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Evolving multi-segment 'super-lamprey' CPG's for increased swimming control

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Abstract. 'Super-lamprey' swimmers which operate over a greater control range are evolved. Propulsion in the lamprey, an eel-like fish, is governed by activity in its spinal neural network. This CPG is simulated, in accordance with Ekeberg's model, and then optimised alternatives are generated with genetic algorithms. Extending our prior lamprey work on single segment oscillators to multiple segments (including interaction with a mechanical model) demonstrates that Ekeberg's CPG is not a unique solution and that simpler versions with wider operative ranges can be generated. This work 'out-evolves' nature as an initial step in understanding how to control wave power devices, with similar motion to the lamprey.

1 Introduction

The system explored in this paper is the lamprey's Central Pattern Generator (CPG) (see [1]) which controls swimming in varying water conditions. Our ultimate endeavour is to develop an adaptive controller based on this architecture to optimise the efficiency of wave power devices operating in irregular sea states. Initial work with a simple controller derived from the lamprey CPG demonstrates improved performance of a single-point Wave Energy Converter (WEC) [2]. However, further exploration of the lamprey CPG is necessary, so this paper assesses the flexibility of the complete multi-segment lamprey CPG; with evolved parameters not previously considered. Recent work [3] generated improved single-segment oscillators; less complex and with a wider range of operability. Interaction with a full scale, multi-segment mechanical model requires the evolution of interconnections between segments also, where optimum performance is signified by their capacity to control swimming at different speeds, oscillation frequencies and segmental phase shifts.

2 Artificial Neural Network Inspired by the Lamprey

2.1 The Neural Model

The lamprey (fig. 1a) is an eel-like fish which propels itself by propagating an undulatory wave with increasing amplitude from head to tail. A system of interconnected neurons along its spinal column are responsible for controlling

$$\dot{\xi}_+ = \frac{1}{\tau_D}(\sum_{i \epsilon \Psi_+} u_i w_i - \xi_+) \quad (1)$$

$$\dot{\xi}_- = \frac{1}{\tau_D}(\sum_{i \epsilon \Psi_-} u_i w_i - \xi_-) \quad (2)$$

$$\dot{\vartheta} = \frac{1}{\tau_A}(u - \vartheta) \quad (3)$$

$$u = \begin{Bmatrix} 1 - \exp\{(\Theta - \xi_+)\Gamma\} - \xi_- - \mu\vartheta & (u > 0) \\ 0 & (u \leq 0) \end{Bmatrix} \quad (4)$$

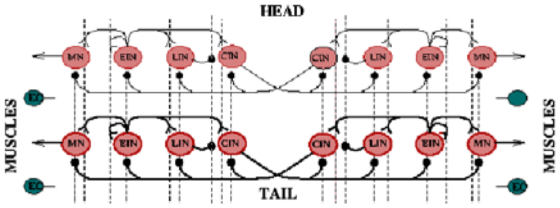

Fig. 1: a) The lamprey, b) Mathematical description of the model CPG neuron, c) Connectionist model of the lamprey's spinal CPG.

the fish's anguiliform swimming movements. This spinal control system (or CPG), consists of several copies of an oscillatory neural network which cause rhythmic activity of motoneurons which in turn alternate motion between the two sides of the fish's body. The lamprey's CPG is relatively simple and it has therefore been possible to isolate the system *in vivo*, determine detailed cell models, analyse electrochemical reactions to stimulation of the neurons and reproduce the network artificially [1, 4].

The entire network can be reduced to a simplified connectionist model. The system's model neuron is non-spiking and represents a population of functionally similar neurons. The CPG receives delayed excitatory and inhibitory input and its output is calculated from first order differential equations (fig. 1b). Output u (eqn. 4, fig. 1b) of each neural unit represents the mean firing frequency of the population. Excitatory (ξ_+) and inhibitory (ξ_-) synaptic inputs (eqns. 1-2) are added separately and are subject to time delays (τ_D and τ_A). The terms Ψ_+ and Ψ_- represent the groups of pre-synaptic excitatory and inhibitory neurons respectively and w_i denotes the synaptic weights associated with the inputs. The excitatory input is transformed by a transfer function which provides saturation at high levels of excitatory input. Finally, a leak is included as delayed negative feedback (eqn. 3). Parameters of threshold (Θ), gain (Γ) and mu (μ) of equation 4 are tuned to match the response characteristics of the corresponding neuron type based on experimentally established connectivity (see [1]).

