RESEARCH NOTE

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Simple artificial neural network models can generate basic muscle activity patterns for human locomotion at different speeds

Abstract A neural network model has been developed to represent the shaping function of a central pattern generator (CPG) for human locomotion. The model was based on cadence and electromyographic data obtained from a single human subject who walked on a treadmill. The only input to the model was the fundamental timing of the gait cycle (stride rate) in the form of sine and cosine waveforms whose period was equal to the stride duration. These simple signals were then shaped into the respective muscle activation patterns of eight muscles of the lower limb and trunk. A network with a relatively small number of hidden units trained with back-propagation was able to produce an excellent representation of both the amplitude and timing characteristics of the EMGs over a range of walking speeds. The results are further discussed with respect to the dependence of some muscles upon sensory feedback and other inputs not explicitly presented to the model.

Key words Central pattern generator · Locomotion · Electromyography · Neural network

Introduction

Neurophysiological research shows that the spinal cord has an intrinsic capacity for generating complex locomotor patterns in response to simple tonic inputs (Delcomyn 1980; Grillner 1981; Grillner 1985). In the decerebrate cat, for example, it has been demonstrated that changes in the level of tonic input can modulate the speed, and even the form, of locomotion (Shik et al. 1966). Similar findings have been demonstrated in spinal animals where application of pharmacological agents can elicit and modify locomotor patterns (see review by Rossignol and

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Dubuc 1994). Evidence for this spinal circuitry, called the central pattern generator (CPG), in humans is beginning to emerge from studies on spinal cord injured patients (Calancie et al. 1994; Bussel et al. 1988, 1989).

While exact decoding of the circuitry has been possible in a primitive vertebrate species (Grillner et al. 1991), indirect methods such as mathematical models have been used to understand the organizational principles of this circuitry in mammals (see Patla et al. 1985). One such model uses a labile synthesized relaxation oscillator (Bardakjian et al. 1983) to suggest that the CPG can be thought of as two modules (Patla et al. 1985). One module, representing the time-keeping function, generates the simple sinusoidal signals at the periodicity of the step cycle; while the second module, representing information storage function, shapes the simple sinusoidal signal into complex waveforms through time-independent non-linear modulators. Experimental work has also proposed the separation of pattern-generating networks into timing and shaping functions based on how sensory stimuli interact with either the cycle timing or the inter-cycle features (Koshland and Smith 1989; Lennard and Hermanson 1985). Additionally, in vivo studies on neonatal rat spinal cord suggest that the locomotor pattern-generating networks are distributed within the spinal cord, with separate elements of these networks being responsible for different aspects of the locomotor pattern, such as oscillatory drive (Cowley and Schmidt 1997). Recently researchers have used artificial neural networks (ANNs) to model the time-keeping function of the CPG (Prentice et al. 1995; Srinivasan et al. 1992). These models, however, only capture one of the organizational structures of a CPG. This paper presents a shaping network designed to mould a simple timing signal into the complex muscle activation patterns. Our goal was to develop a simple network whose weightings and properties are time independent and that can produce muscle activation patterns across a range of walking speeds. ANN models have been proposed for a number of different sensorimotor transformations (see reviews by Fetz 1993; Lasner and Ekeberg 1994) including those where complex mus-

cle activity is generated from simple control signals. Similar approaches have been developed for engineering applications to generate stimulation patterns for paralyzed individuals (Abbas and Chizeck 1995; Abbas and Triolo 1997); however, few studies have used these models to examine the control of human locomotion especially from a theoretical perspective. Preliminary results of our shaping network have appeared in abstract form (Prentice and Patla 1994).

Materials and methods

Experimental protocol

A single subject was required to walk on a motor-driven treadmill at a given speed. Footswitches placed under the ball and heel of each foot served to mark the temporal events of each stride. The speed of the treadmill was adjusted to match the subject's natural walking speed (1.2 m/s). Five trials each consisting of 12 strides were collected for five different walking speeds: 1.2, 1.4, 1.6, 1.8 and 2.0 m/s. The speeds were chosen to include both increases and decreases to the subject's normal speed. This experimental protocol received ethics approval from the Office of Human Research and Animal Care at the University of Waterloo.

