This is a repository copy of *Evolutionary acquisition of complex traits in artificial epigenetic networks*.

White Rose Research Online URL for this paper:
http://eprints.whiterose.ac.uk/140924/

Version: Published Version

**Article:**
Turner, Alexander, Tyrrell, Andrew Martin orcid.org/0000-0002-8533-2404, Trefzer, Martin Albrecht orcid.org/0000-0002-6196-6832 et al. (1 more author) (2019) Evolutionary acquisition of complex traits in artificial epigenetic networks. Biosystems. pp. 17-26. ISSN 0303-2647

https://doi.org/10.1016/j.biosystems.2018.12.001

---

**Reuse**
This article is distributed under the terms of the Creative Commons Attribution (CC BY) licence. This licence allows you to distribute, remix, tweak, and build upon the work, even commercially, as long as you credit the authors for the original work. More information and the full terms of the licence here:
https://creativecommons.org/licenses/

**Takedown**
If you consider content in White Rose Research Online to be in breach of UK law, please notify us by emailing eprints@whiterose.ac.uk including the URL of the record and the reason for the withdrawal request.
Evolutionary acquisition of complex traits in artificial epigenetic networks

Alexander Turner\(^a\)*, Andy Tyrrell\(^b\), Martin Trefzer\(^b\), Michael Lones\(^c\)

\(^a\) Department of Computer Science, University of Hull, UK
\(^b\) Department of Electronic Engineering, University of York, UK
\(^c\) School of Mathematical and Computer Sciences, Heriot-Watt University, UK

**Abstract**

How complex traits arise within organisms over evolutionary time is an important question that has relevance both to the understanding of biological systems and to the design of bio-inspired computing systems. This paper investigates the process of acquiring complex traits within epiNet, a recurrent connectionist architecture capable of adapting its topology during execution. Inspired by the biological processes of gene regulation and epigenetics, epiNet captures biological organisms’ ability to alter their regulatory topologies according to environmental stimulus. By applying epiNet to a series of computational tasks, each requiring a range of complex behaviours to solve, and capturing the evolutionary process in detail, we can show not only how the physical structure of epiNet changed when acquiring complex traits, but also how these changes in physical structure affected its dynamic behaviour. This is facilitated by using a lightweight optimisation method which makes minor iterative changes to the network structure so that when complex traits emerge for the first time, a direct lineage can be observed describing exactly how they evolved. From this we can build an understanding of how complex traits evolve and which regulatory environments best allow for the emergence of these complex traits, pointing us towards computational models that allow more swift and robust acquisition of complex traits when optimised in an evolutionary computing setting.

1. Introduction

Genetic networks are the fundamental systems through which biological cells regulate their function and development, and this realisation has promoted a sustained effort to understand genetic networks through computational modelling and simulation (Hasty et al., 2001; De Jong, 2002; Hecker et al., 2009; Chen et al., 2010; Le Novère, 2015; Akutsu, 2016). Genetic networks can be modelled in various ways, depending on how the model is to be used. For example, Boolean networks (Albert and Thakar, 2014) are a popular formalism for capturing the qualitative dynamics of genetic networks, and continuous-valued models such as recurrent neural networks (Ling et al., 2013) and systems of differential equations (Le Novère, 2015) provide greater insight into quantitative dynamics. Regulatory interactions happen at various spatial and temporal scales within genetic networks, for instance transcription pre-initiation, transcript elongation and RNA interference (Duncan et al., 2014). In all these models, a genetic network is represented as a graph. This gives them sufficient generality to capture most of these regulatory processes. However, they do assume that the structure of the graph remains fixed, and consequently cannot model regulatory processes that change the underlying topology of the genetic network.

An example of such a process, which we consider in this paper, is chromatin remodelling (Narlikar et al., 2013; Lorch and Kornberg, 2015; Zaret and Mango, 2016; Adam and Fuchs, 2016), an epigenetic process that regulates physical access to the genes, and in doing so effectively modifies the topology by turning on and off different parts of the genetic network. The important role that chromatin remodelling, and epigenetic processes more generally, play within biological systems has become increasingly apparent over the last decade (Duncan et al., 2014; Koster et al., 2015). It is known, for instance, that chromatin remodelling is central to the process of cellular differentiation (Kurimoto et al., 2015; Adam and Fuchs, 2016), and hence to the development of multicellular organisms. More generally, epigenetic processes are instrumental for the evolutionary acquisition of complex traits (True et al., 2004; Petronis, 2010). However, exactly how cell fates and complex traits are acquired remains unclear (Adam and Fuchs, 2016), suggesting a need for computational models that can capture and simulate the interplay between epigenetic processes and genetic networks.

Despite some recent progress (Zentner and Henikoff, 2014), experimental data regarding the chromatin dynamics of cells remains

---

* Corresponding author.

