A Novel Strategy for Adjusting Current Pulse Amplitude of FES-Systems with PID based on PSO Algorithm Method to Control the Muscle Force

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Abstract: Adjusting stimulation parameters using control strategy based on mathematical model, that successfully predict muscle force, may improve the efficiency of Functional Electrical Stimulation (FES) systems. It present an interesting task in industrial FES systems applications. In the present study, we investigate the PID control tuning based on the Particle Swarm Optimization (PSO) algorithm at the first time in neuro-muscular systems for updating automatically the stimulation pulse amplitude to track a desired force profiles. In the beginning, The PSO algorithm is used to identify unknown force model parameters. Next, according to the identified model, optimal PID gains are found by the same intelligent algorithm. The preliminary obtained results showed promise of using intelligent algorithm on tuning PID to perform control sessions of FES systems.

1 INTRODUCTION

Functional electrical stimulation (FES) is of a great interest in the medical and sportive domains. Indeed, using such a technique by applying electrical stimulation could treat subjects with motor functions diseases due to neurological disorders. FES is also used in the sportive domain to improve sportive performances levels and to define efficient exercises protocols. Until now, this technique allows to treat some diseases using specific protocols that induce the rapid appearing of the muscle fatigue. In addition, the generated movements of the treated muscles by these protocols are imprecise (Bickel et al., 2011). This is due to the use of a basic stimulation pattern with constant parameters (frequency, amplitude and pulse width). However, using control technique could delay the appearing of the muscle fatigue and give more precise movements (Doll et al., 2015), (Yochum et al., 2012). The control techniques will act on the stimulation parameters of the FES to reach the aforementioned performances.

Determining the appropriate FES strategy for a specific muscle is primordial to obtain a targeted response by maximizing the skeletal muscle performance(Doll et al., 2015). The efficiency of the chosen strategy depends on the physiological conditions of the subject muscle. To perform more efficient strategies, mathematical models that are based on experiments could be used to predict force response and to design closed loop feedback controllers in FES systems. Many control strategies have been proposed in order to track a desired behaviors such as the joint torque and the muscle activation (Liu et al., 2005), (Li et al., 2015), (Kurosawa et al., 2005), (Ferrarin et al., 1996).

The generated force by skeletal muscle was modeled by different ways (physiological activity, black box modeling, etc.). One of the most popular models that reflect as well as possible the muscle behavior is a physiology-based model that was developed by Ding et al (Ding et al., 2000), (Ding et al., 2003). In (Law and Shields, 2006), The comparison of the model of Ding et al with other models showed that the Ding model is the best one to predict the muscle behavior under different physiological conditions. It has also showed that in the case of spinal cord injuries (SCI) subjects, the Ding model is of good accuracy when used to fit the paralyzed muscle forces (Ding et al., 2007). Until the present, the control of the force response actuated by the quadriceps muscles using model-based approaches has not yet well treated (Ben Hmed et al., 2015), (Ben Hmed et al., 2016).

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The main objective of this study is to control the muscle force by adjusting the stimulation pulse amplitude of FES Stimulator using the PSO-based PID controller. The PSO algorithm is firstly introduced to identify the optimal parameters of the nonlinear force model using experimental data. Then, we will discuss the Off-line PID controller design using the PSO algorithm adopting to the identified model. This efficient tuning of the PID control gains is then applied to control the muscle force model. it's performance and effectiveness will be discussed by a set of simulation results.

