A neuromuscular model featuring co-activation for use in driver simulation

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A neuromuscular model featuring co-activation for use in driver simulation

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This paper covers the development of a neuromuscular model for use in driver simulation, focusing on the inclusion of a representation of co-activation. Co-activation is thought to function as a combination of feed-forward control (based on future predictions of the task being undertaken) and feedback control (to reject disturbances). A linear model of the neuromuscular system, muscles, limbs and vehicle was set up. Linear quadratic regulator control was used to minimise path-following error and a representation of the muscle’s metabolic energy consumption. It is shown that the model can be used to generate feed-forward control signals whilst simultaneously minimising the feedback error signal (necessary in real muscles for effective disturbance rejection), but that there is a trade-off between minimisation of the feedback error signal and energy consumption. The controller is able to adapt to the increases in reflex delay and gain to maintain control using the feed-forward mechanism. Large reflex gain and delay increases are shown to destabilise the system, consistent with suggestions that, in humans, the reflex gain is small to avoid instability. The model is shown to be capable of rejecting external disturbances via the stretch reflex.

Keywords: driver modelling; neuromuscular system; co-activation; stretch reflex dynamics; metabolic energy

1. Introduction

The production of realistic driver models for use in closed-loop vehicle simulations may provide designers with a powerful tool that can be used to improve the performance of steering systems (in particular, steer-by-wire). Additionally, there is potential for significant cost and time savings to be made during the development process. The use of realistic driver models can reduce the need for testing, and may help objective measures of vehicle performance to be developed. This paper is directed at developing neuromuscular models appropriate for the driver vehicle system, and extends the earlier work of Pick and Cole [1,2].

The first section of the paper reviews relevant literature, covering pertinent physiology, muscle dynamics, the stretch reflex and co-activation (whereby two simultaneous motoneurone signals are used to operate each muscle as a servo system). Relevant attempts at modelling the neuromuscular system are reviewed. The physiological observations presented form a basis
for the proposed model structure, as outlined in Section 3, whereupon the performance of the model is investigated.

2. Neurophysiology review

2.1. Skeletal muscle

Skeletal muscle is excitable, contractile tissue, and generally connects two adjacent bones to one another via tendons, which form the interface between muscle and bone. Motion can be initiated about the joint between the two bones at will, via α-motoneurone activation signals, with the resultant movement also dependent on applied torque disturbance, shown schematically in Figure 1. Muscles are generally arranged in (opposing) agonist and antagonist pairs, and consist of a number of primary force-generating muscle fibres called ‘extrafusal’ fibres.

The state of each muscle fibre depends on the current flowing into it through the motoneurones. Significant increase in the current causes a twitch: a shortening and corresponding force generation, with magnitudes and rates of the shortening and force generation related to the load against which the muscle must work. Repeated stimulation leads to a number of twitches converging into what appears a smooth contraction [3]. Co-ordination and integration of adjacent motor units is controlled by an extensive neural network of sensory and motor structures [3]. The metabolic energy consumed by a muscle depends on the force being generated and the rate of shortening or lengthening. Control strategies that take into account metabolic energy cost have been shown to produce realistic biomechanic behavioural predictions [4]. The mechanical behaviour of muscle depends on many factors, such as muscle length, fatigue, shortening velocity, neural stimulation and muscle type [5,6].

A large number of muscle models, varying enormously in complexity, have been developed. These models fit broadly into two classes: phenomenological (where the behaviour of the muscle is fitted to a model) and physiological (where the mechanisms by which the muscle functions are modelled). Generally speaking, physiological models can provide good agreement with real muscle behaviour for both mechanical and energy consumption predictions, but are often extremely complicated. Phenomenological models are generally mathematically more tractable, but do not generate good energy consumption predictions. Second order systems have been used to model limbs and attached agonist/antagonist muscle groups, with variable spring stiffness used to represent varying degrees of co-contraction [7].

2.2. Muscle spindles and reflex action

In parallel to the extrafusal fibres are the muscle spindles (or intrafusal fibres) composed of special contractile fibres [3,8,9], and activated by γ-motoneurone signals [8–10]. Like the
extrafusal fibres, they are capable of generating tension when activated, but are few in number and small in size, and generate relatively insignificant forces that cannot, in general, produce movement [9]. The outcome of $\gamma$-initiated contraction is complicated by reflex loops, with the function of the spindles being 2-fold: to provide position and velocity feedback, and hence maintain muscle length through reflex action, and secondly to (indirectly) initiate muscle contraction [3]. Other sensory structures, such as Golgi tendon organs, give additional force and displacement feedback information.