**E-mail address:** alexander.turner@hull.ac.uk (A. Turner).

https://doi.org/10.1016/j.biosystems.2018.12.001

Received 16 May 2018; Received in revised form 30 November 2018; Accepted 3 December 2018

Available online 14 December 2018

0303-2647/ © 2018 The Authors. Published by Elsevier B.V. This is an open access article under the CC BY license (http://creativecommons.org/licenses/by/4.0/).
relatively sparse, of low temporal resolution, and challenging to link to other transcriptional dynamics data (Coulon et al., 2013). This limits the potential for building, and hence studying, models of particular epigenetic circuits. As an alternative approach, we might look to previous work on modelling genetic networks, where significant understanding has come about through consideration of their dynamics at a more abstract systems level, rather than through the study of specific genetic circuits (Albert and Thakar, 2014; Abou-Jaoudé et al., 2016). For example, work on the dynamics of random Boolean networks has given insight into the nature of the dynamical states that correspond to stable cell types (Huang et al., 2005, 2009). Given the development of suitable models at the epigenetic level, it is conceivable that similar studies could lead to insights into the role of epigenetic processes within the dynamics of genetic networks (Bull, 2012, 2014).

However, a limitation of abstract systems-level studies is the absence of realistic evolutionary pressure driving the need to acquire complex traits. To address this, we consider another group of modelling approaches which take a quite different approach, using evolutionary algorithms (or other metaheuristics) to optimise genetic network models so that they carry out designated computational behaviours (Banzhaf, 2003; Lones, 2016). These behaviours vary from the relatively simple, such as the implementation of logic functions (Bull and Preen, 2009), to computationally challenging, such as controlling the movements of robots through complex environments (Taylor, 2004; Trefzer et al., 2010; Joachimczak et al., 2012; Fuente et al., 2013; Sanchez and Cussat-Blanc, 2014). Problems such as the latter require the evolution of behaviours such as homeostatic control and robust pattern generation, i.e. the same kind of traits that have been acquired by biological systems. In general, these models have had a more significant focus on artificial intelligence where the emphasis is on understanding or instigating the emergence of complexity in computational systems. The genetic network models optimised by these approaches are available for full inspection, and it is also possible to record and inspect a complete phylogenetic tree, showing exactly when and how adaptive traits were acquired. This makes them potentially very useful in the study of how complexity emerges in biological systems.

In this work, we consider how higher order structures can be used in the acquisition of complex traits in computational models for problem solving. In particular, we use an artificial epigenetic network called epiNet (Turner et al., 2015), which allows modification of the genetic network’s topology through a mechanism inspired by chromatin remodelling. Using a simple evolutionary algorithm, we study the evolution of this model’s genetic and epigenetic elements when exposed to selective pressure. Selective pressure, in this case, is induced by selecting model instances based on their ability to solve a series of artificial problems that require the model to acquire complex traits such as maintaining homeostasis, orchestrating a series of changes in a complex environment, and robustly generating patterns at the same time. This work has its roots in computational and engineering problems, it serves to provide an understanding of why computational analogues of epigenetic structures can be useful from these perspectives. By showing this, and how epigenetic structures optimise themselves, the hope is that tools such as this can be used in future work to better understand both computational systems and the biological systems by which they were inspired.

The paper is organised as follows: Sections 2–4 cover relevant material on genetic networks, chromatin remodelling and the EpiNet architecture. Section 5 describes the optimisation algorithm and the computational tasks. Section 6 presents results and discussion. Section 7 concludes.

2. Background

The majority of genes encode messenger RNA, which in turn describes the amino-acid sequences of proteins in biological organisms. In this sense, a gene can be considered a section of DNA used to code for a biological molecule which has a particular function (Turner, 2008). In order for gene expression to occur, a gene has to be transcribed and translated using a cell’s processing machinery. This processing machinery is the functional product of other genes within the cell; hence, the genes form regulatory networks, regulating one another’s expression. These genetic networks exist over many scales, from self-contained regulatory processes such as the lac operon to organism wide networks governing the activity and development of the entire organism (Göndör, 2016).

A genetic network can be seen as a graph, comprising a set of connected nodes where each connection has a weight used to define the strength of regulation that one node has upon another. Genetic networks are often modelled in this way. However, it should be noted that in reality these connections are transient and emerge from the stochastic physico-chemical interactions between numerous biomolecules. In this respect, genetic networks differ from another prominent biological network, the neural networks of the brain, where the nodes are physically connected via axons. This has a significant effect on the speed of information travel between genetic and neural networks within an organism. However, from an evolutionary perspective, it allows for the molecular interactions of genetic components to be less constrained and to explore interactions between a wider range of cellular components. This graphical representation highlights the similarities between genetic networks and biological neural networks. Indeed, there are many similarities: for example, in computational models it is commonplace for the nodes of both networks to be modelled as sigmoidal functions. However, there are also many differences. The principal difference is that there is no direct physical connection between the nodes in genetic networks. In biological neural networks, the nodes are physically connected, generally via axons; in genetic networks, the connections are transient and emerge from the physical–chemical interactions between numerous biomolecules. This has a significant effect on the speed of information travel between genetic and neural networks within an organism. However, from an evolutionary perspective, this allows for the molecular interactions of genetic components to be less constrained and to explore interactions between a wider range of cellular components.

