional electrical stimulation (FES) and neuromuscular electrical stimulation (NMES) produce good therapeutic results in patients with Spinal Cord Injury (SCI). This paper presents the proposal of a fine-tuning method based on an improved genetic algorithm (IGA) to a continuous and robust control technique for uncertain nonlinear systems named Robust Integral of the sign of the error (RISE), for knee joint control. Simulation results are provided for three paraplegic and one healthy identified patients on ideal and nonideal conditions. Although in the literature this controller presents good results without any fine tuning method, we provide an approach to improve it, even more, believing on the minimization of fatigue and other problems that often occurs in SCI patients treated with FES/NMES, by selecting adequately the gain parameters of the RISE controller.**

I. Introduction

It is well recognized that spinal cord injury (SCI), which may be caused by diseases that destroy the neurological tissues of the spinal cord or by a tragic accident, causes issues as total or partial paralysis, muscles atrophies and spasms, and it can lead to cardiovascular and pulmonary diseases that directly decreases the well-being of the patient. SCI is often irreversible and it can cause an inability to complete daily activities or occupational ones. The most common SCI rehabilitation, to preserve the integrity of paralyzed muscles, is the use of neuromuscular electrical stimulation (NMES) via surface or intramuscular electrodes, which applies a potential field across the motor neurons to achieve a desired muscle contraction. Strength of muscle contraction is controlled with electrical current pulses by changing the pulses amplitude, width or frequency [1]–[3].

Efforts have been made motivated by the promising therapeutic treatment and beneficial results of NMES to increase the efficacy of motor rehabilitation on accomplishing functional tasks where it is named as functional rlectrical stimulation (FES). Although several researches and development of NMES applications have been reported in the past few decades, there are numerous challenges to be faced on designing automatic stimulation strategies, e.g., the system must run in real-time and safely even in face of bodily uncertainties. Thus, the main reason to continue investigating on this field is that real-world NMES/FES applications to rehabilitate SCI patients require a control strategy that compensates muscle fatigue and spasms, modeling errors, external disturbances, and many other factors [4]–[9].

The present study investigates a continuous and robust control technique for uncertain nonlinear systems that has been reported in the literature as robust integral of the sign of the error (RISE) [10], [11]. The RISE method was chosen because of some intrinsic characteristics, such as it considers disturbances that were not previously modeled and it also has implicit learning characteristics, which are really important on performing rehabilitation experiments. However, the controller parameters adjustment is the key factor to guarantee control performance quality. Considering the stability proof analysis and gains sufficient condition established in the original papers, it is difficult to reach expected control effects in practice just adjusting empirically the gain parameters in the extreme large search space $\mathbb{R}^+$. In daily routines of NMES/FES application to SCI patient rehabilitation, there are problems as muscles fatigue, tremors, and spasms due to incomplete tetanus [5], [8], [12], which would be increased by applying a ‘trial and error’ method to tune the controller.

To overcome this problem, this paper proposes an optimization procedure based on an improved genetic algorithm (IGA) for better acquiring gain parameters of the RISE controller considering a human lower limb properly identified. Fig. 1 illustrates the proposed method, which assumes that if dynamics of a human lower limb is efficiently mapped, put to a simulation process making use of a global search and fast optimization algorithm, which tests numerous gain combinations evaluating a well-defined control task, a controller that has implicit characteristics on learning (as RISE controller, or others) will be better tuned and performance in real world can be improved.

The literature indicates good lower limb tracking performance of the lower limbs using the RISE controller [4], [6], [12]–[17]. However, the motivation of this paper emerges from the lack of intelligent techniques to adjust the RISE controller parameters. Our hypothesis is that the system response can be improved using efficient tools such as artificial intelligence methods. In addition, those controllers were developed and tested only on healthy patients. Our proposal

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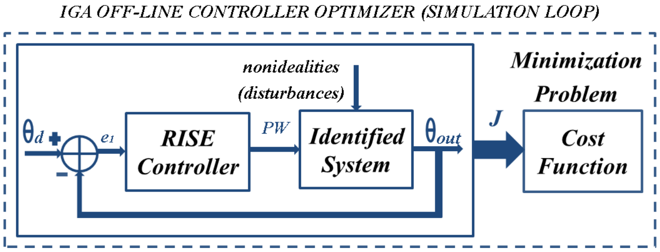

Fig. 1: Optimization procedures to a control task by the IGA.

is to extend the analysis to paraplegic individuals who present non-idealities not present in healthy individuals [8], [18]. Hence, this paper simulates the RISE-based controller fine-tuned by an IGA in a more realistic way taking advantage of three paraplegics and one healthy from [7], providing insights of NMES on ideal and nonideal conditions before experimental validation.

