Curiosity-Based Learning Algorithm for Interactive Art Sculptures

by

Tsz Kiu Chan

A thesis
presented to the University of Waterloo
in fulfillment of the
thesis requirement for the degree of
Master of Applied Science
in
Electrical and Computer Engineering

Waterloo, Ontario, Canada, 2016

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Abstract

This thesis is part of the research activities of the Living Architecture System Group (LASG). Combining techniques in architecture, the arts, electronics, and software, LASG develops interactive art sculptures that engage occupants in an immersive environment. The overarching goal of this research is to develop architectural systems that possess life-like qualities. Recent advances in miniaturization of computing and sensing units enable system-wide responsive behaviours. Though complexity may emerge in current LASG systems through superposition of a set of simple and prescripted behaviours, the responses of the systems to occupants remain rather robotic and ultimately dictated by the will of the designers. In this thesis, a new series of sculptural system was initiated, implementing an additional layer of behavioural autonomy.

In this thesis, the Curiosity-Based Learning Algorithm (CBLA), a reinforcement learning algorithm which selects actions that lead to maximum potential knowledge gains, is introduced to enable the sculpture to automatically generate interactive behaviours and adapt to changes. The CBLA allows the sculptural system to construct models of its own mechanisms and its surroundings through self-experimentation and interaction with human occupants. A novel formulation using multiple learning agents, each comprising a subset of the system, was developed in order to integrate a large number of sensors and actuators. These agents form a network of independent, asynchronous CBLA Nodes that share information about localized events through shared sensors and virtual inputs. Given different network configurations of the CBLA system, the emergence of system behaviours with varying activation patterns was observed.

To realize the CBLA system on a physical interactive art sculpture, an overhaul of the previous series' interactive control hardware was necessary. CBLA requires the system to be able to sense the consequences of its own actions and its surrounding at a much higher resolution and frequency than previously implemented behaviour algorithms. This translates to the need to interface and collect samples from a substantially larger number of sensors. A new series of hardware as well as control system software was developed, which enables the control and sampling of hundreds of devices on a centralized computer through USB connections. Moving the computation from an embedded platform simplifies the implementation of the CBLA system, which is a computationally intensive and complex program. In addition, the large amount of data generated by the system can now be recorded without sacrificing response time nor resolution.

An experimental test bed was built to validate the behaviours of the CBLA system. This small-scale interactive art sculpture resembles previous sculptures displayed publicly by the LASG and Philip Beesley Architect Inc (PBAI). Experiments were done on the testbed at PBAI's Toronto studios, to demonstrate the exploratory patterns of CBLA as well as the collective learning behaviours produced by the CBLA system. Furthermore, a user study was conducted to better understand users' responses to this new form of interactive behaviour. Comparing with prescripted behaviours that were explicitly programmed, the participants of the study did not find this implementation of the CBLA system more interesting. However, the positive correlations between activation level, responsiveness, and users' interest levels revealed insights about users' preferences and perceptions of the system. In addition, observations during the trials and the responses from the questionnaires showed a wide variety of user behaviours and expectations. This suggests that, in future work, results should be categorized to analyze how different types of users respond to the sculpture. Moreover, the experiments should also be designed to better reflect the actual use cases of the sculpture.

Acknowledgements

First and foremost, I would like to thank my supervisors, Dr. Dana Kulić and Dr. Rob Gorbet, for their guidance throughout my study as their student. I am very fortunate to have supervisors whom I can count on for helpful and prompt advice on my research and writing. This thesis would not have been possible without their support.

Second, I would like to thank NSERC, Mitacs, and Philip Beesley Architect Inc. (PBAI) for supporting my Master's program financially through the NSERC Industrial Postgraduate Scholarship and the Mitacs Accelerate program. In addition, PBAI has provided the sculptural mechanisms, equipment, and studio space that I needed for the experiments presented in this thesis. Special thanks to Matt Borland and Mohammadreza Memarian for their contributions on the electrical design of the hardware used in this thesis; Mon Josef and Stephen Saines for their help on the production and testing of the circuit boards and electronics assemblies; Adam Schwartzentruber, Andrea Ling, Darcie Watson, Jordan Prosser, Laura Li, Martin Correa, Mike Hu, Petra Bogias, Siubhan Taylor, and Will Fu for designing and constructing the sculptural components and the experimental test beds; and Philip Beesley for his expertise on interactive arts and providing some of the photos and drawings used in this thesis.

Lastly, I would like thank the people who have taken time out of their busy schedule and travelled far to participate in the user study presented in this thesis. The data obtained from this study were invaluable in providing the insights and validations for the work that I have been working on in the past two and a half years.

Dedication

I dedicate this thesis to my family and friends who have supported me along the way.

Table of Contents

List of Tables

List of Figures

Chapter 1

Introduction[1]

Interactive arts are a type of art form that requires the involvement of the spectators to achieve its purpose. With recent advances in capabilities and miniaturization of computers, sensors and actuators, artists now have access to more tools to create highly complex interactive artworks. In the Hylozoic Series of kinetic sculptures built by Philip Beesley Architect Inc.(PBAI)[2], the designers use a network of microcontrollers to control and sample hundreds of actuators and sensors [3][4]. Each node in the network can perform a simple set of interactive behaviours. While the behaviours have previously been either prescripted or random, complex group behaviours have been seen to emerge through communication among nodes and interaction with the spectators [5]. Figure 1.1 shows a Hylozic Series interactive sculpture that was installed in the Museum of Modern and Contemporary Art in Seoul, South Korea [6].

One of the goals of the Hylozoic Series interactive art sculpture is to invite the users to contemplate whether architecture can become alive, albeit in very primitive ways [5]. Indeed, the name comes from the ancient Greek philosophy, *hylozoism*, which is a belief that all matter is alive in some sense. While previous generations of the sculptural systems have exhibited some primitive responsive behaviours, they are nevertheless manually designed by its designers and remain unchanged over time. To take on the characteristics of a higher level living system, the sculptural system should have the ability to generate and modify its own behaviours, and adapt to changes in its external environment.

Practically, as a public interactive art piece, it should also be engaging and interesting

[1] Parts of this chapter are adapted from papers published in IROS 2015 [1] and Next Generation Building [2]

[2] Philip Beesley Architect Inc.: http://philipbeesleyarchitect.com

Figure 1.1: Photograph of a Hylozoic Series interactive art sculpture, Epiphyte Chamber, installed in the Museum of Modern and Contemporary Art in Seoul, South Korea in 2013 (provided by Philip Beesley Architect Inc.).

to the users. We hypothesize that, if the behaviours do not change, users would find the sculpture less interesting over time as its behaviours become predictable to the users. This is undesirable for a permanent installation in which the same users may interact with the sculpture over an extended period of time. Moreover, in a system with a large number of sensors and actuators, programming a complex set of carefully choreographed behaviours is complicated and requires lengthy implementation and testing processes. Furthermore, manually designing the behaviours requires the human designers to predict behaviours that could induce positive user reactions, which is very subjective.

To address the challenge of long-term, adaptive engagement, and self-motivated autonomy, a new Hylozoic Series was developed. In this thesis, we introduce the Curiosity-Based Learning Algorithm (CBLA) to the Hylozoic series installation. The CBLA re-casts the interactive sculpture as a set of agents driven by an intrinsic desire to learn. Presented with a set of input and output variables that it can observe and control, each agent tries to understand its own mechanisms, its surrounding environment, and the occupants, by learning models relating its inputs and outputs. We hypothesize that the occupants will find the behaviours which emerge during CBLA-based control to be interesting, more life-like, and less robotic than ones generated by prescripted behaviours that are manually designed.

To evaluate the CBLA-based control approach, we implemented a physical manifestation of the learning algorithm in an abstract interactive art sculpture. Working with PBAI, a new series of interactive sculptures was designed and built to generate its own behaviours through learning and interaction with its physical environment.

The learning algorithm was based on the Intelligent Adaptive Curiosity [7] (IAC) algorithm developed by Oudeyer et al. IAC is a reinforcement learning algorithm with the objective of maximizing learning progress. In his experiments, Oudeyer showed that an agent running the IAC algorithm would tend to explore those regions of the state-space that are neither too predictable nor too random, mimicking the intrinsic human drive of curiosity. The learning mechanism developed for this thesis was built on the IAC and applied on an architectural-scale distributed interactive sculptural system. We called it the Curiosity-Based Learning Algorithm (CBLA). A CBLA system comprises a network of asynchronous learning agents that are linked virtually and physically. The asynchronous nature of the system allows learning agents controlling actuators with different operating bandwidths to coexist. Meanwhile, the links among the different learning agents enable information to travel within the system, allowing distributed learning.

Compared to previous generations of control hardware and software used by the Hylozoic Series [4], a CBLA system requires a greatly increased number of sensors and computational power. To maintain a responsive control cycle time, a drastic increase in communication rates also was required. Hence, a new series of electronic hardware and communication architecture with enhanced sensing and communication capabilities was developed to bring CBLA to the Hylozoic Series interactive art sculpture.

Furthermore, to better understand users' response and perception of the learning behaviour, it is important to be able to capture their responses as they are interacting with the sculpture. An experimental test bed running CBLA was therefore constructed and users were invited to interact with the sculpture. Through this user study, we examined how users perceive and respond to the behaviours of the CBLA system. In particular, the relationship between the behaviours of the sculptural system and the level of interest as reported by the users was investigated.

1.1 Contributions

First, an algorithm for generating autonomous behaviours for a large scale kinetic sculptural system during interaction with an occupant was developed. A learning algorithm, which was previously used in developmental robotics, was adapted to an interactive arts environment. In [7], the state space of the robot was relatively small. However, in our case, there is an order of magnitude more input and output variables. In order to make learning such a large distributed system manageable, a network of multiple learning agents was made to run simultaneously, each capturing a specific set of sensors and actuators. In addition, unlike many reinforcement learning problems, acquiring a model of the learning targets as quickly and accurately as possible isn't our main objective. Instead we want to study the learning process itself and study how curiosity affects the way that the system explores the state-space. The behaviour of the interactive art sculptures is a physical manifestation of the learning process. An additional mechanism that alters the actions of the system based on knowledge gain potential is introduced. This gives the users a visual indication of the state of learning agents.

Second, a user study was conducted to validate the proposed algorithm. To enable a physical realization of the proposed algorithm for the study, a new prototype interactive control system with enhanced sensing and control capabilities was designed and constructed. The user study examined how human occupants perceive the behaviours of the sculpture and respond in turn. We analyzed the relationships between the behaviours of the system and the users' perceptions.

1.2 Organization

In Chapter 2, related work in interactive arts, artificial life, and developmental robotics is examined and discussed. In Chapter 3, the proposed Curiosity-Based Learning algorithm is thoroughly described. A new electronic control system was designed and built in order to incorporate the large number of sensors and actuators and to run the CBLA. The design and implementation of the hardware and software of this system are presented in Chapter 4. Then, we observed the behaviours of the sculptural system running the CBLA system under different configurations and examined its interactions with users in a user study. The methodologies and findings of these experiments are presented in Chapter 5. Finally, the conclusions as well as ideas for future work are presented in Chapter 6.

Chapter 2

Related Work[1]

In this chapter, related work in interactive arts is first presented in order to provide a context for this work. Then, previous research on artificial life and developmental robotics, which provide the inspiration and the foundation for our proposed approach, are explored. Lastly, the Intelligent Adaptive Curiosity (IAC) [7] algorithm, which forms the basis of the Curiosity-Based Learning Algorithm (CBLA), is described in detail.

2.1 Interactive Arts

Interactive arts can be categorized as Static, Dynamic-Passive, Dynamic-Interactive, and Dynamic-Interactive (varying) based on the degree of the interaction between the art work and the viewers [8]. A Static type art object does not change or respond to the viewers at all. Though the viewers may react to it, the art object operates on it own irrespective of the viewers' actions. On the other hand, a Dynamic-Passive type art object changes its behaviours depending on some parameters of physical environment such as temperature, humidity, or ambient light level. Although the viewers may affect those environmental parameters, they do not interact with the art object directly. In contrast, a Dynamic-Interactive system gives the human viewers an active role in defining the behaviours of the system. This category introduces an agent that modifies the specifications of the art object. This additional unpredictability introduces a new dimension of complexity to the behaviours of the system.

[1] Parts of this chapter are adapted from a paper published in IROS 2015 [1]

In [9], Drummond examined the conceptual elements of interactive musical arts. For an interactive system to move beyond being simply a complex musical instrument with a direct reactive mapping from inputs to generation of sound, it must possess some level of autonomy in the composition and generation of music. In addition, the interactivity should be bilateral; the performer influences the music and the music influences the performer.

These concepts can easily be extended to visual and kinetic arts. Designing for user engagement is a key to facilitating bilateral influence, central to the success of an interactive artwork. There needs to be an *attractor* that captures the user's attention, a *sustainer* that keeps the user engaged, and a *relater* that fosters relationship between the users and artworks [10].

Variations [11], which is an audio-based sculptural system, engages users by allowing them to influence the sounds that they hear by placing a few balls onto its vertical tubes in different ways. Although the users play an active role in mixing the music, the sculpture remains autonomous in its sound production. The bilateral relationship between the artwork and the users is developed when the sounds generated by the sculpture influence the ways that the users arrange those balls. Likewise, the Iamascope in Beta_space [12] engages the users by capturing the participant's movements using a camera and generating different projected kaleidoscopic images and musical notes depending on the speeds and frequencies of those movements. In addition, the users' perceptions about the working of the system play a critical role in defining the nature of their relationship with the artworks. For instance, some subjects in the Iamascope experiment reported that they felt that the artwork was in fact controlling them.

Works in interactive architecture [13][14] try to provide a responsive and immersive environment where the viewers can feel as if they belong to the system. For instance, the ADA by Sedus described in [13] is a room enclosed by 2.6m tall mirrors with responsive illuminated colour tiles covering the entire floor. The colour of the tiles changes depending on the occupants. In addition, ADA also expresses her "feelings" and interacts with occupants through laser beams, synthetic voices, and the illumination of the tiles. This creates an immersive environment where the occupants may feel like they have been brought inside ADA's "dream".

At the Hyperbody Research Group[2], Oosterhuis and colleagues established the Muscle Projects [15], which is a series of interactive architectural installations that incorporates real-time actuated response. The Muscle Tower is a movable structure that changes its form in response to both the weather and the users. Its second iteration, The Muscle Tower 2, senses the people walking by using motion sensors. It then bends, twists, or deforms in

[2] Hyperbody: www.hyperbody.nl

response to the stimuli. Likewise, The Muscle Space creates an interactive passageway that moves in some dynamic patterns such as bending, twisting, folding, as people are walking through it, triggering the pressure sensors on the floor. It acts as a living structure that tries to reach out to the passerby proactively.

However, these works are the non-varying type of Dynamic-Interactive system, as their responsive behaviours do not change. Over a longer term, as the visitors gain familiarity with the system, the system will become predictable and its effectiveness in engaging the users will consequently decrease. In this work, we aim to create a varying interactive artwork by emulating the characteristics of living organisms such as curiosity and learning.

Metatopia [16] is a dynamically evolving interactive artwork that is a hybrid of architectural installation and performance. A set of flexible and mobile mesh panels form a space with a human performer at the centre of it. Animated digital images are projected from its centre to create an immersive environment. Dynamic and varying interactive behaviours arise from the exchange between the viewers and the system which embodies the human performer. In other words, Metatopia enables a varying-type of Dynamic-Interactive system by incorporating a human performer as part of the system.

Philip Beesley Architect Inc. (PBAI) develops art installations that exhibit qualities shared by living things [2]. The Hylozoic Series of interactive art sculptures use a distributed network of microcontrollers, actuators and sensors mounted within scaffolds of synthetic materials to engage the users. They detect the presence of the users primarily through infrared (IR) proximity sensors. The systems then respond with kinetic movements, sound effects, and visual illuminations. The kinetic movements are primarily actuated by shape memory alloy (SMA) wires that drive mechanisms made of flexible materials; sounds are generated by using vibration motors and audio players; and visual illuminations are provided by both low-power and high-power light emitting diodes (LED).

Previous generations of the Hylozoic Series [5] rely on the superpositions of multiple layers of these simple sets of prescripted activations to generate complexities in their responsive behaviours. The exact implementation of these prescripted behaviours varies in different installation projects. For instance, Aurora [17] features an array of light chains that are suspended from the ceiling. Each light chain is made up of a spiral of LEDs with a IR proximity sensor at the bottom. When an IR proximity sensor detects a change in distance measurement above a certain threshold, it triggers the light chain to activate each of its LEDs successively with overlaps and dimming. In addition, neighbouring light chains would also activate in a similar manner but at a lower level of intensity. Successive activations may superimpose onto existing activation patterns that have not completed yet. The interference among the activation patterns that are triggered at different times and locations creates complex emergent behaviour, analogous to the interference patterns of waveforms.

Although its interactive behaviours might seem fascinating at first, it is nevertheless a non-varying type of dynamic-interactive arts. A living system demonstrates growth and changes its behaviours over time. In addition, the prescripted nature of the responsive behaviours restricts the autonomy of the system as it would only behave exactly as its creators have intended. This work builds on the desire to integrate life-like qualities into the sculptural system beyond a reactive level, by giving it the autonomy to generate its own behaviours that continuously adapt to a changing environment.

2.2 Artificial Life and Developmental Robotics

To emulate life-like behaviours, one can start by observing how human beings behave. Srinivasa and colleagues [18][19] modelled how human beings convey or mask their intentions through movement and applied these models to a humanoid robot. Similarly, Gielniak et al. [20] focused on making a robot's motion more understandable by emulating the coordinated effects of human joints. Those studies focused on making the intent of the robots clear. In contrast, our objective is to make robots more engaging and life-like, where unpredictability might be a desirable quality. For instance, Dragan et al. [19] showed that the robot's perceived intelligence increased when the participants believed that the robot was intentionally deceptive. Our work investigates whether unpredictable behaviours emerging from the learning process will appear more life-like and engaging.

Moreover, one of the open questions in artificial life research is whether we can demonstrate the emergence of intelligence and mind [21]. In the Petting Zoo project by Minimaforms [22], the authors created pets that interact with human users and other pets through kinesis, sound, and light, and gradually develop personality. However, there is generally little in the literature that describes the technical details of this type of work, and it is unclear what their internal learning mechanisms are. Detailed analyses of their behaviours and exploration patterns have not been publically documented.

