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TORQUE CONTROL OF AN ACTIVE UPPER LIMB EXOSKELETON WITH PNEUMATIC ARTIFICIAL MUSCLES USING SURFACE ELECTROMYOGRAPHY (sEMG) AND A MODIFIED HILL-TYPE MUSCLE MODEL

João Luiz A. S. Ramos[a], Marco A. Meggiolaro[b]

[a]*Robotics Laboratory, Mechanical Engineering Department, Pontifical Catholic University of Rio de Janeiro, Brazil.* jlsouzaramos@gmail.com

[b]*Robotics Laboratory, Mechanical Engineering Department, Pontifical Catholic University of Rio de Janeiro, Brazil.* meggi@puc-rio.br

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1 INTRODUCTION

This paper presents an alternative and simple exoskeleton Human-Machine Interface (HMI) for human strength and endurance amplification using a modified version of the Hill-type muscle. Pneumatic Artificial Muscles (PAM) are used as actuators for its high power-to-weight ratio. Genetic Algorithms (GA) approach locally optimizes the control model parameters for the assistive device using muscle surface electromyography (sEMG).

2 MECHANICAL DESIGN OF THE EXOSKELETON

The goal of the exoskeleton is to complete the task of lifting a payload. The mechanical design chosen to reduce the degrees of freedom (DOF) to complete the task was selected as the simplest as possible. In addition, as the exoskeleton is directly connected to the user, it is necessary to guarantee anthropomorphism and smoothness. The solution proposes the use of artificial fluidic muscles to drive the system for its inherent compliance.

2.1 The Pneumatic Artificial Muscle (PAM)

The PAM is composed of a rubber bladder with an inner fiber cloth, see Szepe. When air is pressurized it contracts axially and expands radially, acting as a simple action cylinder.

The force it delivers is proportional to the inner pressure P, relative contraction h and contraction ratio $\dot{h}$. To determine the pressure needed to maintain a certain force F given the current contraction, Szepe suggests a static model of the PAM, with the force given by

$$F(P,h) = (aP + b)\exp\left(\frac{1}{h+c}\right) + (dh + e)P + f. \quad (1)$$

Where $a, b, c, d, e,$ and f are unknown parameters.

2.2 Degrees of Freedom

The proposed design has only three DOF, two of which are active. To lift a payload the shoulder and elbow flexion/extension are required. Flexion actuation assistance is mandatory, while gravity is responsible for extension.

2.3 Determining the PAM

To address the problem of the relatively low contraction capacity of the PAM, we adopted a cable-driven transmission system which places the PAMs in a rear backpack enclosure, allowing these actuators to have a longer extension (about 600mm each).

The transmission system consists of a steel cable that slides inside steel tubes with an inner Teflon coat to reduce friction, the same as parking brake cables.

3 THE MODIFIED HILL-TYPE MUSCLE MODEL

3.1 Muscle Force Estimation

This straightforward method has a relatively high accuracy on predicting the muscle force using the sEMG signal and its kinematic parameters. It defines a passive parallel element (PE), a passive series element (SE) and an active contractile element (CE), as in Fig. 1.

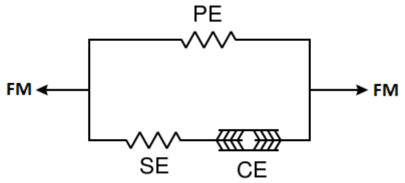

Fig. 1: The 3-element Hill-Type Muscle Model.

The work presented by Rose et al. and Cavallaro et al. proposes a model based on a set of equations for each muscle in order to predict the joint torque. However, the large set of muscles involved on the actuation of a single joint - about 12 for the elbow - presented by their work, demands a proportionally high number of equations and parameters, becoming costly for real-time applications. The present work modifies this method in two different ways: (i) it predicts the torque at the exoskeleton joint instead of the torque at the user articulation; and (ii) it uses only one representative muscle (*Biceps Brachii*) to estimate the torque activity generated by the muscle effort. The first one is sufficient to exclude any type of user sensoring – other than the sEMG's electrodes -, thus no other HMI is needed. The second one, on the other hand, reduces the computational effort for future embedded applications.