Muscle activation patterns and foot switch data were obtained using a custom-built fibre optic telemetry system and stored on computer (f_s=256 Hz). Rectified EMG signals were recorded from the medial gastrocnemius, soleus, tibialis anterior, peroneus longus, biceps femoris, rectus femoris, gluteus medius and erector spinae at the electrode sites suggested by Winter (1991). The rectified EMG signals were low pass filtered (Butterworth, f_c=3 Hz) to generate linear envelope signals and the record length was reduced by sampling every fourth point. The EMG amplitude of each muscle was scaled to the working range of the network (0→1.0) by normalizing to the peak amplitude of the respective muscle observed over all speed conditions. The average stride periods were used to determine the fundamental frequency, or stride rate, for each walking condition.
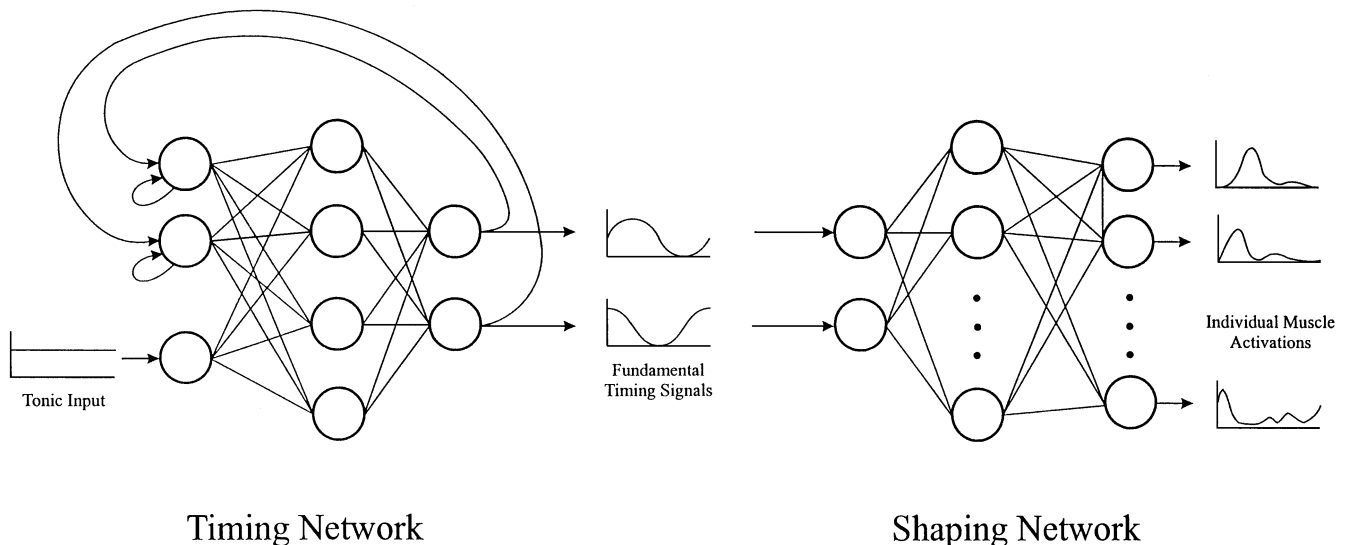
Model development

The proposed shaping model consisted of a feedforward network (see Fig. 1) where the input vector consisted of the two sinusoidal inputs, whose frequency matched the average stride rate for each walking speed, and the individual muscle activations formed the output vector. The time history data were represented through a series of input and output vectors where each vector pair depicted the data of a single time step. The use of a sine and cosine waveform as the model's inputs was based on earlier work using labile synthesized relaxation oscillators (Bardakjian et al. 1983) and it was intended that together these patterns would permit the network to generate output patterns with different phasic profiles. In fact, when the networks were developed using only a single sinusoidal input, the resulting output patterns exhibited sinusoidal bursts of activity which were synchronized with the sinusoidal input rather than when the target muscles were active. A further advantage to using both a sine and cosine input is that the network can be developed to produce the appropriate phasing of the output patterns regardless of the absolute timing of the input signal. For example, when the network was trained using the same input only delayed in time with respect to the walking cycle, the network could still be developed to transform this the relative timing signal into the appropriate output patterns. In the development of the shaping network, true sine and cosine waveforms were used to represent the output of the timing network to permit an accurate representation of the fundamental frequency and thus provide an independent evaluation of the shaping network. The model employed 2 input units, 16 hidden units and 8 output units. Additional versions of this model were developed where the size of the hidden layer was decreased to four, two or one hidden unit(s) to investigate how reducing the complexity of the network would affect the production of muscle activation patterns.

