Combining a 3D Reflex Based Neuromuscular Model with a State Estimator Based on Central Pattern Generators

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Abstract A neuromuscular model (NMC) presented by H. Geyer and extended by S. Song shows very interesting similarities with real human locomotion. The model uses a combination of reflex loops to generate stable locomotion and is able to cope with external disturbances and adapt to different conditions. However, to our knowledge no works exist on the capability of the model to handle sensory noise. In this paper, we present a method for designing Central Pattern Generators (CPG) as feedback predictors, which can be used to handle large amount of sensory noise. We show that the whole system (NMC + CPG) is able to cope with a very large amount of noise, much larger than what the original system (NMC) could handle.

1 Introduction

Previous research [1] has shown that neural connections along the spinal cord contribute substantially to generating gait, and animal studies have provided evidence of mammals performing locomotion-like movements without supraspinal and peripheral input signals [2]. This led to the current idea that these feedforward signals are generated by Central Pattern Generators (CPG), biological neural structures which can create rhythmic patterned outputs without rhythmic inputs [3]. Feedforward systems can govern many aspects of locomotion. Timing, limb kinematics and ground reaction forces can be predicted with high degree of fidelity [4]. Animal experiment have indeed confirmed the existence of CPG networks in many vertebrates [5].

Without feedback, however, animals or humans would be unable to cope with unexpected disturbances during gait. Limbs do not generally behave exactly as

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expected, due to environmental conditions or sensory noise, for example. However, feedback, provided by sensors and reflexes in the body, can compensate for environment instability, as shown by one model of human gait purely based on feedback presented by Geyer [6, 7], later referred to as neuromuscular model control (NMC).

It has already been theoretically shown by Kuo [4] that a pure feedback system, without additional knowledge about the environment, will be very sensitive to sensory noise. A proposed way to deal with this sensitivity is to combine the feedback system with a feedforward component. The author demonstrated that for a simple model of rhythmic movement, the combination of a CPG as state observer system with a feedback system is more stable against perturbations and sensory noise [4]. This type of CPG has already been implemented in the NMC to provide an easy way to adjust for speed changes by Dzeladini et al. [8]. Here, we propose an extension of the 3D NMC model [7] by implementing a CPG state estimator. Our hypothesis is that this combination will make the system more robust against sensory noise.

2 Materials and Methods

The NMC model was not altered or re-optimized from the one made by Song et al. [7], except for adding noise and a CPG state estimator on each of the sensors.

CPG Learning: To learn the average shape of the sensory signals, we implemented a shape learner for each leg and for each phase of gait (e.g. left leg in swing). This learner started at the initial gait event (toe-off for swing) and recorded each time step ($t(i)$) of the (variable time-step) stimulation signal of each sensors provided by the NMC. After the final event the data was linearly interpolated to N points with discrete time steps. The frequency of the event (defined as one divided by the total time of event) was saved. This was done for M steps, and all interpolated signals were then averaged.

CPG Output: The oscillator used the learned shape and frequency of the current phase of gait to output an estimated rate of change (*roc*) for every sensor. The NMC model used variable timesteps, which required an estimation of the current position in the learned CPG shape coupled to the current timestep of the model, using the frequency of the recorded shape and the current timestamp t(i). The CPG estimators are re-initiated for every event of each leg (e.g. heel strike of left leg initiates CPG module of stance of left leg). The *roc* at t(i) was calculated using the finite difference method (8th order).

Combining CPG and NMC: CPG estimated *roc* of the sensor signal was implemented as a state estimator of NMC. Using the previous estimate, estimated *roc* and the noisy NMC measurement, an optimal estimation was made with a Kalman filter [9], using the Joseph Form as covariance update equation. The variance of the sensory noise was assumed to be known by the system. The process noise covariance was hand tuned for the combined model so that the final combined sensory signal output was close to the un-noisy clean sensory data. For optimization purposes, the

Kalman filter was discretized using zero-order hold at set times, instead of the variable time used by the rest of the model.

Signal Dependant Noise: To produce physiological noise signals, the model used signal-dependent noise [10]. The power of the band-limited white noise was scaled by the amplitude of the sensor signal, defined as current signal level minus the minimum signal level of that sensor. The sensory noise was applied on the force, length and velocity sensors of the NMC, and each type of sensor separately was assumed to have the same amount of signal-dependent noise.