Chromatin remodelling is a prominent example of this, and is a specific type of epigenetic process. Epigenetics refers to the study of cellular trait variations which occur as a result of factors which control gene expression (Turner, 2008; Göndör, 2016). Chromatin is the combination of structural proteins and DNA. The structural proteins within chromatin are called histones and are organised along with DNA into nucleosomes, and then through higher order folding into chromatin. Chromatin is capable of condensing the genetic material within a cell to the extent that 2μm of DNA can fit inside a 2μm nucleus. This was originally thought to be chromatin’s principal purpose within a cell; however, in recent studies it has become clear that proteins can interact with the protein scaffolding of chromatin to change its structure (Turner, 2008; Göndör, 2016). This, in turn, changes which parts of the DNA are accessible within the protein complex, and facilitates regulatory control over gene expression. For example, given a set of environmental perturbations, a genetic network can modify itself to allow for the transcription of genes specifically designed to control these perturbations. This allows for a greater specific control over gene transcription, reducing the energy needs of the cell, and also reducing the scope for interference between biochemical processes.

3. Topological morphology

The original motivation for adding a chromatin remodelling analogue to an existing artificial gene regulatory network model (AGRNs) was that it would allow for topological self-modifications to occur throughout execution (Turner et al., 2017). In turn, this was expected to promote the emergence of complex behavioural traits, in a similar way
to how chromatin remodelling within biological systems appears to allow cells to orchestrate more complex regulatory behaviours. This is a departure from standard forms of connectionist computation, where the structure of a network remains invariant during the course of execution. The intended effect of these topological modifications is to allow large changes in the dynamics of a network whilst it is executing. This is not something that has been explored within connectionist models, with the possible exception of models of neuromodulation (such as gas nets, Zhao et al., 2014) where smaller changes to the local dynamics can be induced by switching between different nodal functions.

In a sense, topological modification during execution provides a further layer of complexity when analysing a network's behaviour. In many applications this may not be an issue, since connectionist models are typically used as black boxes where only accuracy of the input–output mapping is a concern. However, in another sense, topological modifications provide extra information about what the network is doing, since changes in dynamics are mirrored by changes in topology, which can be readily observed (Turner et al., 2017). Moreover, from an evolutionary perspective, a single change in a single node can often lead to the acquisition, or removal of a dynamical regime within the network, vastly altering its functionality. In order to understand its behaviour, it is often required to track the dynamic topology of the network alongside its function. In this work, the emphasis is on understanding how modifications to the network during optimisation can lead to the acquisition of complex dynamical traits which in turn are capable of solving complex dynamical tasks.

4. EpiNet architecture

In the epiNet architecture, an analogue of chromatin (referred to more generically as an epigenetic molecule) is added to an existing AGRN, and a mechanism is introduced to allow other nodes to modify its activation state and positioning. The purpose of the epigenetic molecules is to control which genes from the AGRN are active, and hence their activation state and positioning. The purpose of the epigenetic molecules, whose behaviour is akin to the local unwinding of DNA, allowing genes to become accessible. Specifically, genes become active when they are within a given distance of an epigenetic molecule, where proximity is determined using a Euclidean distance metric within a reference space (defined in Section 4.1). Furthermore, the epigenetic molecules are able to move around the network, covering and uncovering different groups of nodes as they do so, with the current position of an epigenetic molecule governed by the dynamical states of genes within the network, through the use of a weighted Sigmoid function. This epigenetic dynamism more closely reflects the biological dynamics of chromatin modification than earlier models which we have used (Turner et al., 2012, 2017). It also differentiates our approach from work by Bull (2012, 2014), who used an evolutionary algorithm to study the effect of adding epigenetic elements to a GRN model within abstract NK landscapes.

4.1. Encoding

During evolution, the connections $I$, $I'$ and $C'$ between components within epiNet are determined via an indirect encoding. Specifically, components are given locations within an indirect reference space. This is based upon earlier works in the AGRNs field (Reil, 1999; Banzhaf, 2003), which were motivated by the manner in which biological components interact through physical and chemical properties rather than their exact location within a DNA encoding. This means that interactions within the network are positionally independent, with a gene functioning identically regardless of where it occurs within the list of genes. In particular, this allows for the preservation of existing gene functions when other genes are introduced or removed from the network, adding to the evolvability of the networks.

