Human Arm Stabilization and Rehabilitation using Intelligent Control Techniques

William S. Barbosa
Eletrical Engineering Department
Pontifical Catholic University of Rio de Janeiro
Rio de Janeiro, RJ, Brazil
wsbarbosa@ele.puc-rio.br

Guilherme P. Temporão
Eletrical Engineering Department
Pontifical Catholic University of Rio de Janeiro
Rio de Janeiro, RJ, Brazil
temporao@puc-rio.br

Marco A. Meggiolaro
Mechanical Engineering Department
Pontifical Catholic University of Rio de Janeiro
Rio de Janeiro, RJ, Brazil
meggi@puc-rio.br

2020 IEEE International Conference on Bioinformatics and Biomedicine (BIBM) 978-1-7281-6215-7/20/$31.00 ©2020 IEEE DOI: 10.1109/BIBM49941.2020.9313118

***Abstract*—This work presents a study of the planar model of movement performed by a human arm with hemiplegia, being actuated through an electro stimulus, with the aim to reduce the angular error of the same movement using techniques of adaptive control and genetic algorithm-based control and comparing with an Integral Proportional Controller. The verification and validation of the proposed methodology are carried out by using a simulation of a eletrostimulation device compared with a given angle reference, aiming regulation.**

***Index Terms*—Electro-Functional Stimulation, PI Controllers, Genetic Algorithms, Human Arm Control, Adaptive Control,**

I. Introduction

Every year, stress and unhealthy life leave the people with circulatory and coronary problems, which can lead to a stroke, which is a clogging or rupture of blood vessels that irrigate the brain. A recurrent consequence of stroke is hemiplegia, which is the loss of motor control on one side of the body. One of the treatments used for rehabilitation, in these cases, is Functional Electrostimulation [1] [2]. Patients with hemiplegia caused by stroke usually have slow and gradual recovery. In this way, many affected by this disease need to do a set of physical therapy exercises, among them, electrostimulation, in order to maintain muscle tone and assist reinnervation through the stimulation of the skeletal muscles.

Skeletal muscles are controlled by the nervous system through motor neurons. There are two classes of motor neurons: upper and lower. Lower motor neurons are still divided into alpha motor neurons and gamma motor neurons. The set formed by the alpha motor neuron and all the motor fibers innervated by it is called the motor unit. The activation of the motor units is responsible for the production of the mechanical tension of the muscles [3] [4](Figure 1).

The control of the degree of muscle contraction performed by the alpha motor neurons begins when the acetylcholine released by the neurotransmitters triggers a post-synaptic excitatory potential in the muscle fiber, which contracts and relaxes rapidly, causing a mechanical concussion [3].

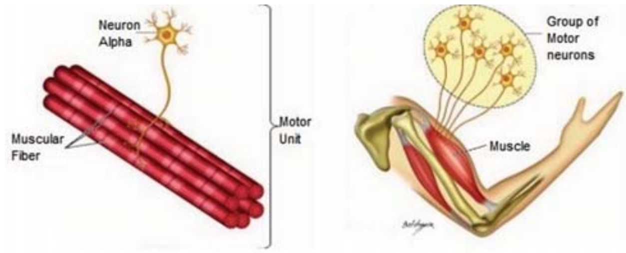

Fig. 1: Figure showing the muscle activation scheme adapted of [3].

At a frequency of a sufficiently high stimulation, produces a sustained or homogeneous contraction, a process known as tetany [5] [6].The normal firing frequencies of motor neurons in human muscles rarely exceed 40 Hz and are rarely less than 6 to 8 Hz. The concept of this type of therapy is called Functional Electrical Stimulation. Such therapy has been used for a long time and currently there are several studies in this line but all in open loop, without the goal of closing the loop, due to several peculiarities of the process.

The purpose of this work is to study the behavior of two types of controllers (PI control and Adaptive control) to cause the patient to reach a target angle, maintaining the same for as long as necessary through an electrical stimulus [7]. It is desired to verify the effectiveness of adaptive control techniques compared to the classical approaches of PI controller, in order to achieve a faster, robust control that has a performance that is as close as possible to the desired reference response, helping to improve the treatment of patients with hemiplegia. Specifically, the PI controller was adjusted first, heuristically (by exhaustive search) and second using genetic algorithm, with the purpose of comparison.