2 MUSCLE FORCE MODEL

The muscle force model developed by Ding et al is comprised of two nonlinear differential equations (Ding et al., 2000), the first one Eq. (1) represents calcium kinetics and the calcium-troponin interaction and the second equation Eq. (2) represents the developed force:

$$\frac{dC_N}{dt} = \frac{1}{\tau_c}\sum_{i=1}^{n} R_i \exp(-\frac{t-t_i}{\tau_c}) - \frac{C_N}{\tau_c}, \quad (1)$$

$$\frac{dF}{dt} = A\frac{C_N}{K_m+C_N} - \frac{F}{\tau_1+\tau_2\frac{C_N}{K_m+C_N}}. \quad (2)$$

The force output is monitored using six constant parameters (A, R_0, τ_c, τ_1, τ_2 and K_m). The definitions of the used symbols in the above equations are detailed in(Ding et al., 2000), (Ding et al., 2003). The term R_i in Eq. (1) is a scaling term that accounts for the nonlinear summation of the Ca^{2+} transient within the muscle fibers in responses to two closely spaced pulses:

$$R_i = \begin{cases} 1 & for \quad i=1, \\ 1+(R_0-1)\exp(-\frac{t_i-t_{i-1}}{\tau_c}) & for \quad i>1. \end{cases} \quad (3)$$

Testing this force model under diversity of physiological conditions (Ding et al., 2007) and with different types stimulation train (type of train, frequency, pulse width) shows a good agreement between measured data and estimated model (Ding et al., 2000).

3 SYSTEM IDENTIFICATION AND CONTROL BASED PSO ALGORITHM

3.1 Particle Swarm Optimization Algorithm(PSO)

PSO technique has been developed by Kennedy and Eberhart in 1995. It is a population-based approach for optimization problem. It is derived from the swarm intelligence such as birds flocking. This method has been chosen thanks to its effectiveness, simplicity and reduced parameters number. The PSO has been investigated in many applications such as complication function, combinational optimization and fuzzy system control (Precup et al., 2014).

At each algorithm iteration, the velocity of each particle will be updated following this equations:

$$\nu_i^{t+1} = \omega\nu_i^t + c_1 r_1(Pbest_i^t - \chi_i^t) + c_2 r_2(Gbest^t - \chi_i^t), \quad (4)$$

where ν_i and χ_i^t are respectively the velocity and the position of the particle i in the t^{th} iteration. ω is the inertia weight, c_1 and c_2 are acceleration coefficients, r_1 and r_2 are two random numbers in the range [0, 1]. $Pbest_i^t$ is the best previous position of this particle (memorized by every particle). Finally, $Gbest^t$ is the best previous position among all the particles in the t^{th} iteration (memorized in a common repository). After calculating the velocity, the new position of every particle can be calculated as follow:

$$\chi_i^{t+1} = \chi_i^t + \nu_i^{t+1}. \quad (5)$$

Finally, the PSO algorithm can be summarized by six steps as shown by the algorithm.1 and its implementation considered in this study is developed with a maximum generation value of 100 (Max iteration), a swarm size =10, a inertia weight ($\omega = 0.9$) and acceleration coefficients ($c_1 = c_2 = 1.2$)

Algorithm 1: Particle Swarm Optimization algorithm

1. Initialization;
while $t <$ *Max iteration* **do**
  $t \longleftarrow t+1$;
  2. Evaluate each particle's position according to the objective function (Eq. (6) or Eq. (10));
  if χ_i^t *is better then* $Pbest_i^t$ **then**
    Update it;
  3. Determine the best particle $Gbest_i^t$ (according to the particle's $Pbest_i^t$);
  4. Update particle's velocities using Eq. (4);
  5. Move particles to their new positions using Eq. (5);
6. Find the *Gbest* particle according to the global best objective function

3.2 Muscle Parameter Identification

In General, the process of system identification consist to compare the system outputs with the parameterized model based on a performance function giving a measure of how well the model response fits the system output (Alfi and Modares, 2011), (Türkşen and Tez, 2016). For simplicity, under nonfatigue conditions, τ_c was fixed at 20 ms. Additionally, Ding et al showed in (Ding et al., 2003) that for all physiological conditions parameter R_0 could be expressed as a function of $K_m(R_0 = K_m + 1.04)$. Thus, only four free parameters need to be identified for each subject (A, τ_1, τ_2 and K_m). This four force model parameters were identified from fitting the model to the force data using the following objective function G:

$$G = \frac{1}{N}\sum_{k=1}^{N}\left(F_p(k; A, \tau_1, \tau_2, K_m) - F_m(k)\right)^2, \tag{6}$$

where F_p is the predicted force by Eqs. (1) and (2) and F_m represents the experimental force data and N is the number of the considered data points. G is minimized using the PSO algorithm (Alfi and Modares, 2011), which is employed to identify the optimum values for the four variables numerically by mean of an objective function.

