35th Annual International Conference of the IEEE EMBS
Osaka, Japan, 3 - 7 July, 2013

Modelling muscle spindle dynamics for a proprioceptive prosthesis

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***Abstract*— Muscle spindles are found throughout our skeletal muscle tissue and continuously provide us with a sense of our limbs' position and motion (proprioception). This paper advances a model for generating artificial muscle spindle signals for a prosthetic limb, with the aim of one day providing amputees with a sense of feeling in their artificial limb. By utilising the Opensim biomechanical modelling package the relationship between a joint's angle and the length of surrounding muscles is estimated for a prosthetic limb. This is then applied to the established Mileusnic model to determine the associated muscle spindle firing pattern. This complete system model is then reduced to allow for a computationally efficient hardware implementation. This reduction is achieved with minimal impact on accuracy by selecting key mono-articular muscles and fitting equations to relate joint angle to muscle length. Parameter values fitting the Mileusnic model to human spindles are then proposed and validated against previously published human neural recordings. Finally, a model for fusimotor signals is also proposed based on data previously recorded from reduced animal experiments.**

I. INTRODUCTION

Nerve receptors in our muscles, tendons, joints and skin provide us with a continuous stream of information about our body's position, motion and how hard our muscles are working. This proprioceptive sense is key to enabling us to move in a smooth coordinated manner, learn new motor skills and move our limbs without having to visually monitor them.

As it is not one of the main '5 senses', proprioception is not something we are generally aware of, instead it is a sense that only becomes conspicuous in its absence. Prosthetic limb users (e.g. amputees or those with a congenital limb deficiency) lack proprioceptive or tactile sensation in their prosthesis and, with the advent of highly dexterous limbs [1] and improved feed-forward control techniques [2], this lack of feedback is likely to become an increasingly important control factor.

This paper develops a model towards creating a proprioceptive neural prosthesis - i.e. a neural implant which would mimic the function of the human proprioceptive system in the same way a cochlear implant mimics the function of the human auditory system. A proprioceptive prosthesis is envisaged to broadly consist of 3 parts: (1) sensors fitted to a prosthetic limb to track its position, motion and the forces exerted on it; (2) processing that translates the sensor data into neural signal patterns that mimic those produced by proprioceptive receptors found in the human body; and (3) an implanted neural stimulator [3] to "transmit" these artificial neural patterns into the user's peripheral nervous system following the natural proprioceptive pathways to the brain. Fig. 1 shows an outline of the proposed proprioceptive system and identifies the part this paper will focus on within the context of the entire system. Specifically, this is to translate angular sensor data into the firing patterns of the human muscle spindle.

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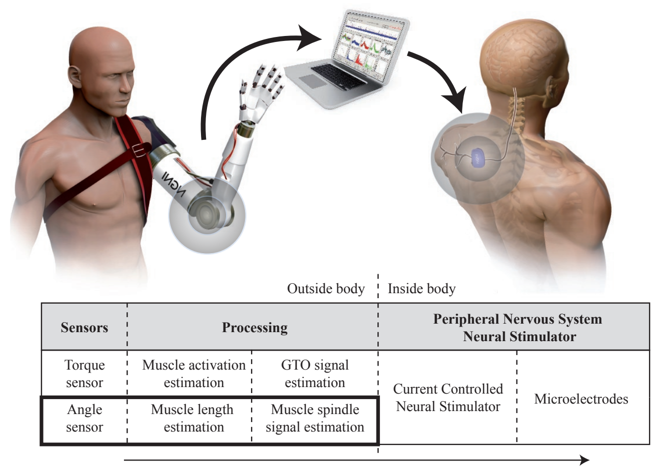

Fig. 1. A proprioceptive prosthesis. Sensors track a prosthetic limb's motion, processing translates this into human proprioceptive signals and a neural stimulator transmits these signals into the user's nervous system. This paper focuses on the cross-hatched portions of the full system

This paper is from here on organised as follows: Section II discusses proprioception in the human body; Section III discusses the methods and details the models used in this paper; Section IV presents the results and Section V summarises the findings, outlines areas of future work and provides a brief discussion on implementation.