II. Modelling

The first model found is the Hill model. He observed that the elasticity of tendons influences the force generated in the muscles, so that the system could be modeled as a mass-spring system (Figure 2), which was knew as a Hill's muscular model of four elements (widely used still today, as shown at [8]), with CE being the elastic component (muscle) and VER and PEE are the elastic components of the tendons.

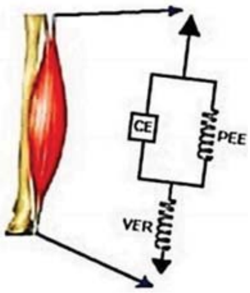

Fig. 2: Figure showing the dynamics of muscular contraction [9].

Exits several studies for activation of neuromotor receptor, as shown at [10]. As a basis for the muscle model and activation of neuromotor receptors, the model described by Houk and Simon [11] was used:

$$T(s) = \frac{F_m(s)}{u(s)} = K\frac{\left(1+\frac{s}{0.15}\right)\left(1+\frac{s}{1.5}\right)\left(1+\frac{s}{16}\right)}{\left(1+\frac{s}{0.2}\right)\left(1+\frac{s}{5}\right)\left(1+\frac{s}{37}\right)}\,, \quad (1)$$

with $\frac{F_m(s)}{u(s)}$ being a function of transference of the motor force performed F_m and the electro-stimulus $u(s)$, K the static muscle gain, which in this study had a conjectural value of 0.01 nA/N.

A. The dynamics

Associated with this we also have the dynamics of arm movement, as shown in (Figure 3), with:

- Y_e the vertical projection of the length of extensor muscle;
- Y_f the vertical projection of the length of flexor muscle;
- X_e the horizontal projection of the length of extensor muscle;
- X_f the horizontal projection of the length of flexor muscle.

From the same model [12] we obtain the following two moments of force:

$$h_f(t) = \frac{Y_f}{\sqrt{1+\left(\frac{Y_f + X_f\cos\theta}{X_f\sin\theta}\right)^2}}\,,$$
$$h_e(t) = \frac{Y_e}{\sqrt{1+\left(\frac{Y_e - X_e\cos\theta}{X_e\sin\theta}\right)^2}}\,. \quad (2)$$

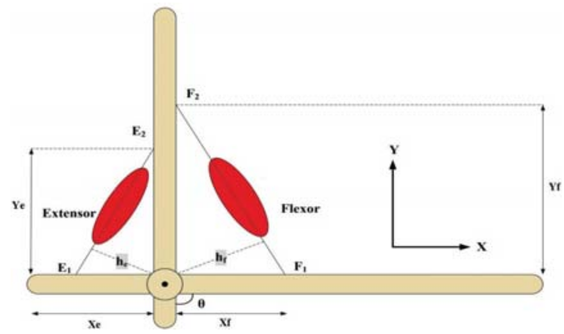

Fig. 3: Figure showing the Schematic diagram of arm movement [12].

A simple rotational momentum model of a rigid rod is used, described by the equation in:

$$I \times \ddot{\theta} = h_f F_m + h_e F_m\,, \quad (3)$$

Applying the equations (1) in (3):

$$I \times \ddot{\theta} = (h_f + h_e)(F_m(t))u_f(t)\,, \quad (4)$$

with $F_m(s)$ being $\mathcal{L}^{-1}[F_m(s)]$:

$$\mathcal{L}^{-1}[F_m(s)] = \delta(t) - 0.15e^{-\frac{t}{5}} - 21.33e^{-37t} - 0.21e^{-2t}\,, \quad (5)$$

applying (5) in (4) we have the system depending only on the stimulus $u_{(t)}$ and the angle θ, described by (6):

$$I \times \ddot{\theta} = (h_f + h_e)u_f(t)$$
$$(\delta(t) - 0.15e^{-\frac{t}{5}} - 21.33e^{-37t} - 0.21e^{-2t}). \quad (6)$$

