Incorporating Sensory Information into Virtually Evolved Creatures with Central Pattern Generator Control Structures

Áron Richárd Ferencz
Vrije Universiteit Amsterdam
Amsterdam, Netherlands
a.r.ferencz@student.vu.nl

***Abstract*—In this paper, modular creatures with central pattern generator based control schemes were evolved to perform locomotion in a virtual environment. From the final populations of the evolved agents a set of morphologically diverse creatures were selected. To steer the agents, a control mechanism incorporating sensory information was proposed; the paths taken by the creatures were analyzed, and the morphological measures of the creatures were correlated to the success of the proposed steering method. The results indicate that the control scheme altered the trajectories in a predictable manner for multiple morphologically unique creatures.**

***Index Terms*—Evolutionary Robotics, Central Pattern Generator, Sensory Input, Locomotion Control, Morphological Analysis**

I. INTRODUCTION

Organisms capable of using the information externally available in the world perform their evolutionary task of reproduction at a higher rate than those who do not. This stems from the fact that, as far as we know, all living multi celled organisms incorporate sensory feedback in some form or other. This argument is further strengthened by the fact that in most definitions of life the agent's capability of responding to external stimuli is crucial. [1] [2]

This is especially pertinent in the context of naturally inspired locomotion. The ability to adapt to changes in an environment is crucial when operating in the natural world. When completing tasks such as gathering goods, obstacle avoidance or simply mapping out a terrain by moving through it, animals and robots alike are faced with the challenge of "comprehending" the external world's most relevant features. This process can be done through integrating sensory input gathered by the sensors available to the agent. This may be visual, auditory, thermodynamic or any other environmental information. [3] Therefore when one wishes to create a robot that is similarly 'intelligent' to living beings one ought to develop the possibility of integrating sensory feedback in order to manage changing environmental factors.

Evolution has led to life forms capable of surviving and thriving in virtually any condition on Earth, therefore it can be stated that adapting to an environment through Darwinian evolution is a successful mode of development. Advancements made in the fields of robotics, Evolutionary Computing (EC), and simulation technology have led to the creation of an active area of research dubbed Evolutionary Robotics (ER). Evolved robots are developed in order to maximize some form of fitness by means of Darwinian principles; this can involve evolving the morphology and/or the control structure of a robot. This method of development can shed light on biological processes and possibly provide more adaptive and intelligent robot designs capable of operating in changing or unknown environments. [4] [5] This approach also limits the design bias inherent in the human robot engineering process. There have been multiple successful attempts at creating morphologies for virtual [6] [7] creatures capable of locomotion in stable environments.

Due to the high degree-of-freedom (DoF) of many bio-inspired robots a popular choice for controlling their movement is the use of a network of interconnected neurons capable of rhythmic output without rhythmic input. This construct is known as a Central Pattern Generator [8] There are many approaches to modeling CPGs with varying levels of biological abstraction and they are used depending on the task at hand. [36] CPG based robot control schemes typically operate in an open-loop fashion, meaning that the output of the control system has no bearing in the subsequent control step.

Closed-loop control is a historically difficult task in the context of CPGs for a couple reasons. In order to achieve optimal locomotion, depending on the CPG model used many parameters need to be fine tuned, therefore even a small disturbance in them can lead to inefficient or even unpredictable behavior. The high cost of precision high precision rotary encoders, accelerometers needed to successfully close the gap between actual angles, and target angles via PD controllers was also a limiting factor until very recently. [36].

In this paper an adaptation of the CPG model outlined in [9] is used to control agents evolved in the framework described in [10]. The objective of the study is to develop a method of locomotion control (steering), suitable for multiple virtually evolved creatures with arbitrary morphologies.

This paper contributes to the field of evolutionary robotics by showcasing a possible locomotion control scheme capable of steering multiple modular robots (left/right) with varying morphological measures by incorporating sensory information directly into a specific CPG of a robot.

II. Background & Related Work

A. CPGs in Biology

Studies of animal locomotion in the 1960s resulted in experimental evidence supporting the concept of CPGs in biological organisms. The first modern investigation was of mutilated locusts' ganglia producing rhythmic output when, deprived of afferent sensory input and externally stimulated similarly to the rhythmic output observed during their normal flight pattern. [11] Similar experiments were conducted in the coming decades with studies of insects [12], crustaceans [13], fish [14] and even larger vertebrates such as rats [15] and cats [16] [17] and even, to a certain extent humans [18]. However the complexity of these systems cannot be understated, as most mechanisms of CPGs found in animals are not yet understood; the most complex organism for which it is mapped out is the lamprey. [8] Its relatively small number of neurons allow for explicit knowledge of the CPG structure responsible for its locomotion.

B. CPGs in Robotics

Models of Central Pattern Generators take on three main forms in the field of robotics: connectionist models, vector maps, and systems of coupled oscillators. [8] Connectionist can be thought of as a middle ground between the detailed biophysical models using Hodgkin–Huxley [19] type of neuron models, and the more abstract mathematical models with less biological characteristics; they typically use leaky-integrators or integrate-or-fire neuronal models. Vector maps, are the most abstract of the three, reducing the physiological attributes of CPGs and motion into a vector space, and performing mathematical operations therein. The most relevant model for this discussion are the models based on systems of coupled oscillators, of which most are adaptations of the connectivity of lamprey CPGs.

The connectivity of the lamprey's CPG network has been a source of inspiration for robots such as the "salamandra robotica" produced by (A.J. Ijspeert et al., 2007), the serpentine robot brought into existence by [20] and more obvious cases such as the lamprey-based robot with an electronic nervous system described in [21]. These examples shed light on the versatility and robustness of the distributed control made possible by CPGs.

C. CPGs and Sensory Information in Biology

Sensory feedback in the context of CPG controllers in [22] is defined as "the return signal from the sensory system in response to this rhythmic muscle movement, which conveys a continuous measurement of the output behavior to the CPG". Incorporating sensory information in CPG models can be broken down into two levels, local and long loop feedback. Local loop feedback in the domain of motor pattern generation is responsible for modulating and adapting CPG activation with respect to the sensory feedback received from internal sensors, most notably via proprioceptive pathways. This is done through altering the phase and magnitude of muscle activity. [23] Creating a robust locomotion strategy capable of handling external perturbations by providing corrective input, or aiding stability during unperturbed motion by initiating phase transitions between movement patterns. [24]. In contrast, long loop feedback refers to the long lasting effects of CPG activity. These effects are much less understood due to the difficulty in studying the long term effects of CPG activity especially related to sensory feedback. Studies show that after complete spinal cord injury in cats, their locomotor recovery capability requires intact sources of peripheral sensory feedback. Furthermore, there are indications that during the neuronal developmental period of animals sensory feedback is necessary for proper coordination to emerge, a lack of sensory feedback in the developmental period has been linked to dysplasia and coordination problems. [25] Is has also been demonstrated that providing phasic sensory feedback can hasten locomotor recovery in rats that suffered spinal cord injuries [26]