3.3 PID Control based PSO

The PID controller is the most widely used controller for industrial applications. In practice, controlled systems usually have some features such as nonlinearity and time delay, which make PID parameter tuning complex. In control tuning literature, Many PID tuning methods (Jaen-Cuellar et al., 2013) such as the Ziegler-Nichols (ZN) method and many other artificial intelligence techniques such as neural networks (Qiu et al., 2014), fuzzy (Bouallègue et al., 2012) and intelligent optimization algorithm such as Genetic Algorithm (GA) (Jaen-Cuellar et al., 2013),(Qiu et al., 2014) and PSO (Alfi and Modares, 2011) were proposed to find the optimal parameters of a PID controller. In this work, we investigate the intelligent PSO algorithm because of it efficiency comparing to others control-tuning methods (Nagaraj and Vijayakumar, 2011).

The continuous form of PID controller can be described as follows:

$$u(t) = K_p e(t) + K_i \int_0^{\tau} e(\tau)d\tau + K_d \frac{de(t)}{dt}, \tag{7}$$

where, $e(t)$ is the error signal between the desired and actual outputs, $u(t)$ is the control input, K_p, K_i and K_d are the usual tuning gains. Using trapezoidal approximation for Eq. (5), the discrete-form of the PID algorithm is generally given as:

$$u(k) = K_p e(k) + K_i \sum_{i=1}^{k} e(i) + K_d \left(e(k) - e(k-1)\right). \tag{8}$$

3.4 Controller Design: Control of the Muscle Force

After achieving the Off-line tuning of the PID controller based on the optimization algorithm (PSO) (see Table.1), we explore the obtained optimal gains to track the desired reference defined by clinicians. The calculated continuous control signal $\alpha(t)$ is used then to compute the pulse amplitude.

$$\alpha(t) = u_{pid}, \tag{9}$$

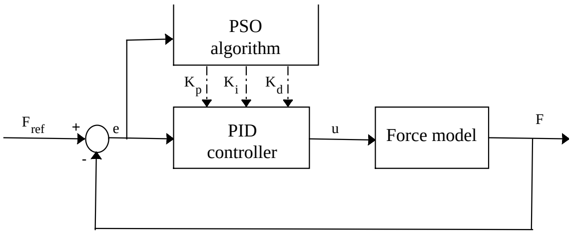

Figure 1: PID controller tuning based on the PSO algorithm for muscular force control.

Fig. 1 illustrates the PID controller design using intelligent algorithm (PSO), where F_{ref} is the desired output and F is the system output. In the control process, the objective is to minimize the fitness function, defined as the Mean Square Errors (MSE), which could be used to determine the performance of any optimization algorithm.

$$MSE = \frac{1}{N}\sum_{k=1}^{N}\left(Fref(k) - F(k)\right)^2. \tag{10}$$

Table 1: Optimal gains tuning of the PSO based PID controller.

K_p	K_i	K_d
0.0935	0.0012	0.1511

In the computer simulation of the controlled force model, the adjusted stimulus output is calculated using the sum of pulses defined in Eq. (1) as muscle model's input where the train of pulses is multiplied by the term α_i correspondent to the amplitude of the i^{th} pulse applied to the muscle as shown in Fig. 2. The modified expression is given as follows:

$$u_n^*(t) = \frac{1}{\tau_c}\sum_{i=1}^{n} \alpha_i R_i \exp(-\frac{t - t_i}{\tau_c}), \tag{11}$$

where, at each pulse, the stimulus output's amplitude α_i delivered by the stimulator toward quadriceps muscle is computed using the discrete formula of the considered PID controller:

$$\alpha_i = \alpha(t) * \delta(t - iT),\ with\ T = t_i - t_{i-1}, \tag{12}$$

where T is the sampling period and δ is a Dirac function used to detect the amplitude given by the continuous control signal, it consist to the TTL trigger signal of the stimulator system in practice.

