Self-Organization of Spinal Reflexes through Soft Musculoskeletal Interactions

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Abstract—There has been a long-standing debate on the question of how basic reflexive behaviours in mammals come about. Recently, it has been hypothesized that soft musculoskeletal interactions, such as intrinsic passive dynamics, might play a crucial role in the development of motor control at an early developmental stage. Inspired by the developmental processes, this paper explores a learning framework that enables us to systematically investigate the sensorimotor activity induced in soft musculoskeletal systems, as well as to self-organize a set of decentralized controllers analogue to spinal reflexes in mammals. This paper particularly focuses on three reflexes: the Myotatic reflex, the Reciprocal Inhibition reflex and the Reverse Myotatic reflex. We tested our framework in a simulated pair of soft muscles assembled in an agonist-antagonist arrangement. Our results show that the reflex circuitry as well as the reflex behaviour obtained are consistent with those observed in the mammal spinal cord.

I. INTRODUCTION

There has been an increasing interest in bio-inspired soft robots as they can substantially enlarge the range of applications of robotic systems. Underlying the design and control of these robots is the notion that deformable body structures can give robots a degree of adaptability which allows them to interact with uncertain and unstructured task-environments, like most animals do. For example, placing a spring at the ankle can avoid the need for precise foot placement.

There are many different aspects involved in soft robotics, from actuation and sensing to mechanical design [1]; but one of the most significant challenges lies in the control framework of such complex systems. In this context soft robotics must address the issue of control of redundant high dimensional systems (which are properties found in most vertebrates); it must answer the question of how the control architecture can integrate appropriately the information coming from a large number of sensor and motor elements.

In mammals the solution for this problem seems to be a decentralized motor control architecture, where a number of low-level circuits support the development of higher level goal-oriented behaviour [2]. These circuits are often expressed in terms of reflexive behaviours such as: the stretch reflex [2], the withdrawal reflex [3], or the stepping reflex [4].

Many of these reflexes are already present at birth and are therefore developed from innate mechanisms. However, there is evidence that learning in the womb is possible [5]. For example the development of the withdrawal reflex has already been explained based on the method of motor-directed somatosensory imprinting (MSDI) which consists mainly of self-organizing processes [6]. An important implication of these findings lies in the fact that the motor control circuitries might not be pre-defined but self-organized through the developmental processes.

In this paper we describe our recent exploration of a learning framework that autonomously develops a decentralized control architecture through the physical soft interactions of musculoskeletal body structures. We extend the MSDI framework to develop different reflexes in using different sensory modalities. We focus mainly on three reflexes: the Myotatic reflex, the Reciprocal Inhibition reflex and the Reverse Myotatic reflex. We implement a biologically plausible model of a musculoskeletal system comprising an agonist and antagonist pair of muscles, and analyze how a self-organizing process can establish the specific sensorimotor circuitry from spontaneous motor activity (SMA).

The remainder of this paper is organized as follows. The second section provides a brief description of our framework. The third section provides the implementation details of each mechanism in the framework. The fourth describes the general methods. The fifth section describes the experimental results. The sixth section discusses the experimental results. And the final section provides the conclusions and the outlook of our research.

II. THE REFLEX LEARNING FRAMEWORK

Our framework is shown in Fig.1; it consists of five interacting models: a musculoskeletal model (and its environment), a peripheral model, a model of SMA, a learning model based on the correlations between sensor and motor activity, and a model of the reflex sensorimotor mapping. The implementation of each of these models is described in the next section. The framework works as follows. First, SMA produces independent contractions in each muscle. This type of behaviour is generally observed during sleep throughout all stages of mammal development [7] and is often referred to as single muscle twitches (SMTs). Second, these muscle contractions produce forces which are propagated through the musculoskeletal system (as well as through the environment where it is embedded). Third, the changes produced in the
musculoskeletal system are captured by the different body sensors, which (fourth) convert them into sensor activity. Fifth, the correlation between the sensor and motor activity is used to learn the reflex circuitry between each sensor and each motor.