D. Incorporation of Sensory Information in Robots with CPG Based Control Structures

There have been successful incorporations of sensory feedback into robots with CPG based control structures of fixed morphology; like quadruped and fish-like robots. The control scheme for the four-legged AIBO robot [27] developed by (Billard, Ijspeert) [28] allowed the robot to perform sitting, lying-down, scratching and walking mechanics. This was done by integrating sensory feedback generated by a motor potentiometer that measured the angle of its joints, and by computing the internal activity of its motor neurons. Aside from the independent locomotor mechanics the design also permitted the smooth transition between walking, trotting, and galloping gaits. The gaits are generated by sets of coupled oscillators. Where each oscillator is composed of four interneurons and two motor neurons. These neuronal units are modeled as leaky-integrators. Connections between the hip and knee joints are predefined in order to facilitate quadruped locomotion. The BoxyBot fish robot developed by EPFL [30] has one caudal and two pectoral fins. It has the capacity to swim and explore a space through swimming forward, backward, left, right, up, down, and by "crawling". The locomotion control for the robot consists of a CPG model to create oscillatory signals to servo motors, extended by a finite state machine that modulates the CPG activity that allows for transitions between behavior. The CPG control structure is modeled as a system of coupled amplitude-controlled phase oscillators, with one oscillator per fin. The oscillators are described by a set of differential equations; they define the phase, amplitude, and the offset of the oscillators in a given time step. Sensory input is integrated into the model via control parameters that change based on visual and touch sensory apparatuses. The system developed is extremely robust against perturbations, in the paper they outline its ability to stabilize into a state of synchronous oscillation for all three DoF by tuning the common frequency, the individual amplitude, and the individual offset of the three motor outputs. They demonstrated convergence to this stable state from random initial conditions, and after a deliberate scrambling of the parameters. A similar approach to a fish shaped robot design was created by (Wang et al., 2014) [9]] They also opted for a CPG model based on coupled oscillators, furthermore they incorporated sensory signals into their design at multiple levels, creating a two-phase CPG control architecture. The two phases consist of the upper decision making, and the lower, automatic adjustment level. The phases are subsequently divided even further into low, medium and highest feedback control models. At the lower level they use a sensory feedback model to create a "lower-reflex" model, inspired by the knee jerk reflex in humans. They propose a mechanic where the sensory signals obtained by exteroceptive feedback are input into a coupling unit after which further coupling with the CPG output will take place. This mechanism is applied to vary the specific output of a single oscillator. At the medium level the sensory information is passed on through the model via the coupling of the neurons; this allows for specific neurons to produce different outputs based on the connection strength between neurons, and the specific sensory information received by their individual sensors. The highest level of sensory feedback mimics a brain-like control center that can shift the coupling topologies of the oscillators in order to produce efficient different locomotion gaits; the transitions between topologies are governed by a finite state machine.

E. Evolution of Modular Robots

Bongard in his work [7] describes a process of artificial ontogeny. The model for development is based on genetic regulatory networks (GRNs); where transcription factors are responsible for creating or modulating specific physiological attributes of the agents. The paper successfully demonstrates the development of evolved agents capable of locomotion in 2D terrain, by using a CPG control structure that actuate motor neurons in the agents.

The work produced by the Computational Intelligence group [10] investigates the potential benefits of Lamarckian evolutionary dynamics in virtual evolved agents that can be realized by 3D printing their morphological components [11]. They employ standard evolutionary operations as well as a learning loop in order to perform selection based on locomotion towards a target region in a given time frame, ushering in more capable individuals for locomotion.

The most relevant aspect of the paper is their outline of the development of agents' morphologies and control structures. The paper describes the use of [31] for determining the morphological unit to be placed at a given segment of the robot. In order to produce complex locomotion patterns the agents control structure (brain) is composed of a CPG model with neurons controlling the actuation level of each individual joint for a given morphology. Therefore the brain structure of the robot co-evolves with its body. The connections between the joints are limited to the D(2,2) neighborhood of each joint, where D stands for the Delanoy number calculated in the 2D grid of each agent's brain genotype.

III. Research Method

This section contains the system description, and the methodology for testing the validity of the sensory input integration in said agents. The framework used for evolving modular virtual robots in this paper called revolve, it is an open source tool that allows for agents' morphologies as well as control structures to be evolved through Darwinian selection. The code for replicating the experiments is publicly available at [https://github.com/ci-group/revolve2] .

A. Body

The body of the agents consists of morphological components equivalent to those found in [10] [11]. More precisely from the set of components created by RoboGen [31], robots only use the core, the block and the active hinge components. Each agent contains one core component, and to each face of the core block or active hinge joint components can be added. Furthermore to each of the attached components, further blocks or hinges may be attached. Using these components allows for physical implementation of developed agents, via 3D printing technology. [11]

B. CPGs and Brain Structure

The control architecture chosen for the robots is a coupled CPG model based on the models developed by (Wang et al., 2014) and [32].

More precisely each robot's controller will constitute a network of CPGs with a coupling scheme between the CPGs.

Each joint of a robot's morphology is actuated to the output signal produced by its corresponding CPG. The CPGs are implemented as follows; a Hopf oscillator [33] is used to generate the rhythmic output needed for the motor control.

The coupling between CPGs is defined as a matrix of weights corresponding to the strength and direction of the connections formed between the joints of a robot. Similarly to [10] the neighborhood $\mathcal{N}_i$ is the set of indices of the joints neighboring it,w_{ij} corresponds to the weight of the connection between the 'neighboring' oscillators i and j. Therefore the complete CPG model is a system of two nonlinear first order differential equations described in (1):

$$\begin{cases} \dot{x}_i = -\omega_i y_i + x_i \left(A_i^2 - x_i^2 - y_i^2\right) + \sum\limits_{j \in \mathcal{N}_i} w_{ji} x_j \\ \dot{y}_i = \omega_i x_i + y_i \left(A_i^2 - x_i^2 - y_i^2\right) \end{cases} \tag{1}$$

As defined in (Wang et al., 2014) the subscript i corresponds to the i-th oscillator (i = 2, 3, . . . , n–1) and n indicates the total number of neural oscillators in the CPG network.

- state variable x represents the membrane potential
- state variable y represents the adjustment potential
- ω_i stands for the intrinsic frequency of the i-th oscillator
- A_i stands for the amplitude of the i-th oscillator

Individually the oscillators are bounded by the amplitude parameter, the addition of connections may lead to an non-executable signal. To ensure that the CPG's output signal uses the entirety of the actuation range, but does not fall outside

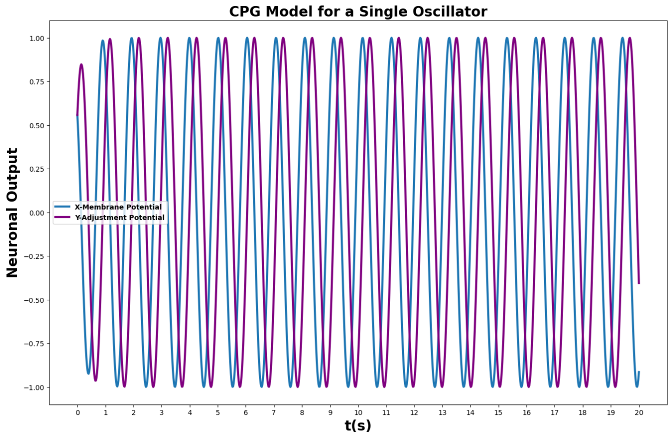


Fig. 1: Base CPG oscillation

range of possible outputs the final signal is normalized by a normalization factor and passed into the hyperbolic tangent function respectively. An example oscillation is shown in Fig. 1 with parameters : $\omega = 0.122$, $A = 0.31415/2$, initial x,y = 0.1.

