Adaptive Dynamic control of Quadrupedal Robotic Gaits with Artificial Reaction Networks

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Abstract. The Artificial Reaction Network (ARN) is a bio-inspired connectionist paradigm based on the emerging field of Cellular Intelligence. It has properties in common with both AI and Systems Biology techniques including Artificial Neural Networks, Petri Nets, and S-Systems. In this paper, properties of temporal dynamics and pattern recognition are combined within a single ARN control system for a quadrupedal robot. The results show that the ARN has similar applicability to Artificial Neural Network models in robotic control tasks. In comparison to neural Central Pattern Generator models, the ARN can control gaits and offer reduced complexity. Furthermore, the results show that like spiky neural models, the ARN can combine pattern recognition and control functionality in a single network.

Keywords: Artificial Neural Networks, Artificial Reaction Networks, Cellular Intelligence, Biochemical Networks

1 Introduction

Researchers have become increasingly interested in the array of complex behaviors displayed by the simple, commonly unicellular organisms called protists. Some can avoid light with photo-sensitive spots; some actively hunt prey; while others can build protective shelters [1]. Such complex behaviors have led researchers to investigate how such traits of primitive intelligence might arise. Well known examples of such work are that by Nakagaki and Yamada, who demonstrated that the slime-mould *Physarum polycephalum* was able to solve a simple maze [2]. Similar research by Saigusa et al showed that this same organism was able to learn and change its behavior in anticipation of the next environmental stimuli [3]. These high level behaviors are mediated by Cell Signaling Networks (CSNs) [4]. Such networks are composed of interacting proteins within the cell's cytoplasm. Several researchers have highlighted the processing capabilities of these networks and similarities between Artificial Neural Networks (ANNs) [4-8]. For example, it has been demonstrated that such networks can perform Boolean and fuzzy logic and are equivalent to a Turing machine. Furthermore CSNs contain topological features such as feedback loops and interconnectivity, thus forming highly complex systems [9].

The overall aim of our research is twofold. Firstly, to continue exploration of our previously developed connectionist representation of CSNs- the Artificial Reaction Network (ARN) [10], in terms of its possible application in AI. Secondly, to investigate and elucidate mechanisms that contribute to high level behavior or "cell intelligence", which may help in the understanding of intelligence in its widest sense.

This paper investigates the ability, of the ARN like a CSN, to combine pattern recognition and control within a single networked system. A complete control system for a quadrupedal robot is explored, where the ARN responds dynamically to input patterns by generating the associated temporal pattern or "gait". The results are compared with those of similar Artificial Neural Network (ANN) models.

The paper is structured as follows: the first section provides an overview of the ARN representation; this is followed by experimental details and results, and finally conclusions.

1.1 The Artificial Reaction Network Representation

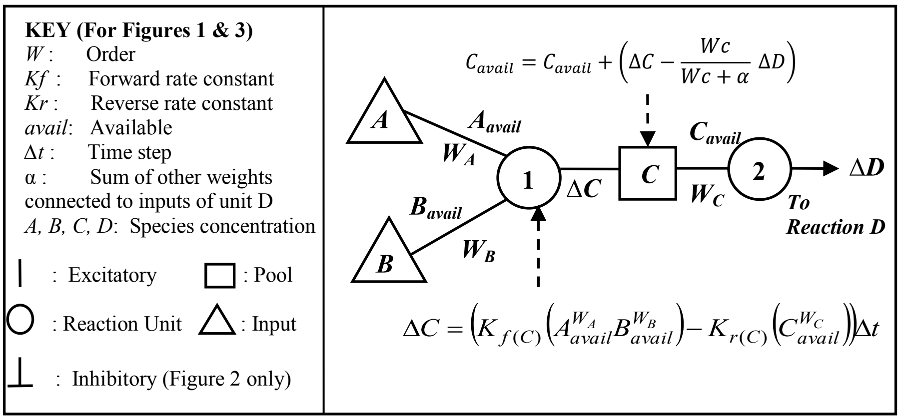

Fig. 1. The Artificial Reaction Network (ARN)