A connection is specified using both a position and a proximity. Genes can be considered connected to each other when their position ± their proximity overlaps another gene's position. Epigenetic molecules exist within the same space as genes. Each epigenetic molecule has a defined extent within the reference space which it uses to connect to active genes. Using the expression values of these genes, it processes their weighted sum and its position is the result of that sum. The position of the epigenetic molecule specifies a region (its position ± its proximity) within the reference space where all genes within that region will become active. System-level inputs are mapped onto the active genes before execution and the outputs are mapped back after execution.

5. Optimisation

In this work, we choose to work with a mutation only hill climbing heuristic, which is similar to an evolutionary strategy (Dong and Zhou, 2014). This is because we want to be able to precisely control the level of change at each optimisation step so that the evolutionary process can be accurately observed. Additionally we want to be able to focus on a single network rather than a population so that we can precisely monitor its development. Although objective performance of the algorithm may change using a mutation only heuristic, the outright performance of the networks is not a key focus of this work. The amount of
mutation applied to the networks at each step is 5%. This means that for every instance of data representing and parameterising the networks, there is a 5% chance that that data instance will be mutated. The individual data within each of the genes and epigenetic structures are mutated using a Gaussian distribution, with its previous values set at the mean, which is a fairly standard approach for mutating real-valued encodings within the context of an evolutionary algorithm (and is also a reasonable model of normally-distributed mutations within a biological context).

Algorithm 1. Optimising epiNet

1: $P \leftarrow$ new random epiNet
2: for numberOfevaluations do
3: CLONE $P$ as $Q$
4: MUTATE($Q$)
5: $Q \leftarrow$ evaluate($Q$)  \hspace{1em}  \text{see Algorithm 2}
6: if $Q$.fitness $\geq$ $P$.fitness then
7: $P \leftarrow Q$
8: end if
9: end for

Algorithm 2. Evaluating epiNet on a task

1: initialize control task
2: $a \leftarrow L$  \hspace{1em}  \text{initialize epiNet state}
3: repeat
4: $L \leftarrow$ state variables from controlled system
5: $\ln \leftarrow$ scale($L$)  \hspace{1em}  \text{input to [0, 1]}
6: for $i \in \{0, \ldots, |E|\}$ do
7: $a_i \leftarrow$ sigmoid($I_i \cdot W_i$)  \hspace{1em}  \text{update positions of epiNet molecules}
8: end for
9: for $i \in \{0, \ldots, |G|\}$ do
10: $a_i \leftarrow$ sigmoid($I_i \cdot W_i$)  \hspace{1em}  \text{update genes closest to the epigenetic positions}
11: end for
12: $\text{fitness} \leftarrow$ progress on control task objectives
13: until

5.1. Computational tasks

To best understand the emergence of complexity within the networks, we apply epiNet to three computational tasks: a coupled inverted pendulums control task (Hamann et al., 2011), a transfer orbit traversal task and a memory task. Each requires different dynamical properties to solve. These tasks are intended both to highlight the emergence of complex traits within the networks as well as being challenging enough to validate the model as a computational system. Additionally, the underlying AGRN model is applied to each of these tasks, so that the impact of adding the epigenetic layer can be measured.

5.1.1. Coupled inverted pendulums

The coupled inverted pendulums control task was designed as a proxy for a range of real world control tasks such as robotic control for legged robots (Hamann et al., 2011). It was designed to be able to test controllers in an environment that produces a range of complex behaviours, where it is difficult for controllers to encompass all the behaviours required to optimally solve the task.

The task consists of three carts on a 1-dimensional track, with a pendulum hanging below each cart. The objective is to move the carts on the track in such a way as to move the pendulums vertically above the cart, and keep them in that position. Additionally, the carts are inelastically tethered together so that all the carts’ movements must cooperate to solve the task. If a tether is extended too far, the simulation stops. If carts hit one another, or leave the set boundaries, the simulation stops.

Each cart is controlled using an actuator which takes the difference between two inputs, allowing it to move towards or away from its neighbours (see Fig. 2). There is a single controller per cart, which is passed 10 state inputs, listed in Table 1. The controller produces 2 outputs which control the actuator of the cart. The overall fitness of the controller is defined as how many time steps each pendulum spends in the upright position. The parameters of the simulation are given in Tables 1 and 2. The simulation is conducted over 100,000 iterations, and 50 runs. To improve the realism of the simulation, there is a stochastic noise function attached to the state variables. This noise is randomly sampled from a normal distribution. To provide a more robust measure of fitness, each controller is evaluated 5 times. A mutant is only considered better, and therefore replaces its parent, if the mean and best scores over these evaluations are an improvement.