Finally, applying (2) in (6):

$$I \times \ddot{\theta} = u_f(t) *$$
$$\left(\frac{Y_f}{\sqrt{1+\left(\frac{Y_f+X_f\cos\theta}{X_f\sin\theta}\right)^2}} + \frac{Y_e}{\sqrt{1+\left(\frac{Y_e-X_e\cos\theta}{X_e\sin\theta}\right)^2}}\right) *$$
$$(\delta(t) - 0.15e^{-\frac{t}{5}} - 21.33e^{-37t} - 0.21e^{-2t})\,. \quad (7)$$

B. The Real Dimensions and Activation

For the values of muscle length, distances of the neurotransmitters, the values of (Table I) [12].

For the real Activation of the muscle, the value of $u_{(t)}$ would be given by the approximate expression [13] [9] given by (8):

$$u(t) = -\frac{1}{\tau_{act_f}}\alpha_f(\beta_f + (1-\beta_f)u_f(t)) + \frac{1}{\tau_{act_f}}u_f(t)$$
$$0 \le u_f(t) \le 1, \quad (8)$$

TABLE I: ergonomic measurements

Dimension	*Adopted Values*
X_f (m)	$7.0 * 10^{-2}$
X_e (m)	$5.5 * 10^{-2}$
Y_f (m)	$14.0 * 10^{-2}$
Y_e (m)	$11.0 * 10^{-2}$
I (Kg*m^2)	$1.6 * 10^{-3}$

with τ_{act_f} as a variable time constant that describes the rate of rise of activation in response to muscle excitation. α_f and β_f as a variable time constants that describes the minimum activation of α and β motor neurons. However for patients with hemiplegia, these stimuli were given via low-frequency square wave signals with low current as described in the next section.

After all the simplifications, the function of the angular movement of the arm was described by (1-7) and using the parameters of (Table I):

$$0.016 \times \ddot{\theta} = u_f(t) * \left(\frac{0.14}{\sqrt{1 + \left(\frac{0.14 + 0.07\cos\theta}{0.07\sin\theta}\right)^2}} + \frac{0.1}{\sqrt{1 + \left(\frac{0.11 - 0.055\cos\theta}{0.055\sin\theta}\right)^2}} \right) * (\delta(t) - 0.15e^{-\frac{t}{5}} - 21.33e^{-37t} - 0.21e^{-2t}) \tag{9}$$

Due to the objective of the control is reach an angle by a electrical stimuli, we can rewrite (9), already simplifying and passing to the Laplace domain, being $P(s) = \dfrac{\theta(s)}{u_f(s)}$:

$$P(s) = \frac{15,7(s^2 + 33.1s + 1180)}{(s + 83.5)(s + 61.7)(s + 56)(s^2 + 4.2s + 12)} e^{-0.012s} \tag{10}$$

The term $e^{-0.012s}$ consists in a time delay, which can be bypassed using the approximation of Padé as shown at [14] and [15], which consists in obtaining an expansion in the irrational function $e^{-\tau s}$ in a rational function whose numerator is a polynomial of degree p and denominator of degree q. For example, if p = q = 1, we have:

$$e^{-\tau s} \cong \frac{1 - \frac{\tau s}{2}}{1 + \frac{\tau s}{2}}. \tag{11}$$

For systems with very small delays, the following trivial approximation may be done [16]

$$e^{-\tau s} \cong \frac{1}{1 + \tau s}. \tag{12}$$

Thus, the final model used at this work, with all simplifies and considerations is:

$$P(s) = \frac{15,7(s^2 + 33.1s + 1180)}{(s + 83.5)(s + 61.7)(s + 56)(s^2 + 4.2s + 12)(0.012s + 1)} \tag{13}$$

C. The Evaluation function

As an evaluation function, we use the mean square error [gauss] of this function:

$$e = \sqrt{\sum_{i=0}^{n} \frac{x_i^2 - \hat{x_i}^2}{n}} \tag{14}$$

Thus, using a square wave of 25 Hz as the input signal (Figure 4)(b), the response can be shown at (Figure 4)(a):