Fig. 1c displays two of 100 replicas of an oscillating segment. Interconnections between neurons within a single segment of the CPG are highlighted. There are four neuron types on each side of the network: Excitatory neurons (EIN), contralateral inhibitory interneurons (CIN), lateral inhibitory interneurons (LIN) and motoneurons (MN) which provide output to the muscles. Edge cells (EC) provide feedback to the neural system and thus allows the network to adjust for external forces while maintaining straight line swimming [5]. Input to the pattern generator consists of tonic (i.e. non-oscillating) signals (also referred to as global excitation) from the brainstem which control the frequency of oscillation. These inputs connect to all the neurons in the CPG. A further tonic input, (referred to as extra excitation), is applied to the first five segments of the CPG. Tonic inputs are not shown in fig. 1c for reasons of clarity. Each segment functions as a non-linear oscillator and is coupled to its neighbours through extensions of interneural connections towards the head (rostral) and the tail (caudal). These are depicted in fig. 1c by the vertical dotted lines.

2.2 A Mechanical Model of the Lamprey and its Environment

In order to view the effects of the neural controller, a simulation of the mechanical model [1, 5] of the lamprey interacting with water is implemented. The body comprises ten rigid links (each 30mm long) whose movement is constrained, forcing them to stay connected, by joints with one degree of freedom. Each mechanical link corresponds to ten neural segments. Muscles are connected to each link and are modeled as a combination of springs and dampers. Three forces act upon each link: (1) water forces which apply pressure perpendicular and parallel to the object, (2) inner forces which exert pressure from neighbouring links, and (3) muscular torques which ensure the link does not bend in both directions at once. The bending torques are controlled by the activation of muscles on both sides of the body. These muscles are assumed to be the length of local curvature of the body. Motoneuron activity alters the spring constants of corresponding muscles which in turn produce forces that cause movements. This enables the neural network to vary both the total bending force and the stiffness locally along the body. Information about the curvature of the body is fed back to the neural network via stretch sensitive edge cells.

The simulation of the mechanical model successfully demonstrates that alternating oscillatory motoneuron activity of the neural CPG produces the expected anguiliform swimming behaviour. Further details of the procedures used to convert neural responses into movement are outlined in [1, 5].

3 Optimising the Model using Genetic Evolution

The lamprey comprises several interconnected oscillatory segments. Single segment controllers, shown to be more efficient than the biological prototype [1], were evolved in prior research [3]. These oscillators operate over a wider range of frequencies and are much simpler in terms of internal connectivity. Furthermore, neural parameters (which describe the dynamics of the model neurons) were evolved which were previously not manipulated [5]. Following on from the results obtained in these tests, intersegmental connections between 100 copies of a fixed segmental network are generated using genetic algorithm (GA) techniques. The best segmental oscillators of the previous evolutionary stage [3] are used, and five evolutions invoked.

An integer value GA is used, with chromosomes of fixed-length strings of 51 genes. Each gene corresponds directly to one parameter of the neural configuration. Left-right symmetry is imposed for interconnections which constitute 48 genes (rostral and caudal). Boundaries for these are 1 to 12, a range which includes the biological prototype values. The sign (excitatory or inhibitory) of each neuron group is contained in three chromosome units. These are preassigned according to the type of connection, and thus not evolved. Connections from motoneurons are also not generated as they only supply output to muscles.

