DYNAMICS OF TORQUE RESPONSES TO VISUAL STIMULI

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INTRODUCTION

Joint stiffness defines the dynamic relationship between the position of a joint and the torque acting about it. Joint stiffness consists of two components:

1. Intrinsic stiffness, which arises due to the viscoelastic properties of the muscle, joint, and connective tissue as well as the inertia of the limb.
2. Reflex stiffness, which arises due to active muscle contractions in response to afferent feedback from muscle stretch receptors [1].

This two component view of joint stiffness is applicable under many contexts, however, it may be inappropriate during certain tasks. When people are instructed to maintain a joint or a limb at a certain position, they create torques voluntarily which are correlated to the position of joint. Hence during these tasks we must consider a voluntary contribution to the total joint stiffness. This voluntary contribution can arise from proprioceptive feedback as well as visual feedback.

Joint stiffness is especially important in the ankle because not only is involved in voluntary movements, it also plays a large role in the maintenance of upright stance. In upright stance there are as many as five mechanisms—intrinsic, reflex, visual, proprioceptive and vestibular—helping maintain the body upright. A number of studies have modeled joint stiffness in upright stance. They modeled it as simply a proportional gain, a derivative gain and a delay [2, 3]. However, they did not try to model each component separately, nor did they have any dynamics in the model beyond a simple delay. Other studies have measured the contributions of the different mechanism to upright stance [4, 5]. It has been shown that velocity is most accurate visual information [5], however, neither study tried to quantitatively measure each component's contribution; rather they measured the resulting change in body sway.

In the following paper we will describe the procedure and the results of our attempts to quantitatively characterize the visual contributions to joint stiffness. To accomplish this we removed all other components of joint stiffness. By performing the experiments with the subject lying down we removed any vestibular feedback. Furthermore we fixed the foot at a constant position which removed all intrinsic, reflex and proprioceptive contributions. We provided subjects with only visual feedback and measured the torque in response to the changes in the visual feedback. We then estimated an impulse response function (IRF) between the visual feedback and the torque. We found that the torque subjects produced was correlated to the velocity of the visual stimulus through a delay and a low-pass filter.

METHODS

Subjects

Two males and one female between the ages of 22-41 participated in the study. None of the subjects had any history of neuromuscular disorders. All subjects gave informed consent to participate in the study, which was approved by the McGill University Research Ethics Board.

Apparatus

A schematic of the apparatus is shown in Figure 1. Subjects lay supine with their left foot attached to an electrohydraulic actuator through a fiberglass boot. The actuator is set to a very high stiffness, preventing any movement of the foot. The left leg was immobilized with a leather strap and was supported with sand bags under the knee. The toe section of the boot was cut out preventing any contributions from the toe muscles. Ankle position, torque, visual feedback and EMG activity from the lateral gastrocnemius, medial gastrocnemius, soleus and tibialis anterior were sampled at 1 kHz and stored.

Procedure

Subjects were provided visual feedback, on an overhead LCD monitor, of a simulated signal which was computed using an inverted pendulum model shown in Figure 2. This model was designed to simulate human stance, where the command signal is the desired body position and the error signal is the difference between the desired and actual body

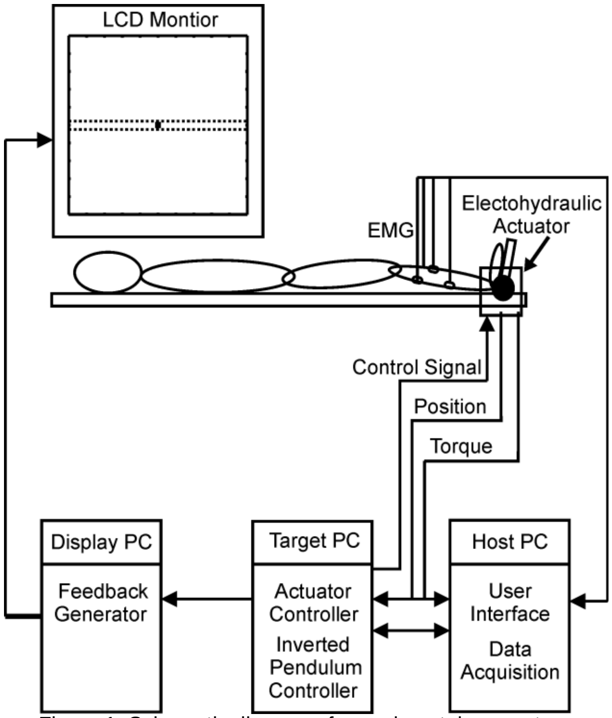

Figure 1. Schematic diagram of experimental apparatus.

position. The visual system will detect this error, and cause the ankle muscles to create a torque which will drive the body back to its desired position. The body was simulated as an inertial load (A_1/s^2) and mass being pulled down by gravity (A_2sin).