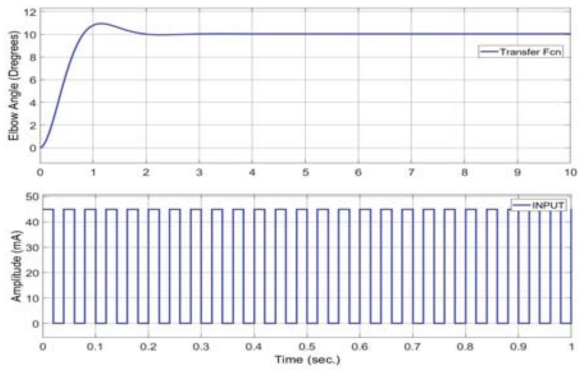

Fig. 4: Figure showing the open loop response (a) and the input of the system (b)

Note that, for a 45 mA amplitude stimulus, the system, after a few seconds, converges, as would be expected for the described modeling.

III. Stability analysis

After all simplifications and linearizations the transfer function described in (13) has the following the poles in open loop are -83.3, -83.52, -61.18, -56.34, -2.1 + 2.75i, -2.1-2.75i.

In respect of BIBO stability, it is enough the poles to be in the SPE, but we can study the frequency response through the BODE diagram (Figure 5):

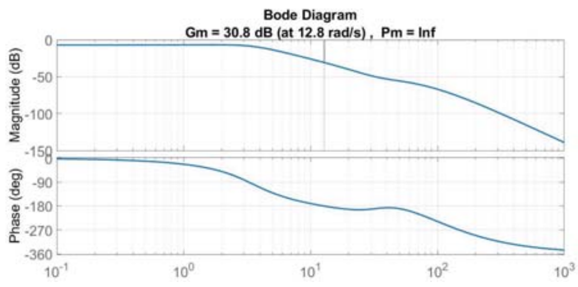

Fig. 5: Figure showing the Bode Diagram

The diagram above shows that the system is stable with 30.8 dB of Margin of Gain.

IV. Proportional Integral Controller

The PI controller is very used to reach a defined set point. However, the PI must be adjusted to give better results. The controller, briefly explained, is composed of a set of two gains a proportion proportional to the error (Kp)and another proportional to the integral of the error (Ki). For the simulation of this controller, the following closed-loop block diagram was used (Figure 6):

Fig. 6: Figure showing the block diagram with a fixed angle at closed loop with PI controller

A. Adjust of the PI controller gains Heuristically

For the tuning of controller gains, the matlab auto-tuning tool was first used and then the order of magnitude defined, the gains were changed heuristically until reaching an optimal point with respect to the error. Thus, the final values of the proportional and integrative gains were, respectively, 3 and 0.5 in the simulations. A target angle of 45 degrees ($\pi/4$) was set and the objective is to minimize the means square error (14).

B. Adjust of the PI controller gains with genetic algorithms

The objective, in sequence, is simply, given the same stimulus $u_{(t)}$, to cause the variation of the angular position θ to be null, after a given time, only now using genetic algorithms.

First, we need to define the chromosomes [17], which after sequential attempts, ended up being defined by angle and time (Table II).

TABLE II: Representation of the chromosomes

Angle	***Time***

Then, it is necessary to define the parameters of the algorithm, such as crossover rate, mutation rate, selection method, among others [17]. In this study, for purely comparative purposes, the three best configurations obtained experimentally were chosen, according to (Table III):

TABLE III: Three Best Configurations

Parameters	**Adopted Values**		
Type of Crossover	Simple	Simple	Simple
Crossover Rate	50%	65%	70%
Mutation	0.8%	0.5%	0.5%
Population	500	500	500
Selection	Geometric Normalization	Geometric Normalization	Geometric Normalization
Number of generations	200	100	50

V. MRAC - Model Reference Adaptive Controller

Adapting means changing behavior according to circumstances. an adaptive controller, has the merit of playing the role of modifying the response of the system at each iteration in order to control the system dynamically. there is examples of adaptive controllers in various areas, such as in pilots automatic airplanes, ABS brakes and other types of supervisory equipment.