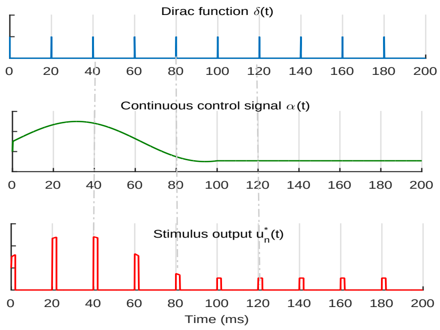

Figure 2: Schematic representation illustrate the proposed method to compute the pulse amplitude on the control of the muscle force by FES systems.

4 RESULTS AND DISCUSSION

4.1 Experimental Setup

As a pilot study, the system tests were conducted on one subject up on his consent (a volunteer sportsman). To test and identify the muscle force model, stimulation pulses were standardized to a fixed amplitude and pulse width. For the test subject the pulse amplitude was fixed to 50 mA and the pulse width was maintained at 500 μs. The quadriceps muscle is stimulated by a pair of surface electrodes connected to the DS7AH Digitimer stimulator (Digitimer Ltd, Welwyn Garden City, Hertfordshire. AL7 3BE. England). Under stimulation session, subject was seated with trunk-thigh angle at 90 and mechanical measurements were recorded using an isometric ergometer that comprised a machine typically used for strength training (Multi-form, la Roque d'AnthÃľron, France) connected one strain gauge (STC 250 kg, sensitivity: 2.9997 mV/V, Celtron Technologies Inc., Santa Clara, CA, USA). During the experimentation, data were digitized and stored for analyses (Biopac MP150 A/D converter and AcqKnowledge v4.2 software, Biopac Systems Inc., Santa Barbara, CA) as shown in Fig. 3.

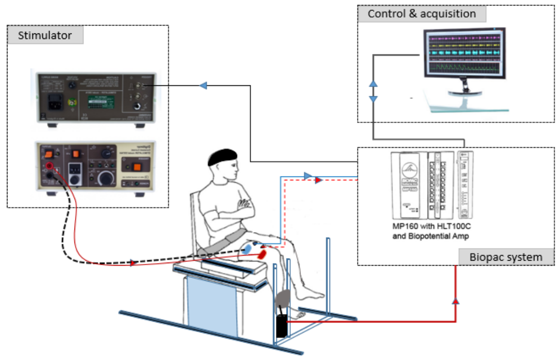

Figure 3: Schematic representation of experimental arrangement for data collection.

4.2 Testing and Identification of the Force Model

In order to identify subject-specific parameters, all of the force model parameters (A, τ_1, τ_2, K_m and R_0) were set as free within reasonable bounds. Furthermore, it should be noted that the identified parameters for this model are depending of the standardized pulse's magnitude, the muscle properties of the test subject, size and placement of the stimulation pads. In this study, the identified muscle parameters for the considered subject were calculated using data collected from a simple protocol (pair of 12.5Hz-33Hz) where muscle is stimulated by a pulse train sequence of a CFT80 during 1s and relaxed from 500ms, followed by a CTF30 during 1s and then relaxed for 500ms. This protocol was chosen to be the most effective train for force model parameter identification. The identified muscle parameters values are provided in Table 2, which cites the mean best parameters values calculated over 10 runs.

Table 2: Identified parameters force model.