A brief summary of the ARN model is given below. A full account is provided in our previous paper [10]. The ARN, as shown in Figure 1, is a connectionist representation of a CSN, and is structured in a similar way to an ANN. It comprises a set of connected reaction nodes (circles), pools (squares), and inputs (triangles). The inputs are external and constant, each pool represents the current available protein species concentration (avail) and each circle corresponds to a reaction unit, representing an interaction (reaction) between a number of proteins. Figure 1 shows the reaction between species A and B to produce species C. Connections symbolize the flow of species into and out of reaction units and their weight (w) corresponds to reaction order. Flux ($\Delta A/\Delta B/\Delta C$) at Δt is given by Equation (1). This is derived from the standard Rate Law equation [11], and is equal to the aggregate of connected incoming pools and connected outgoing pools raised to n powers of weighted connections and multiplied by rate constants. At time interval Δt, each reaction unit's temporal flux value is calculated using Euler's approximation as shown in Equation 1. This value is then used to update the current concentration of each reaction's connecting pools. Thus, the complete set of pool concentrations at time t, corresponds to the current state of the system.

$$\Delta C = \left(K_{f(C)}\left(A_{avail}^{W_A} B_{avail}^{W_B}\right) - K_{r(C)}\left(C_{avail}^{W_C}\right)\right)\Delta t \quad \textbf{(1)}$$

Where:

A, B, C = Species Concentrations W = reaction order (weight)
avail = available species concentration K_f = Forward rate constant
ΔC = Change in species concentration C K_r = Reverse rate constant

2 A Complete ARN System for Robotic Control

By means of their CSNs, cells are able to dynamically recognize and respond to environmental patterns [4]. The response is to update the spacio-temporal activations of intracellular species, which in turn encode the high level behavior of the cell [4, 8]. In the following experiments the computational properties and AI applications of such behaviors are explored using a quadrupedal robot.

A single ARN system was created, as shown in Figure 2 and is functionally divided into 3 components: pattern recognition, control, and a connecting network. This section first discusses the setup, function, and results of each component separately before providing the results for the overall system.

2.1 Control Component

The control component is responsible for generating particular temporal patterns, which correspond to robotic gaits. Terrestrial locomotion of limbed animals is achieved by multiple phase locked patterns of limb movements known as gaits. For example, quadrupeds commonly walk, trot and gallop [12]. The gait phase is a value that ranges from 0 to 1 as the cycle proceeds, and thus each limb can be described relative to the cycle. The ideal quadrupedal gaits are described by Dagg [12] and others [13], and are used as a standard for comparison here and similarly in other studies [14]. The walk gait is characterized where each leg is a quarter cycle out of phase with each other. In the trot gait each pair of diagonal limbs move half a cycle out of phase with one another. Here, the ARN control component was implemented, to generate the trot and walk gaits of a Lynxsmotion dual-servo quadruped 2 (Q2) robot. Each robotic leg is controlled by two servo motors, one for each degree of freedom (DOF), where one raises the leg, the other moves it. Further details of the robot legs are given by Toth and Parker [15]. Signals are sent by the ARN to each motor and control the angle of the rotor for each DOF, using a simple position to pulse width modulator interface circuit to control the servo. The ARN control component is shown in Figure 2 and consists of two copies of the same network- one for walk, the other for trot (each labeled). It comprises four identical modules (one module is shown enclosed in a dotted line), where each controls the two motors (one for each DOF) of a separate leg.