5.1.2. Multi-point traversal through an n-body system

In the second task, we consider the control of a multi-point traversal through an n-body system. The objective of this task is to guide a rocket’s trajectory towards a fixed point, then change orientation in order to land as close as possible to a given location on a planetary surface, and have as low a velocity as possible upon landing. The fitness of a controller is calculated by equally weighting the distance from the target and the final velocity. The planet is of large enough size to have a significant gravitational effect on the dynamics of the rocket at all points. This simulation is time constrained; in order to be able to land on the planet, the first objective must be completed within a reasonable time frame. The simulation is conducted over 100,000 iterations and 50 runs. The input data for this task can be seen in Table 3.

Once the first stage of the task is completed, a fault is injected which

Table 1: Sensory inputs used for the inverted coupled pendulums task. The values are rescaled to [0,1] before they are used as inputs to a network.

<table>
<thead>
<tr>
<th>ID</th>
<th>Sensor name</th>
<th>System to sensor mapping</th>
</tr>
</thead>
<tbody>
<tr>
<td>$S_0$</td>
<td>Pendulum Angle 0</td>
<td>$\sigma \in [0, 0.5 \pi] \rightarrow [127, 0], \theta$ else</td>
</tr>
<tr>
<td>$S_1$</td>
<td>Pendulum Angle 1</td>
<td>$\sigma \in [0, 0.5 \pi] \rightarrow [127, 0], \theta$ else</td>
</tr>
<tr>
<td>$S_2$</td>
<td>Pendulum Angle 2</td>
<td>$\sigma \in [0, 0.5 \pi] \rightarrow [127, 0], \theta$ else</td>
</tr>
<tr>
<td>$S_3$</td>
<td>Pendulum Angle 3</td>
<td>$\sigma \in [0, 1] \rightarrow [127, 0], \theta$ else</td>
</tr>
<tr>
<td>$S_4$</td>
<td>Proximity 0</td>
<td>Distance left $\rightarrow [0, 127]$</td>
</tr>
<tr>
<td>$S_5$</td>
<td>Proximity 1</td>
<td>Distance right $\rightarrow [0, 127]$</td>
</tr>
<tr>
<td>$S_6$</td>
<td>Cart Velocity 0</td>
<td>$v \in [-2, 0] \rightarrow [127, 0], \theta$ else</td>
</tr>
<tr>
<td>$S_7$</td>
<td>Cart Velocity 1</td>
<td>$v \in [0, 2] \rightarrow [0, 127], \theta$ else</td>
</tr>
<tr>
<td>$S_8$</td>
<td>Angular Velocity 0</td>
<td>$w \in [-5 \pi, 0] \rightarrow [127, 0], \theta$ else</td>
</tr>
<tr>
<td>$S_9$</td>
<td>Angular Velocity 1</td>
<td>$w \in [0, 5 \pi] \rightarrow [0, 127], \theta$ else</td>
</tr>
<tr>
<td>$A_i$</td>
<td>Actuators 0</td>
<td>$A_i \in [0, 127], \text{for } i \in 0, 1$</td>
</tr>
<tr>
<td>$u$</td>
<td>Motor Control 0</td>
<td>$2(A_u/127 - A_{u-1}/127) \rightarrow [0, 1]$</td>
</tr>
</tbody>
</table>
Table 2
Physical parameters of the coupled inverted pendulums task.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pendulum length</td>
<td>0.5 m</td>
</tr>
<tr>
<td>Max. positive acceleration</td>
<td>7.0 ms$^{-2}$</td>
</tr>
<tr>
<td>Min. positive acceleration</td>
<td>8.5 ms$^{-2}$</td>
</tr>
<tr>
<td>World width</td>
<td>2 m</td>
</tr>
<tr>
<td>Tether length</td>
<td>0.35 m</td>
</tr>
<tr>
<td>Proximity sensor range</td>
<td>1.0 m</td>
</tr>
<tr>
<td>Cart width</td>
<td>0.1 m</td>
</tr>
<tr>
<td>Time steps (t)</td>
<td>3000</td>
</tr>
</tbody>
</table>

Table 3
Physical parameters of the multi-point traversal task.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Starting Rocket Position</td>
<td>0; 6,571,000; 10,000</td>
</tr>
<tr>
<td>First Target Position</td>
<td>−700,000; 6,671,000; −20,000</td>
</tr>
<tr>
<td>Planet position</td>
<td>0;0;0</td>
</tr>
<tr>
<td>Planet mass</td>
<td>5.972624 kg</td>
</tr>
<tr>
<td>Planet radius</td>
<td>6,371,000 m</td>
</tr>
<tr>
<td>Rocket Mass</td>
<td>2000 kg</td>
</tr>
<tr>
<td>Rocket Acceleration</td>
<td>$(x \pm 50 \text{ ms}^{-2})$</td>
</tr>
<tr>
<td></td>
<td>$(y \pm 50 \text{ ms}^{-2})$</td>
</tr>
<tr>
<td></td>
<td>$(z \pm 50 \text{ ms}^{-2})$</td>
</tr>
<tr>
<td>Time steps</td>
<td>5000 per target</td>
</tr>
<tr>
<td>Integration Step</td>
<td>0.05</td>
</tr>
</tbody>
</table>

An evolved controller receives 5 inputs: a vector representing the target position, the admittance to the target and the rocket’s speed. The controller is required to generate 3 outputs, which correspond to the power of the rocket thrusters in each dimension.