Starting with a randomly generated initial population, the GA loops through selection, variation and rejection operations, each generation. Selection involves a fixed number of parents being chosen according to rank-based probability. Fittest individuals are therefore selected more often to create offspring. Variation imposes operations of two-point crossover and mutation on paired chromosomes. Finally, the worst solutions (denoted by their fitness ranking) are rejected, being replaced by higher ranked new solutions to maintain a consistent overall population size. GA parameters for evolving segmental oscillators are: *population size* (60), *no. of children* (18), *crossover probability* (0.5), *mutation probability* (0.4) and *mutation range* (0.2). The given probability rates and ranges describe the degree to which chromosomes are changed. For instance, each gene in the chromosome is selected for mutation independently with 40% probability.

Evaluation of the complete CPG is based on neural activity and mechanical movements of the simulated body. Solutions are rewarded for their ability to control swimming at various speeds, frequencies of oscillation and lags between segments. More specifically, controllers should (1) be able to change the oscillation frequency or wavelength of the undulation independently through global excitation (*ge*) and extra excitation (*ee*) levels respectively, (2) generate stable oscillations in each segment with coordinated phase differences which enable travelling undulations of the body, and (3) be able to change the speed of swimming by altering either their oscillation frequency or the wavelength of the undulations [5]. To compare results with the biological controller, emphasis is placed on controllers which can swim with a wavelength corresponding to the length of the body (i.e. phase lag of 1% per segment). Mathematically, the fitness is defined as: $fitness = min\_fit\_oscil * fit\_freq\_control * fit\_lag\_control * fit\_speed$ where min_fit_oscil denotes the oscillatory activity of the least stable segment (segments analysed are 1,10,20...100 at the midrange level of global excitation). If this value is below a threshold of 0.45, oscillatory activity is not satisfactory and the candidate CPG is tested no further. Details for calculating this criteria can be found in [3]. The other fitness formula variables are calculated as:

$$
\begin{aligned}
fit\_lag\_control = &\quad 0.05 + \tfrac{lag\_range1}{1+freq\_range1} \quad (if < 1),\ else\ 1 \\
fit\_freq\_control = &\quad 0.05 + \tfrac{freq\_range2}{1+lag\_range2} \quad (if < 1),\ else\ 1 \\
fit\_speed = &\quad 0.05 + speed\_range \quad (if < 1),\ else\ 1
\end{aligned}
$$

To measure lag_range1 and $freq\_range1$, several simulations are made at a fixed level of global excitation (the midrange *ge* value at which the network oscillates) and with an increasing amount of extra excitation (*ee*). The lag range

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is non-zero only when the oscillations are regular in all segments and if the lag increases monotonically with *ee*. Dividing the lag range by the frequency range encourages rewarding solutions according to their ability to alter the lag between segments independently of the frequency.

$Freq\_range2$ and lag_range2 are measured by making several simulations, with *ge* input varying around the midrange level, and this time, with a fixed amount of *ee*. This value is calculated from the previous lag measurements if lag_range1 includes a lag of 1%; the *ee* value corresponding to the lag closest to 1% is used. The frequency range is non-zero only if a lag close to 1% exists, and if frequency increases monotonically with the level of extra excitation.

Finally, *speed_range* corresponds to the range of speeds covered by all the simulations made for the definition of $fit\_lag\_control$ and $fit\_freq\_control$. The algorithms for evolving synaptic interconnections are from [5] but applied to segmental oscillators which evolve neural parameters as well as synaptic weights.

4 Results and Discussion

Results of five experiments demonstrate 80% of the evolved controllers give improved performance over the prototype CPG. Evolutions were terminated after 50 generations since the populations had stabilised by this point and simulation times were significantly greater for this evolutionary stage. Table 1a compares statistics of the best evolved solution with Ekeberg's biological CPG [1] and Ijspeert et al's best segmental fixed parameter controller [5]. Corresponding weights and extensions (rostral and caudal) are given in Table 1b.