II. PROPRIOCEPTION IN THE HUMAN BODY

There are a variety of nerve receptors that contribute to our proprioceptive sense [4], of these receptors, two stand out as prime candidates for a proprioceptive prosthesis: muscle spindles - which are primarily position and motion sensitive - and Golgi Tendon Organs (GTOs) - which are primarily force sensitive - (see Fig. 2). These two have been selected because not only are they major contributors to our proprioceptive sense and encode all the key proprioceptive information, but also because they are the best understood of the proprioceptive receptors. This paper focuses on the position and motion aspects of proprioception and as such will model the muscle spindle.

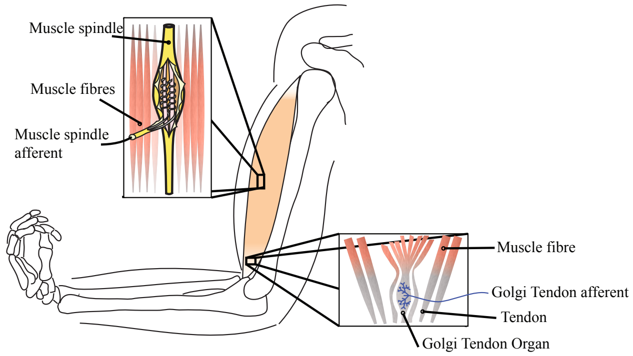

Fig. 2. Muscle spindles lie in parallel with muscle fibres. Golgi Tendon Organs lie in series with muscle fibres at the muscle-tendon boundary

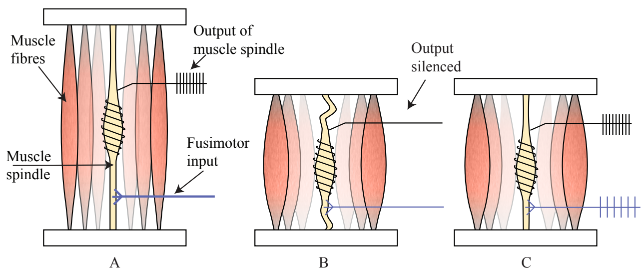

Fig. 3. Simplified muscle spindle operation. **A**: The muscle is stretched, the spindle is under tension and fires action potentials on its output. **B**: The muscle contracts, the spindle goes slack and stops firing. **C**: Fusimotor input contracts the spindle poles, increasing tension in the sensory part of the spindle and causing it to resume firing.

A. The muscle spindle

Muscle spindles are found throughout mammalian skeletal muscle. As muscles stretch and contract the spindles within them stretch or slacken and this modulates the rate at which they fire action potentials (see Fig. 3 A & B).

Each spindle is generally innervated by two afferent axon types - primary (type Ia) axons and secondary (type II) axons - which carry sensory information to the brain; and a number of efferent axons - including gamma static (γ_s) and gamma dynamic (γ_d) motoneurons - carrying fusimotor signals from the brain. These fusimotor signals act to contract the spindle poles and thereby modulate its sensitivity to muscle length (see Fig. 3 B & C).

III. METHODS

In our modelling a Turtlebot robotic arm (with Dynamixel AX12 DC servo motors) was used to represent the prosthetic arm, and all processing was conducted in MATLAB.

At a top level our modelling approach (see Fig. 4) is similar to that used in the Virtual Arm model [5] and can be broken down into two main stages: (1) biomechanical models to estimate muscle length changes as the elbow joint is flexed or extended, and (2) mathematical models of the muscle spindle to convert these muscle lengths into estimates of spindle firing patterns.

Since our target application is a practical, portable, real-time system to stimulate human neurons, we are investigating several key challenges that have not previously been addressed. These include: reducing the computational complexity of the biomechanical modelling; dealing with noisy sensor data; as well as adjusting the model parameters to match human (rather than cat) neural firing rates.