5.1.3. Network sequence memory
The final task is a sequence learning task that tests the memory and recall capacity of the network architectures, and particularly how the epigenetic layer affects a network’s ability to encode new knowledge whilst preserving its existing dynamics. The objective is to recall as many Boolean values as possible from a sequence of 50 values. The networks do not take any inputs, relying on their internal dynamics to generate the appropriate sequence of output states. The single output of a network is mapped to $[0, 1]$; if the value is less than 0.5, its output state is false, otherwise it is true. Fitness is measured by the edit distance from the target sequence. The simulation is conducted over 100,000 iterations and 200 runs (since this task is much faster to evaluate than the previous two). A new target sequence is randomly generated at the start of each run.

6. Results and discussion
For the two control tasks, the objective is to optimise an epinet instance so that it functions as a closed loop controller which is capable of guiding the dynamics of the simulation in a specified manner. For each time step of the simulation, its state is fed into the network by setting the activation levels of the input genes. The network then executes, generating one or more outputs which are then mapped back to the simulation. For the memory task, the epinet instance functions as an open-loop system, generating states which are then fed into the fitness function to evaluate. In both cases, the plots used to describe the behaviour of the networks contain two components. First, the epigenetic trace specifies the location of the epigenetic molecules over a given number of time steps within the reference space. As the epigenetic molecules move, the genes which are active also change. Hence, modification of the epigenetic position results in changes to the topology of the network. The second component describes the dynamics of the network by plotting the expression of each of the genes over a given time frame.

6.1. Coupled inverted pendulums
To solve this task optimally requires multiple dynamical behaviours: each pendulum has to be swung into an upright position; each cart’s controller must cooperate with its neighbours to achieve this; once in the upright position, the controller must keep it there. The transition between swinging and stabilising is an important behavioural inflection point, and in this context is considered a complex trait (many algorithms failed to reach this point, Hamann et al., 2011). Hence, we are particularly interested in whether, and to what degree, the epigenetic layer contributes to its acquisition. In the results for this task (shown in Fig. 3), this optimal behaviour occurs when the fitness is above 0.715. Although objective performance is not a key concern in this work, it can reduces the power to 10% on the $y$ thruster. Hence, as well as navigating to the target, the controller has to react to a change in how the rocket interacts with the environment. The forces exerted on the spacecraft are calculated using Eq. (1), where $m$ is the mass of a body and $q$ is a vector of length 3 specifying the position of an object in 3-dimensional space. To improve the tractability of the system, the planet’s position remains static. The acceleration is then calculated using Newton’s second law of motion. The equations are simulated using leapfrog integration.

$$\dot{\mathbf{q}}_k = G \sum_{l \neq k} \mathbf{m}_l (\mathbf{q}_k - \mathbf{q}_l) / || \mathbf{q}_k - \mathbf{q}_l ||^3$$

An evolved controller receives 5 inputs: a vector representing the target position, the admittance to the target and the rocket's speed. The controller is required to generate 3 outputs, which correspond to the power of the rocket thrusters in each dimension.

5.1.3. Network sequence memory
The final task is a sequence learning task that tests the memory and recall capacity of the network architectures, and particularly how the epigenetic layer affects a network's ability to encode new knowledge whilst preserving its existing dynamics. The objective is to recall as many Boolean values as possible from a sequence of 50 values. The networks do not take any inputs, relying on their internal dynamics to generate the appropriate sequence of output states. The single output of a network is mapped to $[0, 1]$; if the value is less than 0.5, its output state is false, otherwise it is true. Fitness is measured by the edit distance from the target sequence. The simulation is conducted over 100,000 iterations and 200 runs (since this task is much faster to evaluate than the previous two). A new target sequence is randomly generated at the start of each run.

6. Results and discussion
For the two control tasks, the objective is to optimise an epinet instance so that it functions as a closed loop controller which is capable of guiding the dynamics of the simulation in a specified manner. For each time step of the simulation, its state is fed into the network by setting the activation levels of the input genes. The network then executes, generating one or more outputs which are then mapped back to the simulation. For the memory task, the epinet instance functions as an open-loop system, generating states which are then fed into the fitness function to evaluate. In both cases, the plots used to describe the behaviour of the networks contain two components. First, the epigenetic trace specifies the location of the epigenetic molecules over a given number of time steps within the reference space. As the epigenetic molecules move, the genes which are active also change. Hence, modification of the epigenetic position results in changes to the topology of the network. The second component describes the dynamics of the network by plotting the expression of each of the genes over a given time frame.
be seen from the figure that epiNet outperforms the baseline model in the coupled inverted pendulum task. The results are significant, with 8 epiNet instances able to generate an optimum balancing behaviour compared to only 1 AGRN instance.