Based on this framework, this paper explores how three reflexes can be self-organized through soft interactions of musculoskeletal systems; these reflexes are: the Myotatic reflex, the Reciprocal Inhibition reflex, Reverse Myotatic reflex. These reflexes are carried out on two sensor modalities: the Ia and Ib fibers. The former estimate changes in muscle length as well as (positional) muscle length [8]; the latter respond to small variations in muscle force [9]. The reflex circuitry of the three reflexes is shown in Fig. 2; these reflexes are described as follows. The Myotatic reflex is carried out through an excitatory connection between the Ia fibers and the α-motoneurons of the homonymous muscle. This reflex counteracts the effects of an undesired stretch imposed by an external load. The Reciprocal Inhibition reflex is carried out through an inhibitory connection between the Ia fibers with the α-motoneurons of the antagonist muscle; the stretch in one muscle inhibits the antagonist, and prevents it from counteracting the movement initiated by the agonist muscle. The Reverse Myotatic reflex is mediated by an inhibitory connection between the Ib fibers and the α-motoneurons of the homonymous muscle. This reflex is supposed to prevent muscles from producing excessive forces [10, p.445], but its exact function is still disputed [11, p.256-7].

III. METHODS: IMPLEMENTATION OF FRAMEWORK MODELS

A. Implementation of Musculoskeletal System and Environment

Our musculoskeletal system consists of a virtual model of a leg actuated by a pair of agonist-antagonist muscles. The simulation of the leg dynamics is carried out in SimMechanics/Simulink. The skeleton model consists of a 2D model of the hip joint, which is modelled as a simple hinge joint. We have called the muscles actuating the leg Biceps and Quadriceps which in the human leg are responsible for hip extension and flexion, respectively.

Each muscle is simulated as a straight line between two rigid bodies (see Fig. 3). The muscle model used in our investigation is based on a 2-element non-linear Hill model [12] [13]. This model captures in a simple way the contraction of muscle fibers as well as the basic muscle dynamics described in [14]. The two elements in the model are shown in Fig. 4; they consist of an active contractile element in parallel with a passive elastic element. The contractile element models the active force generated by the muscle fibers. This element includes a damping mechanism that simulates the force-velocity relation of biological muscles. The passive elastic element models the muscle fiber’s resistance to deflection and prevents the muscle from getting slack.

The force produced by muscle $i$ at its attachment points is given by:

$$F_{Mi} = F_{CH_i} + F_{SH_i}$$

where $F_{CH_i}$ is the force produced by the Hill contractile.

Note that these muscles are more complex than described here; for example they are also responsible for motions at the knee joint.
Fig. 3: Diagram of the leg model implemented. Each muscle is modelled as a straight line (represented with dashes) connecting two attachment points (filled circles). The leg is actuated by two muscles: the Quadriceps $M_Q$, and the Biceps, $M_B$. Each muscle has two sensors: one that estimates the force, $S'_F$, produced at the attachment points, and one that estimates the length, $S'_M$, of the muscle (the subscripts $Q$ and $B$ stand for Quadriceps and Biceps respectively).

Fig. 4: The schematics of the Hill muscle model. The model includes a contractile element (represented by a rectangle) and a spring element (represented by its standard symbol). The spring element of muscle $i$ and $F_{SH_i}$ is the force produced by the passive spring element of muscle $i$. These forces are given by:

\[
F_{CH_i} = \frac{M_i}{1 + C \cdot l'_i^2}
\]

\[
F_{SH_i} = K \cdot \Delta l_i
\]

where, $C$ is a constant damping factor, $K$ is a constant spring factor, $M_i$ is the motor activation of motor $i$, $l'_i$ is the rate of change of the muscle length relative to muscle $i$, $\Delta l_i$ is the passive deformation of muscle $i$.

In biology the force generated by the passive spring element of the muscle, $F_{SH_i}$, is significantly smaller than the force generated by the contractile element, $F_{CH_i}$. To achieve these properties we set $K = 10$ and $C = 0.1$.

B. Implementation of Peripheral System

The muscle model includes two types of sensors: one that measures the length of the muscle, $S'_M$ (i.e. the distance between the two attachment points), and one that measures the force at the attachment points, $S'_F$; when referring to sensors indiscriminately we will simply use the symbol $S$. In our simulation the sensor activity consists of the derived values of these sensor inputs, and the motor activity consists of the motor activations, $M_i$, of all the muscles.

C. Implementation of Correlation-based Learning

The Correlation-based Learning process identifies the reflex circuitry based on the correlation between sensor and motor activity. All possible combinations between sensor and motor elements are considered (see Fig.5). Here, we use the method of motor-directed somatosensory imprinting (MDSI), which has been used to explain the self-organization of the withdrawal reflex [6]. This methods uses the anti-Hebbian rule [15] which is given by the additive inverse of the temporal correlation between the sensor and motor activity. The reflex connectivity, $Q$, is then given by:

\[
Q_{i,j} = -\eta_{ij} \sum_{t=1}^{T} M_{i,t} \cdot S'_{j,t}
\]

\[
\eta_{ij} = \frac{1}{\max(S'_j) \sum_{t=1}^{T} M_{i,t}}
\]

where $\eta_{ij}$ is a normalization factor, $M_{i,t}$ is the motor activity of motor $i$ at timestep $t$, $S'_{j,t}$ is the sensor activity of sensor $j$ at timestep $t$, and $T$ is the number of timesteps taken by the learning process. Excitatory connections are characterized by positive values and inhibitory connections by negative values. The strength of each connection is given by its magnitude.