A	τ_1	τ_2	K_m
$1.755N/ms$	$68.32ms$	$102.2ms$	0.5631

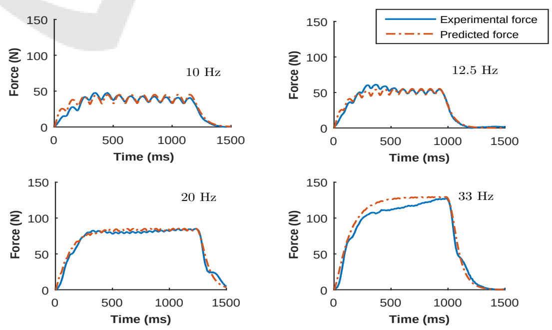

Figure 4: Examples of predicted force to different frequencies stimulation Train (10Hz (CFT100), 12.5Hz (CFT80), 20Hz (CFT50) and 33Hz (CFT30)) when the model is parameterized by the CFT80-CFT30 protocol data for a typical subject.

To validate the identified model, a comparison between experimental and simulation results is shown in Fig. 4. The performance of this model prediction

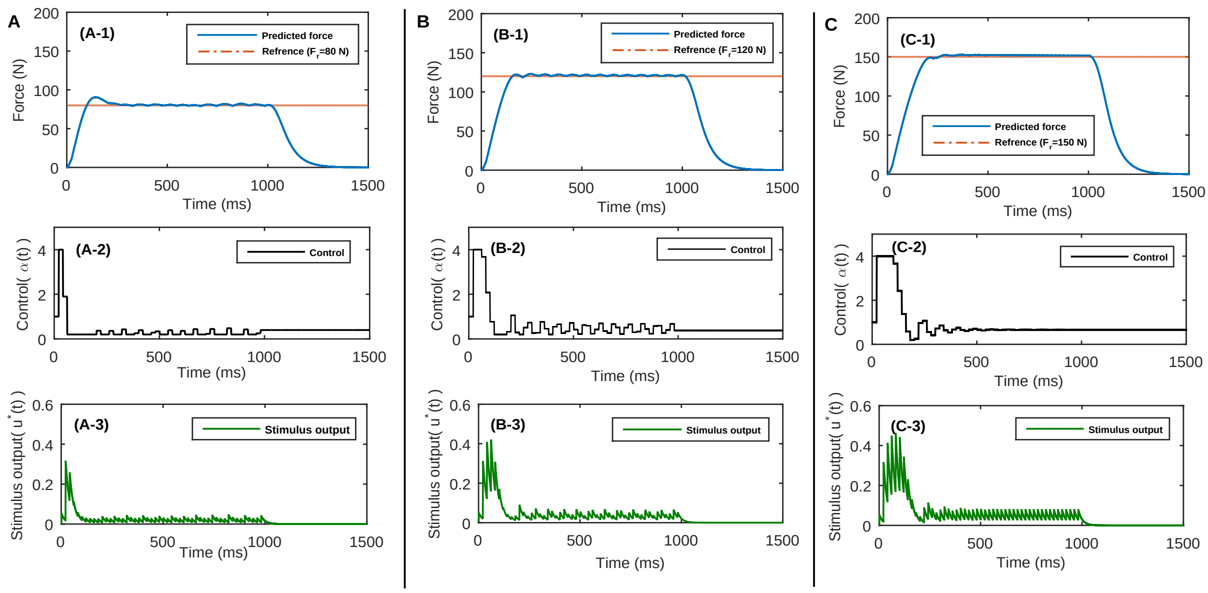

Figure 5: The performance of the PID based PSO control of the muscle force during 1s stimulation session for three desired forces (**A**: F_{ref}=80N, **B**: F_{ref}=120N, **C**: F_{ref}=150N) using the modified pulse train MCFT30. (A,B,C)-1 illustrate the developed force to track the desired force, (A,B,C)-2 illustrate the computed pulse amplitude $\alpha(t)$ and (A,B,C)-3 illustrate the corresponding stimulus output applied to the quadriceps muscle.

was quantitatively assessed by computing the MSE error between the predicted force and the measured one. Fig. 4 proved the ability of the estimated model to predict force response to a wide range of frequencies trains (10Hz, 12.5Hz, 20Hz and 33Hz). In addition, the correspondence with the values identified by Ding et al for the force model justifies the efficiency of using PSO algorithm for nonlinear systems identification.