C. Sensory Input to CPGs

The sensory input passed to the CPGs is an adaptation of the medium sensory feedback concept proposed by (Wang et al., 2014), meaning that each CPG has the capacity to receive sensory information, and this information propagates through the CPG model. In contrast to the fixed coupling weights proposed by (Wang et al.,2014), the model described in this paper leverages learnable coupling weights in order to control varying morphologies.

To accomplish this, the differential equations defining the control mechanism of the robots is extended by a sensory input term, resulting in the equations:

$$\begin{cases} \dot{x}_i = -\omega_i y_i + x_i \left(A_i^2 - x_i^2 - y_i^2\right) + \sum_{j \in \mathcal{N}_i} w_{ji} x_j + s\lambda \\ \dot{y}_i = \omega_i x_i + y_i \left(A_i^2 - x_i^2 - y_i^2\right) - s\lambda \end{cases} \tag{2}$$

The sensory input variable s together with the sensory input coefficient λ control the direction and scale of the sensory input. The default value for the sensory input variable is 0.

Adequate sensory input results in a positive or negative signal while maintaining the oscillation frequency. An example sensory input is shown in Fig. 2, with parameters : $s = \pm 0.1$, $\lambda = 0.1$. Sensory input is passed to the models from t_1=6s, until t_2=14s.

The CPG network can be thought of as a dynamic system, depending on the individual CPG parameters and their initial conditions they can stabilize into an oscillating pattern, or break i.e. become unpredictable or stop oscillating. The latter case should be avoided to continue the rhythmic input to the active hinges controlling the robot.

The sensory input received by the agents approximately falls into the range of (-2, 2), as demonstrated in Fig. 6. Therefore the oscillators continue to function throughout the simulation.

To demonstrate the instability of the network an example of passing a large sensory input signal of s=± 7.4, λ=0.1 is shown in 3. This is the first value that causes the oscillation to completely stop. Again the model is passed the sensory input from t_1=6s to t_2 = 14s.

The resulting chaos manifests itself in unstable behavior in the positive example and total collapse in the negative case.

D. Incorporating Sensory Input in the Agents

As described above the CPG model is capable of responding to sensory information without the loss of rhythmic pattern generation (within certain bounds). However the choice of when and where to add this information is not trivial, especially for unknown morphologies.

The connected structure of the control scheme allows for information to propagate between joints. The first joint attached to the core component receives this input. Introducing local sensory input to one joint will indirectly affect the entire movement pattern, hence the path taken by the robot.

In this paper we propose the incorporation of sensory input proportional to the force experienced by the core module of a creature. The core component of each robot contains an Inertial Measurement Unit (IMU) sensor, that measures the simulated forces experienced by the robots. The sensory input signal passed to the chosen joint's CPG is described by the equation Eq.3 At each point in time.

$$\begin{cases} s_{\text{angle}} = \arctan\left(\frac{F_y}{F_x}\right) \\ s = s_{\text{angle}} \times \left(\frac{F_x + F_y}{20}\right) \end{cases} \tag{3}$$

Where F_x, F_y stand for the x and y component of the force experienced by the core component of a robot at each point in time. The value calculated is then subtracted or added to the CPG controlling the first joint connected to the core component to control the robot's movement. The incorporation of this value is described by Eq. 2.

E. Body

The genotype of an agent's morphology is given by a Genetic Regulatory Network (GRN). It is an adaptation of Bongard's work [7], where he evolves artificial modular creatures for locomotion.

F. Brain

The brain of the agents as discussed above is the control structure of the robot; the evolution of the brain structure follows from the evolution of the body. Optimal locomotion control requires adaptation to a given morphology. Therefore an evolution of the connection matrix representing the coupling scheme of the CPGs is implemented. Each agent starts with an initial random brain genotype, that corresponds to