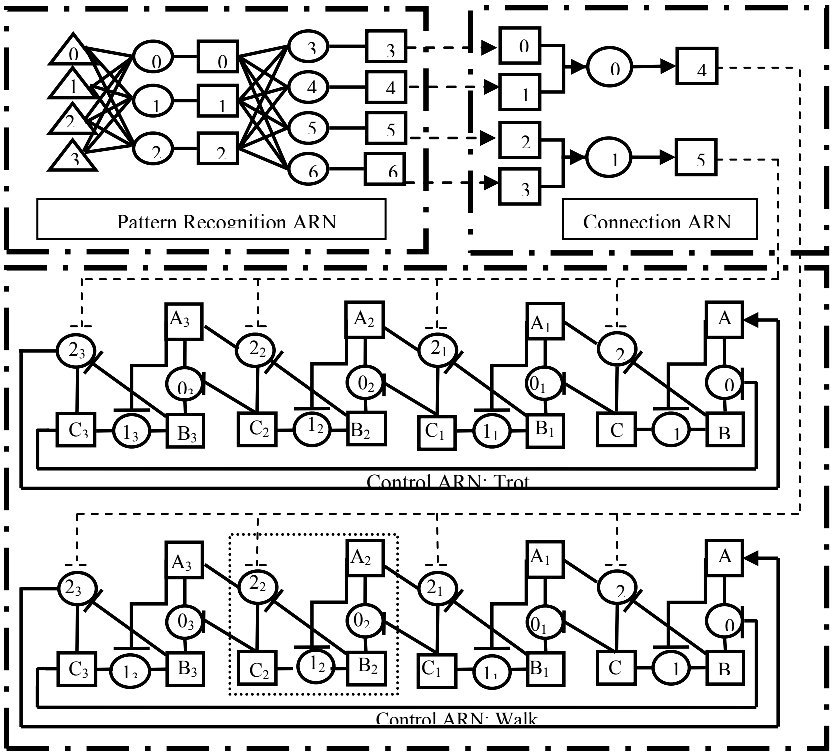

Fig. 2. The complete ARN control system comprising 3 smaller network components: Pattern recognition, Connection and Control.

A module comprises 3 reaction units, and 3 pools: A, B and C. Pool A controls the up/down (U/D) motor, Pool B the back/forward (B/F) motor and Pool C controls the off period for both motors. Pool activity is regulated by a series of excitatory and inhibitory connections between reaction units and represents properties of specialized regulatory proteins common to CSNs such as enzymes. The entire structure is organized as a closed loop, thus chemical species are recycled to the first module, and generate a temporal oscillatory pattern. The network structure and parameters were hardcoded so that the outputs could be directly compared with other published work on similar Central Pattern Generators (CPGs). However, there is no reason why connection weights cannot be set using an Evolutionary Algorithms as will be shown later. The gait produced by this network is modified by adjustment of the initial pool values. For example, initializing one C pool generates a walk gait, where the C pool chosen will determine the starting leg, and the value determines the angle to which the leg is raised (the DOF angle). Similarly, a trot gait is achieved by initializing 2 C pools within alternate modules. The output for the walk subunit is displayed in Figure 3, and shows legs are a quarter cycle out of turn, with phases of 0.0, 0.25, 0.5, 0.75 between limbs in clockwise order from front left (FL) leg. Similarly, the trot gait results were half a cycle out of turn with phases respectively of 0.0, 0.5, 0.0, 0.5. Both phase locked limb patterns match the standard, and compare well with other connectionist models. For example, Billard and Ijspeert present a CPG (central pattern generator) based neural controller for a quadrupedal AIBO robot with 2 DOFs for each leg [16]. The network is composed of 8 coupled non-linear oscillators and each oscillator consists of 6 leaky integrator neurons (total of 96 neurons). Each neuron implements an activation approximately as complex as the ARN reaction unit function. Thus the complexity of this network is equivalent to approximately 96 ARN reaction units. Similar correspondence is found in other sources. For instance, Collins explores a CPG based neural controller for a quadrupedal robot with 1 DOF per limb, and compares 3 types of activation function models. The controller is composed of a network of 4 coupled non-linear oscillators [14], where each oscillator controls a separate limb. These models produce gaits within 10% of the standard, whereas the ARN matches the standard for both gaits. Each model has approximately twice the complexity as the ARN reaction unit, and all require a pulsing signal to drive the network.