4.3 Control of the Muscle Force

The PSO-based PID control method is tested for various references forces (80, 120, 150N) with a Constant Frequency Train (CFT20). The Fig. 5 (A), (B) and (C) show respectively the ability of the developed force to track the desired references in (A,B,C)-1 and the computed pulse amplitude in (A, B, C)-2 and finally in (A, B, C)-3, which illustrate the corresponding stimulus output applied to muscle. In addition, in order to confirm the robustness of our developed strategy to control the muscle force, we present in Fig. 6 the tracking of a set of three point references by increasing the desired force with 50N every 1s. All of the simulations results show that combining both usual control strategy and intelligent optimization method can provide an efficient incorporated model into the feedback control system during FES applications.

This preliminary results prove that our purpose of

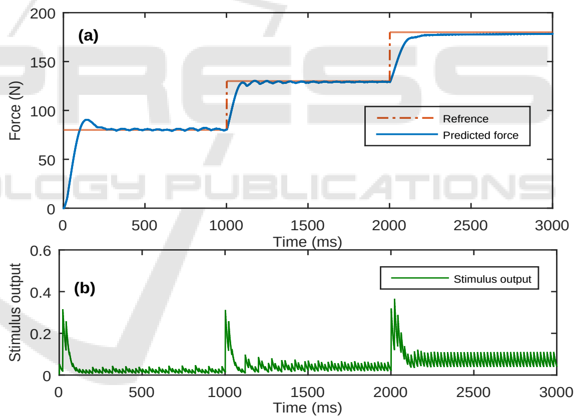

Figure 6: An example of the PID based PSO performance on the control of the muscle force during 3s of stimulation: (a) illustrates the tracking performance with respect to the three set point references (80N, 130N, 180N) by increasing the desired force with 50N every 1s. (b) illustrates the corresponding computed stimulus pulse with the controlled amplitude (the control signal).

controlling muscle force could be approved by the new proposed stimulator DS8R from Digitimer (Digitimer Ltd, Welwyn Garden City, Hertfordshire. AL7 3BE. England).

The new DS8R stimulator monitors the new analogue voltage control applied at this input and adjusts the stimulus current proportionally with this voltage as each trigger input is detected.

5 CONCLUSION

In this paper, a new controlling strategy PID based on PSO algorithm was designed in order to control the muscle force during stimulation sessions. this developed method is used to compute automatically the stimulus pulse amplitude for each pulse applied to the muscle. Also, using experimental data, the PSO algorithm was explored to identify and provide an excellent mathematical model that can simulate perfectly the muscle response and as a result improved the control system. With regard to our current results, we can conclude that designed control method based on optimization approach can enhance performances of control FES systems.

REFERENCES

Alfi, A. and Modares, H. (2011). System identification and control using adaptive particle swarm optimization. *Applied Mathematical Modelling*, 35(3):1210–1221.

Ben Hmed, A., Bakir, T., Binczak, S., and Sakly, A. (2016). Model free control for muscular force by functional electrical stimulation using pulse width modulation. In *Control Engineering & Information Technology(CEIT), 2016 4th International Conference on*. IEEE.

Ben Hmed, A., Bakir, T., Sakly, A., and Binczak, S. (2015). Controlling muscular force by functional electrical stimulation using intelligent pid. In *Sciences and Techniques of Automatic Control and Computer Engineering (STA), 2015 16th International Conference on*, pages 75–79. IEEE.

Bickel, C. S., Gregory, C. M., and Dean, J. C. (2011). Motor unit recruitment during neuromuscular electrical stimulation: a critical appraisal. *European journal of applied physiology*, 111(10):2399.

Bouallègue, S., Haggège, J., Ayadi, M., and Benrejeb, M. (2012). Pid-type fuzzy logic controller tuning based on particle swarm optimization. *Engineering Applications of Artificial Intelligence*, 25(3):484–493.