In a more recent project, Ikegami built an artificial life system called Mind Time Machine [23] to demonstrate that self-organization can emerge from chaotic sensory flow in the real world. He applied adaptive neural networks to a system consisting of three projector screens and fifteen cameras. It consisted of three asynchronous subsystems which were only coupled optically through video feedback. Video frames from the cameras were mixed and projected based on the internal memory and the level of activity. Through inherent instabilities, partly due to changing lighting conditions and people movement, sporadic behaviours emerged. During times of inactivity, the system self-organized into default mode behaviours. Likewise, our system aims to discover systematic behaviours through curiosity-based learning and its interaction with the environment.

The idea of emergence of structure and consciousness is explored in many previous works in the field of developmental robotics [24][25]. Prince at al. proposed that continuous integration of new skills is the core concept in developmental robotics [26]. Kompella et al. developed SKILLABILITY [27], which is an algorithm that enables humanoid robots to learn complex skills from the raw pixels of video streams. The robot first builds lower-dimensional step-like abstractions, or slow features, using Curiosity Driven Modular Incremental Slow Feature Analysis (CD-MISFA) [28]. These slow features then augment the robot's state-space. Its reward function rewards transitions that produce large changes in these slow features, which correspond to high-level goals such as grasping or toppling. They showed that the robot was able to acquire recognition of high-level events and form complex action sets from pixel-level information. This shows that complex, yet structured, behaviours can emerge through explorations of unstructured and noisy data.

Lee et al. proposed a developmental system with multiple stages that are defined by competence levels [29]. Different constraints are placed at different stages to guide the development process. These constraints help in reducing the complexity of inputs and actions, as well as the size of the task space. They allow the learning agents to focus on tasks that they have the maximum chance of learning. More difficult tasks can then be developed in subsequent stages by building onto the experience acquired in the levels before. However, this approach requires a priori knowledge of the tasks and a clear development path, and might not suitable for on-going developments without a specific goal.

Oudeyer et al. developed a learning mechanism called Intelligent Adaptive Curiosity (IAC) [7], a reinforcement learning algorithm with the objective of maximizing learning progress. Their goal was to develop a robot that is capable of life-long learning. The robot makes sense of the mapping between its actuators and sensors through continuous self-experimentation, without explicit instruction from human experts. Fundamentally, the IAC is a reinforcement learning algorithm with an objective to maximize learning progress. Learning progress is defined as the reduction in prediction error. In other words, the agent seeks to explore the region of the sensorimotor space that leads to the highest improvement in prediction error. As a result, the algorithm avoids learning in the parts of sensorimotor space that are either too random or too predictable. This formulation leads to continual change in behaviour over time, as regions of the state space that are initially interesting become less interesting as the system becomes more knowledgeable about them.

In the Playground Experiment [30] the IAC was implemented on a Sony AIBO robot which acts based on five action parameters and detects the environment based on three binary high-level sensors. They showed that the robot was able to acquire complex interaction behaviours with the environment, which was necessary to improved its knowledge about the complex relationships between the sensorimotor contexts and the consequences. This draws parallels to the intrinsic human drive of curiosity, which is hypothesized to drive humans to try to explore areas that have the highest potential for learning new knowledge.

2.3 Intrinsic Adaptive Curiosity

An IAC system [7] consists of two learning mechanisms, the Classic Machine learner (classM) and the Meta Machine learner (metaM). Based on the context (the sensors' inputs) and the action (the actuators' outputs), classM computes a prediction of the consequence, i.e., the resultant sensors' inputs at the next time step. Then, it implements the action and compares the actual consequence with the prediction and modifies its model in order to reduce the error in the subsequent prediction. The Meta Machine learner (metaM) predicts the error of classM. In other words, it estimates how accurately classM is able predict the consequence. The actual prediction error is then fed back to the metaM, and metaM modifies its estimate of prediction error of the newly modified classM. This change in the prediction error is recorded at each time step in the knowledge gain assessor (KGA). The KGA then computes the expected learning progress by calculating the change in error estimation. This expected learning progress is used as the reward, R. As classM prediction gets better in a given area of sensorimotor space, the expected learning progress diminishes and the reward for exploring that area gets smaller. Higher rewards in other as-yet unexplored regions encourage the algorithm to move on, to satisfy its "curiosity".

One important feature of the IAC is the idea of regional experts. Each region collects exemplars of similar sensorimotor context, and has an expert that is trained on the exemplars in the region. Exemplars are the training data for the prediction model and they are collected as the system selects actions and observes the consequences. The "features" are a vector of the sensory inputs $S(t)$, and a vector of selected actions $M(t)$ at time t; and the "labels" are the resultant sensory inputs $S(t+1)$ at time $t+1$. The regional experts constrain the estimate of learning progress within their respective sensorimotor contexts $SM(t)$, which is a concatenation of the vectors $S(t)$ and $M(t)$. This is important because it allows each expert to use a simpler model, as it covers only a small region of the state space.

The following are the steps for the learning algorithm [7]:

1. Read sensory inputs $S(t)$
2. Select action $M(t)$ using the ϵ-greedy selection policy based on the knowledge gain potential, or the action value, q of each region
3. Consult expert specialized in the relevant sensorimotor context $SM(t)$ to predict the expected sensory inputs $S'(t+1)$
4. Perform action $M(t)$
5. Observe actual sensory inputs $S(t+1)$ and add to the expert's training set
6. Compute prediction error $e(t+1) = \|S(t+1) - S'(t+1)\|_2$
7. Compute the actual mean error $< e(t+1) >$ by taking the average error over a window of θ previous errors
8. Compute the predicted mean error $< e(t+1-\tau) >$ by taking the average error over a window of θ previous errors with an offset τ
9. Compute the reward $R(SM(t)) = -[< e(t+1) > - < e(t+1-\tau) >]$
10. Update the knowledge gain potential q for the sensorimotor context $SM(t)$ based on $R(SM(t))$
11. Repeat 1 to 11 indefinitely

In this work, we adapt the IAC and apply it to the Hylozoic Series interactive art sculpture, which is a distributed sculptural system with a large number of sensors and actuators. This gives the sculpture the ability to generate its own behaviours through self-motivated learning. Its interaction with people and people's perceptions of it may be very different from the prescripted, responsive kinds of behaviours used in the previous generations of the system. Indeed, in the experiments done in [7], the human observers were never part the environment that the robot tries to learn. This work focuses on examining the interaction between the learning system and human users, and how the two influence each other.

Chapter 3

Curiosity-Based Learning Algorithm[1]

In this chapter, our approach for adapting and generalizing the IAC algorithm [7] for implementation of the Curiosity-Based Learning Algorithm (CBLA) on a distributed kinetic sculpture is presented. This includes introducing additional parameters, modifications to action selection approaches, and the integration of multiple independent learning agents in a distributed network.

3.1 CBLA Engine

An interactive art sculpture that implements the IAC must first be able to sense the consequences of its actions, similar to the human capability for proprioception. These sensors allow the sculpture to both detect its own actions, and the actions of occupants on its embodiment. For example, an accelerometer that is mounted on a mechanism senses both when the mechanism is activated by its actuators, and also when it is touched by a person during interaction. The sculpture can only improve the estimate of its own dynamics by comparing the proprioceptive feedback with a feed-forward model. For a human being, this capability is implemented through a neural mechanism known as an efferent copy [31]. For example, human eyes are constantly moving while a stable image is reconstructed using the efferent copy. However, the efferent copy can be deceiving when the external environment is disturbed and as a result, conflicts with the predicted model. For instance, a stationary image will appear to be moving when the eye is pressed [31]. However, if the disturbance is permanent, over time the efferent copy will be updated to reflect the

[1] An early version of this chapter has been published in IROS 2015 [1]

new conditions, and an accurate model is once again available for prediction. Hence, not only is an accurate model of an agent's own dynamics difficult to obtain; such a model might change over the life of the installation due to wear and tear and interaction with its surrounding environments. Proprioceptors play an important role in giving the sculpture information about its own state to enable model learning and adaptation.

Furthermore, Oudeyer [30] observed during the IAC experiments that the resulting robot behaviour had similarities to children's learning and playing behaviours. Their experiments showed that robot would focus on interacting with objects that have the next most complex responsive relationships to the its state and action. Since we expect human responses to be difficult to predict, after the robot has modelled its own mechanisms, the robot should then focus on generating behaviours that evoke reactions from the users. We hypothesize that this type of learning mechanism is well suited to interactive architecture systems, as the learning process itself will generate interesting behaviours and be an interesting feature of the installation to the visitors.

We now adapt the IAC algorithm [7] to implement a learning architecture on the distributed architectural system described in Chapter 4. A distributed approach is necessary since the sculptures often contain hundreds of sensors and actuators distributed over an area the size of a large room. Each system node runs its own instantiation of the algorithm, called the CBLA Engine. A CBLA Engine is a thread that is iteratively executing the steps of the learning algorithm. It comprises a Node, an Action Selector, and an Expert, as illustrated in Figure 3.1. The following sections explain the functioning of each of these components.

3.1.1 Node

A node represents a subset of the sculptural system. Each node is specified by a set of sensor input and actuator output variables, and its own set of configuration parameters and functions, embodying the characteristics of the physical system that it represents. It sets the actuator outputs and samples the relevant sensory inputs. The type and number of sensory inputs and actions are configurable; specific configurations used in our experiments will be described in more detail in Chapter 5.

3.1.2 Action Selector

The action selector selects an action based on a list of possible actions, $M'(t)$, and their associated action values. It either selects an action that has the highest value (exploitation),

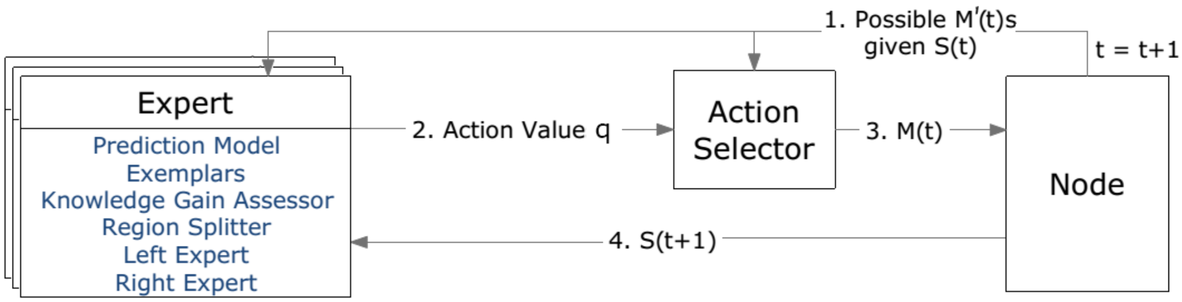


Figure 3.1: (1) At the start of each time step, the Node outputs the current possible actions $M'(t)$s given $S(t)$. (2) Then, the Experts provide the action value q associated with each possible $M'(t)$ to the Action Selector. (3) The Action Selector selects an action and actuates the Node. (4) After the Node has performed the action, it returns the actual resultant state $S(t+1)$ to the Expert. The Expert can then improve its internal prediction model and update the action value q associated with the sensorimotor context $SM(t)$.

or selects an action from the list at random (exploration). In our implementation, a version of the adaptive ϵ-greedy [32] action selection method was used. ϵ specifies the probability that a random action is selected instead of the action with highest action value. The magnitude of ϵ changes linearly based on the magnitude of the highest action value, $\widehat{q}$,among all regions as shown in (3.1).

$$\epsilon = \begin{cases} \epsilon_{max} & \text{, if } q < q_{min} \\ \epsilon_{min} & \text{, if } q > q_{max} \\ m \cdot \widehat{q} + b & \text{, otherwise} \end{cases} \tag{3.1a}$$

$$m = \frac{\epsilon_{max} - \epsilon_{min}}{q_{min} - q_{max}} \tag{3.1b}$$

$$b = \epsilon_{max} - m \cdot q_{min} \tag{3.1c}$$

where ϵ is the exploration probability; ϵ_{max} and ϵ_{min} are constants representing the maximum and minimum exploration probability; $\widehat{q}$ is the highest action value among all regions; and q_{min} and q_{max} are constants representing the minimum and maximum action value thresholds.

When $\widehat{q}$ is low, the probability of selecting a random action, ϵ, is high since the current expected reward is low and it is worth spending time exploring new regions that may lead to higher rewards. On the other hand, when $\widehat{q}$ is high, ϵ is low, since the current expected reward is high and it is worth spending time exploiting a high reward region. Limits on maximum and minimum ϵ are set to ensure that the exploration probability is kept within a range.

3.1.3 Expert

An Expert consists of a prediction model, a set of exemplars, a Knowledge Gain Assessor (KGA), a region splitter, and potentially two child experts.

An expert represents a region in the sensorimotor space defined by its exemplars. Each prediction is generated by the expert in the region with the most similar sensorimotor context. Figure 3.2 shows the internal mechanism of an Expert.

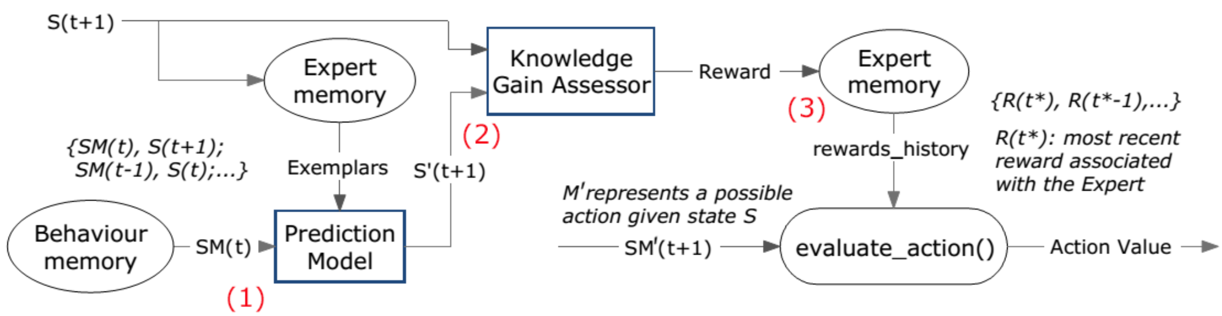


Figure 3.2: (1) The prediction model of the Expert first makes a prediction of the resultant sensor input $S'(t+1)$ based on the current sensorimotor context, $SM(t)$. (2) This prediction and the actual sensor input $S(t+1)$ are then fed into the KGA. $S(t+1)$ is also added to the collection of exemplars, which the prediction model is trained on at every time step. (3) After that, the KGA computes the reward and stores it in the Expert memory. A number of the most recent rewards are then recalled to evaluate a possible action given in the next time step that the Expert is active.

Prediction Model

The prediction model models the relationship between the node's input and output variables. At every time step, this model is used to make a prediction about the immediate future state based on the current state and the selected action. This prediction model is trained on the set of exemplars that were previously observed. These exemplars are represented as $[SM(t), S(t+1)]$ pairs. $SM(t)$ represents the sensorimotor context, i.e., the concatenation of the sensory state S and the action M taken at time t. $S(t+1)$ represents the observed sensory state at time $t+1$.

In all the experiments presented in this thesis, linear models (3.2) were used as the prediction model.

$$S(t+t) = W \cdot SM(t) \tag{3.2}$$

where W is a diagonal matrix.

Linear least squares regression or Lasso (Least Absolute Shrinkage and Selection Operator) [33] was used to obtain W. Nominally, linear regression is used due to its simplicity and the absence of parameters that require tuning. Lasso is used when the sensorimotor space includes input and output variables that are not proprioceptive. These variables tend to have low predictive power as they do not directly detect the changes in the outputs. Using Lasso can improve the model's predictability by driving the associated coefficients that are highly unpredictable non-predictive inputs to zero. Python library *scikit-learn*'s[2],[3] implementations of the two models were used.

Knowledge Gain Assessor

The KGA calculates the reward given the predicted and actual sensory inputs. It is implemented as described in [7]. Figure 3.3 illustrates the internal workings of the KGA. The metaM returns the predicted mean error, $< e(t+1-\tau) >$, which in this case is simply the average error over a window of θ previous errors τ time step before. The reward is calculated by subtracting it by the actual mean error, $< e(t+1) >$. This reward is then used by the action selector to compute the action values. The window size, θ, is a smoothing parameter that determines the KGA's sensitivity to spikes in prediction errors.

[2] scikit-learn LinearRegression: http://scikit-learn.org/stable/modules/generated/sklearn.linear_model.LinearRegression.html

[3] scikit-learn Lasso: http://scikit-learn.org/stable/modules/generated/sklearn.linear_model.Lasso.html

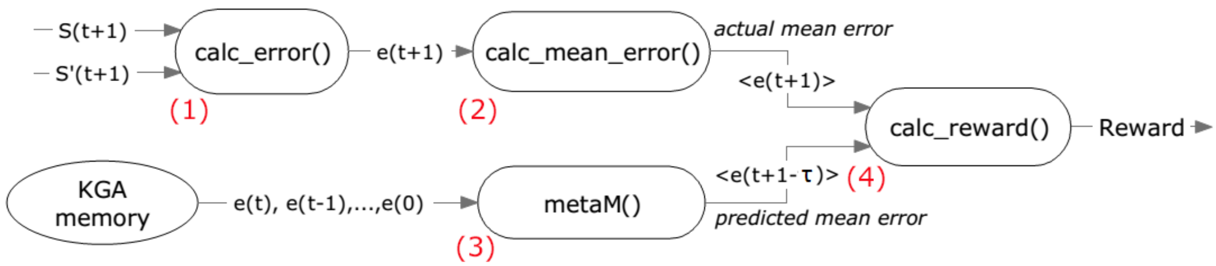


Figure 3.3: $S(t+1)$ and $S'(t+1)$ are the actual and predicted sensor input variables. (1) The KGA computes the error by taking their root-mean-square error difference. (2) After that, it computes the mean error over a window of previously calculated errors. Note that the mean error is only calculated based on errors associated with this particular region. (3) The metaM predicts the error also by taking the mean error a window of previously calculated errors with an offset of τ. (4) Finally, the KGA outputs the reward by taking the difference between the actual mean error and predicted mean error.