3.2 Exoskeleton Joint Torque Prediciton

The torque exerted by the user's arm is given by the muscle force F_M times the muscle moment arm $r(\theta(t))$. This moment arm can be approximately modeled by a third-order polynomial function of the joint angle.
Therefore the join torque is given by

$$T_{Exo} = K(t)\left(F_M r(\theta(t))\right). \quad (2)$$

Where $K(t)$ is the instantaneous nonlinear gain factor.

4 PARAMETER ESTIMATION

In total, each muscle model has 22 floating point parameters to be estimated 18 for the muscle model plus the extra 4 parameters necessary to define the gain $K(t)$. The PAM model, on the other hand, contains six constant values to be calibrated.

4.1 PAM model optimization

The estimation of six constants (*a* to *f*) was performed using *MatLab Genetic Algorithms Toolbox*. The fitness function to be minimized is the Root Mean Square Error (RMSE) between PAM model estimation and the experimental values obtained for the muscle force and contraction at each point.

4.2 Hill Muscle Model Optimization

To find the 22 constants for the physiological muscle, a similar strategy is proposed. However, for this application there is no experimental curve to be used as reference. To address this problem the dynamic equation of the exoskeleton arm is used to calculate the instantaneous torque, which is then compared with the GA estimation. This equation is the same as that of a two-DOF planar serial manipulator which is well known on the literature.

4.3 Model Recalibration

The value of the sEMG will vary depending on anatomical and physiological characteristics. Variations between different sessions are expected because of changeable skin conditions and electrode placements. The solution found to address this problem was to recalibrate the muscle model only evolving the gain factor $K(t)$ parameters for every session. This way, we reduce the problem to find the minimum of a function with only four variables. It was verified that, using the previous parameters as the initial population, only approximately 200 generation are necessary to find the local minimum for the new parameters.

5 CONTROL OF THE EXOSKELETON

The control loop works in the same way as the GA evaluated the chromosomes. Given the 22 parameters of the muscle model and the signal measured, it is possible to estimate the torque the user is applying on the joint. The controller then sends this information to the PAM model which drives the exoskeleton, working as a feedback linearization control. On the other hand, the controller amplifies the torque by a given factor under the PAM limitations. As a result this proposed control algorithm produces the virtual experience in which the user barely feels the weight of the payload.
Fig. 2 shows the neural activation level when lifting a 3.1kg payload with the active and inactive exoskeleton and a torque amplification gain of 1.5. It is possible to verify a significant reduction on the effort done when lifting the load. The bottom graph shows the percentage of increase of the neural activation.

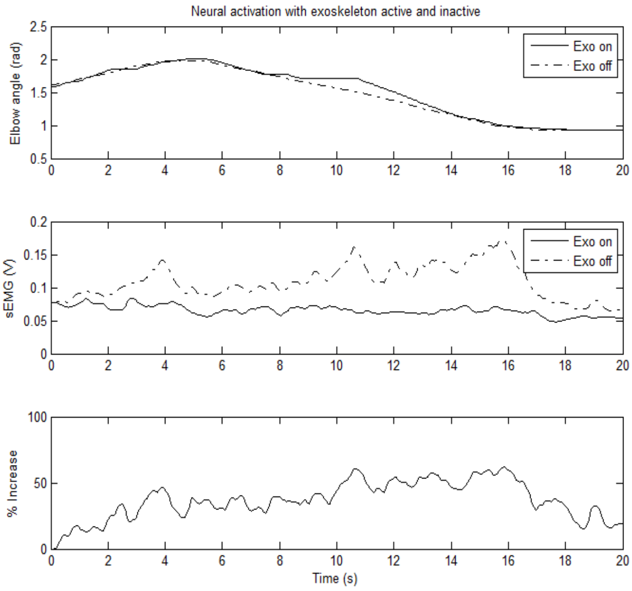

Fig. 2: Neural activation level with and without the exoskeleton assistance.

6 CONCLUSIONS

A real-time sEMG-based controller was developed using a modified Hill-type muscle model to control an exoskeleton actuated by fluidic muscles. The PAM static model parameters were estimated using GA optimization method with satisfactory accuracy. An upper limb exoskeleton was designed from the chosen actuator. For the control algorithm a Hill-type muscle model was used and modified to estimate the torque applied directly over the exoskeleton joint.
The task of lifting a 3.1kg payload was performed and it is shown that a torque gain factor of 1.5 is enough reduce the neural activation level in about 67%. The exoskeleton shares part of the torque necessary to lift the weight and the user supports only a part of the load, avoiding fatigue and increasing endurance.

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