Ding, J., Chou, L.-W., Kesar, T. M., Lee, S. C., Johnston, T. E., Wexler, A. S., and Binder-Macleod, S. A. (2007). Mathematical model that predicts the force–intensity and force–frequency relationships after spinal cord injuries. *Muscle & nerve*, 36(2):214–222.

Ding, J., Wexler, A. S., and Binder-Macleod, S. A. (2000). Development of a mathematical model that predicts optimal muscle activation patterns by using brief trains. *Journal of applied Physiology*, 88(3):917–925.

Ding, J., Wexler, A. S., and Binder-Macleod, S. A. (2003). Mathematical models for fatigue minimization during functional electrical stimulation. *Journal of Electromyography and Kinesiology*, 13(6):575–588.

Doll, B. D., Kirsch, N. A., and Sharma, N. (2015). Optimization of a stimulation train based on a predictive model of muscle force and fatigue. *IFAC-PapersOnLine*, 48(20):338–342.

Ferrarin, M., D'acquisto, E., Mingrino, A., and Pedotti, A. (1996). An experimental pid controller for knee movement restoration with closed loop fes system. In *Engineering in Medicine and Biology Society, 1996. Bridging Disciplines for Biomedicine. Proceedings of the 18th Annual International Conference of the IEEE*, volume 1, pages 453–454. IEEE.

Jaen-Cuellar, A. Y., de J. Romero-Troncoso, R., Morales-Velazquez, L., and Osornio-Rios, R. A. (2013). Pid-controller tuning optimization with genetic algorithms in servo systems. *International Journal of Advanced Robotic Systems*, 10(9):324.

Kurosawa, K., Futami, R., Watanabe, T., and Hoshimiya, N. (2005). Joint angle control by fes using a feedback error learning controller. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 13(3):359–371.

Law, L. A. F. and Shields, R. K. (2006). Predicting human chronically paralyzed muscle force: a comparison of three mathematical models. *Journal of applied physiology*, 100(3):1027–1036.

Li, Z., Hayashibe, M., Andreu, D., and Guiraud, D. (2015). Real-time closed-loop fes control of muscle activation with evoked emg feedback. In *Neural Engineering (NER), 2015 7th International IEEE/EMBS Conference on*, pages 623–626. IEEE.

Liu, C.-L., Yu, C.-h., Chen, S.-C., and Chen, C.-H. (2005). Evaluation of closed-loop control system for restoring standing and sitting functions by functional electrical stimulation. *Biomedical Engineering: Applications, Basis and Communications*, 17(01):19–26.

Nagaraj, B. and Vijayakumar, P. (2011). A comparative study of pid controller tuning using ga, ep, pso and aco. *Journal of Automation Mobile Robotics and Intelligent Systems*, 5:42–48.

Precup, R.-E., David, R.-C., Petriu, E. M., Preitl, S., and Rădac, M.-B. (2014). Novel adaptive charged system search algorithm for optimal tuning of fuzzy controllers. *Expert Systems with Applications*, 41(4):1168–1175.

Qiu, S., He, F., Tang, J., Xu, J., Zhang, L., Zhao, X., Qi, H., Zhou, P., Cheng, X., Wan, B., et al. (2014). Intelligent algorithm tuning pid method of function electrical stimulation using knee joint angle. In *Engineering in Medicine and Biology Society (EMBC), 2014 36th Annual International Conference of the IEEE*, pages 2561–2564. IEEE.

Türkşen, Ö. and Tez, M. (2016). An application of nelder-mead heuristic-based hybrid algorithms: Estimation of compartment model parameters. *International Journal of Artificial Intelligence*, 14(1):112–129.

Yochum, M., Bakir, T., Lepers, R., and Binczak, S. (2012). Estimation of muscular fatigue under electromyostimulation using cwt. *IEEE Transactions on Biomedical Engineering*, 59(12):3372–3378.