Region Splitter

The system initially has only one region. All new exemplars are added to the same region. As more exemplars are added to memory, once split criteria 1 and 2 are met, a region will split into two parts.

Criterion 1:

$$N > \tau_1 \tag{3.3}$$

N is the number of exemplars; and τ_1 is the threshold that is inherited from the expert's parent.

Criterion 2:

$$e > \tau_2 \tag{3.4}$$

e is the mean error of the region and τ_2 is a threshold parameter.

Criterion 1 specifies that a region can only split into two when it contains a sufficient number of exemplars, to ensure that there will be enough training data in the sub-regions. Criterion 2 specifies that a region will only split if prediction error is high. This prevents learnt models with high accuracy from being split indefinitely. If the split criteria are met, the Region Splitter finds a cut value and a cut dimension that minimizes the average variance in each sub-region.

After the best cut value and cut dimension are identified, the exemplars of the parent region are split between the two regions based on the cut dimensions and values. The high-level mechanism of the region splitting process is illustrated in Figure 3.4.

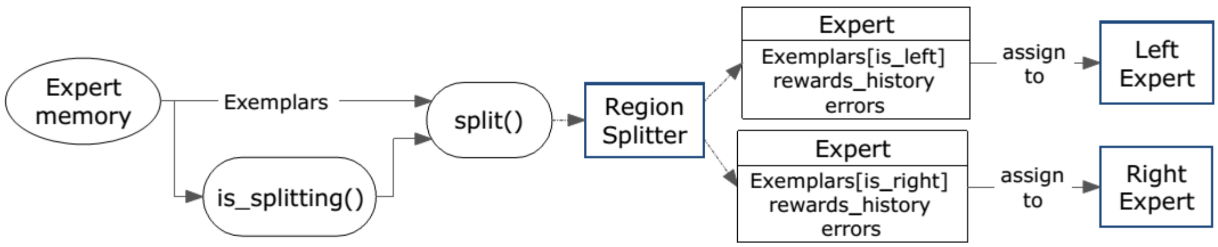


Figure 3.4: When the function split() is called, it first checks if the split criteria are met by calling "is_splitting()". If the split criteria are met, it forwards the exemplars to the Region Splitter. The Region Splitter then splits the exemplars into two and assigns them to the Left and Right Expert. Other properties such as the previous errors and rewards are passed on as well.

3.1.4 Pseudocode of CBLA

The overall process is described in the pseudocode for the CBLA and is shown as Algorithm 1.

Algorithm 1 Pseudocode for the CBLA

$t \leftarrow 0$
$S(t) \leftarrow S(0)$
loop
    $[Possible\_M(t)] \leftarrow Node.get\_possible\_action(S(t))$
    $[Action\_Value(M(t))] \leftarrow Expert.evaluate\_action(Possible\_M(t))$
    $M(t) \leftarrow Action\_Selector.select\_action([Possible\_M(t), Action\_Value])$
    $Node.actuate(M(t))$
    $S(t+1) \leftarrow Node.report()$
    $S'(t+1) \leftarrow Expert.predict(S(t), M(t))$
    $Expert.append(S(t), M(t), S(t+1), S'(t+1))$
    $Expert.split()$
    $t \leftarrow t+1$
end loop

3.1.5 Differences between the CBLA Engine and the IAC algorithm

In developing the CBLA Engine described above, several adaptations have been made to the IAC algorithm to enable application to the kinetic sculpture installation.

Region Splitter

Several improvements are made to the logic of the Region Splitter. As we run the algorithm over an extended period of time, the expert might have already learnt the model of the system as best as possible given the available sensory information. Since Oudeyer's method simply splits a region when the number of exemplars exceeds a certain threshold, it will continue to split regions even when the expert associated with that region has already acquired a good model with low prediction error. This is undesirable as it leads to over-fitting and makes the system harder to adapt when the system itself or the environment changes.

In our implementation, an additional prediction error threshold is added to prevent regions from splitting when the prediction error is low. Moreover, there is no reason to split the region if the split does not improve the prediction accuracy. Therefore, after the split, the split quality must also be above a threshold. If it is not, the split will be retracted. This split quality is measured by the magnitude of the average within-group variance relative to the overall variance.

During the early stages of the learning process, learning opportunities are plenty. Setting the split number threshold too high can hamper the speed of learning. However, over time, easy learning opportunities diminish and complex regions require a larger number of exemplars. Thus, the split number threshold grows at a constant rate every time a split happens. This way, regions that are less explored can maintain low thresholds which promote learning, while mature regions have higher thresholds which promote gathering of more exemplars and reduce over-fitting. Likewise, the split quality threshold decreases after every split because the amount of improvement of the average within-group variance tends to decrease as the regions become smaller and denser.

In addition, in [7], the cut value and cut dimension are determined by generating a set of random cut values for each dimension and computing the corresponding variances of the resultant sensor inputs. The cut value and dimension pair with the lowest total variance is selected. The total variance is the sum of the variances of $S(t+1)$ in each dimension. In our implementation, changes are made to the way regions splitting is done.

First, in order to take the interdependency among dimensions into account, instead of using the $S(t+1)$ value directly when computing variances, herein, its principal components are used. Using its principal components can better reflect the underlying structure of the data by emphasizing the differences among data points along the direction of maximum variance. Note that we do not compute the principal components of the $SM(t)$, where the cut value and cut dimension are specified. Instead, the evaluation is based on the principal components of $S(t+1)$ for which we want to minimize the variance.

Second, in [7], if one dimension tends to have a lower variance than another, that dimension is much more likely to get selected, even if the cut does not lower its resultant variance. Since region splitting aims to separate groups into low variance regions, this is unproductive as it does not decrease the variance. Here, instead of using the variance, relative variance is used. It is computed by taking mean of the variance of the region divided by the total variance of the overall region before splitting as shown in (3.5). This gives a better indicator on whether or not the split results in generating lower variance regions. A relative variance of 1 implies that the split does not improve the variance. On the other hand, a low relative variance implies that the split decreases the regional variance. This method can reduce the number of unproductive splits that fragment the state space.

$$S_{relative} = \frac{S_1 + S_2}{2 \cdot S_{1,2}} \tag{3.5}$$

S_1 and S_2 are the total variances of the two regions split using the candidate cut value and cut dimension; $S_{1,2}$ is the total variance of the two combined regions.

Furthermore, Oudeyer's method is susceptible to leaving a small number of exemplars near the ideal cut value incorrectly split. Figure 3.5 shows an example that illustrates this problem. The blue squares represent the exemplars in a region. In this example, the green dotted line represents the ideal cut value as it would minimize the average within-group variance of the two groups after the split. If potential cut values are selected randomly as done in [30], cut values like those shown as red lines might be selected. In this case, cut value (b) would be chosen, as it would result in the lower average variance than line (a) and (c). This would place the first point on the right side of the line (b) in the wrong group. Next time the regions need be split, another attempt would be made to make a split near the ideal cut value (green dotted line). This would result in an excessive number of similar regions near the ideal cut value.

On the other hand, although one can simply iterate through every exemplar in the region and find the cut value with the lowest variance, this is impractical, as a significant number of iterations are required as the number of dimensions and exemplars increase.

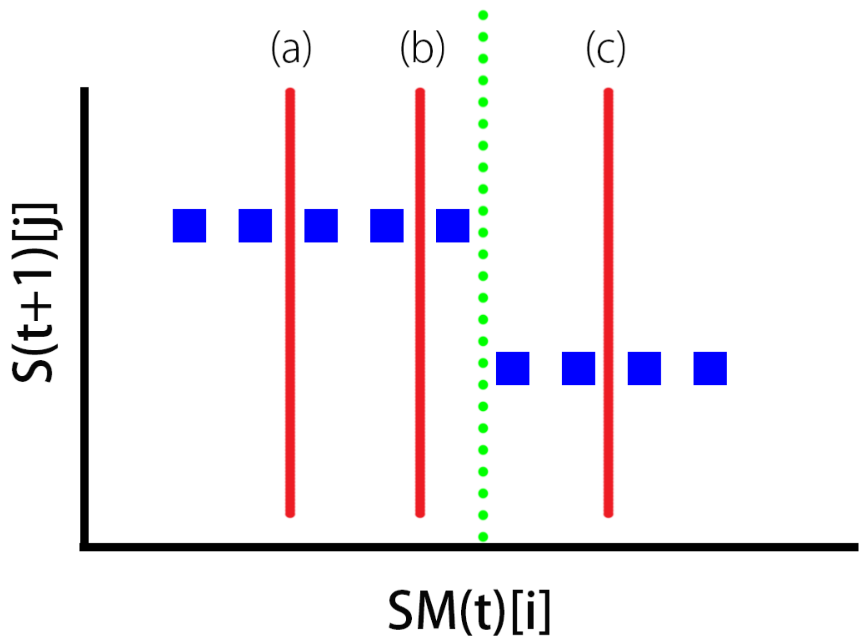


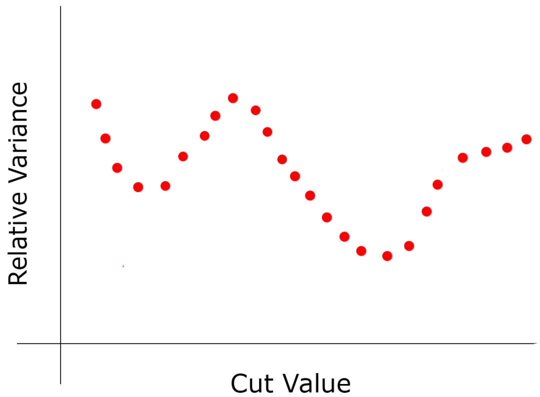
Figure 3.5: An example illustrating the problem with selecting potential cut values at random. The x-axis represents one dimension in the sensorimotor context, which is where the cut values are chosen from. The y-axis represents one dimension of the resultant state, where the variances are computed. Each blue square represents an exemplar in a region that is being split. The green dotted line represents the ideal cut value. The red lines represent a set of potential cut values selected randomly.

To improve the likelihood of finding the best cut value while keeping the number of iterations low, a new divide-and-zoom-in method is implemented to focus on promising ranges of cut values. The toy example in Figure 3.6 illustrates how this method works. In a region with N exemplars, there are $N-1$ possible cut values for each dimension. Each dot represents the actual relative variances if the region is split in between each pair of exemplars. However, the relative variances are not evaluated for all of them. In Figure 3.6a, all possible values are identified by the algorithm and plotted along the x-axis. The y-axis shows their true relative variances, though they are not known by the algorithm. The colour red indicates that the relative variance for the cut value has not been evaluated.

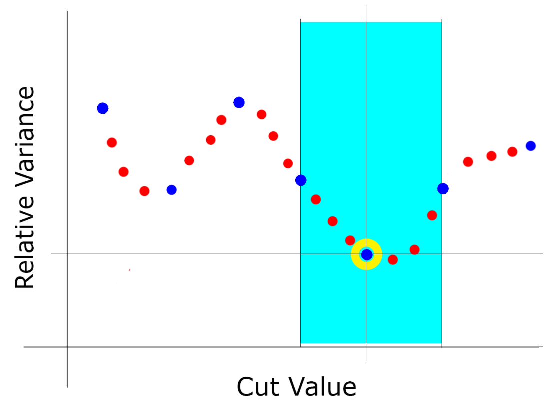
Then, the relative variances of the smallest, largest, and the k potential cut values evenly spaced in the middle are evaluated as shown in Figure 3.6b ($k=5$). The colour dark blue indicates that the relative variance for the cut value has been evaluated. After that, the point with the lowest relative variance as indicated by the yellow ring and its two adjacent evaluated points are identified. In the next iteration, the algorithm zooms in to the range between those two adjacent points as indicated by the light blue region. Note that the value of k must be greater than 3, and if k is set to $N - 1$, it is equivalent to evaluating every possible value.

The aforementioned process is then repeated in the new zoomed-in region as shown in Figure 3.6c. This continues until the number of potential cut values in the zoomed-in range is fewer than or equal to k. When that happens, in the final step shown in Figure 3.6c, the relative variance for potential cut value within the range at that iteration is evaluated. The one with the lowest relative variance is selected as the best cut value for that particular cut dimension. This entire process is repeated for each dimension and the cut dimension and cut value pair with the lowest relative variance is selected for the splitting process.

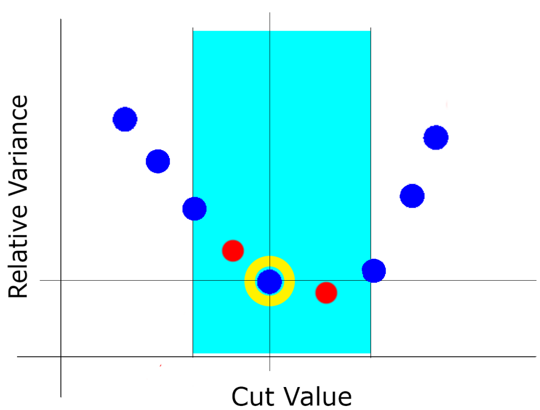
This method can at least find a local minimum that cleanly splits a region into two because it searches for cut value with the lowest variance by checking every possible cut value within a range bounded by higher variance values. It keeps the number of relative variance computations low by focusing on promising regions where cut values with relatively low variances can be found. Though this method may not necessarily find the global minimum, it is better than simply computing the variances of a set of random cut values given the same number of evaluations. It avoids the problem of points near a local minimum being split into multiple regions over successive splitting processes.



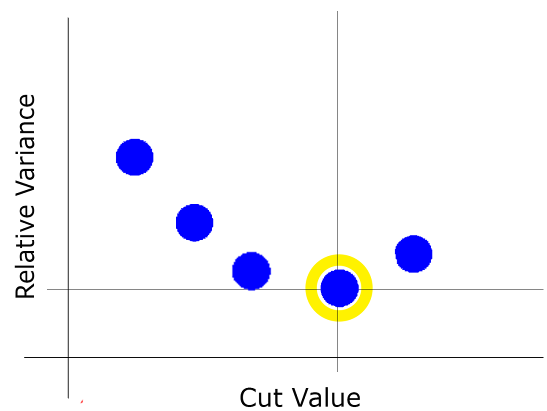
(a) Each dot represents the actual relative variances if the region is cut in between each pair of exemplars in a region. At this point, the relative variances have not been calculated yet and this is indicated by the colour red.



(b) In the first iteration, the relative variance of a subset of all possible cut values (shown as dark blue dots) are evaluated. The one with the lowest relative variance (yellow ring) and its two adjacent evaluated points are identified. This process is then repeated in the range between those two points (light blue) in the next iteration.



(c) In the second iteration, the computation is repeated in a smaller, zoomed-in range. It continues until the number of potential cut values in the zoomed-in range is below a threshold.



(d) In the final step, the relative variance for every potential cut value within the range is evaluated. The one with the lowest relative variance is selected as the best cut value.

Figure 3.6: A toy example explaining the "Divide-and-Zoom-In" region split values computation method.

Action Selection

Visually, it is difficult to distinguish between the periods when the IAC is learning from the periods when the IAC is simply executing random actions after all regions are learnt. In order to better visualize the learning process, we introduce some constraints that produce different actions given different levels of activation.

We considered two different types of implementations. In the first implementation, we introduced Idle mode. The Idle Mode action is chosen as the action that requires the least power. This gives the visitors the sense that the sculpture is resting. During Idle Mode, the system selects the idle action a majority of the time. Otherwise, it will select an action based on its regular action selection policy. The CBLA engine enters Idle Mode when there is small knowledge gain potential. Conversely, it exits Idle Mode hen the knowledge gain potential, or the change of it is higher than a threshold. Once it exits Idle Mode, it must stay out of Idle Mode for at least a certain period of time before being allowed to enter Idle Mode again.

Alternatively, instead of having a hard threshold that moves the system from totally quiet to totally active, we used a sigmoid function shown in Equation (3.6) to define a range of activations from low activation to high activation. In this formulation, we capped the maximum output level m_{max} based on the knowledge gain potential x. This way, there is a visually lower level of activation while the knowledge gain potential is low.

$$m_{max} = \frac{1}{1 + e^{-kx+a}}; \quad k > 0 \tag{3.6a}$$

$$a = \ln\left(\frac{1}{b} - 1\right); \quad 0 < b < 1 \tag{3.6b}$$

m_{max} is the maximum output level which can be a number between 0 to 1; x is the knowledge gain potential; b determines the minimum output level when knowledge gain potential is 0; k determines the steepness of the sigmoid function.

To compute the knowledge gain potential, we either use average action value or relative action value. Average action value requires calibration and is not adaptive to fundamental changes in the system like when a sensor is covered or disconnected.

Relative action value is used to reduce the difficulty of tuning for different actuators as different actuators have different inherent level of action values range. This relative action value is calculated by dividing the squared action value of this time step by average squared action values over the previous W time steps as shown in Equations (3.7) to (3.9).

This means that even if there is a fundamental change to the system, it can still adapt over time.

$$Q_z = [q_{z-W}, q_{z-W-1}, ..., q_{z-1}] \tag{3.7}$$

Q_z is the set of previous W action values q at time step z; W is the window size and it is a constant.

$$\overline{q_z^2} = \frac{1}{W} \sum_{i=z-W}^{z-1} q_i^2 \tag{3.8}$$

$\overline{q_z^2}$ is the average squared action value at time step z over the window of width W.

$$\widehat{q_z^2} = \frac{q_z^2}{max(\overline{q_z^2}, \nu)} \tag{3.9}$$

$\widehat{q_z^2}$ is the relative action value; q_z^2 is the current action value; ν is the sensitivity constant.

One consequence of this formulation is that the denominator will become too small over time and a very small increase in action value can trigger large activation. This can be a desirable feature as it creates a system that periodically wakes up in hope to attract visitors when there is nothing to be learnt for long time. This sensitivity level during low learning period can be adjusted by changing the value of ν. On the other hand the window size W affects how quickly the system can adapt to a new ambient environment.

3.2 Multi-Node CBLA System

One option for controlling a larger system of sensors and actuators is to control them centrally through a single CBLA engine. However, if all output and input variables are grouped into one node, the sensorimotor state will become very large and it might take a very long time for the system to converge and react to changes. Therefore, subsets of related variables are grouped into nodes. Each node runs on its own CBLA engine in parallel. While our implementation uses a centralized high-level processor to compute these parallel CBLA engines, this architecture also allows for distribution of the software agents to local processors.