The connections, weights and bias values for the shaping model were determined using a back-propagation algorithm (Rumelhart et al. 1986). The data from the different walking speeds were separated into a training set and a test set. The training set contained strides obtained at walking speeds of 1.2 and 1.8 m/s. This data set was repeatedly presented to the network to enable the learning rule to resolve the desired network parameters while the remaining conditions (1.4, 1.6 and 2.0 m/s) were reserved to test the ability of the network to generalize its output when receiving inputs different than those used in training. The test set was selected to include a range of speeds that were either within or outside the limits provided in the training set to test the network's ability to both interpolate and extrapolate to different walking speeds.

The length of network training was guided by monitoring the output error of the training set and the output error in the test set, which was evaluated after every ten passes of the training set dur-

Fig. 1 A neural network approach to modelling the timing and shaping functions of a CPG for human locomotion. The connection diagram illustrates the architecture of the proposed shaping network with the direction of processing flowing from left to right. All units of a layer are fully connected to the units of the next layer to the right

Tonic Input

Fundamental Timing Signals

Individual Muscle Activations

Timing Network

Shaping Network

ing the training schedule. The training algorithm was suspended during each introduction of the test set to prevent any influence on the network connections. Training continued until either the test or the training set no longer demonstrated a decreasing error. The output from the final network was then obtained by presenting both the training and test data.

Results

The muscle activation time histories predicted by the model show a strong agreement with those recorded experimentally for all five walking speeds. Profiles from the three test conditions are shown in Fig. 2, where they are superimposed on a band representing the range (±2 SD) of muscle activity recorded across 12 strides for each condition. The model will produce consistent bursts of activity with no variability per cycle since the sinusoidal inputs have a constant frequency and do not differ from cycle to cycle. The differences seen in the

activation patterns from stride to stride reflect the subject's variability in stride period and the normalization procedures used to display the data. The resulting muscle patterns captured the basic features of every muscle over the different rates of walking and exhibited the general magnitude and temporal phasing appropriate for each condition.

The absolute error of magnitude between predicted and actual muscle activations was quantified for each