a) CPG	Fitness Value	Freq. Range (Hz)	Lag Range (%)	Speed Range (m/s)	midrange *ge* value
Biological	0.2	1.74 - 5.56	0 - 1.165	0.01 - 0.45	0.6
Fixed	0.16	1.2 - 8.0	0.73 - 1.37	0.06 - 0.41	1.2
Best Evol.	0.51	0.99 - 12.67	0 - 1.59	-0.1 - 0.6	0.7

b) Run		Synaptic Weights [Rostral, Caudal Extensions]							Parameters		
	from: / to:	EINl	CINl	LINl	EINr	CINr	LINr	BS	θ	Γ	μ
Biological	EINl	0.4 [2,2]	-	-	-	-2.0 [1,10]	-	2.0	-0.2	1.8	0.3
	CINl	3.0 [2,2]	-	-1.0 [5,5]	-	-2.0 [1,10]	-	7.0	0.5	1.0	0.3
	LINl	13.0 [5,5]	-	-	-	-1.0 [1,10]	-	5.0	8.0	0.5	0
	MNl	1.0 [5,5]	-	-	-	-2.0 [5,5]	-	5.0	0.1	0.3	0
Fixed Parameter	EINl	-0.8 [12,4]	-3.8 [12,10]	-	-0.9 [5,10]	-0.7 [1,10]	-	0.8	-0.2	1.8	0.3
	CINl	-	-	-	-3.5 [2,2]	-3.7 [9,9]	-	13.0	0.5	1.0	0.3
	LINl	-	-	-	-	-	-	-	8.0	0.5	0
	MNl	-0.4 [9,2]	-3.2 [8,1]	-	-	-	-	3.8	0.1	0.3	0
Best Evolution	EINl	-	-4.57 [3,4]	-	-	-	-	3.06	-1	0.71	0
	CINl	5.53 [1,8]	-	-	-	-2.9 [10,1]	-	-1.18	-1	0.48	0
	LINl	-	-	-	-	-	-	-5	-1	0	0
	MNl	-	-4.28 [8,6]	-	-	-	-	10.83	-1	0.27	0

Table 1: a) Operative ranges of the biological, fixed parameter and best evolved CPGs, and b) their respective weights [and extent of connections].

Fitness of improved controllers (those with greater objective values than the biological prototype's fitness 0.2 and Ijspeert's fixed parameter controller (0.16 fitness), range from 0.41 - 0.51. The **frequency, lag and speed** ranges of all generated improved solutions are substantially greater than the biological controller and Ijspeert's fixed parameter CPG, with the best evolution operating at a **frequency** of 0.99 - 12.67 Hz (compared to 1.74 - 5.56 Hz and 1.2 - 8 Hz), with **lag** ranging from 0 - 1.59% (compared to 0 - 1.165% and 0.73 - 1.37%) and **speed** of -0.1 - 0.6 m/s (compared with 0.01 - 0.45 m/s and 0.06 - 0.41 m/s). The lag range is recorded at the midrange *ge* level, with varying *ee* and frequency range corresponds to varying *ge* levels with no *ee* as it was considered to provide a better comparison of operation ranges. It is worth noting that Ijspeert's best segmental oscillator did not perform as well as the biological prototype when coupled into a multisegmental unit, also confirmed by his results [5]. Finally, a negative speed recording is due to the kind of wriggling the lamprey performs.

5 Conclusion

Experiments evolving Ekeberg style controllers, where neural connections within a segment are generated, demonstrate that many effective segmental oscillators can be constructed [3]. Extending these to multisegment CPGs shows improved performance over the biological prototype [1] and fixed parameter CPGs [5]; evolved networks operate over a wider frequency, phase and speed range with independency of control. Furthermore the evolved networks are vastly simplified in terms of connectivity and parameter sets used by Ekeberg. The research also confirms that many possible solutions exist for anguiliform locomotion within the structural constraints of Ekeberg's CPG model.

In summary, we have shown that, by relaxing some of the constraints associated with a biological exemplar, controllers (and potentially other computational structures) can be evolved that can capture the strengths of biological "computation" in a simpler, or perhaps more effective manner. We are developing this biological paradigm and architecture without the constraints imposed by the biological computing substrate, to optimise articulated Wave Power Devices. Early, simple experiments [2] suggest that it can. This forms the basis of a wider study that aims to develop or evolve other biological "computer" for new aims and goals, to discover whether the biological substrate upon which they are implemented is optimal, or a constraint to better performance.

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