3.2.1 Sensorimotor Context of a CBLA Node

There are several options for grouping sensors and actuators into nodes. One approach is to group actuators and their associated proprioceptive sensors by function, because these relationships are the easiest to model. In addition, if multiple actuators work together to perform one function that directly affects one sensor, they should be grouped as a node because their relationship must be considered in order produce a prediction model for the sensor input. However, grouping simply by function cannot capture environmental changes and occupants' interaction effectively since nodes with the same functions are typically distributed over the entire sculptural system.

Another approach is to group sensor input and actuator output variables by spatial proximity. Since environmental changes and occupant interaction are likely to affect components that are close together physically, this will allow the system to capture those dynamics more effectively.

However, all sensor input and actuator output variables associated with a particular node are updated once per loop. This means that the loop speed is limited by the slowest actuator or sensor within the node. For instance, an Fin node that is actuated by shape memory alloy (SMA) wire[4] has a heating and cooling cycle time of about 12 seconds, while an LED can be turned on and off many degrees of magnitude faster. This is very inefficient and limiting for the fast components. Therefore, components running at different speeds should be grouped into different nodes. This allows each node to run at its own speed, independently from the other nodes.

In our implementation, each node is constructed of components that are related functionally and proximally. For instance, LED output and ambient light sensor are in one node; Fin motion and accelerometer are in one node. Different nodes run at different frequencies and capture the dynamics of the system at different time scales. We limited the number of outputs per node to one. This structure keeps the system's dimensionality low and flexible. This also allows us to optimize the CBLA loop rate for each type of actuator as the bandwidth is mainly constrained by the bandwidth imposed by the actuators. Also, no more than one node can control one physical actuator since this will result in conflicts.

3.2.2 Inter-Node Connections

Nevertheless, if the nodes perform learning independently, the CBLA does not actually capture the dynamics of the entire system. To integrate the nodes into one coherent entity,

[4] Dynalloy Flexinol Actuator Wire: www.dynalloy.com/tech_data_wire.php

we have used shared sensors and virtual inputs.

By sharing input variables that share the same sensor, system changes effected by one node can be detected by another node indirectly. For instance, two adjacent nodes might share a single IR Proximity sensor. This way, change in the environment can be seen by both nodes. However, when two Nodes share one input variable, if the action of the actuator does not affect the shared sensor, information about that event is not transferred to the other Node.

Another method is to treat output signal from a node as input to other nodes. We called this a virtual input. This way environmental changes happening to one node can be detected by other nodes indirectly in the time steps afterwards. The idea is that external disturbances, like a user standing in front of the sensor of a node, may be represented as an output signal originating from that node, which may be measured by another node. This gives the other node information about the fact that there is someone, albeit being somewhat delayed. Figure 3.7 illustrates how Node 2 can detect changes in the environment that are not covered by its own sensors through Node 1. The reason for doing this is that the changes in the environment that are only detectable by Node 1 might be an effect of an action selected by Node 2. This mechanism allows Node 2 to capture these kinds of complex relationships.

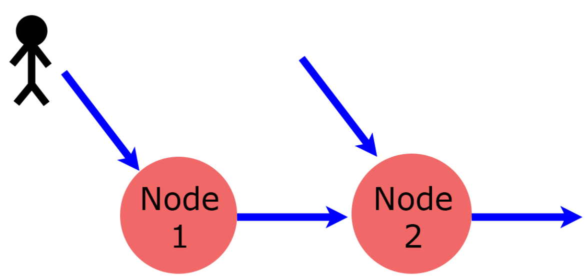


Figure 3.7: An example of illustrating how Node 2 can indirectly detect the presence of a user through Node 1. The presence of the user may affect the output of Node 1. Since Node 2 takes the output of Node 1 as input, Node 2 would in effect respond to the presence of the user indirectly despite not having a sensor that can detect the user in its sensorimotor context.

3.2.3 Summary

In this chapter, the implementation of the CBLA Engine, a reinforcement learning algorithm that selects actions that lead to the maximum potential knowledge gain, is detailed. Each engine represents a subset of the system and constructs a model that predicts the consequences of its actions given its current states. A system is then formed by connecting a network of CBLA Engines through shared sensors and virtual inputs. The distributed approach enables the system to respond to the occupants and adapt to localized changes in the surroundings quickly. Building on this CBLA system, a sculptural system that generates its own life-like, interactive behaviours may emerge.

Chapter 4

Interactive Control System[1]

To enable the sculpture to understand its own mechanisms, in addition to its surrounding environment and the occupants, there must be at least one proprioceptive sensor associated with each actuator. Note that while the nominal purpose of such a sensor is to directly sense the results of activation, they can also be used to detect changes in the environment, such as interaction with visitors. This implies a large increase in required sensing and control capability which the previous versions of the Hylozoic Series embedded electronics [3] are unable to provide. A new Hylozoic Series 3 interactive control system was developed with re-designed hardware, to enable the control and sampling of a larger number of actuators and sensors at a higher frequency. In this chapter, we discuss the design of the hardware and software mechanisms that enable the learning algorithm behaviours, and some of the specific actuators and sensors that we use. The design and implementation of an experimental test bed are also presented.

4.1 System Architecture

In this implementation, we opted for an architecture where a centralized computer controls a number of smaller localized microcontrollers that each interface with the sensors and actuators. By running the high-level algorithm on a central computer, complex algorithms can quickly be developed without the constraints of an embedded platform. In addition, it provides an abstraction layer that enables the designer to build virtual sub-systems

[1] Part of this chapter is adapted from papers published with IROS 2015 [1] and Next Generation Building [2]

using any of the sensors and actuators. These two features allow us to quickly test out different configurations. On the other hand, by distributing the low-level logic on localized microcontrollers, the system can be more modular and the number of wires can be reduced as well as being an important step toward an eventual spatially-distributed CBLA system. In addition, the real-time nature of the microcontrollers allows protection of sensitive actuators in case of central computer failure.

Figure 4.1 shows the high-level system architecture of the Hylozoic Series 3 Interactive Control System. Each component runs asynchronously. At the bottom are the Teensy Devices. They represent the physical components in the sculptural system. Each Teensy Device consists of a Teensy Development Board[2] that communicates via USB with a computer that hosts the abstract components. Each Teensy controls and samples from a number of actuators and sensors. More details about the physical hardware are presented in Section 4.2.

For each Teensy Device, a Teensy Interface thread is created with the corresponding communication protocol and system parameters. Each type of Teensy Device has its own unique set of parameters that dictate or reflect the behaviours of its actuators or sensors, respectively. Examples of some of the parameters are the brightness of an LED, and the readings from an accelerometer. The InteractiveCmd module was created to provide a communication layer for all the physical components. Nodes can be created to control or sample any of the actuators and sensors through the InteractiveCmd module. The InteractiveCmd module handles the commands sent from the high-level algorithm and forwards them to the appropriate Teensy Interface in an efficient manner. A Messenger was created to streamline the message delivery system by periodically pushing commands received from the abstract Nodes in a more compressed form. This reduces the number of commands being sent to and received from InteractiveCmd, enabling the system to operate more efficiently.

The Input Nodes and Output Nodes are the abstractions for sensors and actuators. Their sole purpose is to sample or update a particular sensor or actuator continuously. The second level of abstraction are the Device Nodes. Each Device Node is generally made up of one or more Input or Output Nodes, though it can also be completely virtual. It provides additional functionalities such as providing progressive dimming effects to the LEDs, or calculating the running average of a variable. The third level of abstraction are the CBLA Nodes. They are made up of components of the Device Nodes. This is also where the CBLA Engine and Prescripted Engine reside. The internal working of the CBLA Engine is discussed in Chapter 3. A Prescripted Engine is an alternate set of behaviours

[2] Teensy Development Board: www.pjrc.com/teensy/teensy31.html

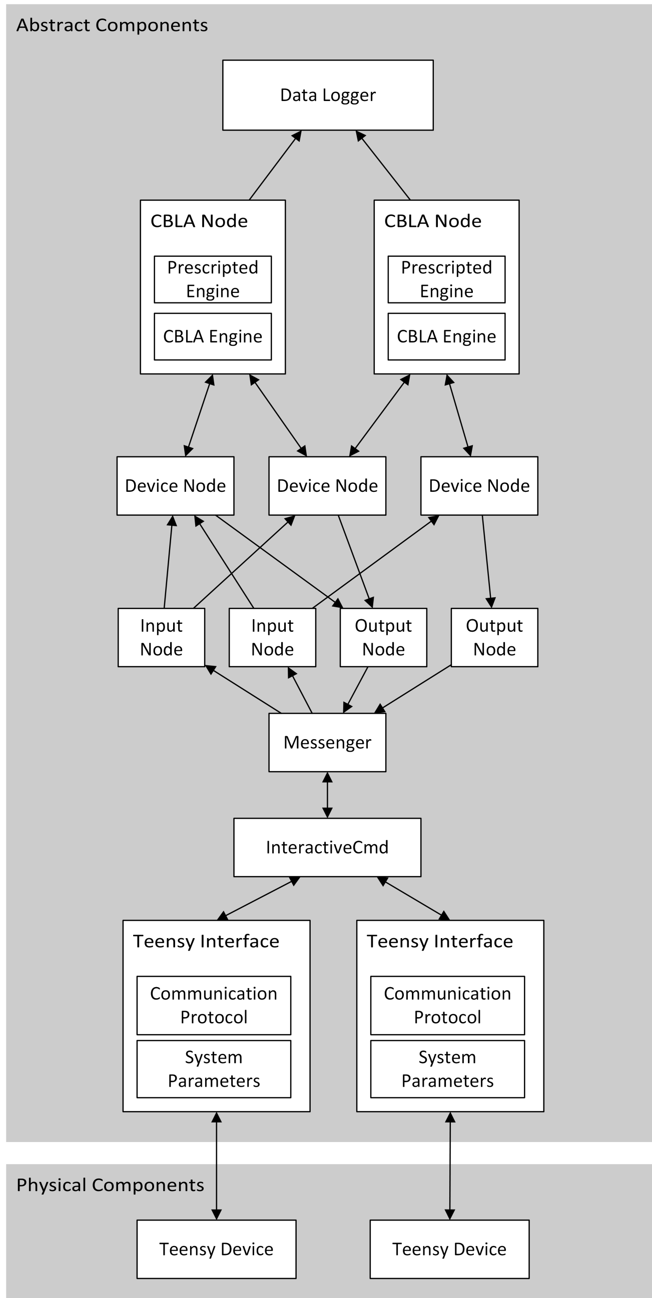


Figure 4.1: The system is comprised of abstract and physical components. Each component runs asynchronously in its own thread. Each arrow represents the data flow from one component to another.

that follow user designed scripts, and do not involve any learning algorithm. A CBLA Node can be switched to either Engine while it is running.

The Data Logger is a special kind of abstract component that periodically samples the abstract variables of each abstract node, packages the data in the memory, and saves data in the hard drive in an efficient manner. The data collected are stored in a persistent key-value database for further analysis. In addition, the entire state of the CBLA Engine is also saved. This allows the CBLA system to recover from a previous state at a later time.

4.2 Hardware

The hardware was custom designed in collaboration with Mohammadreza Memarian. The goal was to develop a system that is modular, flexible, and expandable. Analogue sensors and actuators that were traditionally used in previous Hylozoic Series as well as off-the-shelf sensors that interface via I2C, SPI, or UART are supported. Most importantly, the design enables high-speed two-way communication with a computer over USB. Sensor readings and control signals can be delivered to and from a computer at around 100Hz. This capability allows us to run algorithms that are more computationally intensive; simplify the implementation of multi-threaded and multi-process software; and collect and display a large amount of data at runtime on a standard computer.

The sensors and actuators used in the experiments described in Chapter 5 and their interface types are tabulated in Table 4.1 and Table 4.2 respectively.

Table 4.1: List of sensors that were used in the experiments and their interface types

Sensor	**Interface Type**
IR proximity sensor[3]	Analogue
Accelerometer[4]	I2C
Ambient light sensor[5]	Analogue

[3] Sharp GP2Y0A21YK Infrared Proximity Sensor: www.sharpsma.com/webfm_send/1208
[4] ADXL345 3-Axis Digital Accelerometer: www.analog.com/media/en/technical-documentation/data-sheets/ADXL345.PDF
[5] SparkFun Ambient Light Sensor Breakout (TEMT6000): www.sparkfun.com/products/8688

Table 4.2: List of actuators that were used in the experiments and their interface types

Actuator	**Interface Type**
Shape memory alloy (SMA) wire[6]	PWM
Vibration motor	PWM
LED	PWM
High-power LED[7]	PWM

The aforementioned actuators and sensors interface with the Control Module through some custom drivers called Device Modules. Different actuators or sensors require different Device Modules due to their different power requirements. They are plugged into the Device Ports on the Control Modules (discussed in Appendix A). These Device Modules provide the power switching and voltage regulation needed to drive the actuators and sensors.

Combinations of the actuators and sensors listed in Tables 4.1 and 4.2 are used to form three functional units: 1) Fin Unit, which is composed of two SMA wires, one infrared (IR) proximity sensor, and a three-axis accelerometer; 2) Reflex Unit, which has a pair of LEDs (wired in parallel), a vibration motor, and one infrared (IR) proximity sensors; and 3) Light unit, which comprises a high-power LED and an ambient light sensor. Their spatial configurations are shown in Figure 4.2.

A Fin Unit moves a 2-DOF Fin-like mechanism made of flexible plastic rods, by controlling its two SMA wires. A Reflex Unit actuates a vibration motor and mobilizes the Frond-like mechanism attached to it. The pair of LEDs in the Reflex Unit shine on to the Frond for additional effect. A Light Unit contains a very bright LED and it is hung in the canopy of the sculpture, above the visitors. The IR proximity sensors detect the position of the occupants or objects within their ranges. The accelerometers detect contacts with the occupants and the deformations of the Fins. The ambient light sensors detect the light intensities of the ambient environment and their associated LEDs.

[6] Dynalloy Flexinol Actuator Wire: `www.dynalloy.com/tech_data_wire.php`

[7] Indus Star High-Power LED Light Module: `www.luxdrive.com/content/A007_A008_Data_Sheet_V1.2.pdf`

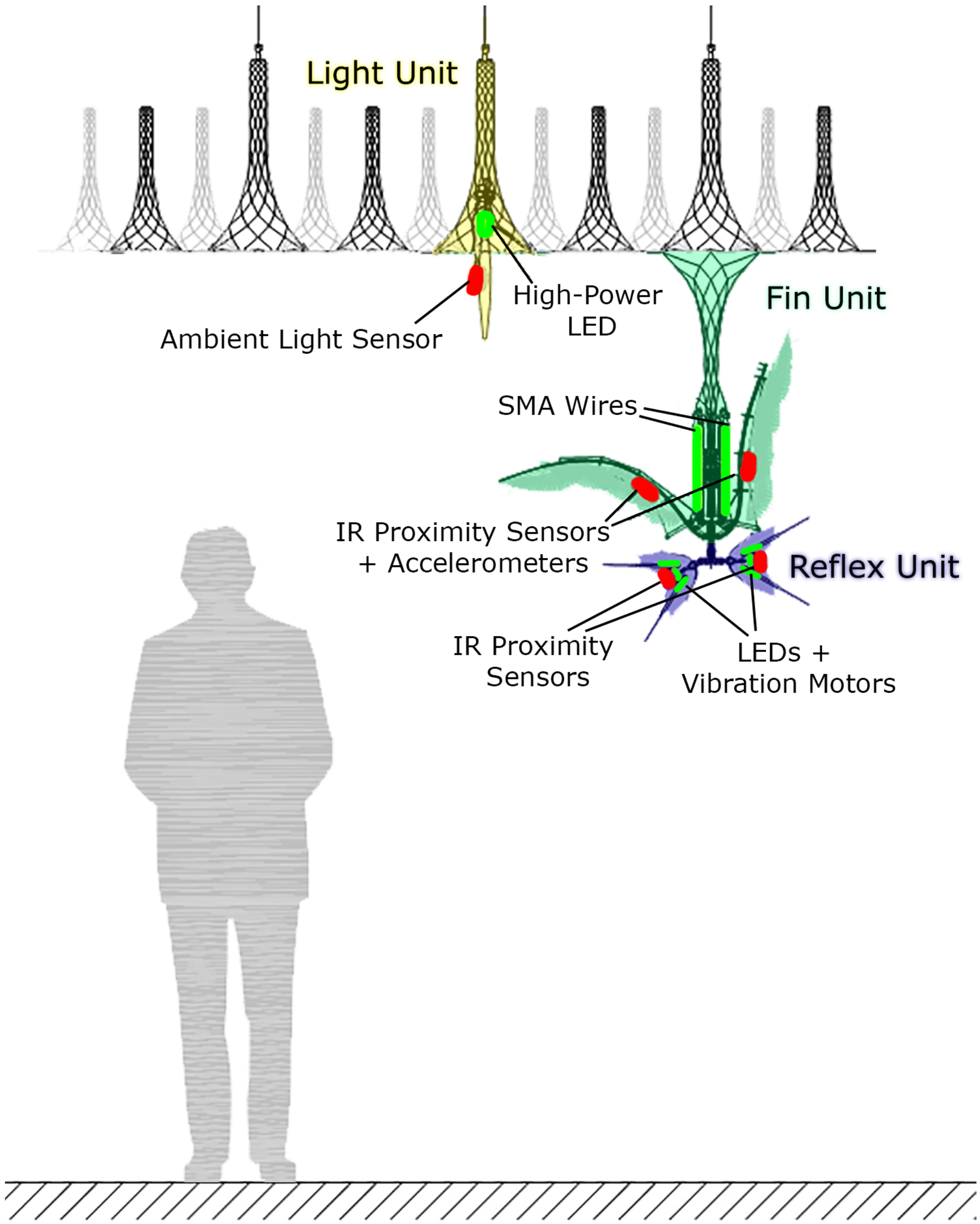


Figure 4.2: This is a typical spatial configuration of the functional units (figure adapted from an image provided by Philip Beesley Architect Inc.). Bright green denotes actuators and bright red denotes sensors. Light Unit is shaded yellow (1 shown); Fin Unit is shaded green (2 shown); and Reflex Unit is shaded purple (2 shown).