Fig. 2 Muscle activation patterns predicted by the 16 hidden unit network **(A)** are shown for each of the three test walking conditions (1.4 m/s, 1.6 m/s and 2.0 m/s), while *the leftmost column* **(B)** shows the results for one of the test walking conditions (1.4 m/s) using the four hidden unit network. *Each solid line* represents the model's output from one stride, normalized for time between RFC and RFC, while *the shaded area* is a 2-SD band about the mean of the actual muscle activity recorded from the subject over 12 strides. The amplitude of activity for each muscle has been scaled to the peak activity found across all walking conditions
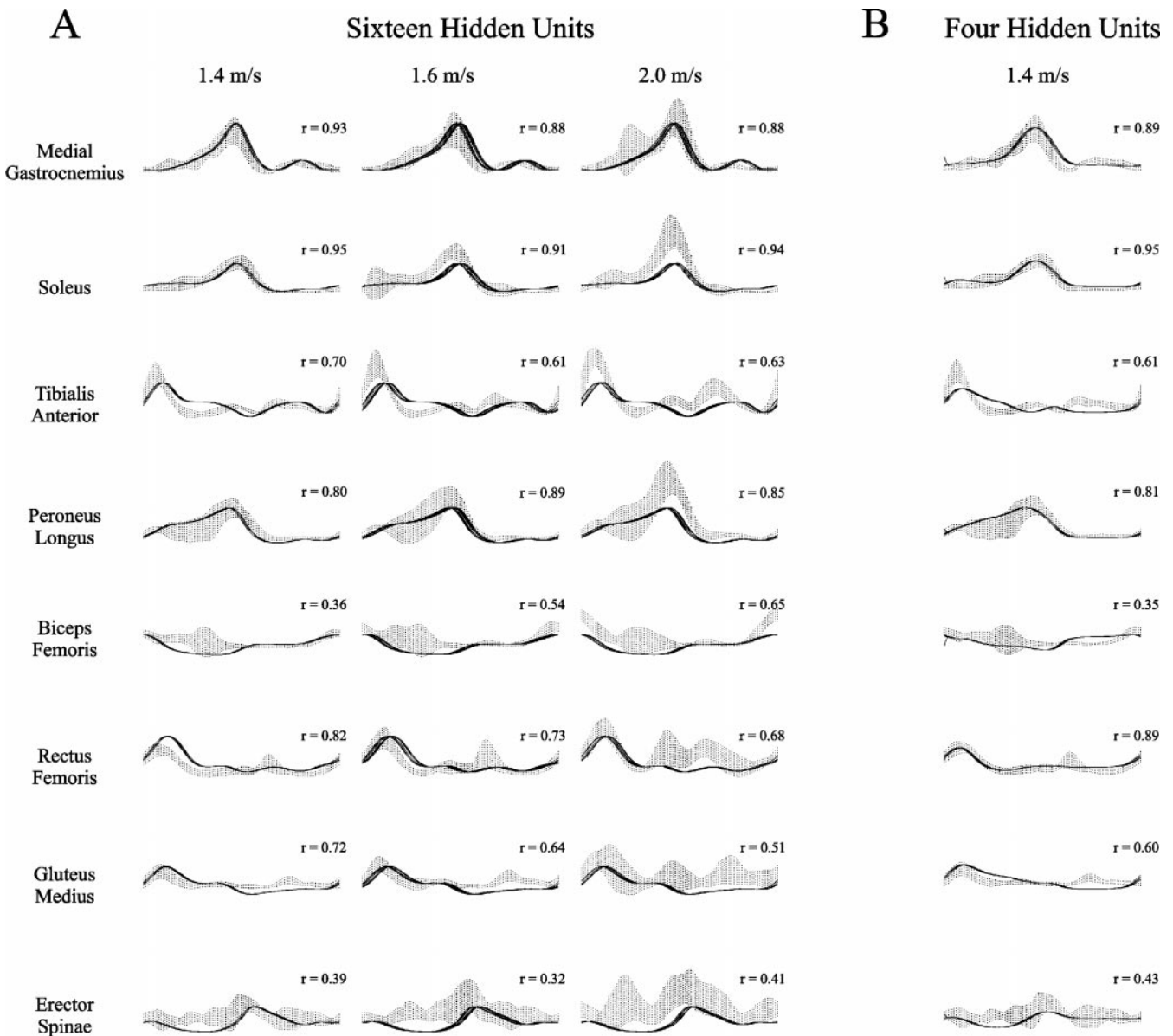
muscle-speed combination using an RMS difference expressed as a percentage of the operating range of the output units. The majority of the values (33/40) were below 20%, indicating a good match between predicted and actual activation of individual trials. The level of 20% RMS error, although a liberal criterion for goodness of fit, was selected more to indicate whether the output from this simple model captured the majority (80%) of the magnitude information contained in the muscle activity pattern. The magnitude of error increased with the speed of locomotion, with the 2.0 m/s condition having the highest RMS error. Errors greater than 20% were observed in the soleus, tibialis anterior, peroneus longus, rectus femoris and the erector spinae for the fastest speed condition. The erector spinae was the only muscle which showed consistently high errors with the three fastest speeds, showing RMS differences above 20%. Those muscles which showed higher errors for the fastest conditions generally had greater RMS differences at lower speeds.

Correlations between predicted and actual muscle activity evaluated the ability of the model to capture the temporal modulation of muscle activity across successive strides. The correlation values for each muscle-speed combination of the test conditions are shown in Fig. 2. Consistently high correlations were exhibited in the gastrocnemius, soleus and peroneus longus muscles while lower values were seen in the biceps femoris and erector spinae activity. The remainder of the muscles displayed moderate to high correlations. There was no clear trend between the correlation values and the speed of locomotion.

Effect of decreasing hidden units

When four hidden units were used, the predicted activity showed a strong resemblance to those obtained for 16 hidden units despite the fourfold decrease in hidden units (see Fig. 2). The resulting waveforms did lack some of the subtle features that were captured using more hidden elements. For example, the model with four hidden units failed to preserve the burst in both the gastrocnemius and tibialis anterior during toe off (approximately 60% of the stride). Aside from these specific examples, the profiles exhibited less phasic detail than when a larger hidden layer was utilized.

The mean RMS differences for the four hidden unit network confirmed the good agreement between predicted and actual muscle activations; in fact the values for many conditions only differed by 1 or 2% from the error observed with 16 hidden units. As with the larger model, most conditions (32/40) showed differences below 20% and the RMS differences increased with speed. Essentially the same muscle-speed conditions were responsible for the high RMS values.