The following sections are organized as: Section II describes the dynamic lower limb model including nonideal muscle conditions, and presents the RISE control method. Section III shows the procedures for numerical simulation. Section IV presents simulation results to the regulation and tracking problem and discusses the metrics derived from the results obtained by the empirical and IGA tuning. Finally, the conclusions are presented in Section V.

II. Background

A. Human Lower Limb Model

The mathematical muscle model used in this paper considers the relationship between electrical stimulus and knee joint dynamics based on [7], [8], which considers a subject seated with the lower leg freely suspended. Further, this model includes nonideal muscle conditions, such as fatigue, spasms, and tremors. The knee angular acceleration $\ddot{\theta}(t)$ is expressed as

$$\ddot{\theta}(t) = \frac{1}{J}(-mgl\sin\theta(t) - \tau_{stiffness} - B\dot{\theta}(t) + \upsilon(t)), \quad (1)$$

where J is the moment of inertia of combined shank and foot, $\theta(t)$, $\dot{\theta}(t)$, $\ddot{\theta}(t)$ are the knee angular position, velocity and acceleration respectively, B is the viscous damping coefficient, m is the combined mass of shank and foot, g is the gravity acceleration, and l is the distance between the knee joint and center of mass of shank and foot. The stiffness torque is

$$\tau_{stiffness} = \lambda e^{-E(\theta+\frac{\pi}{2})}(\theta + \frac{\pi}{2} - \omega), \quad (2)$$

where λ, E are exponential term coefficients and ω is the resting elastic knee angle. Additionally, this paper modeled muscle fatigue $fat(t)$, tremor $tr(t)$, and spasms $spm(t)$ to modify the active knee torque $\tau_{quad}(t)$ generated by an electrical stimulus in three levels (smooth, moderate and critical), according to [8]. Mathematically, it is expressed as

$$\upsilon(t) = (1 + spm(t) + tr(t))\tau_{quad}(t)fat(t), \quad (3)$$

where $\upsilon(t)$ is the active knee torque under nonideal muscle conditions, in which $\tau_{quad}(t)$ can be expressed in the frequency domain as

$$\tau_{quad}(s) = \frac{G}{1+\eta s}PW_{quad}(s), \quad (4)$$

where $PW_{quad}(s)$ is the Pulse Width (PW) and G, η are constants of muscle activation function.

B. RISE Control Development

The RISE control technique has been proposed as a continuous-time and high gain feedback control approach for uncertain nonlinear systems, which even in spite of bounded smooth external disturbances and bounded modeling uncertainties, the control law can guarantee asymptotic tracking [10], [11]. For our control purpose, a position tracking error $e_1(t) \in \mathbb{R}$, is defined as

$$e_1(t) = \theta_d(t) - \theta(t), \quad (5)$$

where $\theta_d(t)$ is the desired angular trajectory assumed to have bounded continuous time derivatives, and $\theta(t)$ the actual position. Additionally, to facilitate the control design, filtered tracking errors $e_2(t) \in \mathbb{R}$ and $r(t) \in \mathbb{R}$ are defined as

$$e_2(t) = \dot{e}_1(t) + \alpha_1 e_1(t), \quad (6)$$

$$r(t) = \dot{e}_2(t) + \alpha_2 e_2(t), \quad (7)$$

where $\alpha_1, \alpha_2 \in \mathbb{R}$ denote positive and adjustable control gains. Authors in [4], [13], proved semi-global asymptotic stability for an uncertain nonlinear muscle model with the RISE control law defined as

$$u(t) = (k_s+1)e_2(t) - (k_s+1)e_2(0) + \int[(k_s+1)\alpha_2 e_2(\tau) + \beta sgn(e_2(\tau))]d\tau, \quad (8)$$

where $k_s, \beta \in \mathbb{R}$ are also positive and adjustable control gains, and $sgn(\cdot)$ denotes the standard signum function.