For the proposed, an adaptive controller was used by reference model, using projection [18]. Observing that the plant used is stable, another plant was proposed as a reference [19] of the same order and relative degree, the simulation being as follows (Figure 7):

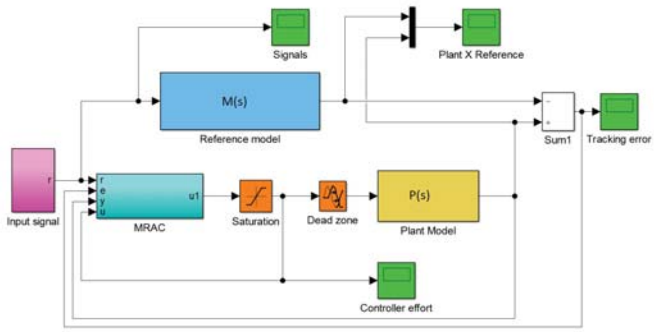

Fig. 7: Figure showing the Closed-loop block diagram with adaptive controller with feedback projection

The main idea is to make the ”defective” plant follow the Hill model [9] after a step is applied, causing the system to adapt its internal gains automatically, taking the same cost function. The adaptive control used was defined according to the table from the Ioannou book [20] Chapter 6.

In the simulation a step was applied as a reference, resulting in a 45 degrees angle, so that we have the same reference proposed for the PI.

VI. Initial Results

A. Adjust of PI gains

Once all the parameters were defined, it was possible to observe from the Proportional Integrative Controller (PI) what was simulated, generating the data according to (Figure 8):

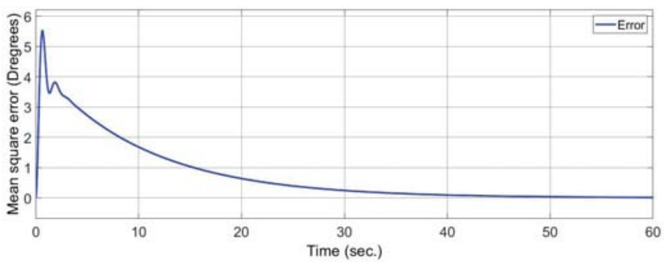

Fig. 8: Figure showing the Simulation of Proportional Integral Controller (PI).

The behavior of the controller was relatively good, having a quadratic error variation peak of 5.2 and soon after, in about 30 seconds, the system stabilizes between 0 zero and -0.15.

The transient was very oscillatory, though its response, even with the simplification of the input signal (a square wave), was satisfactory.

Using the GAOT algorithm [21], and considering the minimization of the quadratic error, according (10), fixed populations of 500 individuals were used and altered other parameters of the genetic algorithm, such as Crossover rate and mutation, in order to achieve better performance.

Thus, the following results were obtained for the value of the effective error (target angle-best angle described by the genetic algorithm) (Table IV):

TABLE IV: Effective error values found by the GAOT algorithm

Configuration	*Error (degrees)*
1	17.286
2	1.9336
3	7.515

For a more interesting analysis, besides checking the error, the chromosome was composed of time, in order to verify the convergence time of the minimum error value, obtaining the following best individual values for the proposed configurations (Table V):

TABLE V: Best Angles and Time Responses

Configuration	Angle (degrees)	Time Response(Sec.)
1	27.714	0.005
2	43.0664	0.002
3	37.485	0.007

Thus, in comparison to the PI Controller heuristically adjusted, it can be estimated that the genetic algorithm achieves significantly better results, while the classical Integrative Proportional Control (PI) does not obtain such precise values, besides having a rather oscillatory character (meanwhile as the parameter was the average of the error, it remained null).

Another relevant comparison is the analysis with respect to the optimum settling time / time. It can be observed that the control made by genetic algorithms achieves a result of 0.002 seconds, while the other controller achieves the value of 0.3 seconds. This demonstrates that the system is much faster compared to Proportional Integrative (PI).