Table 4 summarises the average number and sizes of positive mutations that took place during the evolution of a controller, showing information for each task and architecture. For this task, it is notable that evolved epiNet controllers underwent on average 29% the number of positive mutations that AGRN controllers underwent, whilst at the same time achieving a higher average fitness. Given that the size of the mutations were similar for both architectures (last column in Table 4), this suggests that the positive mutations for epiNet led to more significant changes in behaviour. A likely explanation for this is that the positive mutations are causing (either directly or indirectly) changes to the epigenetic dynamics of the system, i.e. causing topological modifications that result in larger behavioural changes.

An example of this can be seen in Fig. 4, which shows the dynamics of an evolved network before and after a mutation led to the acquisition of the optimum behaviour. The figure shows the positions of the epigenetic molecules and the expression values of every gene over 1500 time steps of the coupled pendulum simulation before the optimum behaviour was acquired. Figure b shows the same but after the optimum behaviour was acquired. The positions of the genes in reference to the epigenetic molecules can be seen to the right of the plots. In this instance the optimum behaviour was acquired by a mutation to the positions within the reference space of 2 genes, mutations to the regulatory functions of a further 3 genes, and a mutation to the regulatory function of one of the epigenetic molecules. Prior to the pendulums being in the upright position (time steps 500-900), these mutations do not produce a pronounced change in the dynamics of the epigenetic molecules, but a significant change is reflected in the gene expression values. After 900 time steps, the dynamics of the epigenetic molecules and gene expression values show pronounced change. In particular, an epigenetic molecule oscillates at a high frequency only when the pendulum is in the upright position, producing a behaviour capable of keeping it there.

Fig. 5. Evolutionary pathway from random initialisation to the acquisition of complex behaviours. Every positive mutation detailed through the evolutionary process. Each box details the mutations required to improve on the previous instance, along with the score of that instance. Each mutation is listed as a mutation to a specific gene. The actual data which is mutated is not listed, but was not specific to a type of data within the gene. There are three complex behaviours which can be seen (pink boxes, blue borders). The first complex behaviour is being able to swing the carts consistently. The second is swinging the carts with significantly more force, so that the pendulums are spinning around each cart. The third is being able to catch the pendulums in the upright state and balance them there.
behaviour is achieved, the second molecule only moves between 0 and 0.13. However, as soon as the swinging behaviour is achieved, the network (b) with the balancing behaviour shows abrupt rapid movements between 0 and approximately 0.4. These epigenetic dynamics correspond with rapid selection of varying genes which generate the required behaviour to keep the pendulum in the upright position, and lead to significant changes in the dynamics of gene expression. Before the final mutation, these epigenetic dynamics did not occur, and the network was not able to produce the optimum behaviour.

Fig. 5 shows a full evolutionary pathway from random initialisation to the acquisition of complex behaviours. This emphasises that positive mutations were generally the result of multiple synchronised changes to the network. However, most of these changes are to genes rather than epigenetic elements, and where epigenetic elements are targeted, there is rarely more than one mutated at the same time. The fact that most mutations are genetic suggests that changes to the epigenetic dynamics

Fig. 6. Multi-point traversal through an n-body system. The performance of all controllers which were capable of navigating to both targets. The red diamonds represent AGRN controllers, and the blue circles represent epiNet controllers. The best performances was achieved by epiNet in both the velocity upon landing and the distance from the target.

Fig. 7. N-body dynamics. The dynamics of 3 epiNet controllers from the same optimisation lineage. The first (a) shows networks capable of navigating to the first point, but not landing on the planet. (b) shows the epiNet controller the instance before it was capable of navigating to the first point and landing on the planet, and (c) is a controller capable of navigating to both points and landing on the planet.

Fig. 8. Memory results. The difference in performance between epiNet and the AGRN when applied to remembering Boolean states. The differences are statistically significant and indicative that epiNet is able to hold more memory states than that of the AGRN.
are generated indirectly through changes to the genes that regulate them. This makes sense, given that direct changes to epigenetic elements would likely lead to comparatively large changes in the network’s behaviour.

Although there was no general trend regarding the type of mutation that caused the optimal behaviour to first appear within the evolved epiNet controllers, it always followed from a modification to an existing gene or epigenetic molecule rather than through the addition or deletion of either of these. However, all optimal networks underwent several genetic or epigenetic deletions or insertions before the optimum behaviour was acquired. The smallest number of optimisation steps from random initialisation to optimum behaviour was 27, with 7 modifications resulting in the acquisition of the optimum behaviour. The average mutation size, that is, the average number of simultaneous modifications which resulted in an improvement of the network, was 6.18.