The effect of $\gamma$-activation with no prior $\alpha$-activation is to cause the muscle spindles to contract. However, the muscle spindles are too weak to cause movement of the limbs and instead go into tension, which causes activation of $\alpha$-motoneurones. This in turn causes contraction of the extrafusal fibres [3], but is subject to a delay due to finite motoneurone signal transmission velocities. This response is known as the stretch reflex, and it contributes to maintaining muscle length in the presence of external (unexpected) disturbances. Reflex loops help maintain muscle stiffness and linearise what is, when reflexes are removed, pronouncedly non-linear behaviour [5,11–13].

Carpenter likens $\gamma$-motoneurone only initiated contraction to a simple servo system [14], with $\gamma$-motoneurone signals telling the system how short the muscle should be, and the muscle spindle acting as the comparator and hence generating an error signal used in the feedback loop (Figure 2). Theoretically, however, the gain of the stretch reflex is too small to entertain the possibility of driving real movements solely through $\gamma$-activation [9,13,14].

### 2.3. Co-activation

Until recently, it was thought that muscle contraction was controlled exclusively through $\gamma$-motoneurone activation. It is now widely acknowledged that $\gamma$-initiated contraction is practically unfeasible, and advances in microneurographic techniques have demonstrated that independent $\alpha$- and $\gamma$-motoneurone activation occurs instead [9,10,15]. This is known as co-activation. An investigation into the degree to which $\alpha$- and $\gamma$-motoneurones are synchronously co-activated in cats [10] concluded that the co-activation of $\alpha$- and $\gamma$-motoneurones during the flexion reflex occurs through largely independent motoneurone signals, a view supported by other research [16,17].

Despite independent central nervous routes, there has been a large degree of co-activation observed in both lower mammals and humans whilst performing a diverse range of motor tasks [18–22], with certain findings suggesting that co-activation does not always occur in fixed ratio, but rather it adjusts to suit the task’s conditions [9]. Whilst the techniques used in these investigations could not be used on a live human subject due to their invasive nature, they give a good indication of typical motoneurone firing patterns and feedback signals.

There are compelling hypotheses to suggest why this occurs. If a single, isolated, muscle is considered, contraction may be initiated via $\alpha$-motoneurone activation. Contraction of only
the extrafusal fibres would unload the muscle spindles, causing them to go slack, and rendering the stretch reflex – which helps reject unexpected muscle stretch – useless.

Concomitant α- and γ-activation causes the muscle spindle to shorten at the same rate as the extrafusal fibres, and can be thought of as having several functions. First, co-activation adjusts the degree of muscle tension in step with willed movement [14] (ensuring that the muscle does not become slack). Secondly, co-activation ensures that the spindles are not unloaded during volitional movement and hence helps them to maintain their sensitivity [9].

Consideration of an agonist/antagonist muscle pair provides further justification for co-activation: if an agonist is stretched – through voluntary contraction of an antagonist – the stretch reflex (which counters muscle stretch with contraction) would be energetically counterproductive, as it would oppose the voluntary movement. In order to avoid energy wastage through this reflex response, during voluntary movement there is a simultaneous γ-motoneurone discharge, which causes muscle spindle contraction in synchrony with extrafusal muscle contraction, avoiding movement suppression via the reflex loop. Intended movement of the muscle can continue unhindered [3,9,14].

It can be concluded that, in the control of movements there are two separate signals or commands that are sent to the spinal cord by the brain. One is a position command, which indicates, via the γ-fibres, what the desired length of a muscle is to be; the other is a force command, an estimate of the load that is to be encountered [14]. Both past experience and the use of senses such as vision, force receptors in the skin, Golgi tendon organs and balance, all play a role in providing sensory feedback whilst performing a motor task. Carpenter hypothesised that, ‘if the estimate of the force is an accurate one, the system behaves, in effect, [as a feed-forward system], and there is no error for the spindles to correct [14]’. In such a system, the stretch reflex helps correct for unexpected variations in the load (imposed noise) and knowledge of the results of one’s actions can contribute to improved future performance as parametric feedback.

These findings indicate that a model including co-activation might be an appropriate approach to modelling the neuromuscular system. There have been, however, very few attempts at developing such a model. Oguztoreli proposed an agonist/antagonist muscle pair, coupled to a single load, which included both α- and γ-motoneurone input signals, but there was little quantitative analysis [23]. Lan proposed a similar structure, using a linear Hill-type muscle model, but did not investigate simultaneous co-activation [24].