III. Material and Methods

Primarily, based on [7], a Matlab/Simulink® system model that maps stimulation PW and quadriceps torque, using a nonlinear second-order dynamics of knee and lower leg, was developed. Additionally, to perform a more realistic simulation process including muscle fatigue, tremors and spasms, the 'non-idealities' block from [8] was reproduced and implemented. Fig. 2 illustrates waveforms of all non-idealities included at the same time $t = 15s$ as smooth, moderate and critical to the normalized nominal torque. A saturation block is attached to the system model to mimic applications of NMES to patients, bounding control signal from 0 μs to 1000 μs.

In this paper, the performance of the RISE controller was evaluated considering both time transient and stationary responses. From [7], identification parameters corresponding to three paraplegics (P1-P3) and one healthy (H1) were used to simulation considering two reference trajectories. The first one is a sinusoidal trajectory ranging from 12.6° to 44.7°

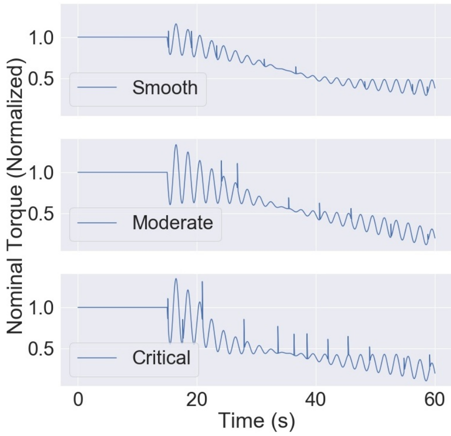

Fig. 2: Normalized nominal torque with smooth, moderate and critical non-idealities.

to mimic an isotonic contraction with a repetitive pattern, and the second one is a $45.82°$ step trajectory replicating an isometric contraction.

Firstly, simulations will try to tune the RISE controller to the worst case scenario, i.e., with all non-idealities (fatigue, tremors, and spasms) included to the model as critical to finding the best gain parameters. Afterward, with these 'best' parameters, it will also be tested to the other cases, which combines non-idealities as smooth, moderate and the ideal case with none of them. The motivation to follow this methodology is that the SCI population generally presents diagnostics with these problems, which will allow examining if and how the RISE controller would compensate in real-world experiments instead of ideal cases. In addition, simulation results are compared for the empiric and IGA tuning on ideal conditions.

A. Improved Genetic Algorithm

The proposed IGA to better optimize gains parameters of the RISE controller is based on the standard methodology of the greedy randomized adaptive search procedure proposed by [19], which runs in a multistart framework (k iterations) and has three mainly steps preprocessing, construction and local search phases. Firstly, the preprocessing step is applied to initiate the search efficiently by bounding gain limits. In the construction phase, we used a simple Fast Genetic Algorithm (FGA) to generate a good set of solutions named the Real Initial Population (RIP) to finally run a local search based on a complete genetic algorithm (CGA). More details on the GA for control applications are in [20], [21].

The proposed IGA is different to general approaches of GA in some aspects as encoding, where a solution to our problem is a chromosome consisting of four real and positive numbers representing the gains parameters. The tournament selection procedure is used to determine the two best chromosomes according to fitness values and a single-point crossover operator is applied in the middle of the selected solutions. The mutation algorithm developed to our problem randomly select one point of each chromosome (concerning to a mutation rate), add or subtract small or medium value to this point according to the preprocessing step, and take its absolute value. Further, as the purpose of our problem is to optimally stimulate the knee joint to track a desired reference, a minimization problem is defined as

$$\min : J(\alpha_1, \alpha_2, k_s, \beta) = RMSE + penalty, \tag{9}$$

$$RMSE = \int_0^T \sqrt{E((\theta_d - \theta)^2)}, \tag{10}$$

$$penalty = \int_0^{TR} \sqrt{E((\theta_d - \theta)^2)}, \tag{11}$$

where T is the whole period and TR is the transient response. In other words, the main objective is minimizing the Root Mean Squared Error (RMSE) between the actual and desired knee angle, penalizing poor transient response aiming to obtain fast responses with low overshoot. The whole algorithm description is detailed below and Fig. 3 illustrates a generation of the FGA, where the best solution of this new population is selected to be part of the RIP.