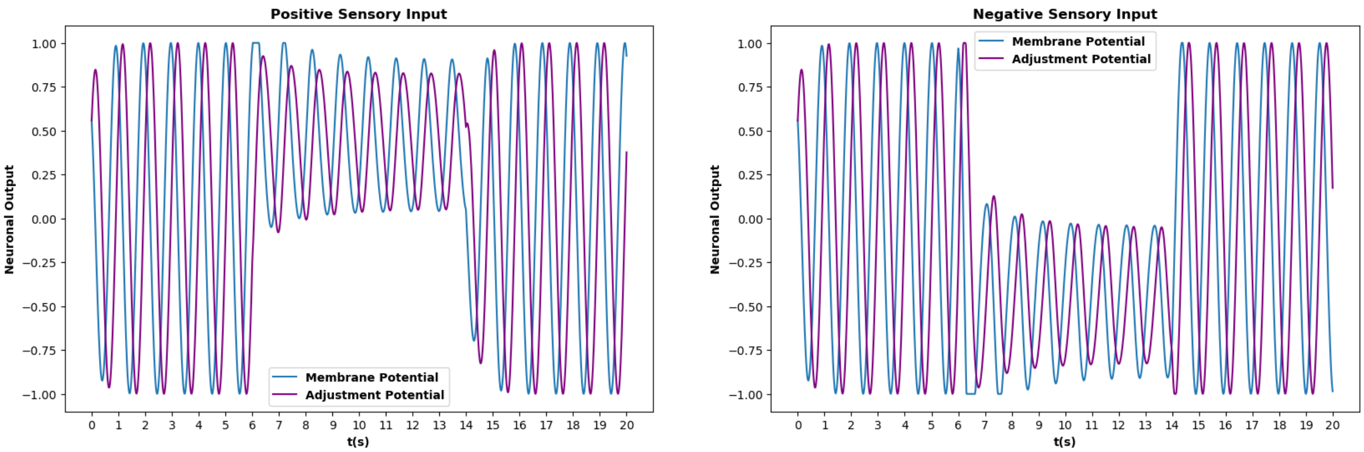


Fig. 2: CPG oscillation with positive or negative sensory input

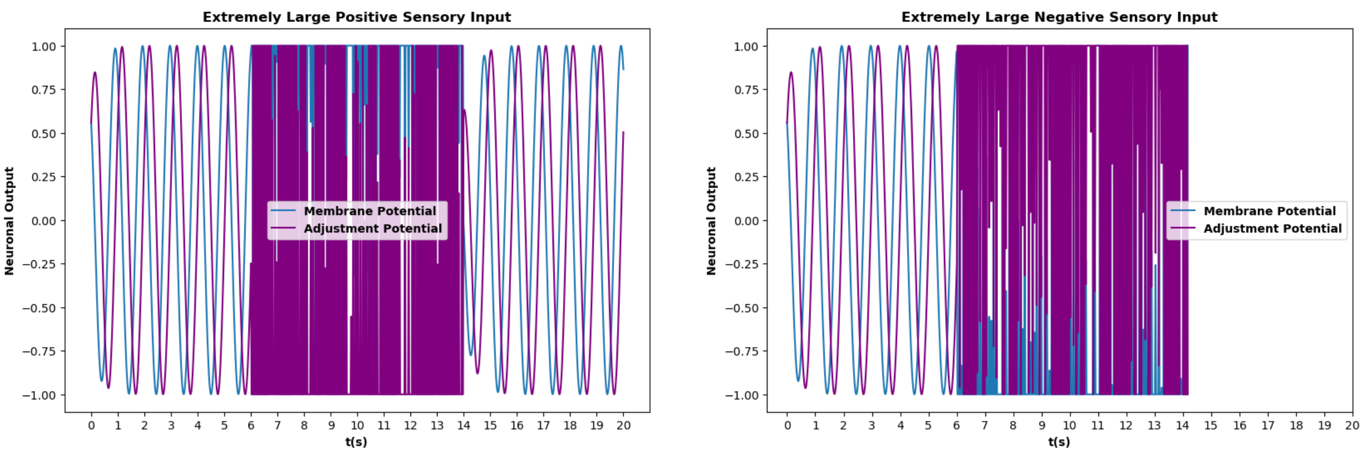


Fig. 3: CPG oscillation with large positive or negative sensory input

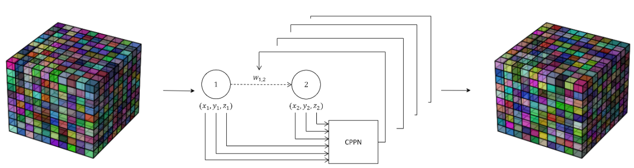


Fig. 4: Schematic overview of brain evolution

the a CPG connection scheme. The weights between joints are initially formed by querying a Compositional Pattern Producing Network (CPPN) [31] that receives as input the coordinates of the two (or in case of self coupling the same coordinate twice) and a bias, and returns the associated weight.

This genotype is then evolved through selection based on the fitness associated with the developed phenotype, and mutation. A visual demonstration of querying a CPPN to evolve the brain is shown in Fig. 4

G. Evolutionary Search

Darwinian selection was employed to evolve agents capable of moving across flat terrain via directed locomotion [34]. Their fitness is defined as the final xy-displacement reached by the agent. The fitness function maximized is defined as follows:

$$f = \sqrt{x_{\text{final}}^2 + y_{\text{final}}^2} \tag{4}$$

Two evolutionary searches took place in order to develop a multitude of heterogeneously developed robots, resulting in arbitrary morphologies. The searches were conducted with varying evolutionary parameters; the number of creatures in a given population was altered. Each evolutionary cycle consisted of one-hundred-and-fifty generations for each populations. Two population sizes were used to conduct the evolutionary searches; (i) 10, and (ii) 50, evolutionary searches for the two configurations were repeated ten times over. The fitness values of all searches are shown in Fig. 5

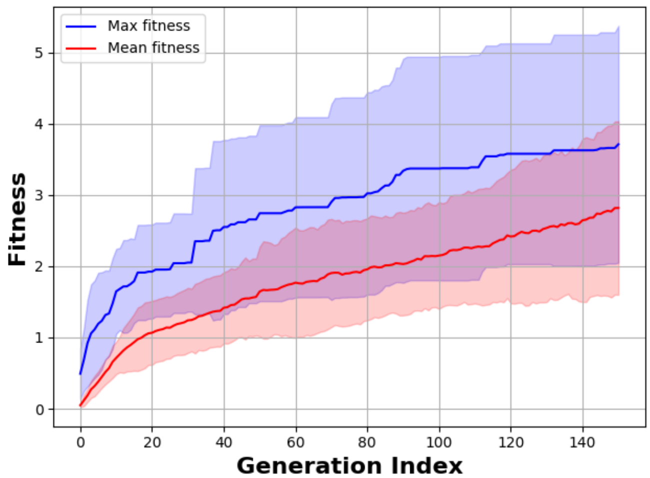


Fig. 5: Fitness values

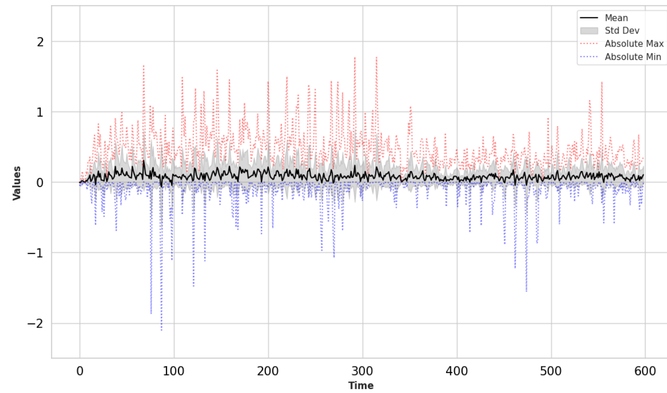


Fig. 6: Mean Sensory Input Values Passed to Joints

H. Selection of Agents for Testing

Specific agents were chosen to partake in the sensory input testing based on morphological diversity. The ten most distinct individuals of each terminal generation from the set of evolutionary searches conducted were chosen based upon their morphological measures compared to their companions in the population. However, some generations contained less diverse populations, and the overly-similar morphologies had to be excluded in order guarantee analysis of physically contrasting robots. This resulted in nine, nine selected agents per experiment.

Their morphological diversity was determined by calculating the Euclidean distance between a creature's morphological measures to all other creatures':

- `attachment_length_max`: Maximum length of attachments on the creature.
- `attachment_length_mean`: Mean length of attachments on the creature.
- `attachment_length_std`: Standard deviation of the lengths of attachments on the creature.
- `joint_brick_ratio`: Ratio of joints to bricks in the creature's structure.
- `symmetry_incl_sum`: Symmetry measure of the morphology taking into account the types of the attached modules.
- `symmetry_excl_sum`: Symmetry measure excluding the types of the attached modules.
- `coverage`: Ratio of the module count, the product of the maximal x and y expansion of the robot.
- `branching`: Measure of the branching complexity in the creature's structure.
- `surface`: Total surface area of the creature's structure.

I. Sensory Input Testing

Sensory input testing refers to the analysis of the evolved agents' paths while being subjected to sensory inputs of varying degree. To evaluate the proposed integration of sensory input, the evolved agents were passed sensory signals continually while they wander across the terrain they were evolved to traverse.

In the experiments conducted, sensory input is roughly comparable to proprioceptive force sensing. The mean sensory input values passed to agents during testing are presented in Fig. 6.

Each agent was subjected to three configurations of sensory input; (i) Negative Sensory Input, dubbed -0.05 because of the division by 20, (ii) No Sensory Input, dubbed 0 i.e. the base case for each robot, leaving the motion of the robot as it evolved, (iii) Positive Sensory Input, dubbed 0.05 because of the division by 20.

The main objective of sensory input testing was to map out, which morphological measures allowed for the sensory input variable to shift the path taken by the robot in a predictable manner. To quantify, what "predictable" means, three metrics were used; the Pearson correlation between the sensory input variables and the final x-coordinates , the final y-coordinates reached by the agent, and the final theta-angles (the angle in which the robot was facing at the end of the simulation). These metrics, despite losing information from compared to analysing the full path, permitted us to conduct a quantitative analysis of the simulations with respect to the sensory input variable.