Pick proposed a model structure that included rudimentary co-activation (Figure 3) [1]. The γ-motoneurone signal, which is essentially a steering wheel angle demand, was fed forwards through an internal model to generate α-motoneurone signals, which represent the expected torque. A similar scheme was used by Burdet to investigate stability of limbs during motor tasks [25], whilst experimental results show that the brain generates independent α- and γ-motoneurone signals – possibly based on internal models of the open-loop system being controlled – no models have been found in which a predictive or optimal controller

![Figure 3](image-url)
generates both $\alpha$- and $\gamma$-motoneurone signals. Many of the hypotheses put forward to account for co-activation might be tested by constructing such a model. In particular, it might be instructive to determine whether the model proposed here operates by reducing the muscle spindle error signal to zero when knowledge of the plant being controlled is perfect, and what the impact of imperfect knowledge of the plant on the controller performance is.

3. Proposed model structure

The model proposed in this paper is an evolution of Pick and Cole’s linear model [1,2]. The new model, shown in Figure 4, includes a representation of co-activation, with $\alpha$- and $\gamma$-motoneurone signals ($\alpha_s$ and $\gamma_s$, respectively) provided by a linear quadratic regulator (LQR) controller, which operates as a path-following controller. A representation of the muscles’ metabolic energy consumption is included as a cost within the LQR controller. The model was implemented in Matlab™ and Simulink™.

Muscle activation initiated by $\alpha$- and $\gamma$-motoneurone signals occurs via the mechanisms discussed in Section 2. Contraction initiated by $\gamma$-motoneurone signals passes through the reflex dynamics block, which includes a delay, in agreement with physiological observations. Stretch reflex dynamics, $H(s)$, were modelled using a phase compensator in addition to time delay, $T_r$ (default value = 0.04 s), as per [2]. Parameter $k_r$ (default value = 1) was used to adjust the gain of the stretch reflex block:

$$H(s) = \frac{30k_r(s + 5)e^{-sT_r}}{s + 30}.$$ (1)

Steering column and limb dynamics are represented by a second order system, $G_s(s)$, with transfer functions fitted to experimentally obtained data [2]. Pick used two sets of parameters, fitted to low and high co-contraction levels, representative of ‘relaxed’ and ‘tensed’ conditions. Driver limb spring stiffness, inertia and damping are represented by parameters $K_{dr}$, $J_{dr}$ and $B_{dr}$, respectively (default values $K_{dr} = 3.7$ Nm rad$^{-1}$, $J_{dr} = 0.098$ kg m$^2$ and $B_{dr} = 0.55$ Nm s rad$^{-1}$, corresponding to the ‘relaxed’ case).

$$G_s(s) = \frac{1}{J_{dr}s^2 + B_{dr}s + K_{dr}}.$$ (2)

The vehicle was modelled using a linear, two-degree-of-freedom, ‘bicycle’ model, as detailed in [2]. Steering wheel torque feedback, $T_{fb}$, can be generated as a function of steering
wheel angle, $\theta_{sw}$, steering wheel angular velocity, $\dot{\theta}_{sw}$, and front tyre slip angle, $\alpha_f$ [2]. Gain $k_{fb}$ (default value = 1) was used to adjust the magnitude of the steering torque feedback.

$$T_{fb} = k_{fb}(2.29\theta_{sw} + 1.15\dot{\theta}_{sw} - 120\alpha_f).$$  \hfill (3)

Front tyre slip angle $\alpha_f$ can be calculated, for small angles, through consideration of the vehicle’s longitudinal and lateral velocities ($U$ and $v$, respectively), the distance from the centre of mass to front tyre contact patch, $a_f$, the yaw rate, $\omega$, and the ratio of steering wheel to road wheel angles, $\eta_{rsw}$ (default values: $U = 30 \text{ m s}^{-1}$, $a_f = 0.92 \text{ m}$, $\eta_{rsw} = 16$).

$$\alpha_f = \frac{v + a_f\omega}{U} - \frac{\theta_{sw}}{\eta_{rsw}}. \hfill (4)$$

Vehicle states ($v$, $\omega$, $y$ and $\psi$), neuromuscular states ($a_0$–$a_4$ including delay states), and activation state ($e_1$), at a given timestep $k$, were combined with path preview states ($y_0$–$y_{Np}$) into state vector $w_k$:

$$w_k = [v \omega y \psi a_0 \cdots a_4 e_1 y_0 y_1 \cdots y_{Np}]^T. \hfill (5)$$