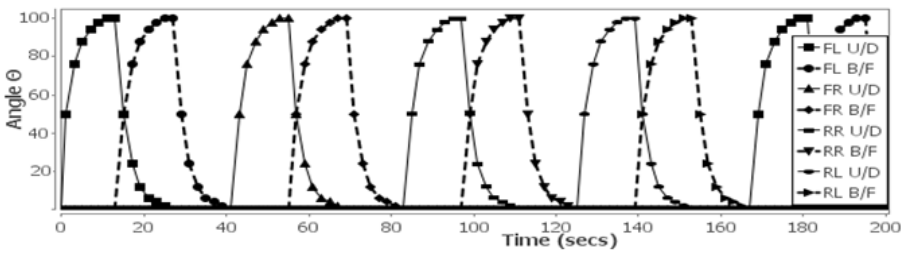

Fig. 3. Output generated by ARN controller for walk gait. Solid lines are legs up/down motor, dashed lines are back/forward motor. Legs move independently in order: FL, FR, RR, RL.

2.2 Pattern Recognition Component

The pattern recognition component serves as the interface between the environment and the ARN system. Here external concentrations are processed, where particular patterns switch off or on robotic gaits through the connecting network. The network was trained to recognize 3 patterns, each comprising 4 inputs (triangles 0-3) and these were associated with 4 output values. Each pattern comprised values of either 0.1, representing low concentration or 1 corresponding to high concentration. This component (shown in Figure 2) consists of 4 inputs, 7 pools, and 7 reaction units organized into 2 layers. The associated output generated corresponds to the steady state values of the final layer of pools (squares 3-6). The input and associated output patterns are given in Table 1. A genetic algorithm (GA) was used to train the network to associate the required outputs before being connected to the other components. In this GA a population of 100 solutions was randomly initialized, where each comprised a complete set of network parameters including the forward and reverse rates for each unit and the weights for each connection. Due to its temporal properties, the network was run for 100 cycles (a cycle ends when the complete set of pools are updated once) in order to obtain steady state output values. The solution fitness was then calculated, where fitness was the error on output. The least fit half of the population was discarded, and the remainder was subject to rates of 0.4 single point crossover and 10% uniform mutation and trained to the target error value of 0.01. On completion of training, the network was able to associate all 3 patterns within the target error. Although there is not room for a full comparison, multilayer perceptron ANNs (MLPs) [17] produce comparable results. However, MLPs lack an explicit time dimension, whereas the ARN processes continuous inputs over a time period.

Table 1. Patterns applied to the pattern recognition network and their outputs (output is the input to connection component). Connection component output and expected gait generated.

Pattern	Pattern Recognition Network Input Pool No.	Pattern Recognition Network Input Value	Connection Network Input Pool No.	Connection Network Input Value (also output of the pattern ecognition network)	Connection Network Output Pool No.	Connection Network Output Value	Gait
1	0	1	0	1	4	1	Inhibit Walk
	1	0.1	1	1			
	2	1	2	0	5	0	Trot
	3	0.1	3	0			
2	0	0.1	0	0	4	0	Walk
	1	1	1	0			
	2	0.1	2	1	5	1	Inhibit Trot
	3	1	3	1			
3	0	1	0	1	4	1	Inhibit Walk
	1	0.1	1	1			
	2	0.1	2	1	5	1	Inhibit Trot
	3	1	3	1			

2.3 Connection Component and Results for the Complete System

The connecting module functions to process the output from the pattern recognition network, and produce a signal which switches off/on the required gait. This module comprises 6 pools and 2 reaction units, as shown in Figure 2. Each input (pools 0-3), is linked directly to a corresponding output pool of the pattern recognition network (pools 3-6). Essentially the network operates as two parallel Boolean AND gaits, where a value of 1 at pools 0 and pool 1 outputs a value of 1 at pool 4, as will a value of 1 at pools 2 and 3 output a 1 at pool 5.

Table 2. Pattern applied to the network and expected durations of gaits.