The process for calculating these metrics is described in Fig. 7

IV. Results

The creatures selected for sensory input incorporation from the evolutionary searches are presented in Fig. 8, Fig. 9. Their paths on the xy-plane, and their polar coordinate's angular component (θ) over time is shown in Fig. 10, Fig. 12. In order to compare the paths, the correlative behavioural attributes were calculated for each individual selected in the manner described in the Sensory Input Testing subsection. The results of these tests are shown for the two evolved populations in Fig. 11, and Fig. 13 respectively

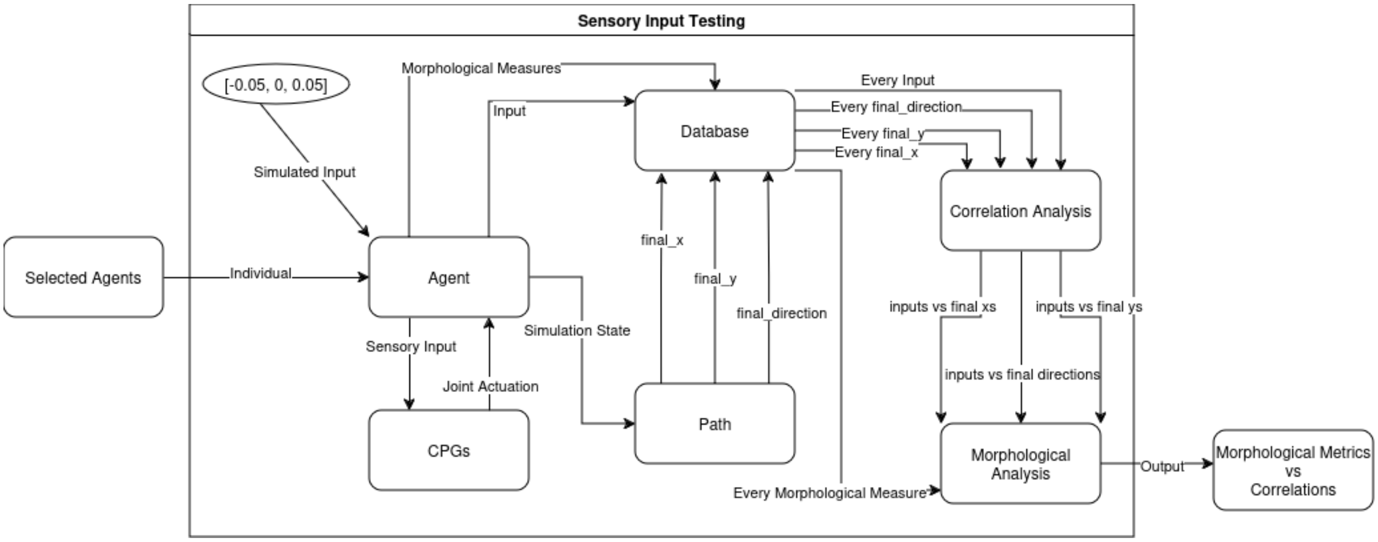


Fig. 7: The selected agents are individually tested with three types of sensory input, and their paths are analysed; The relevant information, i.e. the final x, final y and final θ, values are saved into a database. After all robots have been tested the morphological measures are correlated to each of the three calculated metrics.

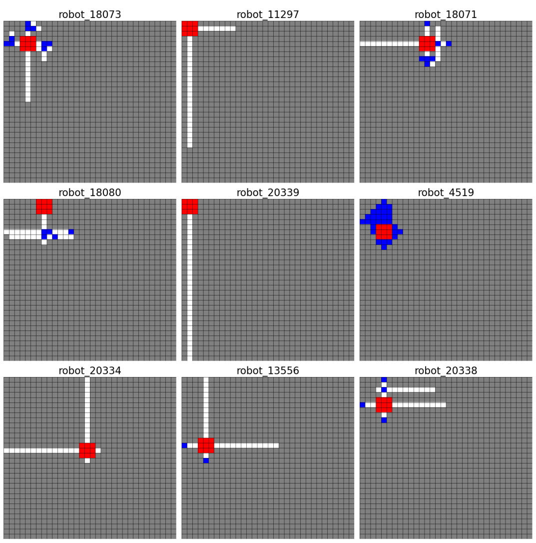


Fig. 8: Morphologies Selected From Population Size 10 Group

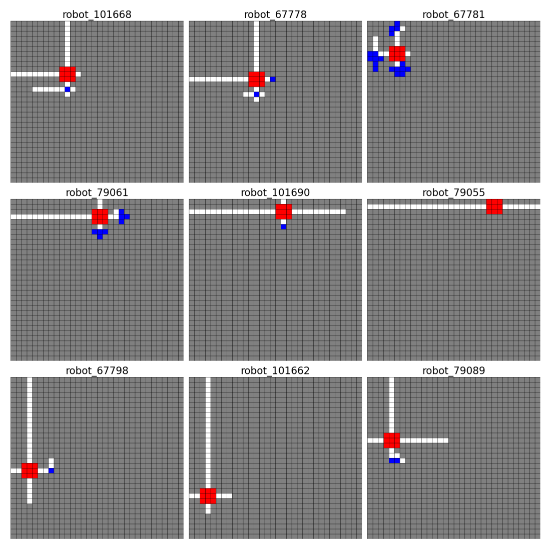


Fig. 9: Morphologies Selected From Population Size 50 Group

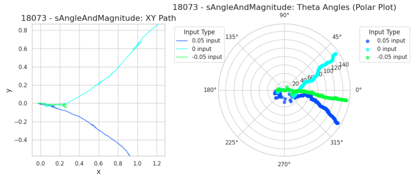
Following this the correlations between the morphological measures and the three metrics calculated per robot were computed. . The correlations between morphological measures and the calculated metrics input vs final X, Y, and θ are shown in TABLE I.

A. Analysis and Interpretation of Results

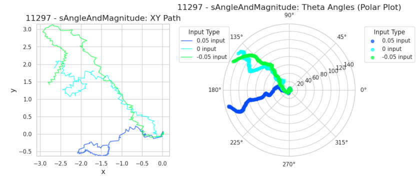
The results indicate that the sensory incorporation scheme has some success in controlling the robot's trajectories, although it is not completely clear when, why the sensory input steers the path left, right. The success can be inferred by analysing the cases where the path of the no sensory input case is bounded by paths of negative and positive sensory inputs. The paths and correlations demonstrated in Fig. 10, Fig. 12, and Fig. 11, Fig. 13 respectively.

The robots for which the input performed as expected from the individuals evolved with a population size of 10 were robot_20339, robot_20338, while from the individuals evolved with a population size of 50 only robot_79061 performed as expected.