D. Implementation of Spontaneous Motor Activity

The generation of single muscle twitches is done by sequentially twitching one muscle after the other, generating a total of two SMTs. Each twitch consists of a short rectangular pulse of amplitude $1mu$ (motor units) and duration of $1s$. The time between twitches is set to a value large enough to allow the system to stop oscillating. We start with both muscles relaxed ($M = 0$). In this condition the leg falls straight down due to the effect of gravity.
E. Implementation of Sensorimotor Mapping

Intuitively, the connectivity in \( Q \) describes motor-to-sensor connections, as the directed flow of information is from motors to sensors. However, \( Q \) can also describe directed sensor-to-motor connectivity (see [6]).

In this way the reflex activity is given by the external sensor stimulation measured in each sensor, weighted by the respective connection strength:

\[
M_i = G \cdot \sum_{j=1}^{m} Q_{i,j} \frac{S_j'}{\max(S_j')},
\]

where \( G \) is the reflex gain, and \( m \) is the number of motors in the system.

IV. RESULTS

The sensor data obtained in response to the muscle twitches is shown in Figs. 6 and 7. Fig. 6 shows the changes in length of the two muscles during a SMT carried out by the Quadriceps (Fig. 6a) and by the Biceps (Fig. 6b). As can be observed, the length sensors change their values in response to contractions of the homonymous as well as the antagonist muscles.

Fig 7 shows the changes in muscle force during a SMT carried out by the Quadriceps (Fig 7a) and by the Biceps (Fig 7b). As can be observed during contractions of the homonymous muscle but not during contractions of the antagonist muscle. This is because when a muscle is relaxed the only force in the muscle is due to the passive spring element which has a negligible magnitude when compared with the active force that can be produced by the contractile element of the muscle.

The data collected suggests a connectivity between the force sensors and their homonymous motor, and a connectivity between the length sensors and both their homonymous and antagonist muscles. The adjacency matrix, \( Q \), is shown in Fig. 8. As can be seen, the connectivity obtained is in qualitative terms similar to that observed in relation to the human reflexes (see Fig. 2). First, we obtain excitatory connections between the length sensors and their homonymous muscles in the Myotatic reflex. Second, we obtain inhibitory connections between the length sensors and their antagonist muscles as in the Reciprocal Inhibition reflex. And third, we obtain inhibitory connections between the force sensors and their homonymous muscles as in the Reverse Myotatic reflex. The lower weight obtained from the force sensors is justified by the fact that significant changes in force are only observed when the twitch starts, which decreases the value of the sensorimotor correlation for the entire duration of the muscle twitch.
Fig. 9: Muscle activity generated by the reflex circuitry in reaction to an external load of 5 N imposed on the Quadriceps (see text). From top to bottom 1) the external load, 2) the length change in the Quadriceps, 3) the motor activity triggered in the Quadriceps (m.u. stands for motor units), 4) the motor activity triggered in the Biceps (m.u. stands for motor units), and 5) the force change in the Quadriceps. The figures from 2 to 5 show the sensorimotor activity generated with $G = 1$ (blue) and with $G = 5$ (green).

The reflex activity is shown in Fig. 9 and Fig. 10. Fig. 9 shows the sensor and motor activity induced by an external load of 5 N imposed on the Quadriceps. This load causes the length change of the Quadriceps, $S'_Q$, to increase and the length change in the Biceps, $S'_B$, to decrease (the latter is not shown). This sensor activity leads to an excitation of the Quadriceps, $M_Q$, and an inhibition of the Biceps, $M_B$. These results are consistent with the Myotatic and Reciprocal Inhibition reflexes observed in mammals.