To remove contributions from intrinsic, reflex or other proprioceptive mechanism, the ankle was held at a fixed position by the actuator. The gain A_1 differed from trial to trial, while the gain A_2 was set to zero to make the task as easy as possible for the subjects to complete.

Each subject participated in one session lasting between 1 and 2 hours. Subjects were shown the error signal on the overhead monitor and were instructed to minimize the error signal. Two types of trials were run: random perturbation and ramp trials. In the random perturbation trials, the command signal was a normally distributed random variable with a sampling interval of 5 s. In the ramp trials, the command signal consisted of ramps of constant amplitudes but different velocities. The ramps alternated direction and repeated every 5 seconds.

<u>Data Analysis</u>

For the random perturbation trials, the data were filtered with an 8th order type I Chebyshev lowpass filter with a cutoff of 8 Hz and then decimated to 20 Hz. IRFs were calculated between the command signal, error signal, error velocity, torque, and EMGs. Step

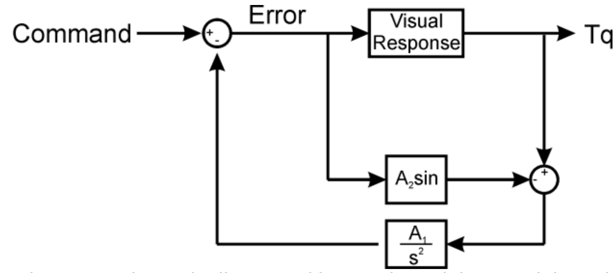

Figure 2. Schematic diagram of inverted pendulum model used to generate visual feedback. Subjects are shown the error signal on an overhead monitor. The error is calculated as the difference between the command signal and the 2nd integral of the torque (Tq) multiplied by gain A_1.

responses were estimated by integrating the estimated IRFs. For the ramp trials, the error signal, velocity, torque and EMGs were filtered with an 8th order Bessel filter with a cutoff of 10 Hz, aligned on the start of the ramp and then ensemble averaged.

IRFs between the velocity and the torque were fit to a 2nd order low-pass filter with a delay. The filter was defined in the Laplace domain (*s*) as

$$VTQ_{IRF}(s) = \frac{G\omega^2}{s^2 + 2\omega z s + \omega^2} e^{-s\tau} \qquad (1)$$

where *G* is the gain, *z* is the damping ratio, ω is the natural frequency and τ is the delay. Fitting was done using Matlab's non-linear least-squares parameter estimate which uses the Gauss-Newton algorithm with Levenberg-Marquardt modifications for global convergence.

The quality of the estimated IRFs as well as the fits, were measured by finding the percentage of variance accounted for (%VAF)

$$\%VAF = 1 - \frac{var(x - \hat{x})}{var(x)} \qquad (2)$$

For the %VAF of IRFs x is the output and $\hat{x}$ is the predicted output estimated by convolving the input with the estimated IRF. For the fits, x is the non-parametric IRF, while $\hat{x}$ is the parametric fit.

RESULTS

Figure 3 shows the error signal, the error velocity and the torque in response to a step change in the command signal. The step change in the command signal caused a step change in the error signal and a spike in the velocity. Following a delay of a few hundred milliseconds, the subject produced a torque which brought the error back to near zero. The most intriguing aspect of the figure is that there was a large negative torque occurring at approximately 1.5 s following the step despite the fact that error signal was