The $\alpha$- and $\gamma$-motoneurone inputs were combined into vector $\theta_k = [\alpha_s \gamma_s]^T$. Inputs to the open-loop system are the lateral path displacement $\hat{y}_k$ and $\theta_k$:

$$w_{k+1} = Fw_k + E\hat{y}_k + G\theta_k. \hfill (6)$$

A quadratic cost function, shown in Equation (7), was used to produce the LQR controller gain, using the Matlab™ LQR function. The cost function can be minimised based on weighting matrices $R$ and $R_1$ over $N_u$ future time steps, ‘the control horizon’.

$$J = \lim_{N_u \to \infty} \sum_{j=0}^{N_u} (w_{k+j}^T R_1 w_{k+j} + \theta_{k+j}^T R \theta_{k+j}), \hfill (7)$$

where:

$$R_1 = H^T Q_1 H$$

$$Q_1 = \begin{bmatrix} q_1 & 0 & 0 \\ 0 & q_2 & 0 \\ 0 & 0 & q_3 \end{bmatrix}; \quad R = \begin{bmatrix} q_4 & 0 \\ 0 & r_{\gamma} \end{bmatrix}$$

$$H = \begin{bmatrix} 0 & 0 & 1 & 0 & 0 & \ldots & 0 & 0 & -1 & 0 & \ldots & 0 \\ 0 & 0 & 0 & 1 & 0 & \ldots & 0 & 0 & 1/UT & -1/UT & \ldots & 0 \\ 0 & 0 & 0 & 0 & 0 & \ldots & 0 & 1 & 0 & 0 & \ldots & 0 \end{bmatrix}. \hfill (8)$$

The cost function puts weightings $q_1$ and $q_2$ on path lateral error and yaw error, respectively, and cost weightings $q_3$ and $q_4$ on attempting to minimise an approximation of the rate of energy consumption, referred to here as the ‘activation cost function’, $q_3(e_1)^2 + q_4(\alpha_s)^2$ (a weighted sum of the signals entering the $\alpha$-motoneurone pool). A (trivial) weighting, $r_{\gamma}$, is placed on $\gamma$-motoneurone signals. Weighting $r_{\gamma}$ is ideally zero (since energy is accounted for with $q_3$ and $q_4$), however, in practice this gives numerical problems and unstable solutions to the matrix Riccati equation (used to generate the LQR controller gain). Instead, small non-zero values must be used instead ($r_{\gamma} = 10^{-6}$, which gives adequate stability). Simulations were carried out in discrete time, with sample time 0.02 s, and a preview horizon of 250 points (5 s).
4. Parameter study

The portion of the state feedback gain vector corresponding to both preview horizon and state gains can be studied to determine the effect, if any, of varying different aspects of the model. In addition, the time-domain path following operation of the model can be used to evaluate performance, using a double lane change manoeuvre [2]. The magnitude of the $\alpha$- and $\gamma$-motoneurone signals, $\alpha_s$ and $\gamma_s$, and the spindle error signal, $\varepsilon_s$ (Figure 4) were inspected to give insight into the model’s operation.

The effect of varying several factors was investigated: the provision, and gain, of the stretch reflex; the magnitude of the torque feedback; the significance of the stretch reflex delay and the robustness of the controller and closed-loop performance of the system when faced with inaccurate knowledge of the vehicle dynamics. Noteworthy findings are summarised here.

For reference, the performance of the system using default parameter values (omitting torque feedback and with the stretch reflex feedback path disconnected) was investigated. Path-following performance, motoneurone and muscle spindle error signals, and an evaluation of the activation cost function, $q_3(e_1)^2 + q_4(\alpha_s)^2$, are shown. The default parameters used were:

\[
q_1 = q_2 = 1, \quad q_3 = 0.5, \quad q_4 = 0.025, \quad r_\gamma = 10^{-10}, \quad k_r = 1, \quad k_{\text{fb}} = 0.
\]

It can be seen that path-following performance is good, with the controller tracking the lateral path and yaw angle well (Figure 5). Without the stretch reflex feedback loop connected, the $\gamma$-motoneurone signal, $\gamma_s$, is equal to the muscle spindle error signal, $\varepsilon_s$; both are small compared to the $\alpha$-motoneurone signal, $\alpha_s$, commensurate with a factor of 20 in the relative cost weighting on $e_1$ compared to $\alpha_s$, and the gain of the reflex dynamics block (Figure 6). This discrepancy in the size of $\alpha_s$ and $\gamma_s$ is reflected in the preview gains, with gains for the $\alpha$-channel consequently much larger.