The impact of the Reverse Myotatic reflex is to small too be observed in Fig 9. To investigate the behaviour of this reflex we carried out an additional experiment, where we remove the circuitry relative to the length sensing ($S'_Q = 0$ and $S'_B = 0$). In this experiment we contract the Quadriceps following a ramp function. The expectation is that the increase in force induced by this muscle contraction, would decrease the overall motor activity of the muscle. The results are shown in Fig. 10. The top plot shows the motor activity produced in the muscle. The middle plot shows the increase in force change in three different conditions: $G = 0$ (i.e. no reflex), $G = 10$ and $G = 100$. The bottom plot shows the motor activity due to the reflex circuitry in each of the three conditions. The overall muscle activity is given by the summation of the motor activity in the top and bottom plots (not shown). As can be seen the force change in the Quadriceps, $S'_{QF}$ as well as the motor activity, $M_{QF}$, decrease with the gain of the reflex. This is because the higher the reflex gain the stronger is the inhibitory connection between the force change, $S'_{QF}$, and the motor activity, $M_{QF}$ (see Section V-C for a discussion).

V. DISCUSSION

A. Reflex Connectivity

The main goal of this paper is to show that the circuitry of three basic reflexes, carried out in two different sensor modalities, can be autonomously developed using SMTs and a simple correlation-based learning method. The success of our framework in self-organizing meaningful reflex circuitry provides a double contribution. On the one hand, it provides a clear testable hypothesis for the development of these reflexes in natural systems; one relatively simple experiment would be to imitate the normal functioning of the Ia and Ib at early stages of development and to investigate the subsequent development of the reflex circuitry. On the other hand, our framework provides a mechanism that can automatically endow artificial systems with useful feedback responses. It is noteworthy the fact that we have successfully obtained the three reflexes investigated here in a musculoskeletal robot comprising an agonist-antagonist muscle pair as well as in a larger-scale (simulated) leg model comprising 6 muscles (including bi-articular muscles) [16].
B. Biological Plausibility of the Framework

We believe that at the conceptual level a system close to the framework described here can potentially be present in the human spinal cord to learn low-level reflexes. In [6] it has been shown that the delivery of false tactile stimuli in response to single muscle twitches could reconfigure the withdrawal reflex at the spinal level; such a system could potentially be in place when configuring the motor system before birth. However, we do not want to make any claims yet in this regard since our sensor and muscle models are not yet accurate enough and they are paramount to the learning of the reflex connectivity. From a qualitative analysis analysis we believe that more accurate models will not affect the reflex connectivity obtained but this needs to be proved.

C. Timing, Thresholding, Linearity and Modulation of Reflex Activity

Although the behavioural expression of the three reflexes is not the main goal of this paper, there are some points that are worth considering. First, different reflexes require different activity thresholds. At the moment it is not clear how these thresholds can be developed in our framework.

Second, the sensor models we used are inaccurate; the length and force derivatives are large simplifications of the responses given by \( I_o \) and \( I_b \) fibers. This has an effect on the strength of the connectivity obtained. We are currently investigating the incorporation of more biologically plausible sensor models in our framework.

Third, different reflexes appear at different times depending on the number of interneurons they include. For example, the Reverse Myotatic reflex takes longer to be activated than the Myotatic reflex because it includes one interneuron in its pathway while the Myotatic includes none.

Fourth, it is quite unlikely that the motor signal is a linear combination of the sensor values. Typically a non-linear function such as the sigmoid is used. Although that can easily be incorporated into our system, we see no direct benefit in doing so at such a preliminary stage of our work.

Fifth, and the most important aspect, all the reflex connectivity seems to be modulated by the supra-spinal systems according to the behaviour being executed [17] [18], i.e. the weights of all the connections can be manipulated from hierarchically superior systems [19]. This is important because it reduces the relevance of the exact strength of the connectivity identified, and places the highest emphasis on the nature of the connectivity identified (inhibitory or excitatory) which in biological creatures cannot be modified.

VI. CONCLUSIONS AND FUTURE WORKS

A. Conclusions

In this paper we proposed a framework to develop three low-level reflexes. We have shown that a model of spontaneous activity acting on a musculoskeletal system and a self-organization process acting on the resulting sensorimotor activity are sufficient to develop the appropriate reflex circuitry. In addition we have shown that the behaviours obtained are consistent with those observed in mammals.

B. Future Works

In the long run, we hope to be able to endow high dimensional artificial systems with hundreds of these reflexes in an automated way. To achieve this we will need to incrementally test our framework in more complicated muscle arrangements eventually involving synergistic as well as multi-articular interactions. We also plan to develop a more biologically inspired framework by using biologically plausible spiking models of sensor and motor activity.

VII. ACKNOWLEDGMENTS

The research leading to these results has received funding from the NCCR Robotics, as well as from the European Community’s Seventh Framework Programme FP7/2007-2013 - Challenge 2 - Cognitive Systems, Interaction, Robotics - under grant agreement no. 231864 – ECCER-OBOT and no.270212 – eSMCs.

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