- I Bound gain limits (preprocessing step);
- II FGA to generate the RIP (construction phase):
  - i Define the following initial parameters: size of population N_p (small), number of generations N_g, crossover C_R and mutation rate M_R;
  - ii Randomly generate the initial population and evaluate its fitness value;
  - iii Select two solutions via tournament selection and apply the crossover and mutation operators;
  - iv Substitute only these two solutions in place of the two worst individuals in the current population;
  - v Evaluate and select the best individual of this small population to be a member of the RIP;
  - vi Repeat steps (iii) to (v) until the algorithm reach the predefined N_g.
- III CGA to improve solutions (local search phase):
  - i Check for and exclude repeated solutions from RIP;
  - ii Select two individuals via tournament selection and apply the crossover and mutation operators;
  - iii Evaluate if the two new individuals are able to replace others from population. The individual is accepted if, and only if it is not equal to another one in the population, and if it performs better than the worst individual in the current population;
  - iv Repeat steps (ii) and (iii) until the algorithm reach the predefined N_g.

Initial parameters of IGA used in this paper were $N_p = 10$, $N_g = 50$ (size of the RIP set), $C_R = 1$, $M_R = 0.3$ and $k = 1$ iteration. Algorithm performed 30 trials given probabilistic properties of GA to ensure convergence pattern to global minimal.

B. Metrics

Different metrics for ideal and nonideal conditions were considered to both tracking and regulation problems with $\pm 5°$ of tolerance. To the sinusoidal trajectory under ideal

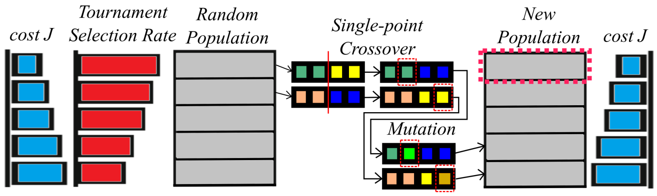

Fig. 3: One generation of the FGA.

conditions, metrics were the lag to the desired and actual knee angles $lag(t)$; and the RMSE $E_{rmse}(deg)$ between the desired and actual knee angles. Considering nonideal conditions, these metrics were the exact time where the controller could not compensate tracking anymore for at least 5 seconds $uncT(t)$, and the E_{rms}.

For the step trajectory along ideal conditions, these metrics were calculated as 10%–90% rise time $\tau_{rise}(t)$; the steady-state error $e_{ss}(deg)$ between the actual and desired knee angles; the percent overshoot $M.O(\%)$ past the steady-state knee angle; and the 2% settling time $\tau_{settling}(t)$. For non-ideal conditions, these metrics were calculated as the exact time where the controller could not compensate regulation anymore for at least 5 seconds $uncR(t)$, E_{rms}, peak angular position $PA(deg)$ (upper or lower the desired knee angle), and the time to peak angular position $PT(t)$ respectively.

IV. Results and Discussion

Tables I and II indicate the metric performances for control systems obtained from H1, P1, P2 and P3 on ideal conditions using the empiric and IGA tuning respectively. Similarly, Tables III-V present the metric performances using the IGA tuning on nonideal conditions. Fig. 4 illustrates example results using the empiric and IGA tuning on ideal conditions for patients H1 and P2 to the sinusoidal trajectory and for patients P1 and P3 to the step trajectory. Lastly, Fig. 5 presents results for tracking and regulation problems to all subjects under critical non-idealities using the IGA tuning.

As one can notice from Table I, results for an empirical tuning approach to the RISE controller could also guarantee stability (i.e., there are no $e_{ss}(deg)$ to the step wave and in less or equal to 6 seconds the actual knee angle followed the desired sine wave). However, once gains selections are immense it is likely to one choose combinations that would not guarantee the best performance and accuracy during rehabilitation (e.g., see results in Fig. 4, which were commonly found in our simulations). The use of an empirical approach on clinical procedures would present a large amount of poor performance trying to rehabilitate SCI patients with NMES/FES by not taking full advantage of the RISE controller that can better compensate with the right selection of gains. The attempt to improve the rehabilitation procedure directly affects the well-being of SCI patients providing fast recovery in the best performance.

TABLE I: Empiric ideal response metrics.

Trajectory	Metric	H1	P1	P2	P3
Step	$\tau_{rise}(t)$	0.6138	0.7995	3.2453	3.0694
	$e_{ss}(deg)$	0	0	0	0
	$M.O(\%)$	16.687	24.380	0.0289	0.0206
	$\tau_{settling}(t)$	6.2046	8.1102	6.5566	6.3417
Sine	$lag(t)$	5.4	6.0	0.8	0.6
	$E_{rms}(deg)$	2.4956	2.8409	0.7007	0.6913

TABLE II: IGA ideal response metrics.