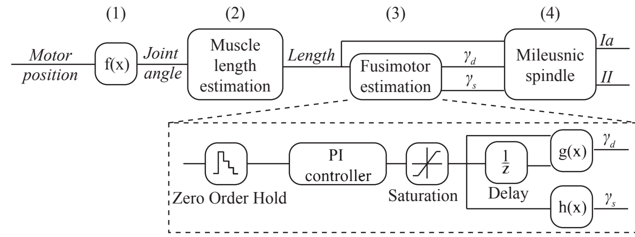

Fig. 4. The full system model. Functions f(x), g(x) and h(x) are described in Section III.

In order to obtain a high accuracy model of the spindle firing this paper also proposes and incorporates models for the γ_s and γ_d fusimotor signals.

A. Joint Angle model (1)

The only input to our system is the angular sensor readings from the servo motor. These position readings are in integer format and are updated at approximately 500 Hz and with 0.3° resolution. The readings are noisy (which is then greatly magnified by the spindle model) and as such the first processing step applies a median filter (window size 7) to mitigate this. The angular position data is then linearly transformed (function f(x) in Fig. 1) to obtain the joint angle.

B. Muscle length model (2)

There are numerous muscles that span the elbow, however, it will be impractical for a proprioceptive prosthesis to provide feedback on all these muscles because of limitations in (1) sensor data, (2) the number of implants possible and (3) computational resource.

For a 1 degree of freedom joint (like the elbow), requirements in these 3 areas can be minimised, by selecting just a pair of mono-articular, antagonistic muscles which are innervated by the same nerve. Our final prosthesis will also provide feedback on muscle force and as such we imposed a further requirement: that the muscles should be powerful flexors and extensors of the elbow. This led to the selection of the brachialis (flexor) and the tricep medial head (extensor), which, although innervated by different nerves, meet all the other criteria.

The open source Opensim biomechanical modelling software [6] has been used to establish the relationship between muscle fibre lengths and elbow flexion (see Fig. 5). MATLAB line fitting tools were then used, to obtain an empirically derived model to describe the relationship between their muscle length and the elbow joint angle.

C. Fusimotor model (3)

Taylor et Al [7] described fusimotor signals as carrying a 'temporal template' of the expected movement of a muscle. It has been proposed that an important role of the fusimotor

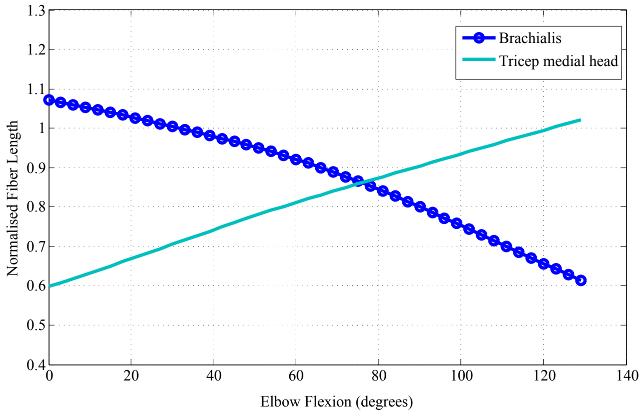

Fig. 5. Opensim predicted changes in normalised muscle fibre length.

signals is to help identify when the body's movement does not match the motion intended by the brain (e.g. because of an obstruction or unexpected resistance). For a first approximation in describing this behaviour, a downsampled Proportional Integral controller is included in the fusimotor model. This aims to predict future motion on the basis of current motion and as a result creates an element of overshoot in the event of sudden changes of motion.

γ_d signals were described in [8] as appearing 'interrupted' (by the onset of muscle contraction) and function g(x) models this using a time delay and a magnitude comparison (see Fig. 4) to implement the following function:

$$\gamma_d = \begin{cases} 0\,\text{pps} & \text{if muscle is contracting} \\ 100\,\text{pps} & \text{if muscle is static or lengthening} \end{cases}$$

where pps stands for pulses per second. In contrast to this binary output, function h(x) smoothly modulates the γ_s signal between 20 pps and 150 pps (as observed in [7]) according to the equation:

$$\gamma_s = 20 + 130 \times \frac{L_{max} - L}{L_{max} - L_{min}}$$

where L_{max} and L_{min} are the maximum and minimum normalised lengths of the muscle.