Correlations also reflected a slight loss of phasic information with fewer hidden units even though the values were comparable to those of the original model (see Fig. 2). Higher correlations were again seen in the gastrocnemius, soleus and peroneus longus and similar to the previous model the biceps femoris and erector spinae exhibited rather poor correlations. There was also no clear relationship between the correlation values and the speed of walking.

Reducing the size of the model further to either two or one hidden units resulted in a gradual breakdown of the muscle output patterns. Models with two hidden units could still generate those muscles best predicted by the larger models (i.e., medial gastrocnemius, soleus, and peroneus longus), while for most other muscles the model could generate the appropriate timing of activity but both the size and form of the phasic profiles were only crude representations of the target muscle activity. Models with only one hidden unit demonstrated a much greater breakdown where the model could only generate activity during a single phase of the walking cycle. Essentially, all outputs were scaled versions of the same activity pattern which matched the timing of the medial gastrocnemius, suggesting that activity during this phase was the most common activity pattern shared amongst the muscles.

Assessing the network structure

To address how the network is operating, we will only examine the structure of the four hidden unit network given that its structure is much simpler while its performance was comparable to the larger model. Figure 3 shows the activity of the four hidden units (HU_{1-4}) and their network connections to the eight muscle outputs. While the network connections remain constant for all walking conditions, the hidden unit and muscle activity patterns are shown for a single stride during the 1.4-m/s walking condition. The hidden units act as building blocks and take on quite different forms, where HU_1 and HU_4 show more discrete bursts during different periods of the stance phase while HU_2 and HU_3 show more cyclical patterns of activity with the HU_2 being the only unit with increased activity during the swing phase. In general the projections from these hidden units show excitatory connections to those muscles that have increased activity during the same phase and inhibitory connections to those muscles that show a decrease in the same period as the hidden unit activity. This is most easily seen in the projections from HU_1 to the first four muscles: where the peak activity of the medial gastrocnemius, soleus and peroneus longus (each receiving excitatory connections) coincides with that of HU_1, while the tibialis anterior shows a decrease in activation during this period and receives an inhibitory connection. It should be noted that each of the units in the network has a bias activity level and the incoming connections will act to increase or decrease the units' activity from this resting level of activity. The lower three figures in Fig. 3 isolate the network connections from the four hidden units to three individual muscles in order to further
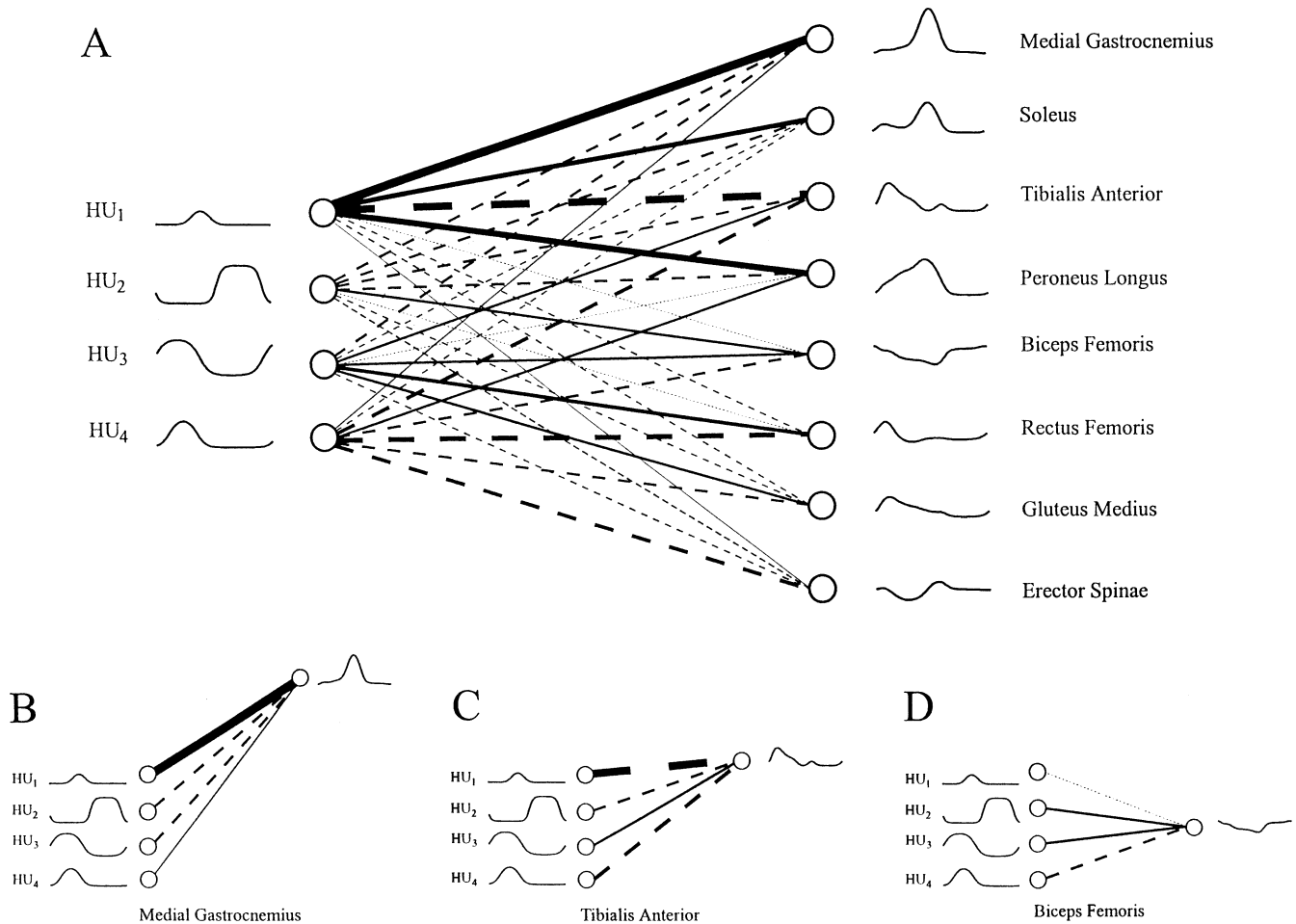
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Fig. 3A–D Hidden unit activation patterns and their projections to the individual muscle outputs are shown for the four hidden unit network. *The top figure* (**A**) illustrates all of the connection weights from the four hidden units (HU$_{1-4}$) to all eight muscles, while *the lower three figures* (**B–D**) each isolate the connections to an individual muscle. *The lines between units* represent both excitatory (*solid lines*) and inhibitory (*dashed lines*) connections, with *the thickness of the line* representing the relative strength of the connection. The hidden and muscle output activity profiles are taken from a single stride (RFC to RFC) of the 1.4-m/s walking condition