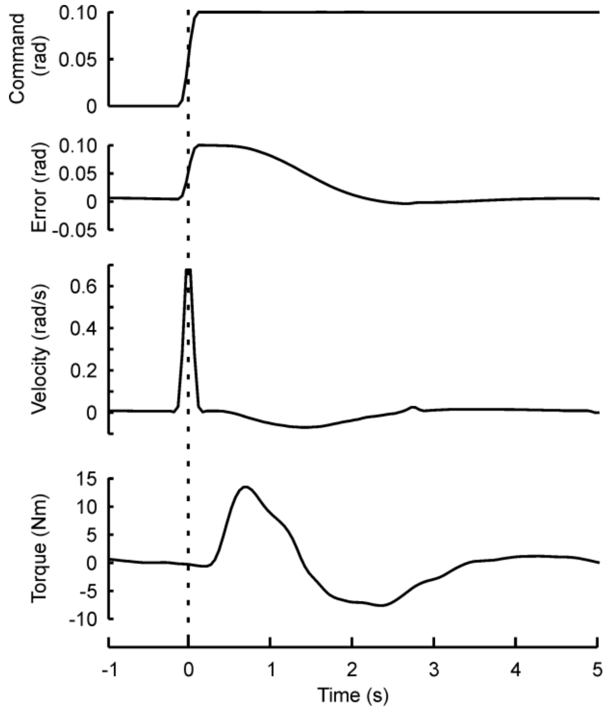

Figure 3. Error signal, error velocity and torque in response to a step change in the command signal. A step change in the command signal caused a step change in the error signal and a spike in the error velocity. Following a delay of a few hundred milliseconds, there was an increase in the torque which brought the error signal back to zero.

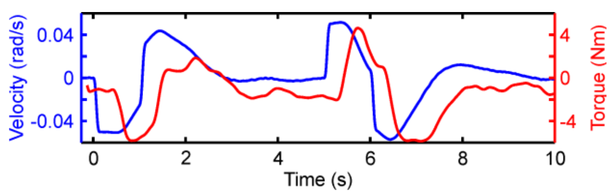

Figure 4. Velocity (blue) and torque (red) recorded during ramp trials. It is apparent that the velocity and torque, recorded from Subject B during the ramp trials, are correlated through a delay and a low-pass filter.

never negative. Therefore this system must be more complex than just a gain and a delay.

Velocity-Torque Correlation

Figure 4 shows both the error velocity and the torque recorded during a ramp trial. It is immediately apparent from this figure that there was a strong correlation between the error velocity and the torque. We can see that the torque seems be a low-pass filtered version of the error velocity with a delay of a few hundred milliseconds.

Using the data collected during the random perturbation trials we estimated an IRF between the error velocity and the torque (Fig. 5). While this IRF accounted for the majority of the torque (%VAF = 60.4%), its coherence squared at frequencies below

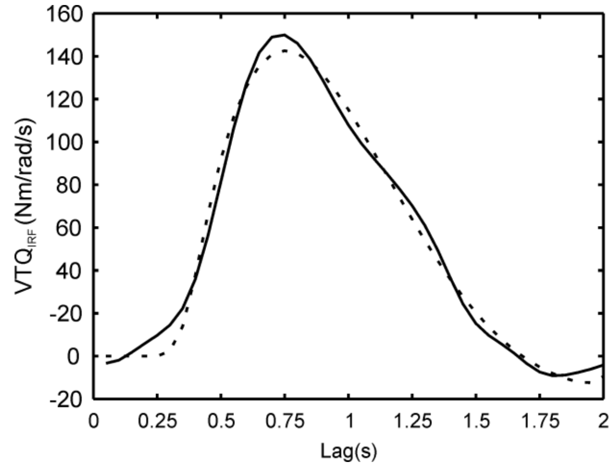

Figure 5. IRF (solid line) found between error velocity and torque with parametric fit (dotted line). The IRF found between the error velocity and torque, in Subject A, was a good fit (%VAF = 98.3 %) to a 2nd order low pass system with parameters G = 101 Nm/rad/s, z = .64, ω = 3.0 rad/s and τ = 0.3 s.

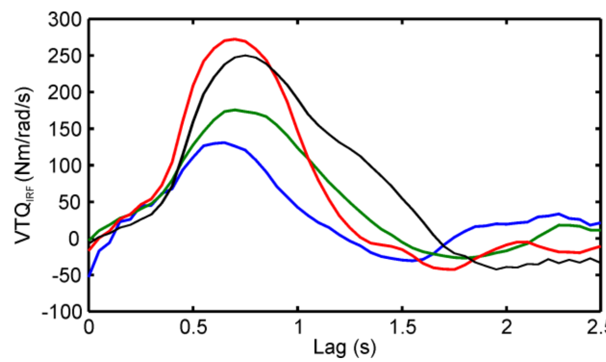

Figure 6. Response to the visual stimulus changed with changing simulated loads. Subject C increased the gain of his response to the visual stimulus when the simulated load was increased. The simulated load was increased by decreasing the feedback gain (Fig. 2 A_1). Blue: A_1 = .02; Green: A_1 = .01; Red: A_1 = .0067; Black: A_1 = .005.