6.2. Multi-point traversal through an n-body system

This task measures a network’s ability to control a trajectory between multiple points whilst responding to a changing environment, again requiring it to switch between dynamical regimes during the course of execution. Although not all runs led to acquisition of the target behaviours, 20 epiNet controllers were successfully evolved, compared to only 4 AGRNs. Fig. 6 shows the behavioural characteristics of these successful controllers, showing that in general the epiNet controllers achieve a better balance between target error and minimising final velocity.

Similar to the previous task, Table 4 shows that epiNet controllers underwent considerably less positive mutations that the AGRNs in order to reach their final behaviour. Again, this suggests that epigenetic changes play an important role in the acquisition of the behaviours required to solve this task. Fig. 7 shows an example of the change in epigenetic and gene expression dynamics as an evolving network acquires increasingly complex behaviour. In particular, a large change in epigenetic dynamics can be seen between (a) and (b), and this appears to set the scene for a very subtle change in epigenetic dynamics (and a more significant change in gene expression) that led to the acquisition of the optimal behaviour in (c).

It is interesting to observe that the number of simultaneous changes that occur during positive mutations is relatively high for this task (Table 4) in comparison to the other two. This is not due to differences in the sizes of the networks, so is presumably a characteristic of the problem being solved. A possible explanation is that the fitness function is non-continuous, in that controllers that do not achieve certain
behaviours can receive zero fitness. However, it is also worth considering that many of the component changes will be neutral and not have an effect upon fitness, so the actual number of co-occurring changes required may be much lower than this figure suggests.

6.3. Network sequence memory

This task is quite different to the previous two. Rather than moving between a small number of dynamical regimes in a context-sensitive manner, this task requires the dynamics to generate a large number of expression states in a fixed sequence, meaning that the acquisition of traits is a more gradual process. Also, there are no external inputs, so the dynamics must be created and sustained internally.

As shown in Fig. 8, epiNet solutions again outperformed the baseline AGRNs, recalling significantly more states and finding better solutions overall. Notably, this was the one task in which epiNet solutions underwent more positive mutations than AGRNs during their evolution, although this is likely to be offset somewhat by the fact that epiNet controllers evolved more complex behaviours on average. Despite this, changes in epigenetic dynamics still appear to be important in the development of complex traits: Fig. 9, for example, shows that the epigenetic dynamics become increasingly complex as the fitness of a solution increases. It was common for the dynamics of AGRN solutions in particular to settle into an attractor (similar to Fig. 9a) and this hints that topological changes play an important role in solving this task by maintaining complex, constantly changing, dynamics. This may explain the different mutational pattern seen in this task, with the epigenetic layer playing a general role in stimulating dynamics rather than switching between behaviours.

7. Conclusions

In this paper we have investigated how complex behaviours arise within EpiNet, a form of artificial genetic network that captures the important role of biological epigenetic processes such as chromatin modification, allowing for dynamical topological modification during execution. Using a simple optimisation algorithm, we studied how EpiNet instances evolve over time, identifying when and how they acquire the complex traits required to solve three different challenging computational tasks. Although not the focus of this work, EpiNet was shown to outperform a standard artificial genetic network on all tasks, showing the important role that epigenetic elements play within the acquisition of complex traits.

In this work, we focused on observing the points of evolutionary optimisation just before and after complex traits were acquired within the networks, and the underlying causes of this increase in behavioural complexity. One of the significant findings was that it was often not a single mutation which caused a complex behaviour to arise, but rather a collection of mutations occurring at the same time. These behaviours almost always emerged as a result of mutating existing elements of the model, rather than adding or removing genes or epigenetic molecules. It was, however, common for genes and epigenetic molecules to be added and removed throughout the optimisation process, but not at the point a complex behaviour arose.

Our results suggest that the epigenetic components of EpiNet play an instrumental role in reducing the amount of optimisation effort required to acquire complex traits. This has clear implications for the field of artificial genetic networks, and demonstrates the benefits of modelling regulatory processes other than direct transcriptional regulation. Additionally these results, which are underpinned by biological theory, give support to the idea that work such as this has the potential be used in the future to inform evolutionary theory. If computational epigenetic structures allow for the faster acquisition of complex traits, could the same be said for biological models? Abstract level studies of epigenetic processes such as this could also play an important role in our understanding of the role of epigenetic processes in biological regulatory systems, which are very difficult to study directly due to challenges such as data sparsity.

Acknowledgment

The authors acknowledge the support of the EPSRC through the platform grant grant EP/K040820/1.

References

Lorch, Y., Kornberg, R.D., 2015. Chromatin-remodeling and the initiation of