In the aspect of gains,the following best individual values for the proposed configurations (Table VI) was obtained:

TABLE VI: Best PI Gains

Configuration	Proportional	Integral
1	0.9	0.4
2	0.3	0.2
3	0.4	0.4

In the aspect of the genetic algorithm, we can show the best configuration showing the graph of the convergence of the mean square error x generations (Figure 9:

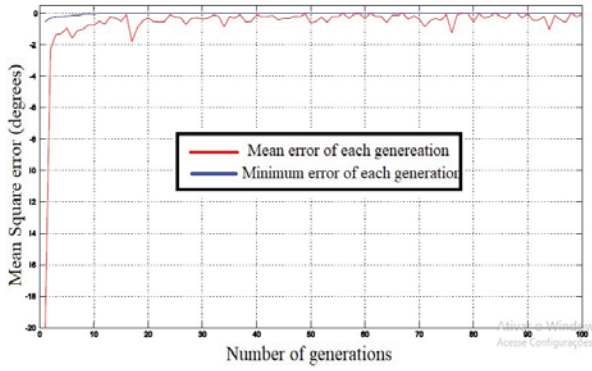

Fig. 9: Figure showing the graph of the convergence of the mean square error x generations of configuration 3

The mutation rate influenced in the sense of increasing the exploratory character of the algorithm (according to the definition itself), however, its decrease favored the convergence and the decrease of the mean oscillation of the errors. With respect to the number of generations, due to the speed of convergence of the algorithm, it can be observed that with far fewer generations than the proposed algorithm converges (Figure 9).

With respect to the crossover rate, it can be observed that if very low, the effective error (best individual) increases and the same happens if the error is too high. Therefore, the adjustment of this element must be done with caution.

Applying the same reference in the closed loop system with adaptive control [20], the following response was obtained expressed in (Figure 10):

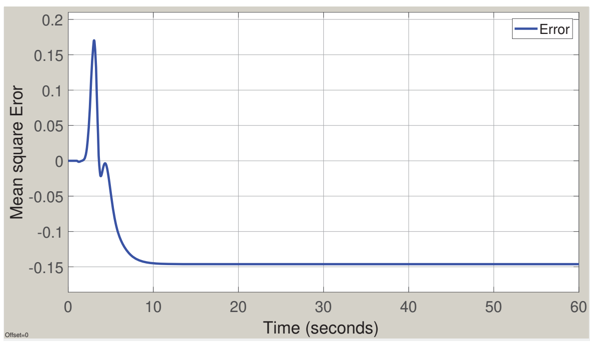

Fig. 10: Figure showing the MRAC simulation

The controller behavior are much better than the simple PI, with a peak of 0.15 degrees and after 10 seconds the quadratic error falls and the error of the system stabilizes to -0.15 degrees. Comparing with PI controller, the MRAC controller converges more quickly and at the transient, the MRAC controller had a minor error.

VII. Final Comments and Future Developments

the union of the intention of movement with FES is a powerful tool in improving the health condition of patients. Thus, a control technique that aims to facilitate and automate these physiotherapy exercises is essential.

With the aim to improve and explore new controllers, a next step would be the application of these algorithms in a real system, using logic controllers, microprocessors and digital control elements, in order to verify the differences between the simplifications and conjectures of the model and the real system, which is in fact nonlinear and variant in time, not to mention that the "system" varies from person to person and from injury to injury.

For PI, another tunning method, like Extremum seeking [22] or a fusion of another control techniques with the aim to optimize the gains and minimize overshoot and some characteristics.

For MRAC, a next step would be the consideration of other factors such as muscle fatigue, dead zone and delay, which are already being studied in adaptive control [23], but without any application for FES systems proposed in this study.

Acknowledgment

The authors are grateful to the Brazilian Research Funding Agencies, CNPq, CAPES and FAPERJ for the financial support.

References

[1] W. J. Shribner, *A Manual of Electrotherapy*. Lea & Febiger, 1982.

[2] R. Dolhem, "Histoire de l'electrostimulation en medecine et en rééducation: the history of electrostimulation in rehabilitation medicine," in *Annales de readaptation et de medecine physique*, no. 51, 2008, p. 427–431.

[3] M. F. BEAR and M. A. CONNORS, B. W.and PARADISO, *Neurociências. Desvendando o sistema nervoso*, 2nd ed. Artmed editora, 2002.