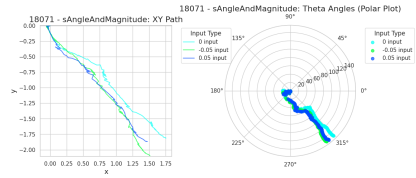
Interestingly robot_13556 demonstrated the expected behavior, with the caveat that the sensory input variables roles changed. Meaning that the effects of the negative and positive sensory inputs swapped, this may be an indication that symmetries in morphology play a role in determining what effect the sensory input has on the paths of robots, although further



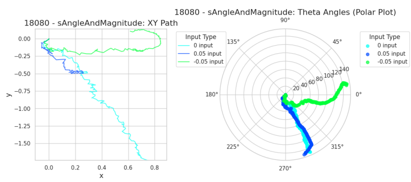
(a) robot_18073



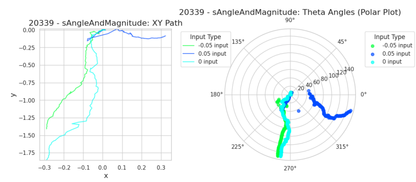
(b) robot_11297



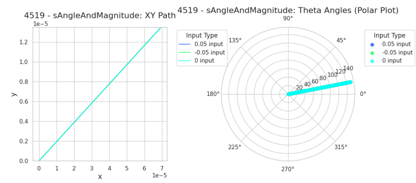
(c) robot_18071



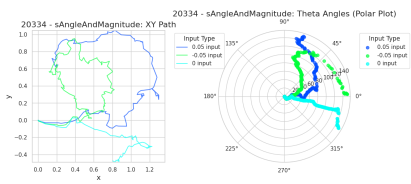
(d) robot_18080



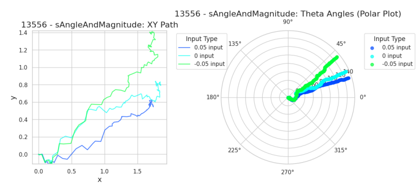
(e) robot_20339



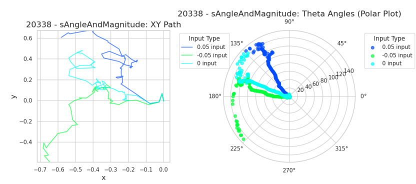
(f) robot_4519



(g) robot_20334



(h) robot_13556



(i) robot_20338

Fig. 10: Paths Taken, Movement Directions for the Robots Selected from the Populations Evolved with Population Size 10; Displayed in Fig. 8 Where the bright blue, green, dark blue lines represent the cases with no, negative, positive sensory input.

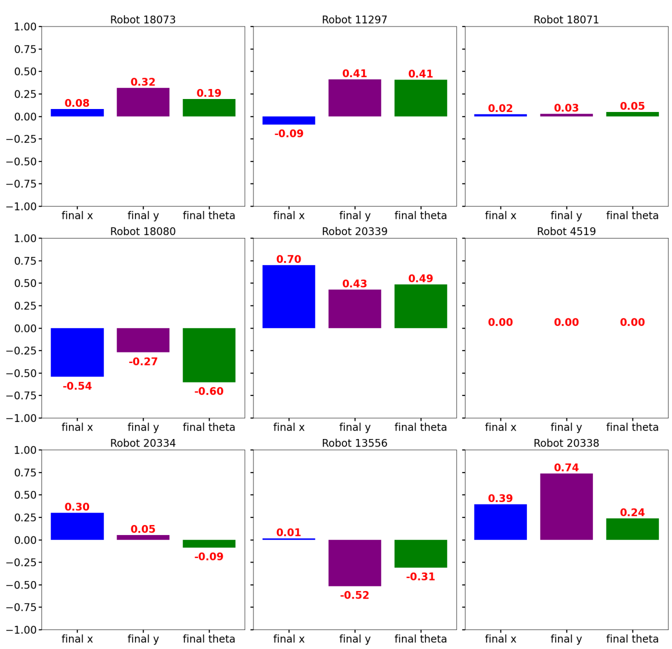


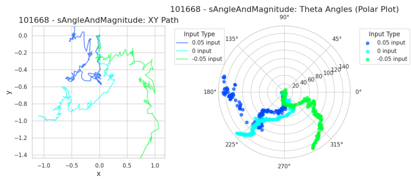
Fig. 11: Correlations for the Population Size 10 Group : Sensory Input vs Behavioural Measures

Morphological Measures	Final X	Final Y	Final θ
attachment_length_max vs	**0.8859**	0.2340	**0.5719**
attachment_length_mean vs	**0.7969**	0.3783	**0.5792**
attachment_length_std vs	-0.1223	-0.3345	-0.2987
joint_brick_ratio vs	0.4444	0.4147	0.0632
symmetry_incl_sum vs	-0.4396	0.0272	**-0.6077**
symmetry_excl_sum vs	**-0.6416**	-0.1788	**-0.6607**
coverage vs	0.2777	0.3490	0.3870
branching vs	**-0.7407**	0.4493	**-0.8044**
surface vs	0.1774	0.2956	0.3423

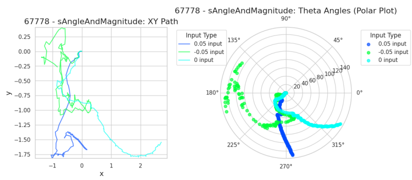
TABLE I: Correlation cascade analysis: the coefficients on the table show the correlation between the rows and the columns. The rows regard the values of the morphological traits, and the columns regard previously calculated correlations between the sensory input and a behavioral measure.

analysis is needed to claim this with certainty.

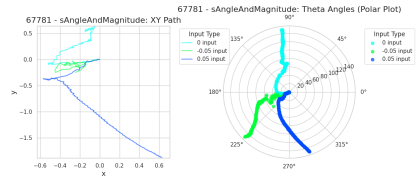
The large positive correlation between a morphological trait with respect to a correlation metric means that an individual for which that trait is prominent, the corresponding input vs final X, input vs final Y or input vs final θ is positive and large, and that an individual for which that trait has a low value, the corresponding correlation metric will be negative and large. Conversely a large negative correlation between a morphological trait with respect to a correlation metric means that an individual for which that trait is prominent, the corresponding input vs final X, input vs final Y or input vs final θ is negative and large, and that an individual for which that trait has a low value, the corresponding correlation metric will be positive and large. While a small correlation between a morphological measure and a correlation metric means that there is no obvious connection between the the morphological measure and the successful incorporation of sensory input into



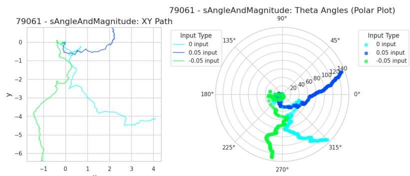
(a) `robot_101668`



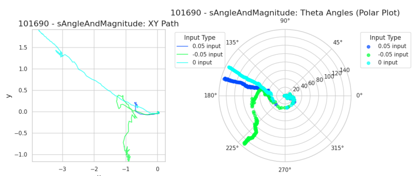
(b) `robot_67778`



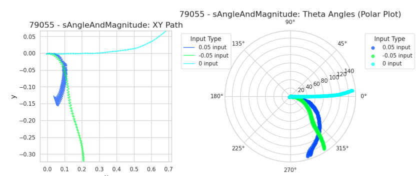
(c) `robot_67781`



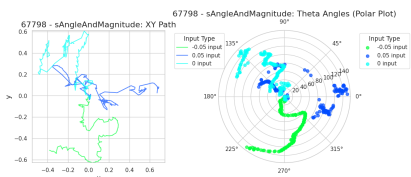
(d) `robot_79061`



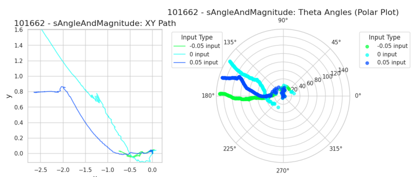
(e) `robot_101690`



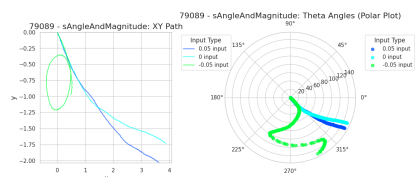
(f) `robot_79055`



(g) `robot_67798`



(h) `robot_101662`



(i) `robot_79089`

Fig. 12: Paths Taken, Movement Direction for the Robots Selected from the Populations Evolved with Population Size 50; Displayed in Fig. 8. Where the bright blue, green, dark blue lines represent the cases with no, negative, positive sensory input.