With the stretch reflex loop connected, the muscle spindle error signal, $\varepsilon_s$, remains unchanged (since cost function weightings are unvaried). However, because of the steer angle feedback, maintaining $\varepsilon_s$ at its former level requires significantly larger $\gamma$-motoneurone signals, $\gamma_s$ (Figure 7). Subsequent increases in the stretch reflex gain, $k_r$, were found to reduce the $\gamma$-channel preview gain, causing a small reduction in the size of the $\gamma$-motoneurone signals and, consequently, the muscle spindle error signal (Figure 8). The $\alpha$-channel preview gains were unaffected by the change in $k_r$, as was path-following performance and the activation cost function, which indicates that the controller modifies the $\gamma$-motoneurone signal (with no cost penalty) as reflex dynamics change to maintain consistent $e_1$ at the $\alpha$-motoneurone pool.

Inspection of the system poles showed that increases in $k_r$ had a destabilising effect on the

![Figure 5. Showing path-following performance during a double lane change manoeuvre for a model using default values, with the stretch reflex feedback loop disconnected. (Key: path: fine dashed; path-following performance: bold solid.)](image-url)
Figure 6. Showing how (a) $\alpha$- and $\gamma$-motoneurone signals ($\alpha_s$ and $\gamma_s$), and (b) muscle spindle error signal ($\varepsilon_s$), and an evaluation of the activation cost function, vary for a model using default values (with the stretch reflex feedback loop disconnected) during a double lane change manoeuvre. (Key: signal: bold solid.)
Figure 7. Showing how (a) α- and γ-motoneurone signals ($\alpha_s$ and $\gamma_s$), and (b) muscle spindle error signal ($\varepsilon_s$), and an evaluation of the activation cost function are affected by the inclusion of the stretch reflex block, with varied stretch reflex gain $k_r$. All other parameters set to default values. (Key: $k_r = 0.5$: bold dashed; 1.0: bold solid; 2.0: bold dotted.)
closed-loop system, with gains of \( k_r > 7 \) producing unstable poles. This lends credibility to suggestions that stretch reflex gains are usually kept low to avoid delay-induced instability [25].

It has been hypothesised that the muscle spindle error signal, \( \varepsilon_s \), would be zero if (a) the controller has perfect knowledge of the system and if (b) no noise is present, indicative of suppression of the stretch reflex during voluntary movement. This was not observed in practice, due to the limitations of the linear controller. Whilst cost weightings \( q_3 \) and \( q_4 \) can be adjusted to give small muscle spindle error signal relative to the size of \( \alpha_s \) and \( \gamma_s \) (as is the case for the default weightings chosen), for a linear controller, \( \varepsilon_s \) will always be finite for finite \( q_3 \) and \( q_4 \).

It is possible that these limitations stem from the use of linear muscle and energetics models to describe what are, in reality, highly non-linear systems.

To investigate the possibility of reducing the muscle spindle error, the cost weighting \( q_3 \) was changed, keeping other parameters constant. Increasing \( q_3 \) was found to lead to significant reduction in the size of the muscle spindle error signal, \( \varepsilon_s \), as expected, at the expense of increases in the size of \( \alpha_s \) and the activation cost function (Figure 9).

For a control cost based purely on minimising the activation cost function, it might be expected that \( q_3 \) and \( q_4 \) should be equal, as there is no basis for assuming that \( \alpha \)-motoneurone initiated contraction is any more (energetically) costly than \( \gamma \)-motoneurone initiated contraction. However, in practice, setting \( q_3 \) and \( q_4 \) equal results in the LQR controller generating \( \alpha_s \) and \( e_1 \) signals approximately equal in magnitude. Placing higher cost on minimising spindle error (via \( q_3 \)) can be thought of as a trade-off between increased metabolic energy consumption and the requirement to maintain muscle spindle sensitivity by minimising \( \varepsilon_s \) (which ensures that spindles are not unloaded, and operate at low contractile forces and thus at maximum sensitivity (Section 2.3)).
Figure 9. Showing how (a) $\alpha$- and $\gamma$-motoneurone signals ($\alpha_s$ and $\gamma_s$), and (b) muscle spindle error signal ($e_s$), and an evaluation of the activation cost function are affected by variations in the $\gamma$-motoneurone signal activation cost $q_3$, for a model with the stretch reflex feedback loop connected, and all other parameters set to default values. (Key: $q_3 = 0.05$: bold dashed; $0.5$: bold solid; $5$: bold dotted.)
The significance of the stretch reflex delay, $T_r$, was investigated, keeping other parameters constant. Path following performance, and $\alpha$ and $e_1$ signals were unchanged due to unvaried cost weightings. To maintain $e_1$ despite more delay existing in the stretch reflex block, the $\gamma$-channel path preview gains are observed to shift further along the preview horizon (Figure 10).