demonstrate how the hidden units combine to form very different activity patterns. Here the reciprocal nature of the network can be seen where those inputs serving to excite the medial gastrocnemius (HU$_2$ and HU$_4$) also inhibit the tibialis anterior. Further examination of the weights and hidden units also demonstrated that the muscle activity best predicted by the network (e.g., medial gastrocnemius) tended to receive more directed hidden unit input where one hidden unit may be dominant, while muscle activity with less favourable results (e.g., biceps femoris) was often dependent on input from all four hidden units. This would agree with the results of networks that utilize only two or one hidden unit(s) where activity from certain muscles could not be generated in an oversimplified network.

Discussion

It is proposed that a simple feedforward ANN model is a suitable candidate for modelling the shaping function of a CPG for human locomotion. Although recurrent dynamic neural networks have been used to model other sensorimotor systems and may be better suited to perform many complex transformations involving temporal sequences (see Fetz 1993), the use of recurrent/feedback connection would add a temporal dynamic that would limit the ability to independently represent and examine the timing and shaping functions of the pattern generating network. The simplicity of the current model is reflected in the size of its hidden layer, which embodies much of the intermediate processing. Hidden units of feedforward networks function much like principal component analysis, where the basic features of a set of waveforms are extracted and can later be used to reconstruct the individual signals. Here the hidden unit activation representing features from the sinusoidal locomotor rhythm are combined to build the individual muscle activity patterns of the eight muscles. The original model used 16 feature signals to construct the muscle activations while a reduced model used only four feature signals. The primary difference between these two models was that the more detailed model preserved more of the

subtle phasing information contained in the actual signals; however, the results of the reduced model were only slightly poorer despite the fourfold decrease in the number of hidden units. Decreasing the size of the hidden layer below four units failed to generate reasonable activity patterns for all muscles. This suggests that four fundamental signals were sufficient to generate a basic representation of the activation patterns and a more complex model added some finer phasing details of the signals. Using principal component analysis, Patla et al. (1985) identified that only four feature signals were required to construct profiles that account for the majority of activation during locomotion. Although there are differences between their shaping functions and the hidden units of these models, together these results suggest that the locomotor system, if it utilizes similar operations, may only require a limited number of features to produce the activation patterns for most limb muscles.