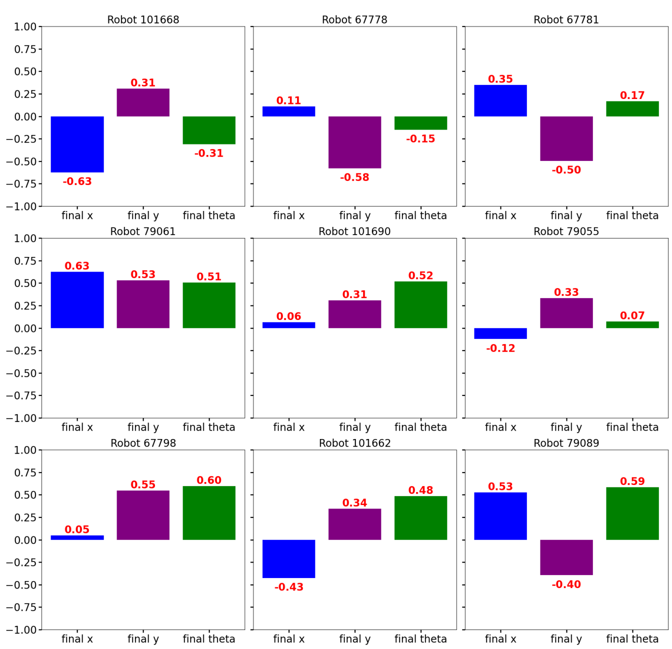


Fig. 13: Correlations for the Population Size 50 Group : Sensory Input vs Behavioural Measures

the robots.

The results of the complete sensory input testing scheme, shown in TABLE I point towards the conclusion that agents with long attachments depending on the sensory input (negative, or no) they receive, the final X coordinate can be predicted to a high degree. Symmetrical morphologies (without considering block attachment type) demonstrate a strong negative association with the final X, and final θ correlations. Branching has a very strong negative association with final X, and final θ correlations.

V. Discussion

The analysis conducted contains a limited number of agents due to the similarities in the evolved populations, hence individual successes of robots greatly influence the morphological correlations. Furthermore the fitness function used does reward any specific movement direction, therefore the control method of passing the sensory input to the first attachment of the core component may lead to different effects based on the initial direction in which the robot was evolved to move. Furthermore, the control scheme analysis might not completely capture the success of control.

VI. Conclusion

This paper demonstrates a method for creating artificial creatures. Furthermore we show the effectiveness of the CPG control scheme from the work produced by (Wang at al., 2014) extended by learnable connection weights between oscillators; establishing that a modular morphologies in combination with a CPG based control architecture initially developed for aquatic locomotion can produce varying gates on land as well.

The results of the experiments show that the control approach proposed functioned for four out of eighteen robots as intended, i.e. the trajectory with no sensory input was bounded by the trajectories with positive/negative sensory input, where the positive, negative signals corresponded to steering the robot left and right respectively. Moreover, for two robots the trajectories were bounded, however the role of positive, negative input switched and shifted the robots paths right and left respectively. The variability in the correlations between the sensory input type, and the paths indicate that the steering method is not equally viable for any robot, the morphological analysis demonstrates that the control scheme developed has a greater success for morphologies with specific traits, while performs less predictably for others. Illustrating that the proposed steering method does not function for all morphologies uniformly well.

From this we can conclude that although the control mechanism brought forth by this paper is promising -as it operated as intended for multiple morphologically unique robots- it does not function for arbitrary morphologies.

Future analyses relevant to this study may include researching the effect of the proposed sensory input versus the efficiency of movement, other behavioural measures, and researching the niches for which the developed control scheme may be applicable.

References

[1] Margulis, Lynn, Sagan, Carl, and Sagan, Dorion. "Life." *Encyclopedia Britannica*, 29 May 2024. Accessed 1 August 2024. [Online]. Available: https://www.britannica.com/science/life

[2] Benner S. A. (2010). Defining life. *Astrobiology*, 10(10), 1021–1030. https://doi.org/10.1089/ast.2010.0524

[3] Cohen, Avis and Boothe, David. "Sensorimotor Interactions During Locomotion: Principles Derived from Biological Systems." *Auton. Robots*, vol. 7, pp. 239-245, Nov. 1999. https://doi.org/10.1023/A:1008920420634

[4] S. Doncieux, N. Bredeche, J.-B. Mouret, and A.E. Eiben. "Evolutionary robotics: what, why, and where to." *Frontiers in Robotics and AI*, vol. 2, no. 4, 2015. https://doi.org/10.3389/frobt.2015.00004

[5] Nygaard, T. F., Martin, C. P., Howard, D., Torresen, J., and Glette, K. "Environmental Adaptation of Robot Morphology and Control Through Real-World Evolution." *Evolutionary Computation*, vol. 29, no. 4, pp. 441-461, Dec. 2021. https://doi.org/10.1162/evco_a_00291

[6] Sims, Karl. "Evolving virtual creatures." In *Proceedings of the 21st Annual Conference on Computer Graphics and Interactive Techniques*, 1994, pp. 15-22. https://doi.org/10.1145/192161.192167

[7] J. Bongard. "Evolving modular genetic regulatory networks." *Proceedings of the 2002 Congress on Evolutionary Computation. CEC'02 (Cat. No.02TH8600)*, Honolulu, HI, USA, 2002, pp. 1872-1877 vol.2. https://doi.org/10.1109/CEC.2002.1004528

[8] Ijspeert, Auke Jan. "Central pattern generators for locomotion control in animals and robots: A review." *Neural Networks*, vol. 21, no. 4, pp. 642-653, 2008. https://doi.org/10.1016/j.neunet.2008.03.014

[9] Wang, Ming, Yu, Junzhi, and Tan, M. "CPG-based Sensory Feedback Control for Bio-inspired Multimodal Swimming." *International Journal of Advanced Robotic Systems*, vol. 11, 2014. https://doi.org/10.5772/59186

[10] Luo, Jie, Miras, Karine, Tomczak, Jakub, and Eiben, A. "Enhancing robot evolution through Lamarckian principles." *Scientific Reports*, vol. 13, Nov. 2023. https://doi.org/10.1038/s41598-023-48338-4

[11] Bucher, Dirk, Haspel, Gal, Golowasch, Jorge, and Nadim, Farzan. "Central Pattern Generators." In *Encyclopedia of Neuroscience*, Nov. 2015. https://doi.org/10.1002/9780470015902.a0000032.pub2

[12] Pearson, K. G. "Central Pattern Generation: A Concept Under Scrutiny." In H. McLennan, J. R. Ledsome, C. H. S. McIntosh, and D. R. Jones (Eds.), *Advances in Physiological Research*, pp. 167-185, Springer US, 1987. https://doi.org/10.1007/978-1-4615-9492-5_10

[13] Chrachri A, Clarac F. "Synaptic connections between motor neurons and interneurons in the fourth thoracic ganglion of the crayfish, Procambarus clarkii." *J Neurophysiol.*, vol. 62, no. 6, pp. 1237-50, Dec. 1989. https://doi.org/10.1152/jn.1989.62.6.1237

[14] Ayers, J. "Neuronal Oscillators." In *The Clinical Neurosciences*, vol. 5, pp. 203-266, 1983.