0.5 Hz is especially good (≈ 0.8). In addition to the estimated non-parametric IRF (solid line), Figure 5 shows a parametric fit (dotted line). We can see that the non-parametric IRF is a good fit (%VAF = 98.3%) to a 2^{nd} order low-pass system with the following parameters G = 101 Nm/rad/s, z = .64, ω = 3.0 rad/s and τ = 0.3 s.

Response Changed with Different Loads

For one subject, we measured the torque response to the random perturbations under different simulated loads. The change in loads was simulated by changing the gain A_1 in Figure 2. Figure 6 shows the estimated IRFs between the error velocity and the torque, while Table 1 shows the estimated parameters of the parametric fit. For all loads, the value of the delay was equal to 0.3 s. From Table 1 we can see that as the gain A_1 decreased, which simulated an increased load, the gain of the torque response increased. Though there was a general decrease in frequency with increasing load, the trend was not perfect. The amount of torque each IRF accounted for also increased with increasing load, but this is expected as the gain of the system increased.

Table 1. Parameters estimated from the parametric fits for Subject C when the simulated load changed. A decreased value of the feedback gain (Fig. 2 A_1) resulted in an increase in the simulated load.

Feedback Gain (A_1)	**Gain $\left(\frac{Nm}{rad/s}\right)$**	**Damping**	**Frequency (rad/s)**	**VAF of Fit (%)**	**Tq VAF (%)**
0.02	56	0.42	4.1	91.3	40.2
0.01	107	0.54	3.2	96.7	54.5
0.0067	144	0.51	3.5	97.5	55.1
0.005	167	0.50	2.6	98.8	63.2

DISCUSSION

Maintaining upright stance is essential for the daily lives of all people of all ages. There are as many as five mechanisms which help maintain upright stance: intrinsic, reflex, visual, proprioceptive and vestibular. Studies have shown that removing any single mechanism increases body sway [4, 5]. While intrinsic and reflex mechanisms have been thoroughly quantified [1, 6-8], the other mechanisms have not. A number of studies have measured the effect of visual information on sway, however, none have attempted to quantify the relationship between the visual information and the torque produced at the ankle.

Using system identification techniques, we found a model which can predict the torque at the ankle in response to visual feedback. We found that there was strong a correlation between the velocity of the error signal and the torque, hence we estimated an IRF between these two signals. Though the %VAF of this model is average (60.4 %), the coherence is quite high at low frequencies. Using a non-linear least squares algorithm, we found that the estimated IRF fits a 2^{nd} order low-pass system with a delay of 0.3 s extremely well (%VAF = 98.3 %). Finally, we found that when increasing the simulated load, the subject increased the gain of the response in a nearly linear manner.

The first important finding of this study is that subjects can control an unstable load using only visual information. This is not too surprising, as people are able to control many objects using almost only visual information, such as playing video games and driving a car. What is surprising is that the response was correlated to the velocity of the visual feedback and not the amplitude of the visual feedback. While subjects were able to successfully perform this task, it may be too premature to say that humans can maintain balance only using visual feedback, as the model we have used in this study removed the gravitational effect of standing and used simulated loads which are smaller than the load of the body.

A second important observation was the frequency of the response. Based on the parameter estimates from the parametric fit, the natural frequency of the response was approximate 3 rad/s or about 0.5 Hz. This estimate agrees with the coherence squared, which was high for frequencies below 0.5 Hz. This frequency is much lower than that of the ankle muscles (≈ 2-5 Hz [6]), therefore it must be the dynamics of the response to the visual stimulus. Thus, the visual response might be able to help maintain quiet stance and adjust to low frequency perturbations, but will be unable to contribute to balance when faced with high frequency perturbations. Nonetheless, the frequency response of the visual response is complimentary to the reflex response which has a high coherence between 5 and 10 Hz.

Finally, the third interesting finding is that Subject C changed the gain of his response to the visual feedback. This demonstrated that subject tuned the parameters of his internal controller in order to perform the task in a more efficient manner. Furthermore, the subject was given less than one minute to adjust to the new load, hence the subject was able to perform this tuning very quickly.

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