4.3 Control Software

The control software of the sculpture consists of a low-level firmware layer and high-level application layer. The two layers are connected via USB. The low-level layer consists of the firmware that interfaces with the peripherals that connect with the actuators and sensors. It resides on a custom Control Module that interfaces with the physical electronic components. The implementation details of the Control Module can be found in Appendix A. The high-level layer consists of the tools that facilitate communication between the two layers and the application that dictates the system behaviour. The abstraction provided by the high-level layer allows flexibility in defining the nodes and their relationships to each other.

4.3.1 Communication and Interface

A low-level layer of firmware written in C++ runs on the Teensy 3 USB-based development boards which interface with the peripherals that connect with the actuators and sensors. High-level software written in Python 3.4 runs on a central computer. The use of the central computer as a development platform provides flexibility for development free from the limited processing power and specialized functions inherent to the Teensy microcontroller hardware. Moreover, Python 3.4 is cross-platform and supports multi-threading, permitting operation within many operating systems and allowing multiple sets of software instructions to be executed in parallel. Code that is necessary for communicating with the low-level layer is packed into a Python Package named *interactive-system*. Developers can then develop applications that control and retrieve information from the sculptural system firmware using the software utilities provided by the Python Package. Each application can run on its own thread. While care should be exercised to avoid conflicts among threads, this should permit multiple applications to execute simultaneously.

CBLA executes as an application that communicates with the low-level layer using the *interactive-system* Python package. Other applications such as an occupancy map that uses the sensors on the sculpture to interpret the locations of the occupants can run simultaneously, taking advantage of the multi-threading properties of the high-level platform.

Figure 4.3 illustrates how an application communicates with the Teensy devices. At the high-level layer, the Teensy Interface module in the *interactive-system* package is used to create a thread for each Teensy device. The thread looks for changes in those parameters and performs synchronization. Each Teensy device on the low-level layer is represented by a Teensy Interface thread on the high-level layer. Teensy devices are considered as slave devices in this communication mechanism. Only the Teensy Interface, the Master, can initiate a read or write request. An InteractiveCmd thread can modify a Teensy's output parameters and retrieve its input parameters through its Teensy Interface.

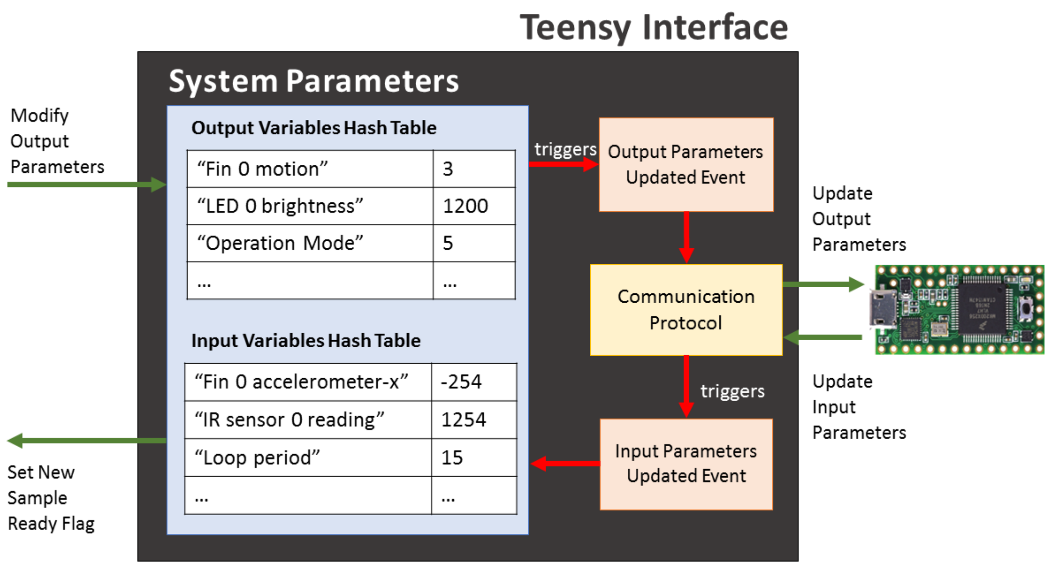


Figure 4.3: Teensy Interface is the connection between the InteractiveCmd and its associated Teensy device. InteractiveCmd modifies output parameters on its corresponding Teensy Interface's output hash table. This triggers an event that pushes the changes to the Teensy device. The Teensy device would then respond by triggering an event that updates the input hash table with newly sampled input values and notifies the InteractiveCmd.

4.3.2 Node Abstraction

Between the Nodes and the Teensy Interface, there is the InteractiveCmd. Its job is to forward messages to the correct Teensy Interface and hide the physical implementation of the low-level layer devices from the Nodes. In addition, since the InteractiveCmd module enables the control and sampling of any actuators and sensors in the system, a Node can be constructed unconstrained by spatial or hardware specificities. Each Node, physical or virtual, is represented by a set of input and output variables which can be accessed by any other nodes in the system, and each runs continuously in its own thread. Input variables are simply variables in the memory that Nodes have read access to. Similarly, output variables are variables that Nodes have write access to. Multiple Nodes can share one input variable while only one Node can be associated with one output variable. Figure 4.4 illustrates the relationships between different Nodes.

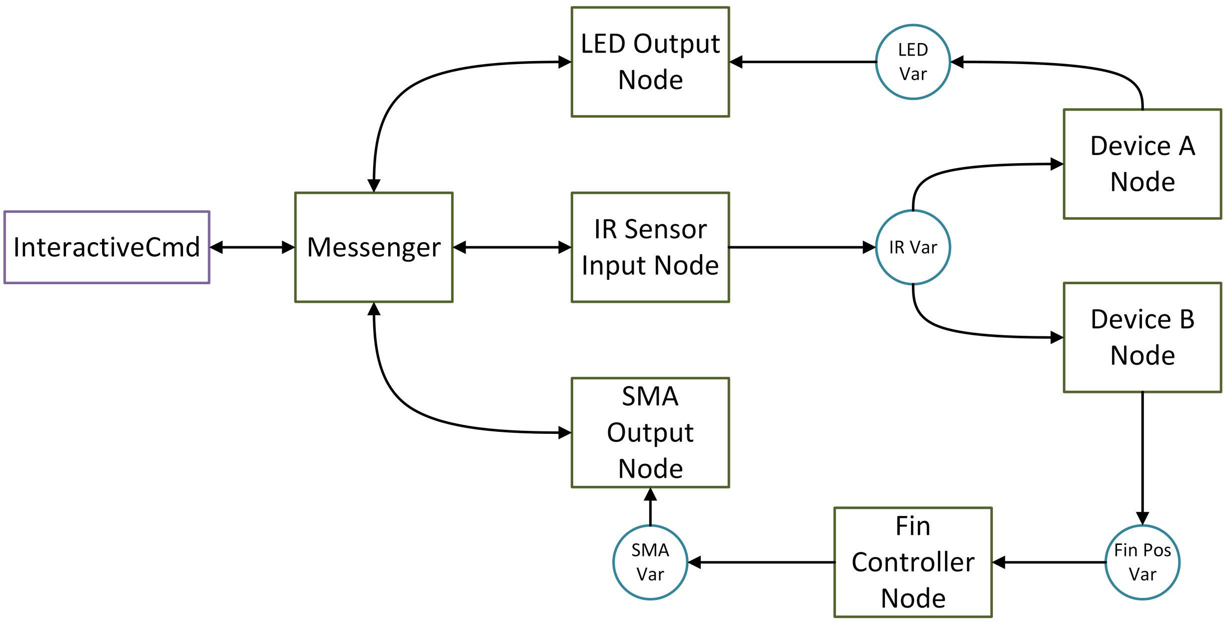


Figure 4.4: Illustration of how abstract nodes work. Each rectangle represents a thread. The purple one represents InteractiveCmd module and each green one represents a Node. The blue circle represents a variable in the memory. The arrow represents the direction of access. Multiple Nodes can share read access to a variable while only one Node can have write access to one variable.

At the lowest level, Input Nodes continuously update their associated variables, and Output Nodes continuously send output requests to InteractiveCmd through the Messenger. Different types of Input and Output nodes are configured to run at a loop period compatible with the physical components that they represent. This mechanism makes implementation of the higher level Nodes much easier by eliminating the need for communicating with the InteractiveCmd by means of sending individual messages. Instead, each of the input and output variables can be accessed from the memory at any time. These variables are used as building blocks for higher level Nodes. In addition, intermediate level Nodes can embed extra functionalities. For instance, a LED Driver ramps up or dims an LED to the desired brightness level. A higher-level Node controlling that LED using the

LED Driver can then operate at a lower update period and process more complex logic. This Node Abstraction system makes developing CBLA Nodes much simpler by eliminating the need for managing logic requiring different frequencies of control under one thread.

The addition of the Messenger node between the InteractiveCmd, and Input and Output Nodes streamlines the communication by reducing the number of messages. Over USB, each packet can contain up to 64 bytes. If each Node communicates with the InteractiveCmd directly, there will be many messages that might only require one or two bytes. A large portion of the communication bandwidth will be wasted and the update rate of the Nodes will be significantly throttled. Since many messages are likely to be delivered to the same Teensy, those messages can be combined and delivered as a single packet. The job of the Messenger Node is to collect all the messages, combine them appropriately, and deliver them to the InteractiveCmd periodically. Although this means that each message must wait for the next delivery cycle to be sent out, this mechanism allows the system to handle a much higher throughput. To avoid commands or requests being missed, the rate of each Input or Output node is set to be at least three times the Messenger's update period.

4.4 Data Logging

For secondary analysis, the values of all input and output variables of every Node, as well as the internal variables within each CBLA Engine must be collected and stored on the hard drive. In addition, the state of the CBLA Learner, including all the exemplars, the prediction models, and the definitions of the regions must be stored such that it can be recovered at a later time.

The CBLA system contains a large number of asynchronous threads that run at their own speeds. As a result, a large amount and variety of data are generated at high frequencies and at different times. These data must be handled in a way that does not slow down the system. In addition, in case the program fails to terminate safely, the majority of the data should still be recoverable. Also, the data must be saved to disk and be discarded from the memory continuously as the CBLA system is expected to operate for a long period of time. A specialized Data Logging module was developed to facilitate the collections of the high volume of data needed for validation purposes. Details about the implementation can be found in Appendix B.

4.5 Multi-Cluster Test Bed

An experimental test bed was built to investigate how users interact with the CBLA system. The four-cluster test bed resembles a typical interactive sculpture produced by Philip Beesley Architect Inc. (PBAI) and was used in the experiments described in Sections 5.3 and 5.4. A photograph of the complete test bed is shown in Figure 4.5.

Figure 4.5: Photograph of the multi-cluster test bed with the LEDs actuated. The names of the Clusters from left to right are: Cluster 1 ($C1$), Cluster 2 ($C2$), Cluster 3 ($C3$), and Cluster 4 ($C4$).

4.5.1 Electronic Components

A Light Unit is made up of one high-power LED and one ambient light sensor (shown in Figure 4.6a). The high-power LED is mounted on top of a flask containing coloured liquid. The ambient light sensor is mounted on the side of the flask under the LED. This allows the ambient light sensor to measure the intensity of the light emitted by the LED.

A Fin Unit is made up of two SMA wires, a pair of LEDs, a vibration motor, a 3-axis accelerometer, and two IR proximity sensors. The two SMA wires pull on two levers that move a Fin, which is a mechanism made of soft plastic rods that curls up (shown in Figure 4.6b). An IR proximity sensor and an accelerometer are mounted at around midway between the tip to the root of the Fin. At the bottom of the Fin, a vibration motor, a pair of LEDs, and an IR proximity sensor are mounted in the middle of two frond-like objects (shown in Figure 4.6c).

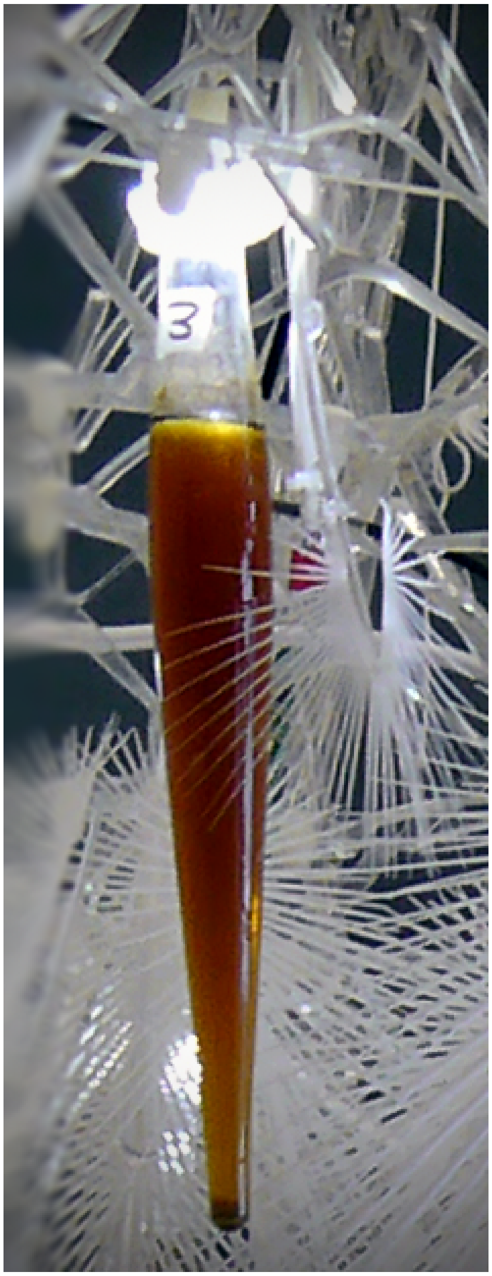
4.5.2 Device Nodes

Device Nodes further abstract the Output and Input Nodes to enable higher level functionality. This frees the CBLA Nodes from managing the constraints imposed by the physical attributes of the actuators and sensors.

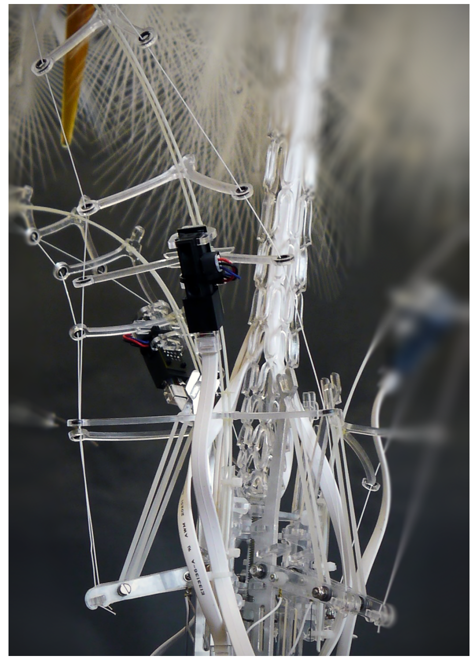
SMA Controller Node

In the experiment described in Section 5.2, the SMA wires were only operated in fully-off or fully-on mode. This means that a Fin with two SMA wires can only have four possible states. In addition, each actuation must be a cycle since the SMA wires cannot be fully actuated at 5V for more than 2 seconds. Empirically, we determined that the cooling period takes around 10 seconds. This means that the loop period for a CBLA Node cannot be lower than 12 seconds since it does not have the freedom to actuate the SMA wires again during the cooling period, in order to protect the wire. These restrictions are problematic during interaction with the users since the learning period and response latency would likely take longer than what a typical visitor would spend in front of a section of a sculpture. In addition, only a very coarse model can be made with only four possible actions that the Fin can choose from. This means that the Fin Node would likely be very unresponsive since the variance in resultant state for each kind of action is likely to be very high.

To improve the action resolution of the Fin subsystem, a position controller Node is needed to enable the SMA wire to hold its contraction while keeping the SMA wire at a safe temperature. Since the length of an SMA wire is related to the temperature, and current is passed through the SMA wire to generate heat, to maintain a position, the controller needs to adjust the output voltage to a level that can maintain the desired temperature. This can reduce the loop period as the SMA wires no longer need to cool down after actuating. In addition, the number of actions is no longer limited to four as the Node can select any value between fully-off and fully-on. However, it is difficult to attach a temperature sensor



(a) Light Unit



(b) Fin Unit (top)

(c) Fin Unit (bottom)

Figure 4.6: Photograph of components in the multi-cluster test bed.

to the SMA wire. Thus, instead of using a feedback controller, only an open-loop controller with a model that estimates the temperature of an SMA wire is used.

This controller essentially produces a control signal that allows the SMA wire to quickly reach its desired temperature by setting the output voltage very high. It then gradually lowers the voltage as the SMA wire reaches its desired position according to an internal model. The implementation of this SMA Controller Node can be found in Appendix C.1. Due to the lack of feedback control and the simplifications and approximations made when developing the model, this controller is unlikely to be accurate. However, the main purpose of this SMA Controller is to enable the CBLA Node to hold the Fin at a particular position. As a result, this allows the CBLA Engine to run at a higher rate and expands the number of possible actions.

LED Driver Node

If a CBLA Node controls an LED directly, any change in brightness would be set instantly. As a result, the LED may appear to be flicking or flashing erratically to the viewers as it rapidly jumps between different brightness levels. To improve the aesthetic, an LED Driver that brightens and dims the LED gradually was developed. It allows a Node to set a particular target brightness level and the LED driver would increment or decrement the brightness of the LED linearly by adjusting the output PWM voltage until it reaches the target. Its design details can be found in Appendix C.2.

4.5.3 Isolated CBLA Nodes

Each Isolated CBLA Node is associated with one actuator. A CBLA system, as discussed in Section 3.2, is constructed by linking these Isolated CBLA Nodes through virtual inputs. The prediction models are fitted using Lasso [33]. In this test bed, three main types of Isolated CBLA Node exist: Half-Fin Node, Light Node, and Reflex Node.