Pattern	Walk ARN Network	Trot ARN Network	Start Time	End Time	Duration
2	On	Off	0	210	210
1	Off	On	210	440	230
2	On	Off	440	560	120
1	Off	On	560	700	140
3	Off	Off	700	800	100

Two negative feedback connections between the connecting network and both ARN control system sub units (shown as dashed line connections) are responsible for switching between the gaits. Therefore if a value of 1 is output at pool 4, it will inhibit all the reaction 2's of the ARN trot subunit, thus stopping the trot gait from being generated. Conversely if a value of 0 is output at pool 4 the trot will be generated. In the same way pool 5 controls the switching on/off of the walk control subunit. Table 1 shows the input, and associated output of this component and the range of behaviors that should be generated in response to particular outputs. The complete system was tested to confirm its ability to both generate the correct behavior and automatically transition between the behaviors in response to firing input patterns 0-3. The time periods in which patterns were applied, and the expected output states are shown in Table 2. As shown in Figure 4 the on/off periods of both trot and walk gaits are in agreement with the expected durations displayed in Table 2 with a slight transitional delay, in order: walk, trot, walk, trot, off. The gait transitions are now compared with the same models used to compare the ARN controller, and gait phases in section 2.1. The results given for the Billard and Ijspeert model [16], show smooth transitions from walk to gallop in approximately 4 leg cycles. The ARN similarly transitions from walk to trot smoothly within 1 leg cycle. In the Collins paper [14], gaits transition quickly within approximately 2 leg cycles, whereas the transitions are very irregular in contrast to the ARN and the Billard and Ijspeert model.

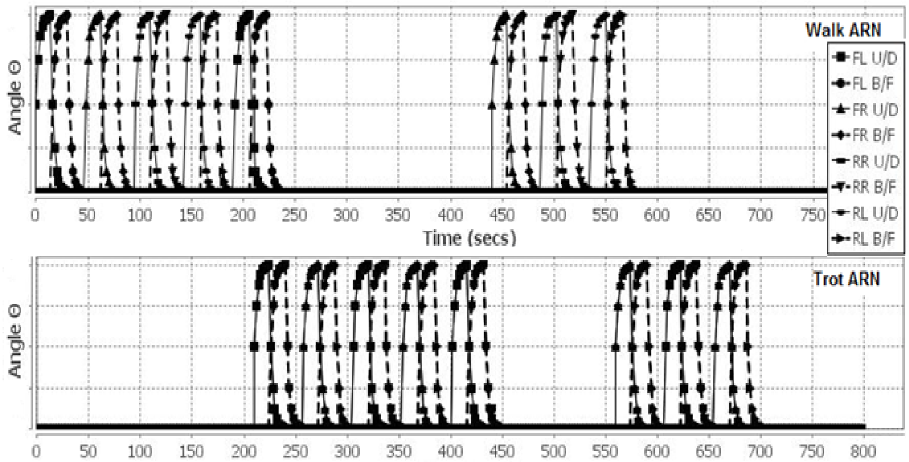

Fig. 4. The output of the complete ARN control system over 800 seconds.

3 Conclusions

The ARN is a bio-inspired connectionist representation based on properties and mechanisms found in CSNs that together result in emergent behavior or “cell intelligence”. A complete ARN based control system was constructed to dynamically respond to external patterns, where each pattern triggers a specific gait of a quadrupedal robot. This system was designed to exploit topological features found in CSNs including negative feedback, and cycles. It was demonstrated that the ARN, like a CSN, is capable of both recognizing patterns and controlling overall behavior in a single network. With the exception of spiky models few ANNs can easily achieve this functionality, and thus the ARN provides an alternative in similar applications. The gait phases and transitions compared well with CPG neural controllers and showed that the ARN has application in similar robotic control tasks where it can offer lower computationally complexity. These experiments illustrate how a CSN might perform the complex processing associated with the high level behaviors displayed by single celled organisms. Furthermore it shows that abstractions of both neural networks and CSNs operate in similar ways, and have comparable functionality. Thus this work illustrates a close relationship between emergent neural intelligence and emergent cell intelligence.

In future work, it is intended to further explore the AI applications of the ARN, including more complex networks that can recognize patterns and control simultaneous behaviors.

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