Trajectory	Metric	H1	P1	P2	P3
Step	$\tau_{rise}(t)$	0.3352	0.7628	0.6209	0.2638
	$e_{ss}(deg)$	0	0	0	0
	$M.O(\%)$	23.894	30.414	9.0326	11.678
	$\tau_{settling}(t)$	4.97	7.4267	6.2543	4.9745
Sine	$lag(t)$	4.87	5.3	0.55	1.2
	$E_{rms}(deg)$	2.4413	3.2284	0.6755	0.7308

TABLE III: IGA smooth response metrics.

Trajectory	Metric	H1	P1	P2	P3
Step	$uncR(t)$	60	60	44.4	31.4
	$E_{rms}(deg)$	3.8453	4.7022	5.0076	7.5408
	$PA(deg)$	56.8	59.386	18.208	20.714
	$PT(t)$	1.5875	2.455	58.6	58.5
Sine	$uncT(t)$	60	57.1	52.5	52.1
	$E_{rms}(deg)$	2.4531	3.6173	1.6189	2.9452

TABLE IV: IGA moderate response metrics.

Trajectory	Metric	H1	P1	P2	P3
Step	$uncR(t)$	60	50.1	40.3	26.9
	$E_{rms}(deg)$	4.1903	6.0676	8.3207	10.058
	$PA(deg)$	29.178	16.555	6.3058	12.741
	$PT(t)$	58.71	58.54	58.5	58.5
Sine	$uncT(t)$	60	53.2	52.2	40
	$E_{rms}(deg)$	2.7362	4.4485	3.6215	4.3497

TABLE V: IGA critical response metrics.

Trajectory	Metric	H1	P1	P2	P3
Step	$uncR(t)$	54.3	15.45	33.6	15.2
	$E_{rms}(deg)$	4.8935	7.71	10.325	11.86
	$PA(deg)$	24.863	16.365	3.652	12.049
	$PT(t)$	58.69	56.7	58.5	58.52
Sine	$uncT(t)$	60	52.3	40.3	27.25
	$E_{rms}(deg)$	3.3695	5.6544	4.9096	5.8021

Furthermore, from Table II, one can observe just a few improvements to IGA tuning compared to the empiric one, which is due to the fact that the controller was tuned considering the worst scenario considering practical purposes instead of the ideal conditions. In this situation, responses showed great results for paraplegic patients. However, the results adding non-idealities to the model showed different muscular behavior. For smooth non-idealities included to the model patient H1 well compensated the whole period with very low increment of RMSE (from $E_{rms}(deg) = 2.4413°$ to $E_{rms} = 2.4531°$), P1 presented small variations and compensated much better than P2 and P3, where P2 in the final cycle and P3 in the two final cycles failed on tracking the sine wave. In moderate and critical scenarios, H1 well compensated the whole period still with a low increase of RMSE, P1 full failed on compensating in the last cycle, and patients P2 and P3 full failed in the last cycles (e.g., see Fig 5 for system responses to sinusoidal trajectory under critical non-idealities).

Further, results for the step trajectory considering ideal conditions lead to zero steady-state error with good performance. Similarly to tracking situations, responses of H1 and P1 with smooth non-idealities are well compensated the whole period, while P2 and P3 failed on compensating after 44.4 and 31.4 seconds respectively. For moderate and critical scenarios, H1 could still compensate the whole period in the first and until 54.3 seconds in the later, P1 presented good compensation on moderate and poor one on critical situation, P2 presented problems on compensating after 30 seconds approximately, and P3 failed compensation after introducing the non-idealities in 15 seconds (e.g., see Fig 5 for system responses to the step trajectory under critical non-idealities).

In all cases, transient response presented interesting results, where it seems that stronger muscles present bigger overshoot. However, strong muscles demonstrate less sensitivity to external disturbances modeled in this paper. Moreover, responses are according to reality where a healthy patient even in spite of non-idealities could track and regulate the angular position very well; an SCI patient with strong muscles (P1, as informed in [7]) could also compensate, but not as well as a healthy one; and SCI patients with weak muscles do not reach well tracking and regulating results with non-idealities in the model. As commented before, it can be due to numerous factors that some papers did not take into account the existing problems with the SCI population assuming that results would be the same for healthy patients.