Figure 4.7 presents the make-up of the different Isolated CBLA Nodes in a cluster. Two Half-Fin Nodes control the bending of a Fin through their respective SMA Controller Nodes (Fx.SMA-L and Fx.SMA-R). The pair of Half-Fin Nodes share a Fin-mounted IR proximity sensor (Fx.IR-F), and the 3 axes of the accelerometer (Fx.ACC). A Light Node controls the brightness of a high-power LED through an LED driver Node (Lx.LED) and its sensory space consists of an ambient light sensor (Lx.ALS). There are two types of Reflex Nodes, one associated with a pair of LEDs (Fx.RFX-L), and one associated with a vibration motor (Fx.RFX-M). They are both controlled through LED Driver Nodes. In their sensory space, they share one bottom-mounted IR proximity sensor (Fx.IR-S).

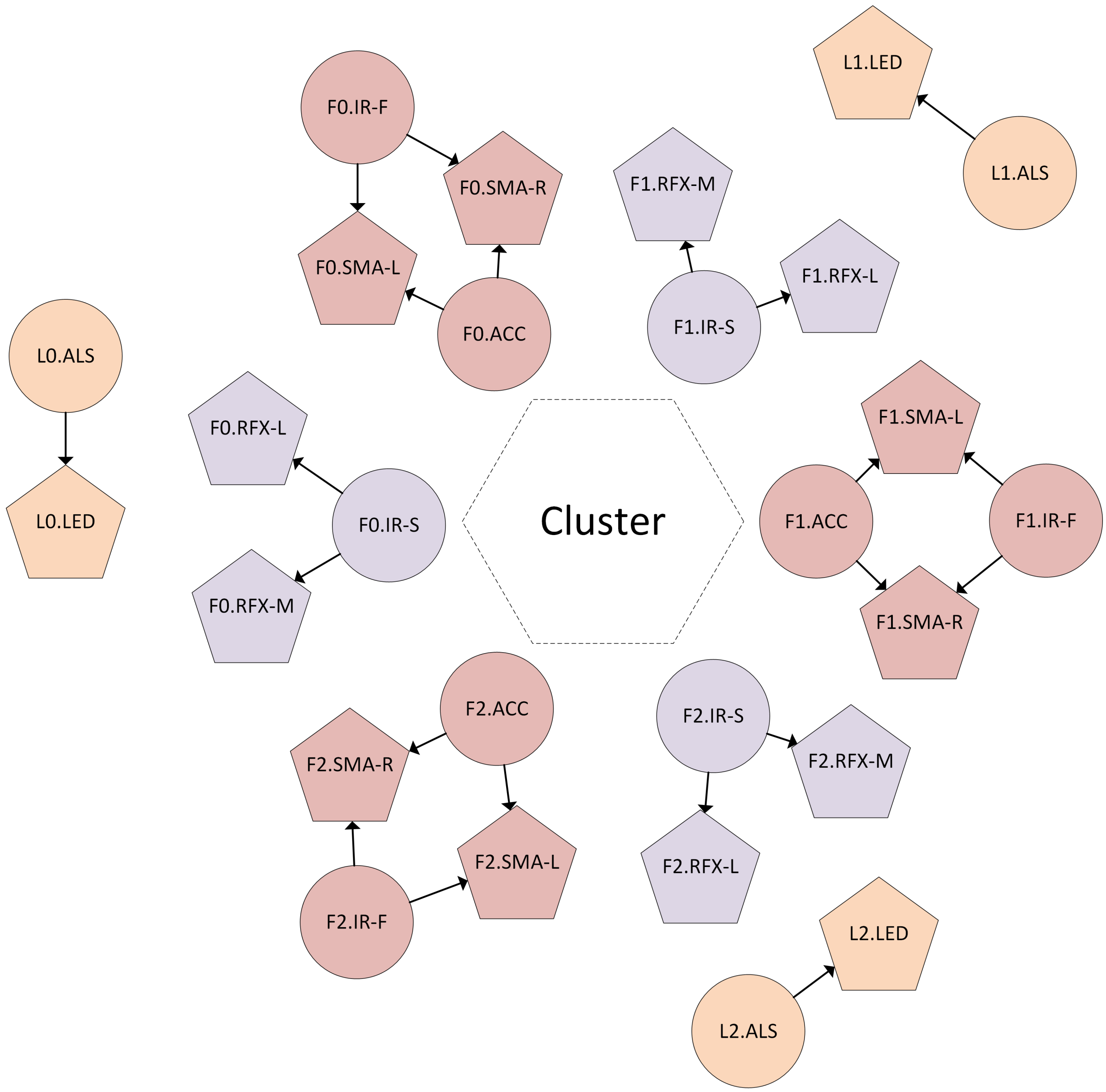


Figure 4.7: Make-up of a cluster of Isolated CBLA Nodes. Half-Fin Nodes are shown in red; Light Nodes are shown in orange; and Reflex Nodes are shown in blue.

The loop periods of the CBLA Engine for the three types of CBLA Nodes are shown in Table 4.3. They were set to give their associated actuators sufficient time to reach the given target output values.

Table 4.3: Loop periods of the three types of CBLA Nodes

CBLA Node Type	**Loop Period**
Half-Fin	5.0s
Light	1.0s
Reflex	0.5s

4.5.4 Network Configurations

The Isolated CBLA Nodes described in Section 4.5.3 are connected to each other via virtual inputs. In essence, the output of a CBLA Node is treated as an input variable to other Nodes, much like input variables associated with their own sensors. This creates a interconnected network of CBLA Nodes that spans across the entire sculptural system. This allows information regarding the external environment to travel through the sculpture.

Different network configurations produce different system behaviours. Here we investigate two types of network configurations which are called Spatial Mode and Random Mode. For fair comparisons, the two configurations have exactly the same number of links. In the experiment, the number of links was arbitrarily chosen to be 111 so that there are sufficient links to cover the entire system. In addition, each Node is linked to at least one other Node via a virtual input.

Spatial Mode

In Spatial Mode, CBLA Nodes are linked based on their spatial proximity. Figure 4.8 shows the connections among Nodes within a cluster. Neighbouring Nodes are connected via bidirectional links. Two connected Nodes take each other's output as input variables. Nodes in neighbouring clusters that are in close proximity are linked via unidirectional links as shown in Figure 4.9. The circular connections that daisy-chain the four clusters allow information to spread throughout the test bed.

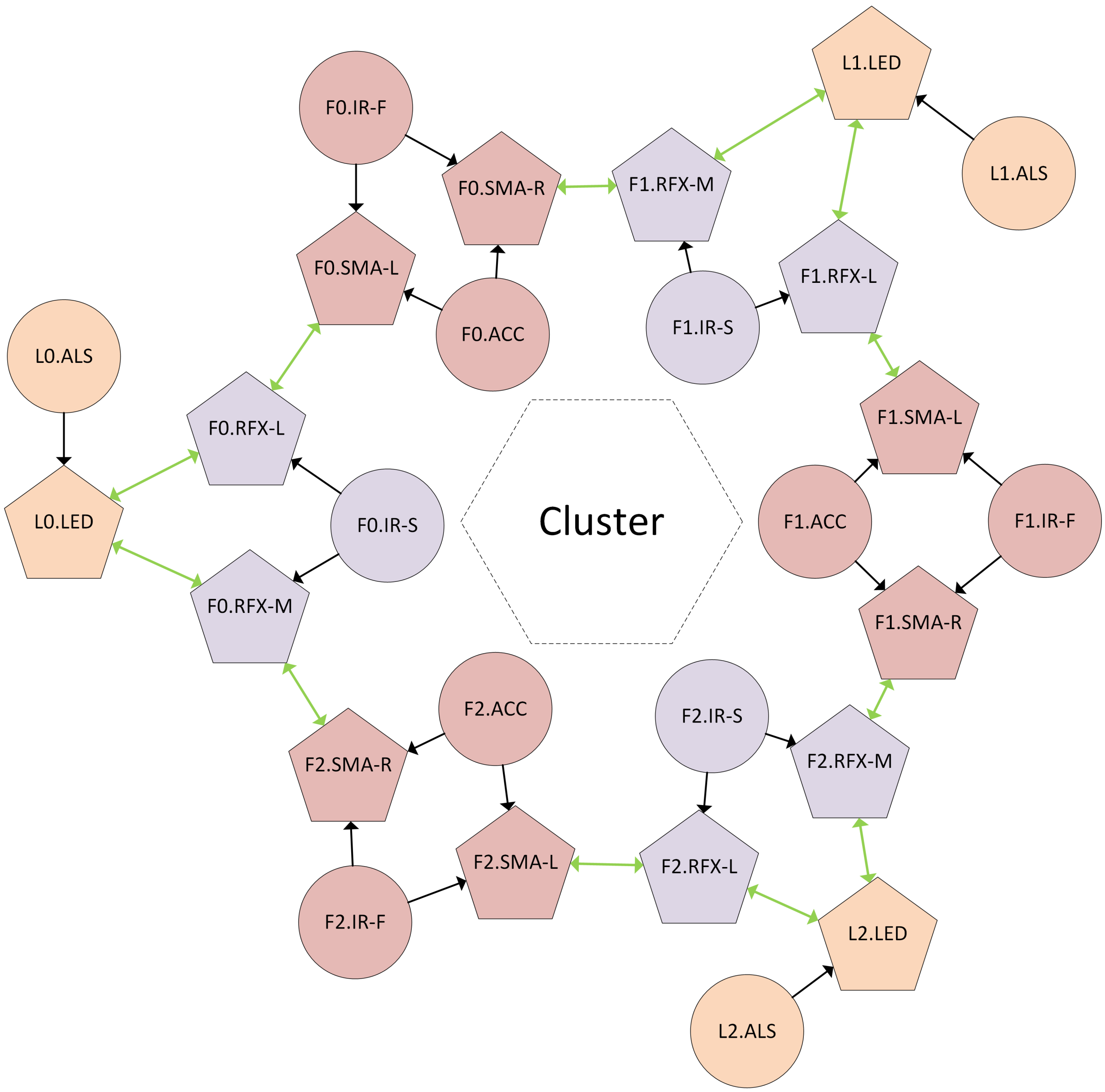


Figure 4.8: Connectivity graph within a cluster in Spatial Mode. Each bidirectional green arrow represents a pair of input links. Two connected Nodes take each other's output as input variable.

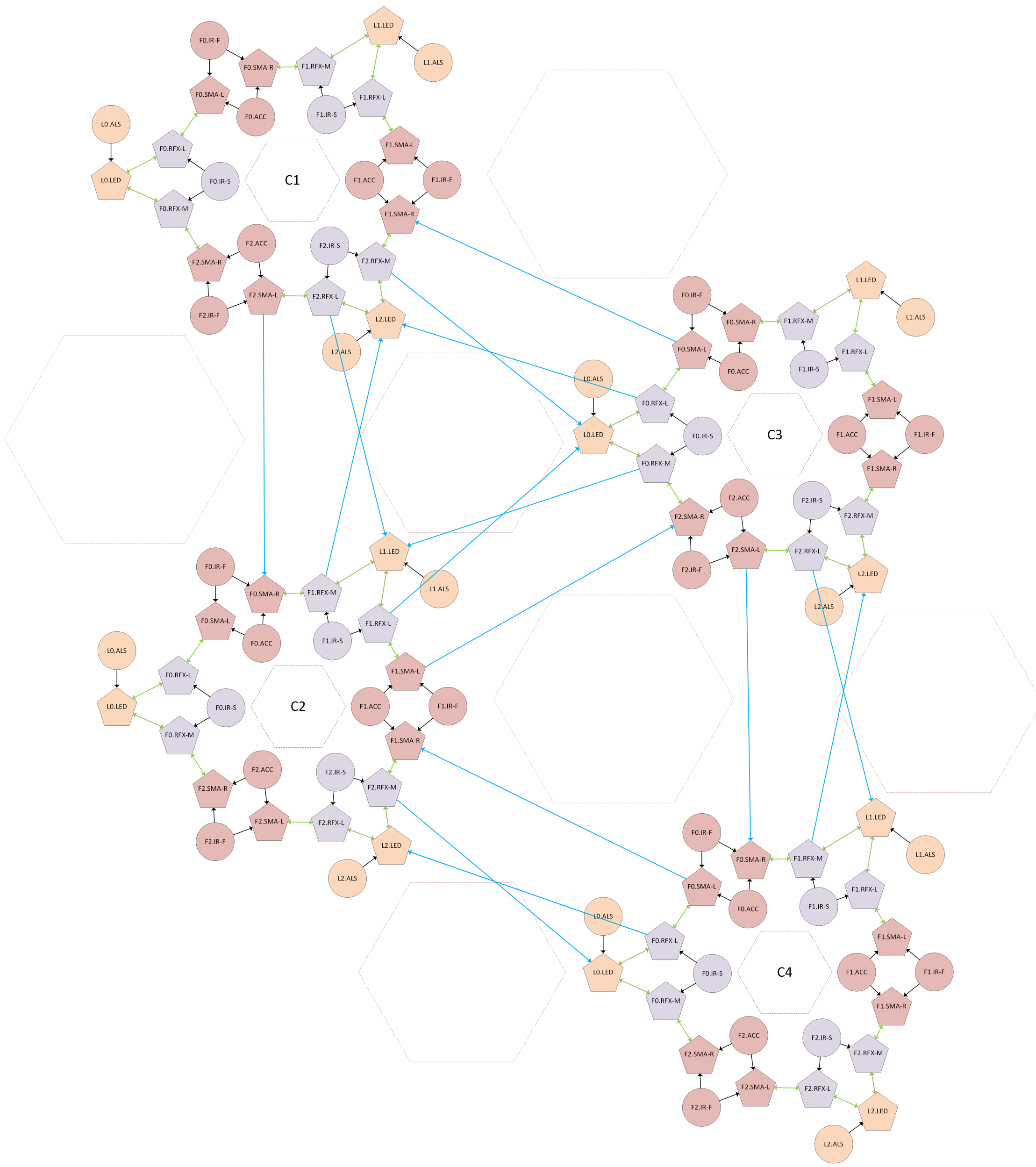


Figure 4.9: Connectivity graph of the entire test bed in Spatial Mode. Each blue unidirectional arrow represents an input link. The output of the Node at the origin of an arrow is fed into the Node that it is pointing toward as an input variable.

Under this configuration, Nodes' responses to external disturbances or environmental changes are expected to concentrate close to the source, and spread to other Nodes gradually.

Random Mode

In Random Mode, CBLA Nodes are linked to other CBLA Nodes randomly. This means that the output of a Node might be fed into another Node that is on the other side of the sculpture. Since there are 60 Nodes and 111 links are required, the algorithm first links the output of each Node to another random Node to ensure that each Node has an effect in the overall system. Then, the algorithm picks 51 unique Nodes at random and links each of them to another random Node. This ensures that the state space of each Node is relatively even.

The specific random configuration is generated at run-time and is different every time. In addition, it should be noted that this method does not guarantee that there will not be any disconnected sub-networks. It is possible that a set of Nodes is completely isolated from another set of Nodes under this network configuration scheme.

4.5.5 Prescripted Behaviours

For the purpose of comparing between CBLA and prescripted behaviours, each CBLA Node has a Prescripted Engine in addition to the CBLA Engine. This allows us to quickly switch between the two kinds of behaviours during the user study described in Section 5.4. Although the two engines are both associated with the same actuators, they may have different sensors in their sensory space.

The prescripted behaviours are implemented based on a specification by a human designer, and are similar to previous behaviours of the Hylozoic series [2]. For the Fin mechanism, when its Fin-mounted IR proximity sensor detects an object, it bends down toward the direction of a neighbouring bottom-mounted IR proximity sensor that has also detected an object. If both or neither of the IR proximity sensors have detected an object, it simply bends straight down. It returns to an upright rest position when its Fin-mounted IR proximity sensor no longer detects an object in its proximity.

For the high-power LEDs, its output ramps up and down continuously when its corresponding Fin-mounted IR proximity sensor has detected an object. It then dims gradually when the object is removed.

For the reflex vibration motor and LED pair, its output also ramps up and down continuously when its corresponding bottom-mounted IR proximity sensor has detected an object. It then ramps down gradually when the object is removed.

An additional virtual node is added to provide cluster-level group behaviours. This node counts the number of outputs within its cluster that are active. It then determines a probability of random activation by mapping this count to a Gaussian function. The Fin mechanism or the high-power LED may turn on at random based on this probability. Using a Gaussian function allows the probability of random activation to increase when a number of outputs are activated. However, when too many outputs are activated, this probability decreases which makes random activations less probable.

The prescripted behaviours described above were designed to be highly responsive, along with elements of group behaviours and random actuations. These kinds of behaviours are more similar to the types of behaviours of a typical interactive sculpture produced by LASG and PBAI than the CBLA-based behaviours introduced in this thesis. Its main purpose was to serve as a reference point when the visitors' responses to the CBLA system are studied in the user study described in 5.4.

4.5.6 Summary

In this chapter, we presented the design of the electronic hardware and control software of the Hylozoic Series 3 interactive control system, which supports the large number of sensors and actuators required by the CBLA. This new system architecture also enables the creation of abstract components and simplifies the implementation of a multi-threaded CBLA system. Different sensors and actuators were put together to form the functional units that make up the interactive art sculpture. Moreover, the control software enables high speed communication between the distributed embedded microcontrollers and a standard computer. This allows the CBLA to run remotely on a more powerful computer and enables the creation of system-wide abstract components. In addition, a custom data logging module was created to store the large amount of data generated for secondary analysis. A multi-cluster test bed was built to investigate the behaviours of the CBLA system and the users' perception of its behaviours.

Chapter 5

Experimental Validation

In this chapter, we demonstrate the behaviours generated by the Curiosity-Based Learning Algorithm (CBLA) on an interactive art sculpture. We first investigated the behaviour of the simplest form of a CBLA system, one with a single node with one sensor and one actuator. This allows us to visualize the exploration pattern of the CBLA engine in two- or three-dimensional space. Then, we applied the algorithm on a small multi-node system with shared input variables. We observed its self-learning behaviours as well as the way it responds to external disturbances. After that, on the multi-cluster test bed described in Section 4.5, we investigated the different emergent behaviours resulting from different connection schemes. Finally, we conducted a user study using the test bed. Participants were invited to interact with the sculpture and report on their interest levels. The observations collected in this user study enabled us to understand the relationship between the participants' behaviours and engagement level under different conditions as well as different configurations of the CBLA system.