[15] Smith JC, Feldman JL. "In vitro brainstem-spinal cord preparations for study of motor systems for mammalian respiration and locomotion." *J Neurosci Methods.*, vol. 21, no. 2-4, pp. 321-33, Oct. 1987. https://doi.org/10.1016/0165-0270(87)90126-9

[16] Shik ML, Severin FV, Orlovskiĭ GN. "Upravlenie khod'boĭ i begom posredstvom elektricheskoĭ stimulatsii srednego mozga [Control of walking and running by means of electric stimulation of the midbrain]." *Biofizika.*, vol. 11, no. 4, pp. 659-66, 1966. Russian.

[17] Jordan, L.M. "Initiation of Locomotion from the Mammalian Brainstem." In S. Grillner, P.S.G. Stein, D.G. Stuart, H. Forssberg, R.M. Herman (Eds.), *Neurobiology of Vertebrate Locomotion*, pp. 203-266, Wenner-Gren Center International Symposium Series, Palgrave Macmillan, London, 1986. https://doi.org/10.1007/978-1-349-09148-5_2

[18] Danner, Simon, Hofstoetter, Ursula, Freundl, Brigitta, Binder, Heinrich, Mayr, Winfried, Rattay, Frank, and Minassian, Karen. "Human spinal locomotor control is based on flexibly organized burst generators." *Brain*, vol. 138, pp. 577-588, Mar. 2015. https://doi.org/10.1093/brain/awu372

[19] Hodgkin, A. L., and Huxley, A. F. "A quantitative description of membrane current and its application to conduction and excitation in nerve." *The Journal of physiology*, vol. 117, no. 4, pp. 500–544, 1952. https://doi.org/10.1113/jphysiol.1952.sp004764

[20] Conradt, Jorg. "Distributed Central Pattern Generator Control for a Serpentine Robot." *Autonomous Robots*, vol. 5, Mar. 2004.

[21] Westphal, A. "Controlling a lamprey-based robot with an electronic nervous system." Doctoral dissertation, Northeastern University, 2013.

[22] Stein, W. "Sensory Input to Central Pattern Generators." In D. Jaeger, R. Jung (Eds.), *Encyclopedia of Computational Neuroscience*, Springer, New York, NY, 2014. https://doi.org/10.1007/978-1-4614-7320-6_465-3

[23] Pearson, K.G. "Generating the walking gait: role of sensory feedback." *Prog Brain Res.*, vol. 143, pp. 123-9, 2004. https://doi.org/10.1016/S0079-6123(03)43012-4

[24] Wolf, Harald. "The Locust Tegula: Significance for Flight Rhythm Generation, Wing Movement Control and Aerodynamic Force Production." *J Exp Biol*, vol. 182, no. 1, pp. 229–253, Sep. 1993. https://doi.org/10.1242/jeb.182.1.229

[25] Suster ML, Bate M. "Embryonic assembly of a central pattern generator without sensory input." *Nature*, vol. 416, no. 6877, pp. 174-8, Mar. 2002. https://doi.org/10.1038/416174a

[26] Rossignol S, Frigon A. "Recovery of locomotion after spinal cord injury: some facts and mechanisms." *Annu Rev Neurosci.*, vol. 34, pp. 413-40, 2011. https://doi.org/10.1146/annurev-neuro-061010-113746

[27] Fujita, M., and Kitano, H. "Development of an autonomous quadruped robot for robot entertainment." *Autonomous Robots*, vol. 5, pp. 7-18, 1998.

[28] Billard, A., and Ijspeert, A. J. "Biologically inspired neural controllers for motor control in a quadruped robot." *Proceedings of the IEEE-INNS-ENNS International Joint Conference on Neural Networks. IJCNN 2000. Neural Computing: New Challenges and Perspectives for the New Millennium*, Como, Italy, 2000, pp. 637-641 vol.6. https://doi.org/10.1109/IJCNN.2000.859467

[29] Hopfield, J. J. "Neurons with graded response have collective computational properties like those of two-state neurons." *Proceedings of the national academy of sciences*, vol. 81, no. 10, pp. 3088-3092, 1984.

[30] Crespi, A., Lachat, D., Pasquier, A., and Ijspeert, A. J. "Controlling swimming and crawling in a fish robot using a central pattern generator." *Auton Robot*, vol. 25, pp. 3–13, 2008. https://doi.org/10.1007/s10514-007-9071-6

[31] Auerbach, Joshua, Aydin, Deniz, Maesani, Andrea, Kornatowski, Przemyslaw, Cieslewski, Titus, Heitz, Grégoire, Fernando, Pradeep, Loshchilov, Ilya, Daler, Ludovic, and Floreano, Dario. "RoboGen: Robot Generation through Artificial Evolution." *Proceedings of the 2014 Conference on Genetic and Evolutionary Computation*, pp. 136-137, Jul. 2014. https://doi.org/10.7551/978-0-262-32621-6-ch022

[32] Stanley, Kenneth O. "Compositional pattern producing networks: A novel abstraction of development." *Genetic Programming and Evolvable Machines*, vol. 8, no. 2, pp. 131–162, Jun. 2007. https://doi.org/10.1007/s10710-007-9028-8

[33] Lan, Gongjin, De Carlo, Matteo, van Diggelen, Fuda, Tomczak, Jakub M., Roijers, Diederik M., and Eiben, A.E. "Learning directed locomotion in modular robots with evolvable morphologies." *Applied Soft Computing*, vol. 111, p. 107688, 2021. https://doi.org/10.1016/j.asoc.2021.107688

[34] Strogatz, S. "Nonlinear Dynamics and Chaos." Reading, MA: Addison-Wesley, 1994. ISBN: 9780201543445.

[35] Rebolledo, Margarita, Zeeuwe, Daan, Bartz-Beielstein, Thomas, and Eiben, A.E. "Co-optimizing for task performance and energy efficiency in evolvable robots." *Engineering Applications of Artificial Intelligence*, vol. 113, p. 104968, 2022. https://doi.org/10.1016/j.engappai.2022.104968

[36] Garcia-Saura, Carlos. *Central pattern generators for the control of robotic systems*. arXiv preprint arXiv:1509.02417, 2015. https://arxiv.org/abs/1509.02417