Noise Tuning: We found the maximum noise level the NMC could handle alone by increasing the noise for each type of sensor separately until the NMC system became unstable (i.e. the model was unable to walk for 100 s at 1.2 m/s). When one sensor type was tuned, the variance of other noise sources was set to zero. The found levels are referred to as the maximum noise level. After this, the CPG state estimator was turned on, and the process was repeated.

3 Results and Discussion

We found that the combined signal was less noisy than the pure NMC signal, even among the different sensors types (Fig. 1). The absolute mean difference between NMC and the clean signal was also higher than that of the absolute mean difference between the combined and the clean signal.

The maximum amount of noise variance the system can stand without CPG was set at 100 %. For the force sensors, the system could stand up to 2300 % noise variance compared to no CPG, and an infinite amount of noise variance on the velocity sensors (i.e. completely trusting CPG). For the length sensors, the maximum amount of noise variance was 390 %, indicating length sensors were influenced more by an offset compared to the other sensors (Fig. 1).

We observed a higher sensitivity for error on the length sensors compared to the other sensors. This effect was caused by the length sensor on the hamstring. In the NMC model length feedback of the hamstring is used to stop the knee from overextension at the end of the swing phase, activating multiple muscles to provide flexion torque. An offset in this value can cause flexion torques, not only countering overextension but also causing actual flexion of the knee. This greatly decreased the stability of the model, and removing only the noise on the length sensor of the hamstring enabled the combined model to withstand higher noise levels (>3000 %).

Velocity sensors, on the other hand, can stand an infinite amount of noise. In this case the sensory output is completely accomplished by CPG, indicating that small offsets from the true value do not cause instability to the model. This does not mean these signals do not need feedback, but that they are highly repetitive and predictable during steady state gait.

In our model, the variance of the sensory noise is known, which is ideal but unrealistic in some situations. If the estimated variance is wrong, the Kalman filter would be less optimal. The effects of this on the model need to be tested in the future.

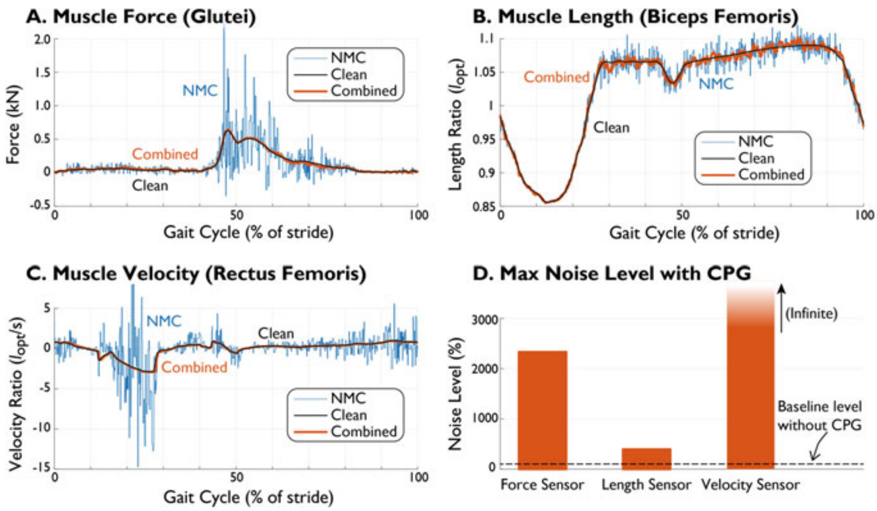

Fig. 1 Example of NMC sensor signals: **A** muscle force feedback, **B** muscle length feedback and (**C**) muscle velocity feedback without noise (*black*), with noise (*blue*), and the combined results with NMC + CPG with noise (*orange*). **D** shows the maximum level of noise that the NMC + CPG with noise can handle in percentage of the noise handled by the NMC model without CPG

4 Conclusion

These preliminary results demonstrate that implementation of a CPG state observer in combination with NMC makes the model more robust against sensor noise and yields a better estimate of the real sensory value, without needing new optimization runs. In further research, we want to investigate the robustness of the CPG and NMC combination against perturbations from the outside world (e.g. uneven terrain), the effect of full optimization of the model including the CPG state estimator, and implement a CPG state observer against noise in other models of periodic motion or in robotic devices. For example, the proposed combined model could accommodate for sensory error or missing sensory information on robotic devices with relatively rhythmic output, predicting the most probable sensory output.

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