5.1 Single Node Experiment[1]

Although the CBLA was designed for a distributed system with multiple nodes, it is not be easy to visualize the modelling process due to the high-dimensionality of the data and the models. To demonstrate (and verify) the action selection pattern and the learning process, the CBLA was first tested on a simple toy example which is easily visualizable in

[1] An early version of this section has been published in IROS 2015 [1]

3-dimensional space. In this experiment, idle mode was disabled as the main objective was to observe and verify the exploration pattern of the CBLA.

5.1.1 Set-up

The system in this experiment consists of a Light node, which is a single-input, single-output system. For the single-input system, S is a scalar value that represents the measurement from an ambient light sensor. It was recorded directly as a 12-bit value. M corresponds to the voltage duty cycle supplied to the LED, ranging from 0 to 100, with 0 being completely off (0V) and 100 being the maximum allowable voltage (4.7V). The loop period is the time between each actuation and was set to 0.05s. Least-square method was used to fit its prediction models.

5.1.2 Procedures and Expected Results

In this experiment, the system ran for 2500 time steps without any external interference. Based on the reward structure, which favours learning first the most predictable regions of the state-space, the CBLA is expected to first explore the regions of the sensorimotor space that have low variance. Once the model in that region is learnt, it should move onto areas with higher variance.

5.1.3 Results

Figure 5.1 shows the evolution of the prediction model and actual exemplars over time. As expected, the CBLA first selects actions associated with lower LED output levels, as this leads to measurements in the low variance regions. Over time, once the model in the low variance region is acquired, it moves toward higher brightness regions. Figure 5.2 shows that the best action and the actual selected action were completely random at first. The system then focused on the easy-to-learn areas in the lower brightness level. After that, it moved toward the higher brightness and harder-to-learn regions when it hadn't seen much improvement in the low brightness regions. After some exploration of the bright regions, prediction error is reduced in those regions, and the system returns again to explore the low-brightness region. The resulting pattern of activation is interesting visually, as it results in non-random activations that have the potential to convey a notion of intent to the viewer.

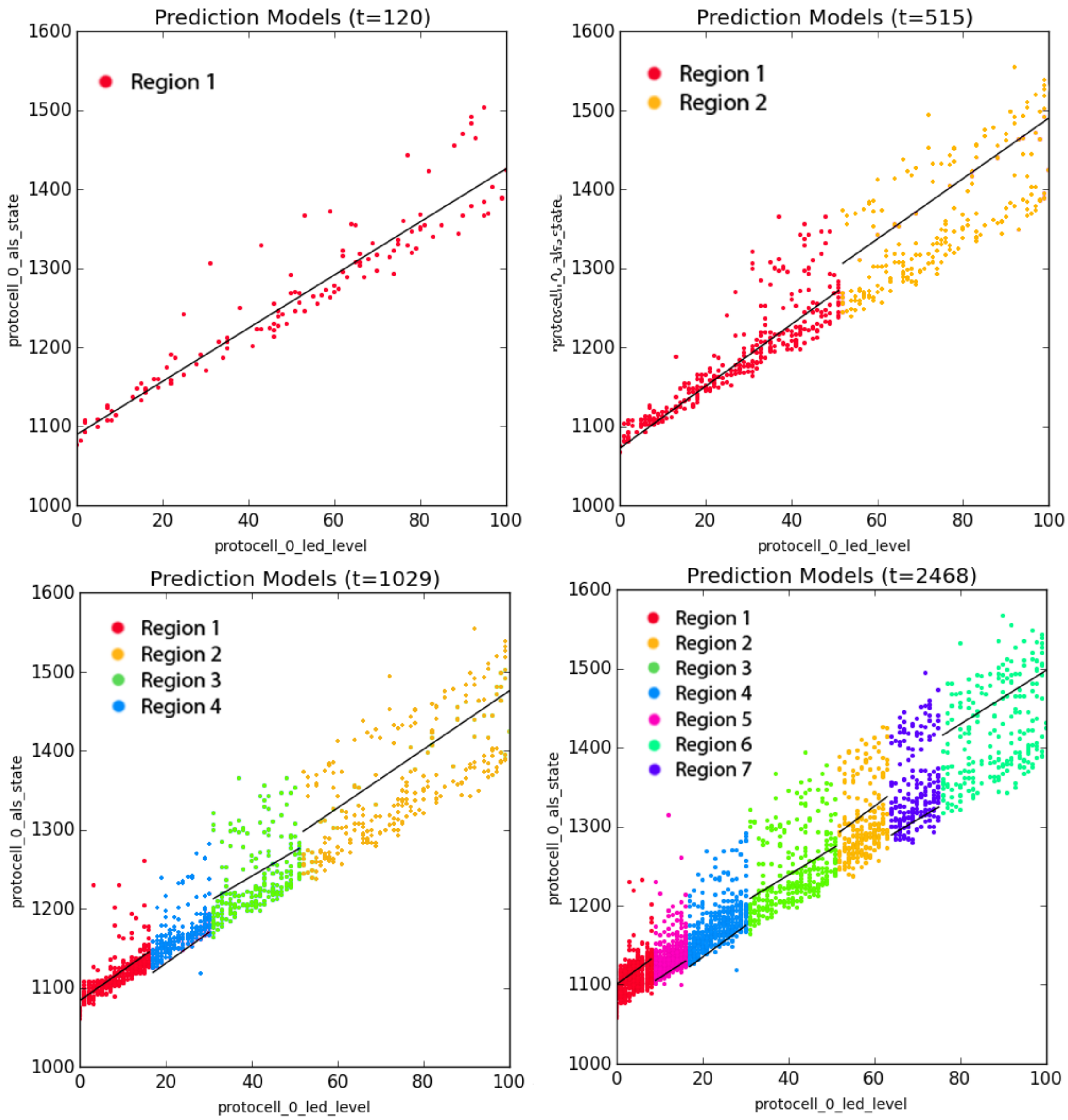


Figure 5.1: Evolution of the prediction models for the single node experiment. Each point represents an exemplar. Points with the same colour are in the same region and the black lines are the cross-section of the linear models at $S(t) = 0$. The regions are numbered in the order that they were created.

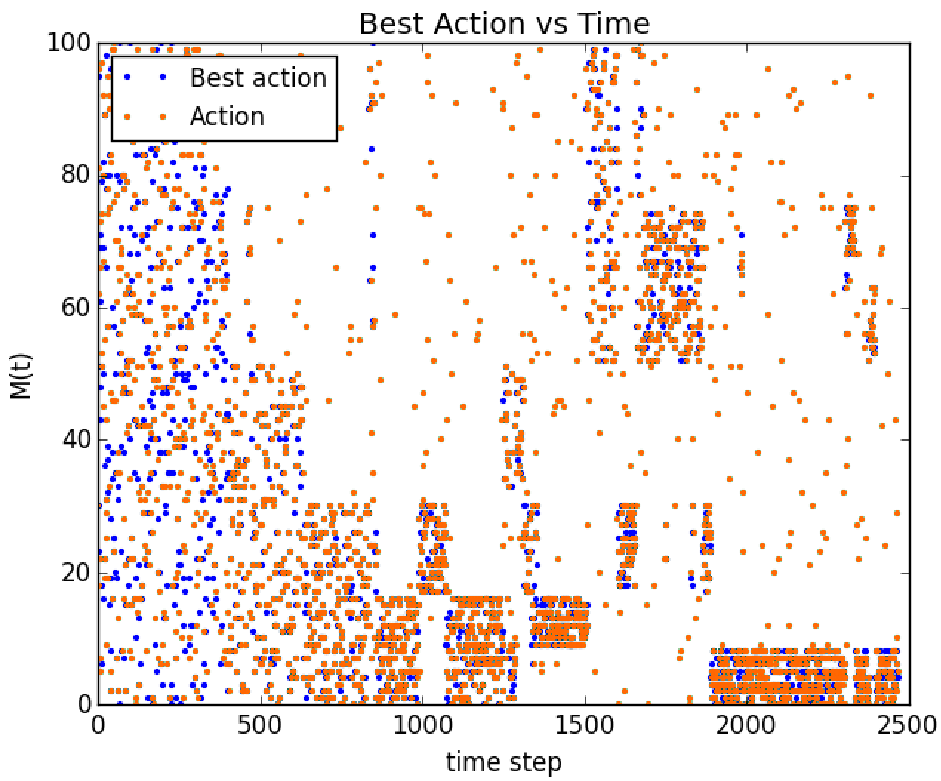


Figure 5.2: Action vs. time graph for the single node experiment; the y-axis is the output of the LED M(t) and the x-axis is the time step. Orange dots represent the actual action taken and blue dots represent the best action given the sensorimotor context. The best action is defined as the action with the highest action value given the current state. Non-best actions are selected occasionally in order to explore the state space.

Figure 5.3 shows the mean error vs. time graph. Here we see that the prediction error quickly drops to a relatively low level. To improve its prediction further, the state-space was split into regions with low and high error. This allows the Region 1 (low variance region) to further reduce its prediction error.

In Figure 5.4, one can that see the action value of a region does not stay constant. This shows that as the prediction improves, the value of actions in that region decreases over time as the region becomes "learnt" and further learning potential decreases.

After approximately 1750 time steps, the action value of Region 3 began to rise. This was because the prediction error of that region also began to fall as shown in Figure 5.3.

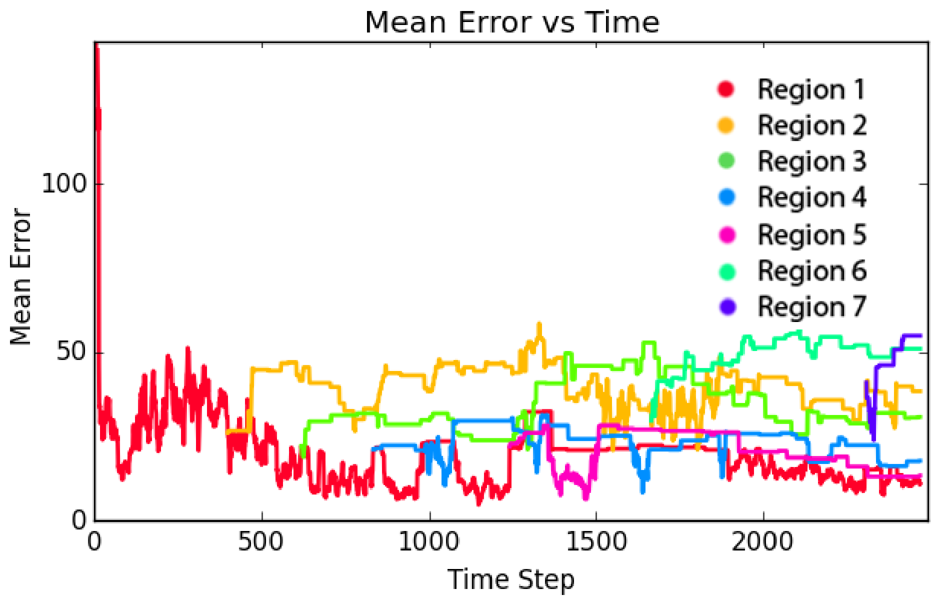


Figure 5.3: Mean error vs. time graph for the single node experiment. Each colour represents a region and the colour code corresponds to final prediction model graph in Figure 5.1

At that time, the system had just explored the higher brightness regions as shown in Figure 5.1. This shows that as the system covered its entire state-space and the action value of the more difficult-to-learn regions became lower, the system returned to the other regions to further improve their prediction models more frequently.

5.1.4 Conclusions

This simple toy example validated the exploration pattern of a CBLA Node. The region splitting mechanism was demonstrated visually. It was shown to first explore the easy-to-learn regions before moving on to the difficult-to-learn regions. In addition, the action value associated with a region was shown to respond to the rate of reduction in prediction error. The validation of the simple CBLA Node allowed us to further examine the behaviours when multiple Nodes were connected together in subsequent experiments.

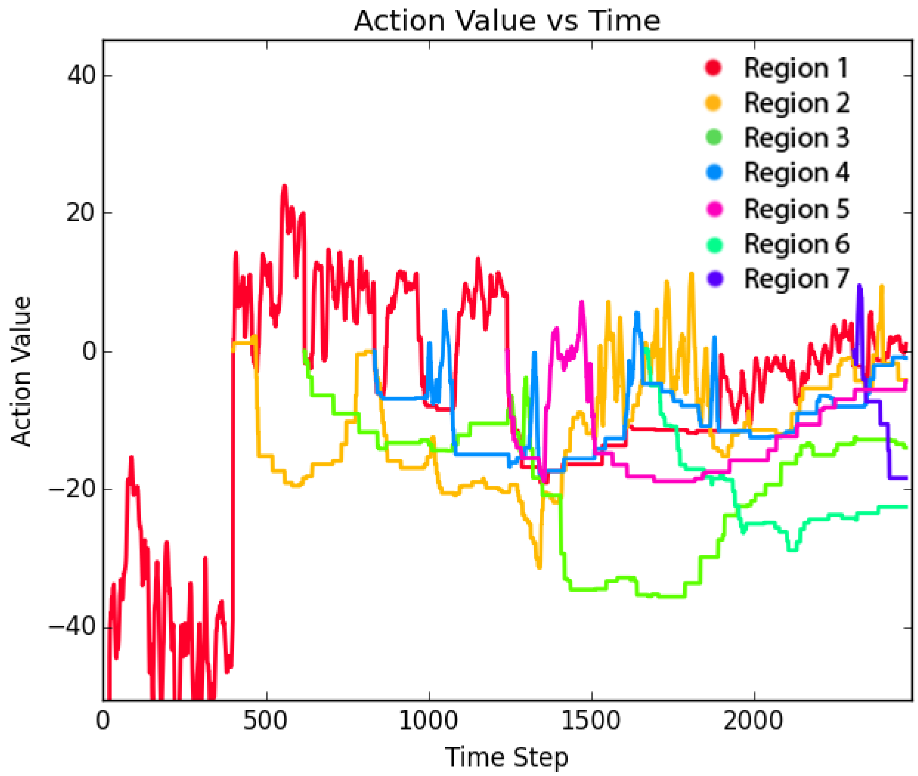


Figure 5.4: Action value vs. time graph for the single node experiment. Each colour represents a region and the colour code corresponds to final prediction model graph in Figure 5.1

5.2 Multi-Node Experiment [2]

In this Section, we describe a demonstration of an integrated system consisting of multiple CBLA Nodes. In addition, in this experiment, threshold-based Idle Mode was introduced. When the knowledge gain potential is low, a Node would enter Idle Mode and turn off its actuators. The behaviours of the system during the self learning period and its response to external interference was examined.

[2] An early version of this section has been published in IROS 2015 [1]

5.2.1 Set-up

The Light node was the same as in Section 5.1, with the addition of the shared IR proximity sensor. For the Fin node, the input variables are the average accelerometer readings of the three axes, and the shared IR proximity sensor reading over the 12.5s loop period; the output variable is the action of the Fin. There are four discrete actions: rest (0), lower to the right (1), lower to the left (2), and lower to the centre (3). Note that in this set up, the two types of nodes run with different loop periods, but coupling between them is accomplished through the shared IR sensor, which measures proximity as a 12-bit value. Least-square method was used to fit its prediction models. Note that in this experiment all four nodes share one single IR sensor. The set-up of the experiment is shown in Figure 5.5.

5.2.2 Procedures and Expected Results

The system runs undisturbed until, after some initial learning, all of the nodes enter Idle Mode. During this time, the IR proximity sensor pointed toward an empty area. Afterwards, a participant enters into the sculpture space in an area detectable by the IR proximity sensor. The system should then exit idle mode and begin learning the changed model introduced by the change in the environment. Since the IR sensor is shared by all nodes, they are all expected to recognize the change and exit idle mode at approximately the same time.

5.2.3 Results

Figure 5.6 shows how the action values change over time for each of the nodes. The coloured lines represent the action values and each colour represents a region. The blue dots underneath the plot indicate when the node was in idle mode.

All the nodes first started learning their own models and entered idle mode. At around 390s, a human participant walked in front of the IR proximity sensor. This triggered a large reduction in action value at first, due to an increase in prediction error. However, as more data was collected, the action values for all four nodes quickly jumped up. This prompted the nodes to exit idle mode and begin generating actions to learn the model. After a period of readjustment, all four nodes re-entered idle mode after the new environment is learnt.

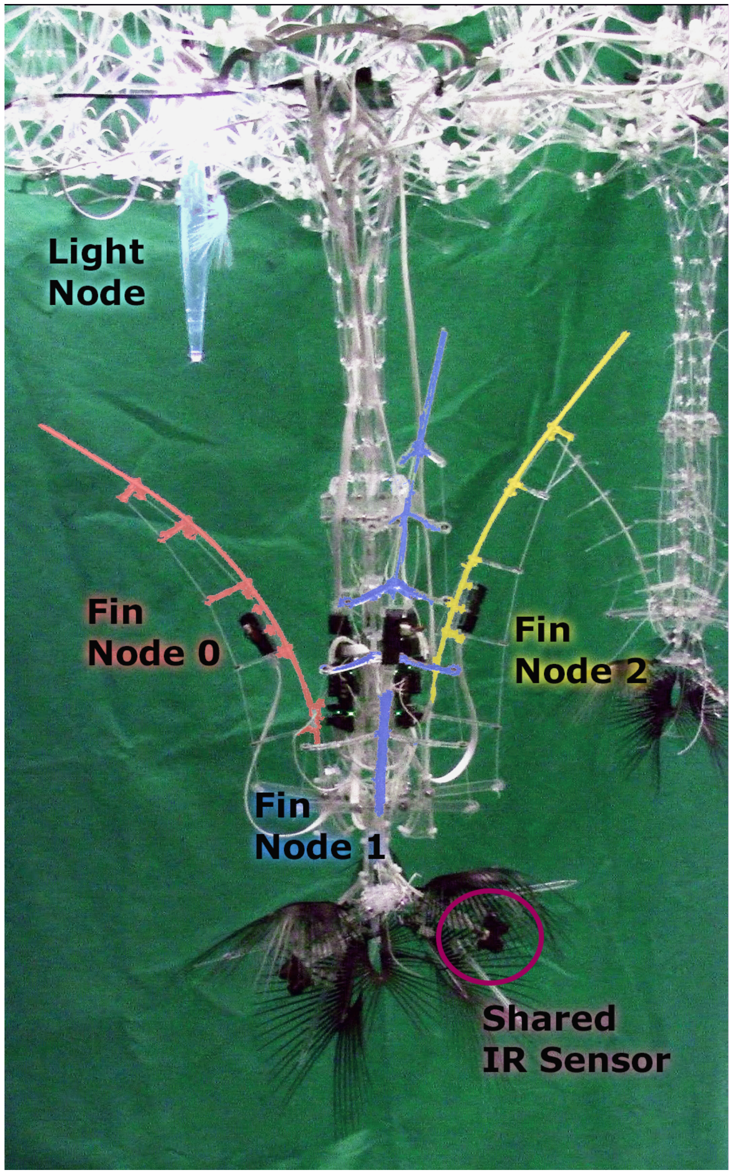


Figure 5.5: The set-up of the multi-node experiment. The Light Node is shaded light blue, and the three Fin Nodes are shaded red, blue, and yellow. All four nodes share an IR proximity sensor in the purple circle.