The current feedforward model only receives information regarding the fundamental locomotor rhythm and holds the assumption that the amplitude of EMG is a constant function of its temporal position within the step cycle. At the higher speeds most muscles exhibit an increase in recorded EMG amplitude during the primary phases of activity and some muscles also included additional bursts of activity. The model by definition would be limited to predicting activation patterns in those muscles and/or conditions where this relationship changes. It has been shown that changes in cadence during overground walking have little effect on the relative phasing of muscle activity while the amplitude of the muscle activity is speed dependent (Yang and Winter 1985). These changes in EMG amplitude were attributed to the mechanical demands associated with the different rates of walking and it was further demonstrated that the more proximal muscles are more affected by these demands. Walking at faster rates places additional requirements upon the locomotor control system to ensure safe foot placement, maintain postural equilibrium and compensate for muscle fatigue while increasing the propulsion needed over successive strides. Not only will these demands vary with different walking speeds, they will also vary from stride to stride within any one speed. This model did not explicitly receive any inputs conveying this information and thus some of its inability to represent certain aspects of the actual EMG profiles is unavoidable and might reflect the locomotor control system's dependence on inputs from other levels of the nervous system.

It is well recognized that supraspinal and sensory information will contribute even in the control of normal steady-state locomotion, and the degree of their contribution will certainly vary across muscles and walking conditions, where they may influence both the timing and shaping of muscle activity (see reviews by Armstrong 1988; Rossignol 1996). In studies of cat locomotion, it has been demonstrated that certain muscles are more dependent on sensory feedback than on central commands (Engberg and Lundberg 1969; Smith et al.

1993). Additionally, some muscles such as the semitendinosus (Smith et al. 1993) have one burst linked to sensory feedback while a second burst seems to have a central origin. Researchers have suggested that information arising from the motor cortex is important for the control of limb trajectory as well as the regulation of the timing of individual strides (Drew 1993; Drew et al. 1996), while input from specific brainstem regions has shown to be necessary to maintain and modify postural tone as well as modifying other aspects of locomotor activity on a step-by-step basis (Drew et. al 1986; Drew 1991; Mori et al. 1991). This dependence on phasic information during normal treadmill walking is an important component in generating appropriate muscle activity and one would expect the absence of this information to limit the model's ability to predict EMG patterns of a normal subject whose locomotor control system included this rich information. Although the model produced the basic muscle activation patterns for a range of walking speeds, the lack of phasic input could be a factor in the model's predictions for muscles like the tibialis anterior, biceps femoris and erector spinae whose results were weaker even at the lower speeds. Examining the structure of the network and the results of the networks using fewer hidden units suggests that activity of these same muscles seems to require a more complex transformation of the timing input.

The shaping model in its current form has demonstrated how a simple arrangement of uncomplicated processing elements whose sole input was the basic locomotor rhythm can produce complex muscle activations for a range of different walking conditions. Although some of the model's deficits may be attributed to the network's structure, the absence of phasic information from peripheral and supraspinal sources is a limiting factor in producing the activity for certain muscles and walking speeds. If future models are to represent skilled locomotor behaviour, a better understanding of the role of supraspinal and sensory information and how they interact with the pattern generator is needed. Aside from characterizing these inputs, it must be established how this information influences the CPG network. It has been suggested that inputs to a CPG for rhythmic limb movements may affect either the timing or the patterning of muscle activity (Lennard and Hermanson 1985; Koshland and Smith 1989). A model that can incorporate these additional inputs and resolve effects on both the timing and shaping of muscle activity will be better suited to address the generation of normal locomotor behaviour. Preliminary work using a variation of this shaping network has included data from cat experiments to add motor cortical inputs in order to step over obstacles (Prentice and Drew 1997). These models may also have practical uses in the development of functional electrical stimulation systems for the restoration of gait in paraplegic patients, where researchers have begun to adopt similar control strategies (Abbas and Chizeck 1995; Abbas and Triolo 1997). Developing a suitable controller to generate the skilled locomotor activity required for ev-

eryday life must incorporate the information arising from higher brain centres and sensory feedback from the periphery.

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