[4] R. Neptune and S. Kautz, "Muscle activation and deactivation dynamics: The governing properties in fast cyclical human movement performance?" *Exercise and sport sciences reviews*, vol. 29, pp. 76–80, 05 2001.

[5] A. C. GUYTON and J. E. HALL, *Tratado de fisiologia médica*, 13th ed. Elsevier, 2017.

[6] M. Shourijeh, K. Smale, B. Potvin, and D. Benoit, "A forward-muscular inverse-skeletal dynamics framework for human musculoskeletal simulations," *Journal of Biomechanics*, vol. 49, 04 2016.

[7] J. SANTANA, V. Santana Filho, E. A. Candido, and R. d. F. Freire, "Eletroestimulacão funcional no controle da espasticidade em paciente hemiparetico," *revista fafibe online*, vol. 9, no. 1, 2010.

[8] R. Rockenfeller and M. Günther, "Hill equation and hatze's muscle activation dynamics complement each other: enhanced pharmacological and physiological interpretability of modelled activity-pca curves," *Journal of Theoretical Biology*, vol. 431, 07 2017.

[9] F. Zajac, "Muscle and tendon: Properties, models, scaling, and application to biomechanics and motor control," in *CRC Crit Rev. Biomed. Eng.*, vol. 17, 1989, pp. 359–411.

[10] A. Santuz, L. Brüll, A. Ekizos, A. Schroll, N. Eckardt, A. Kibele, M. Schwenk, and A. Arampatzis, "Neuromotor dynamics of human locomotion in challenging settings," *iScience*, vol. 23, no. 1, p. 100796, Jan 2020.

[11] J. Houk and W. Simon, "Responses of golgi tendon organs to forces applied to muscle tendon," *Journal of neurophysiology*, vol. 30, pp. 1466–81, 12 1967.

[12] G. N. N. V. de Brito Nunes, "Modelac ao e controlo n ao-linear do sistema motor humano," Master's thesis, Universidade Nova de Lisboa, 2009.

[13] B. NIGG and H. W., *Biomechanics of musculo-skeletal system*. John Wiley & Sons, September 1994.

[14] W. Barbosa and T. Roux Oliveira, "Rastreamento de trajetória com controle por modos deslizantes para eletroestimulação funcional," in *Proc. of the XVI Congreso Latinoamericano de Control Automático (CLCA 2014)*, 10 2014.

[15] T. R. Oliveira, L. R. Costa, J. M. Y. Catunda, A. V. Pino, W. Barbosa, and M. N. de Souza, "Time-scaling based sliding mode control for neuromuscular electrical stimulation under uncertain relative degrees." *Medical engineering & physics*, vol. 44, pp. 53–62, 2017.

[16] G. F. Franklin, J. D. Powell, and A. Emami-Naeini, *Feedback Control of Dynamic Systems*, 7th ed. Upper Saddle River, NJ, USA: Prentice Hall Press, 2014.

[17] B. SICSU, *Algorítmos Genéticos*. Ed. Ciência Moderna, 2012.

[18] K. J. Astom and B. Wittenmark, *Adaptive Control*. Prentice Hall, 1989.

[19] H. GOLLEE, "A non-linear approach to modelling and control of electrically stimulated skeletal muscle," Ph.D. dissertation, University of Glasgow, 1998.

[20] I. P. and J. Sun, *Robust Adaptive Control*. Prentice Hall, 1996.

[21] C. R. Houck, J. Joines, and M. G. Kay, "A genetic algorithm for function optimization: a matlab implementation," *Ncsu-ie tr*, vol. 95, no. 09, pp. 1–10, 1995.

[22] K. B. Ariyur and M. Krstic, *Real Time Optimization by Extremum Seeking Control*. USA: John Wiley & Sons, Inc., 2003.

[23] Y. Yildiz, A. Annaswamy, I. Kolmanovsky, and D. Yanakiev, "Adaptive posicast controller for time-delay systems with relative degree," *Automatica*, vol. 46, pp. 279–289, 02 2010.