D. Muscle spindle model (4)

The muscle spindle firing patterns are estimated using the model proposed by Mileusnic et Al [9]. This model has been parametrised and validated on muscle spindle recordings from cats published in the literature. Although there are not believed to be major differences in the way human and cat muscle spindles work, it has been noted that human muscle spindle recordings show much lower neural firing rates.

The parameter 'G' in the Mileusnic model is the key term scaling the spindle firing rates and was estimated based on changes in spindle firing rates of up to 150 pps, that occur due to fusimotor stimulation in a cat muscle. There is limited data about the fusimotor sensitivity of human muscle spindle, but the maximum observed change in spindle output due to fusimotor signals has been observed to be < 30 pps [10] and as such we scaled the Mileusnic et Al [9] derived values of 'G' by a factor of $\frac{1}{5}$.

IV. RESULTS

A. Human parameter validation

In order to validate our 'G' parameter for human spindles, the output of our model was compared with human spindle recordings from the extensor carpi radialis brevis (ECRB) from a paper by Kakuda and Nagaoka in 1998 [11]. Software was used to estimate the firing rates from the paper and OpenSim modelled values of normalised ECRB fibre length were used. The results are shown in Fig. 6 and indicate that the proposed scaling factor aligns well with the range of observed spindle firing rates.

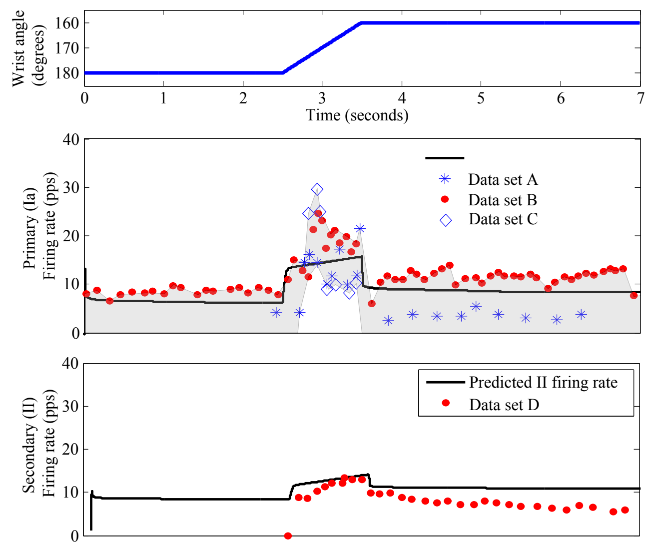

Fig. 6. Top: wrist angle and timing. Middle: modelled vs. recorded human primary (Ia) muscle spindle output (from Fig. 2 A, B, C of [11]) the shaded area indicates the range of recorded data. Bottom: modelled and recorded human secondary (II) muscle spindle output from Fig. 2D of [11].

B. Fusimotor signals and obstructed motion

Prochazka et Al [12] investigated the role of fusimotor signals in detecting unexpected motion by introducing obstructions to the movement of a cat's hindlimb. Fig. 7 compares the results obtained in that experiment with our modelled system response. Data points were taken from the paper and assumptions were made about the experimental cat's muscle length to best fit the firing rate. As this experiment is based on cat spindle firing patterns, the 'G' parameter values used were those given in the Mileusnic paper [9].

C. System data flow

Fig. 8 shows the outputs of each subsequent stage of our system model (for both the brachialis and triceps medial head muscles) during a repeated, rapid (∼130° per second) flexion and extension of the elbow.