It is worth to highlight that, responses to the step and sine wave trajectories are very similar to real experiments on SCI patients and healthy ones reported in the literature [4]–[7], [12], [13], proving the effectiveness of simulating knee-joint and non-idealities that are regularly encountered on the real world. Thus, our methodology is based on simulation procedures optimizing a control task by an intelligent technique before implementing a controller on real tests. Moreover, this method will provide a lot of information about human identified system behavior to NMES/FES, permitting to avoid unfeasible cases, to save time and resources. Another highlight to simulation procedures is that one can try to the extreme case scenario before really implement on the real world, to guarantee controller robustness and a bigger space to cover feasibility, as performed in this paper.

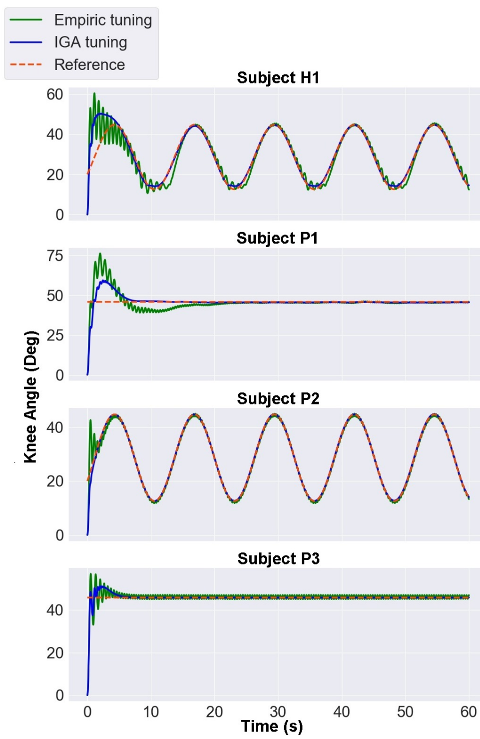

Fig. 4: Analysis of system responses using empiric and IGA tuning on ideal conditions.

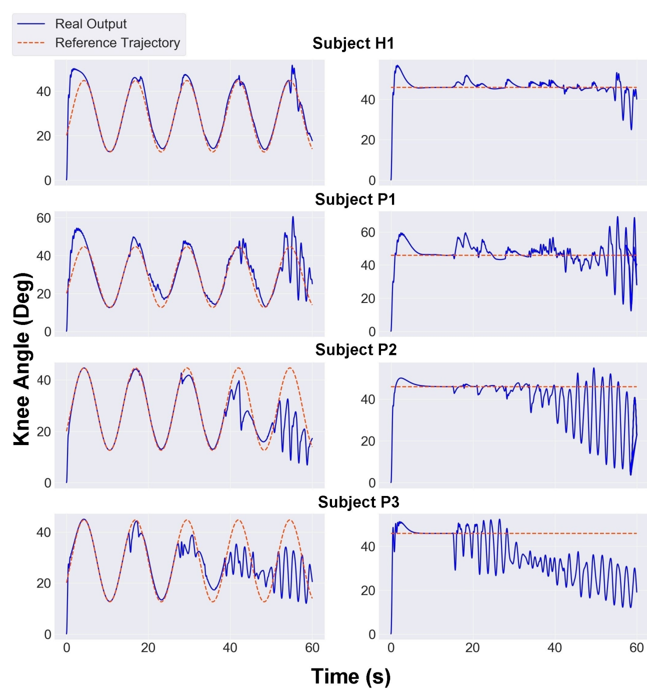

Fig. 5: Analysis of system responses using IGA tuning considering critical non-idealities.

V. Conclusion

Aiming to propose an improved genetic algorithm to cover the lack of intelligent techniques and better tune the parameters of the RISE controller, this paper focused on the attempt to improve the lower limb tracking control of SCI patients via NMES. Simulations results for tracking and regulation problems on ideal and nonideal conditions were presented for three identified SCI patients and one healthy from [7]. As hypothesized in this paper, control performance can be improved via the proposed procedure, by selecting adequately the gain parameters of the RISE controller instead of an empirical tuning, avoiding premature fatigue and other problems of SCI patients during rehabilitation.

Considering that the RISE control method presented a good performance for healthy patients in [4], [6], [12]–[17] without any fine-tuning method, we believe that results can be improved making use of our proposal. Therefore, we intend to design this controller on the original and improved way (i.e., to better deal with SCI patients), planning to evaluate and validate this proposal with experimental results. Moreover, as clearly highlighted in the literature, we are aware that a good nonlinear system identification will be necessary to model the knee-joint before put it on an offline controller optimizer to achieve fine-tuned parameters and continue the rehabilitation procedure in the best performance.

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