Simulations were carried out to investigate how the controller’s performance is affected by incorrect knowledge of the plant being controlled. LQR controller gains were calculated, assuming $T_{fb} = 1$, whereupon the controller was used to control plants in which $T_{fb}$ was varied. Path following performance was optimal for the controller with correct knowledge.
Figure 12. Showing how (a) $\alpha$- and $\gamma$-motoneurone signals ($\alpha_s$ and $\gamma_s$), (b) muscle spindle error signal ($e_s$) and an evaluation of the activation cost function are affected when the LQR controller’s knowledge of the plant’s torque feedback gain, $k_{fb}$, is incorrect (controller always assumes $k_{fb} = 1$), for model including stretch reflex and torque feedback. (Key: plant’s $k_{fb} = 1$ (correct knowledge): bold solid; 2: bold dash-dot; 3: bold dashed.)
of the system, with increases in the plant $T_{fb}$ resulting in more overshoot during the double lane change manoeuvre (Figure 11). Increasing $T_{fb}$ results in larger steering torque input requirements to achieve identical path following behaviour, and consequently $\alpha$-motoneurone signal can be seen to increase. The steer angle input demand remains constant (since the cost weightings, and path, are unchanged) and it can be seen that the $\gamma_s$ signals remained approximately constant, leading to an increase in the muscle spindle error signal size as $T_{fb}$ is increased (Figure 12). This increase in $\varepsilon_s$ represents disturbances acting on the system (in this case, due to incorrect knowledge of the plant) being rejected via the stretch reflex, consistent with hypotheses (Section 2.3).

5. Conclusions

This paper focuses on the development of neuromuscular models for use in driver simulation. Whilst muscles have been extensively modelled, the control mechanisms by which muscles are activated have received relatively little attention.

Two principal methods exist for initiating muscle contraction, via $\alpha$- and $\gamma$-motoneurone signals. Contraction can be initiated directly via $\alpha$-motoneurones, or indirectly via $\gamma$-motoneurones (subject to delays present in the reflex system). Independent co-activation of muscle fibres via $\alpha$- and $\gamma$-motoneurone has been observed in humans whilst performing a diverse range of motor tasks. The $\gamma$-motoneurone signal can be thought of as a muscle length demand – which operates as a feedback servo system – whilst the $\alpha$-motoneurone signal is an estimate of the load the muscle will operate against (functioning as a feed-forward control system).

Co-activation is thought to perform several functions: (a) adjusting the degree of muscle tension in step with voluntary movement, (b) ensuring that muscle spindles are not unloaded during voluntary movement and (c) suppressing the reflex loop during voluntary movement.

There have been very few attempts at developing models featuring co-activation, and no models have been proposed that include both $\alpha$- and $\gamma$-motoneurone signals generated by an optimal or predictive controller. The model proposed in this paper includes a representation of co-activation, with $\alpha$- and $\gamma$-motoneurone signals generated by an LQR controller that places a cost weighting on activation cost (an approximation of the muscle’s rate of metabolic energy consumption) and path-following performance.

The cost function developed in this paper is able to minimise muscle spindle error when the system’s dynamics are known. A fundamental trade-off between minimising spindle error and minimising the activation cost – using the linear cost-function proposed here – is demonstrated.

The controller is shown to be able to adapt to changes in reflex dynamics, including increases in the reflex gain and delay, to maintain control via the feed-forward mechanism. It is shown that increases in reflex gains and/or delays have a destabilising effect on the feedback control mechanism, in agreement with suggestions that reflex gains are low to avoid delay-induced instability.

It is demonstrated that the stretch reflex is effective at rejecting noise disturbances applied to the plant (in this case, modelled by giving the controller incorrect knowledge of the plant being controlled), consistent with hypotheses within the neurophysiology literature.

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