V. DISCUSSION

A proprioceptive neural implant could be of great benefit to prosthetic limb users and the work presented here is a first stage in identifying and addressing the signal processing challenges that remain. Our results indicate that existing

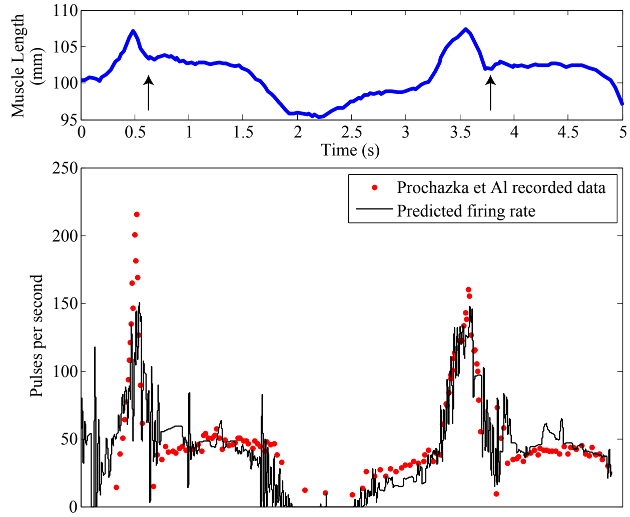

Fig. 7. Experimentally observed and modelled secondary (II) cat muscle spindle firing patterns during hindlimb motion (top) with unexpected obstructions (indicated by arrows). Experimental results are taken from (Fig. 4A in [12])

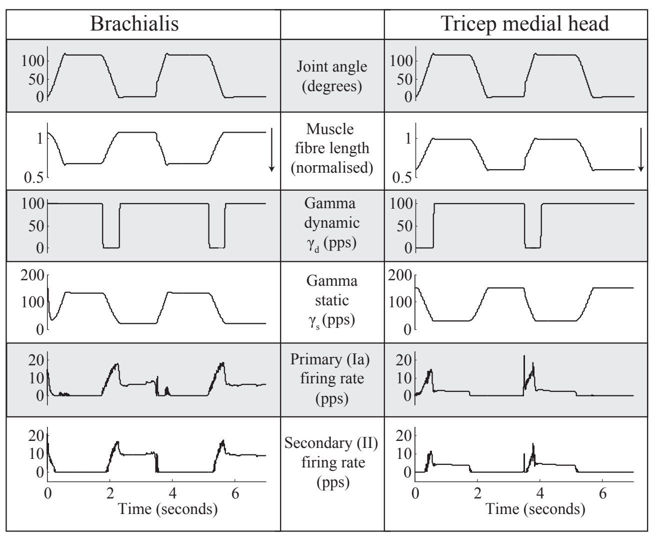

Fig. 8. Top to bottom: output of each stage of our model (see Fig. 4) for two arm muscles - brachialis on left and tricep medial head on right. Arrows indicate direction of muscle contraction. Bottom 2 graphs are the final output of the model

muscle spindle models should be suitable for this application, requiring only minor parameter adjustment. Fusimotor signals are still relatively poorly understood, but have been repeatedly identified as playing a role in learning new skills, and we believe the implementation and inclusion of models of fusimotor dynamics is also an important step for achieving the benefits offered by a proprioceptive prosthesis.

A. *Future work*

Areas which will be addressed in future include:

- Integration of muscle force information, which can have a substantial impact on the spindle output [11], [13].
- Refinement of the Mileusnic model, in terms of parameters for human muscle spindles as well as to improve its stability (in the presence of noise).
- A redesign of the fusimotor model to take input from motor control signals (rather than motor output) to better differentiate between intended, passive and obstructed movements.

B. *Implementation*

In order to achieve a practical, portable, real time implementation the model is being ported to a C-language implementation using a Euler approach to solve the differential equations in the Mileusnic spindle model. Initial estimates of the algorithm indicate that it requires between 2 and 4 MIPS per muscle modelled. We therefore believe that the 2 muscle system model proposed here could be run on a low power 32 bit microcontroller (such as the EFM32 zero) while consuming under 10mW of power.

ACKNOWLEDGEMENT

This work was supported by the UK EPSRC (DTA award and Grant ref: EP/I000569/1) and thanks go to Professor Peter Ellaway for advice and guidance.

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