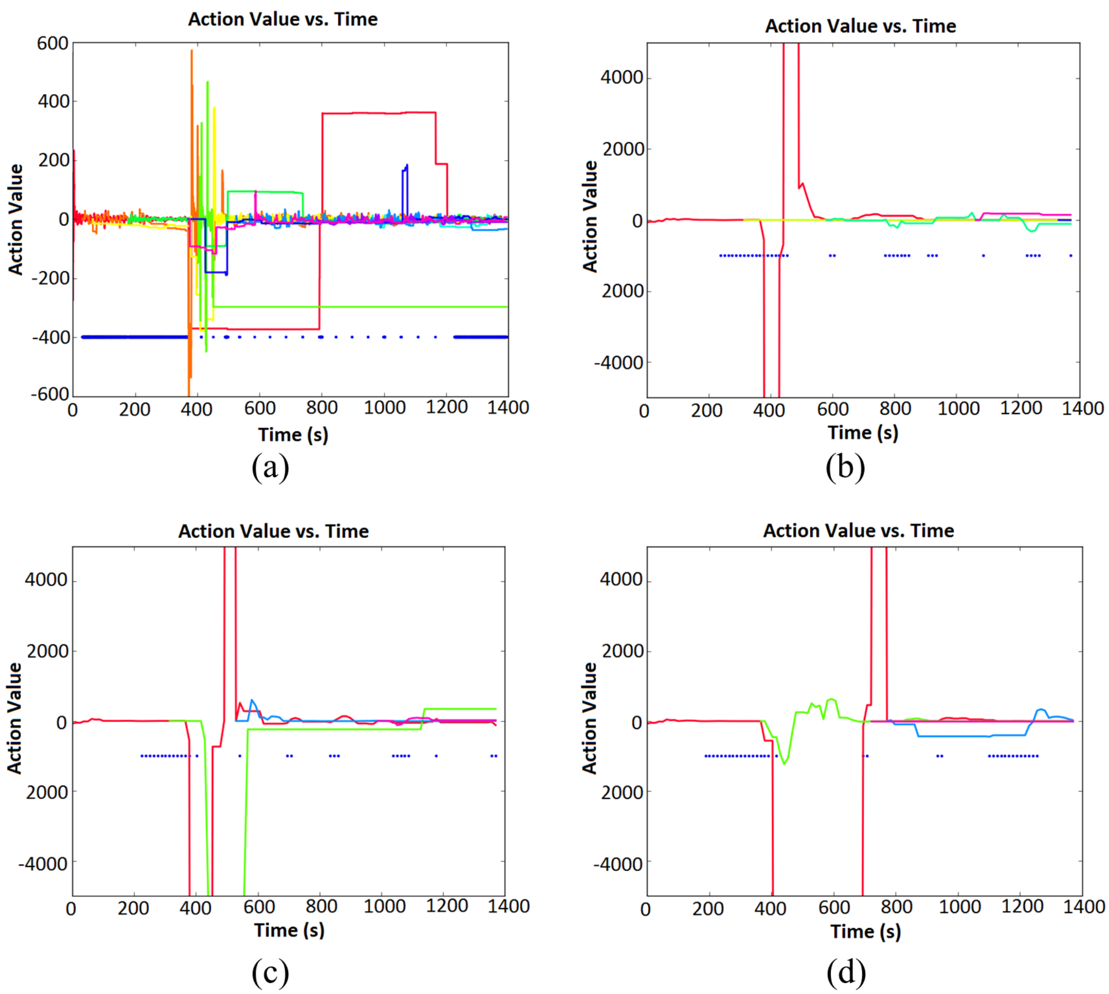


Figure 5.6: Action-value vs. time graph for the Light node (a) and the three Fin nodes (b), (c), (d).

5.2.4 Conclusions

From Figure 5.6, one can see that the Light Node and the three Fin Nodes reacted to the environmental change nearly simultaneously. They exited the idle state and shifted to more exploratory actuation patterns. This showed that the shared sensor input variable was able link the CBLA engines together, even though they run independently at different frequencies. This experiment demonstrates that the reaction of the system to the changed environmental conditions creates an interaction with the visitor without any explicitly pre-programmed behaviours. The system appears to respond to the participant and their action, as its internal model of the environment cannot predict the behaviour of the participant.

The system's intrinsic curiosity drives itself to perform actions and elicit responses from this new environment with the participant's presence, and update its prediction model. We anticipate that the visitors will find such behaviours engaging as the visitors can recognize that the sculpture is responding to their presence and action but they would not be able to easily predict how it might respond. This quality provides the CBLA System the potential to be more life-like than a prescripted or a random system.

5.3 Multi-Cluster Experiment

This experiment investigates the behaviours of the CBLA system on the four-cluster test bed described in Section 4.5. The test bed has two different network configurations: Spatial Mode and Random Mode. Under different network configurations, the CBLA system is expected to behave differently. We hypothesize that users would find activations closer to them more relevant, and hence more interesting. Therefore, a metric to quantify this proximal activation is devised. The configuration with higher proximal activation is then used for the subsequent user study described in Section 5.4.

In addition, the effects of sensitivity constant ν in the idling function as described in Equation (3.6) was also examined. We expected that, with higher ν value, the system would be less responsive to ambient noise as well as to users' interaction. This would result in a lower overall level of activation.

Furthermore, the response time of a CBLA system was examined and compared against the system running prescripted behaviours.

5.3.1 Set-up

The multi-cluster test bed described in Section 4.5 was used for this experiment. In addition, within the CBLA Engine, a sigmoid function based idling function as described in Equation (3.6) was used.

5.3.2 Procedures

Two types of procedures were conducted in this experiment. The first type is the "Single Trigger" procedure. In this procedure, the CBLA system first starts from a blank state without any preexisting exemplars or prediction models. It operates without any external interference for 450 seconds. At 450s, the "trigger" is applied by placing an object in front of the IR proximity sensor C3.F2.IR-S (referring to Figure 4.9) for approximately 30 seconds. Then, the object is removed and the experiment continues on for another 450s seconds before the program is terminated. The second type is the "No Trigger" procedure. In this procedure, the CBLA system simply runs for 900s without any external interference. The results from the "No Trigger" procedure serve as a reference comparison for the Single Trigger procedure.

Both procedures were repeated on combinations of Spatial Mode/Random Mode and low sensitivity/high sensitivity settings on the CBLA Engine. This allows us to examine the effects of the two factors on activation levels due to the trigger.

In addition, the "Single Trigger" procedure was applied in Prescripted Mode which runs the Prescripted Engine as described in Section 4.5.5. This allows us to compare the response time of the CBLA system against the system that is running prescripted behaviours.

5.3.3 Expected Results

The level of output by an actuator is referred to as its activation. All clusters are expected to have approximately the same level of activation during the initial learning period. After that, the amount of activation is expected to reduce as the knowledge gain potential decreases.

For Spatial Mode, it is expected that the activation as a result of the trigger at 450s point should be concentrated around the trigger location, which is near Cluster 3 ($C3$). On the other hand, for Random Mode, since Nodes are connected randomly, activation should be more spread out and no one cluster should have a larger than average level of activation. To quantify the activation level, metrics that evaluate the average total activation and average cluster activation are devised.

The total activation level at time step t is the average output levels of all CBLA Nodes at time step t. For this experiment, a time step of 1.0s was chosen. It can be calculated as follows.

$$a_t = \frac{1}{N}\sum_{j=0}^{N}\overline{m}_{jt} \tag{5.1}$$

where a_t is the total activation level at time step t; N is the total number of CBLA Nodes; $\overline{m}_{jt}$ is the average output value of CBLA Node j at time step t.

We are interested in the total activation level during the period immediately after the trigger is applied. Therefore, we compute the average total activation between the time of the trigger, t_{trig}, and the end of the readjustment period, t_{readj}, as follows.

$$\overline{a} = \frac{1}{|\left\{a_{T_{trig}}, ..., a_{T_{readj}}\right\}|}\sum_{t=T_{trig}}^{T_{readj}} a_t \tag{5.2}$$

where $\overline{a}$ is the average total activation from T_{trig} to T_{readj}; and $|\left\{a_{T_{trig}}, ..., a_{T_{readj}}\right\}|$ is the number of time steps between T_{trig} and T_{readj}.

By looking at the cluster activation level, we can determine if the activations are concentrated in any particular cluster. To find the cluster activation level, we apply (5.1), but only for the CBLA Nodes within a particular cluster.

$$a_{ct} = \frac{1}{N_c}\sum_{j=0}^{N_c}\overline{m_{jt}}, \text{ for all Nodes } j \text{ in cluster } c \tag{5.3}$$

where a_{ct} is the cluster activation level at time step t; N_c is the total number of CBLA Nodes in cluster c; $\overline{m}_{jt}$ is the average output value of CBLA Node j at time step t.

Similarly, we can calculate the average cluster activation level during the period between t_{trig} and t_{readj} as follows.

$$\overline{a_c} = \frac{1}{|\left\{a_{cT_{trig}}, ..., a_{cT_{readj}}\right\}|}\sum_{t=T_{trig}}^{T_{readj}} a_{ct} \tag{5.4}$$

where $\overline{a_c}$ is the average cluster activation from T_{trig} to T_{readj}; and $|\left\{a_{cT_{trig}}, ..., a_{cT_{readj}}\right\}|$ is the number of time steps between T_{trig} and T_{readj}.

In this experiment, we set T_{readj} to 480s. This means that we are looking at the behaviours of the system in the 30 seconds following the trigger at $T_{trig} = 450$s. This time interval was chosen in order to investigate the response of the CBLA system to emulate the relatively short time interval after a user approaches the system and introduces a change in the system's perception. We assumed that the users would not associate their actions with the activations that appear after more than 30s have passed.

Furthermore, we also expected to see some spontaneous activations for both kinds of network configurations. They are caused by the way in which the relative action value, $\widehat{q_z^2}$, is calculated, as mentioned in Section 3.1.5. Recalling Equation (3.9),

$$\widehat{q_z^2} = \frac{q_t^2}{max(\overline{q_z^2}, \nu)}$$

we can see that when the average squared action value, $\overline{q_z^2}$, hovers close to 0 for a long time, the relative action value, $\widehat{q_z^2}$, would become very large. Fundamentally, this pattern is caused by the system's sensitivity to ambient sensor noise and can be adjusted by changing the sensitivity constant, ν. In this experiment, ν values of 0.00015 and 0.00025 were tested. With the larger ν, the sensitivity of the system is lower, and therefore, fewer Nodes in the neighbouring clusters would activate since a higher action value is required to reach the same relative action value after a prolonged period of low activations. We refer to the lower ν value as "high sensitivity setting" and the higher ν value as "low sensitivity setting". In this experiment, we expected to see the magnitude of activations of the trials using the low sensitivity setting to be more dampened compared with the ones using the high sensitivity setting.

Lastly, we expected the response time of a CBLA system to be longer than that of a system in Prescripted Mode. When a trigger is applied on a CBLA system, it first explores the sensory context associated with the trigger by performing near-idling actions, and accumulates prediction errors. It then activates when it has some success in improving its prediction models. In our implementation, the fastest type of CBLA Node, which is the Reflex Node, runs at a loop period of 0.5s. This means that since each exploration and learning cycle requires time, it will take longer for it to activate in response to a trigger, in comparison to Prescripted Mode, which simply reacts to the trigger as soon as it is detected.

5.3.4 Results

The average total activation and average cluster activation values for the Spatial and Random Mode trials under different procedures and different sensitivity settings are listed in Table 5.1.

Table 5.1: Results of the multi-cluster experiments; $\overline{a}$ is the average total activation value; $\overline{a_{c1}}$, $\overline{a_{c2}}$, $\overline{a_{c3}}$, $\overline{a_{c4}}$ are the average cluster activation for Cluster 1, 2, 3, and 4, respectively.

Trial	$\overline{a}$	$\overline{a_{c1}}$	$\overline{a_{c2}}$	$\overline{a_{c3}}$	$\overline{a_{c4}}$
1. Single Trigger, Low Sensitivity	0.02622	0.01343	0.01262	0.06764	0.01121
2. Single Trigger, High Sensitivity	0.02937	0.01436	0.01100	0.05645	0.03567
3. No Trigger, Low Sensitivity	0.01228	0.01247	0.01256	0.01247	0.01162
4. No Trigger, High Sensitivity	0.01227	0.01231	0.01191	0.01308	0.01180

(a) Spatial Mode

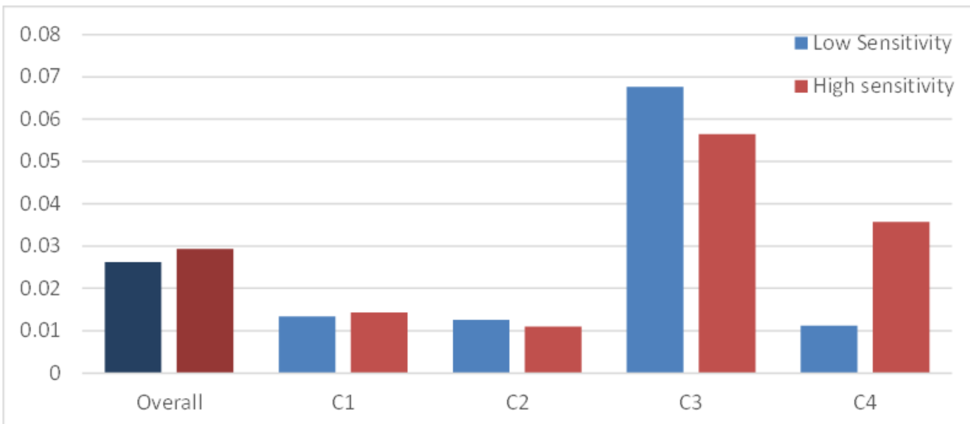
Trial	$\overline{a}$	$\overline{a_{c1}}$	$\overline{a_{c2}}$	$\overline{a_{c3}}$	$\overline{a_{c4}}$
5. Single Trigger, Low Sensitivity	0.02825	0.03461	0.01311	0.03959	0.02568
6. Single Trigger, High Sensitivity	0.06453	0.06465	0.06046	0.07551	0.05748
7. No Trigger, Low Sensitivity	0.01592	0.01477	0.01434	0.01636	0.01821
8. No Trigger, High Sensitivity	0.04914	0.03320	0.06110	0.06034	0.04191

(b) Random Mode

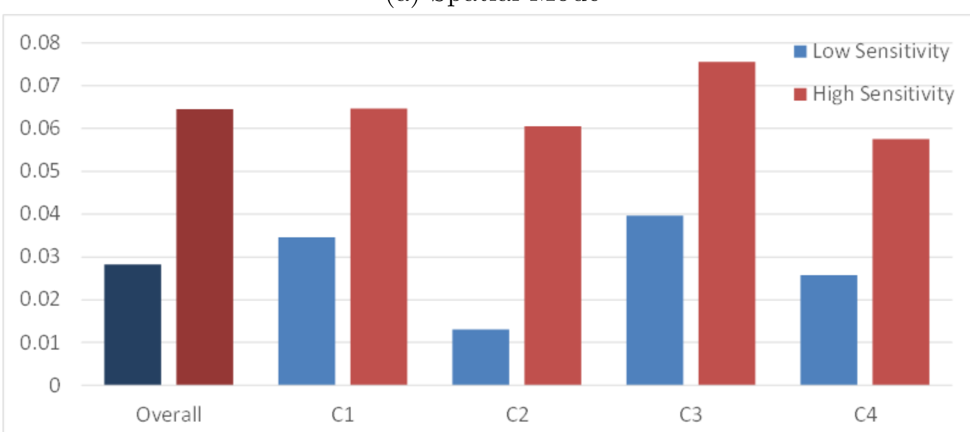
In each of the four cases, the total activation values for Random Mode are higher than the ones for Spatial Mode. This shows that Random Mode network configuration tends to produce higher overall activations when compared to Spatial Mode. This may be attributed to the larger number of inter-cluster unidirectional links within a Random Mode CBLA system. In contrast, most of the links in a Spatial Mode CBLA system are bidirectional and intra-cluster. This means that information about the trigger is less likely to spread as far since some links loop back to their origins. In addition, for Random Mode, since there is a $\frac{7}{8}$ chance that a Node would be linked to a Node in another cluster, many more inter-cluster links would form in comparison to Spatial Mode which only has 15 inter-cluster links. Since some Nodes within a cluster are linked through shared inputs, information about the trigger would spread within a cluster quicker as well.

On the other hand, with the Single Trigger procedure, cluster activation values for both Spatial Mode and Random Mode tend to be higher in Cluster 3 than in other clusters. This is expected since some Nodes within a cluster are also linked through shared inputs.

However, the Cluster 3's activation values for Spatial Mode are 2.58 times (low sensitivity setting) and 1.91 times (high sensitivity setting) larger than their respective total activation values. For Random Mode, the Cluster 3's activation values are only 1.17 times (high sensitivity) and 1.40 times (low sensitivity) higher than their respective total activation values. The differences in cluster activations at Cluster 3 are much larger for Spatial Mode than for Random Mode as illustrated in Figure 5.7. This shows that activations do tend to concentrate more around the origin of the trigger in Spatial Mode in comparison to Random Mode as we expected.



(a) Spatial Mode



(b) Random Mode

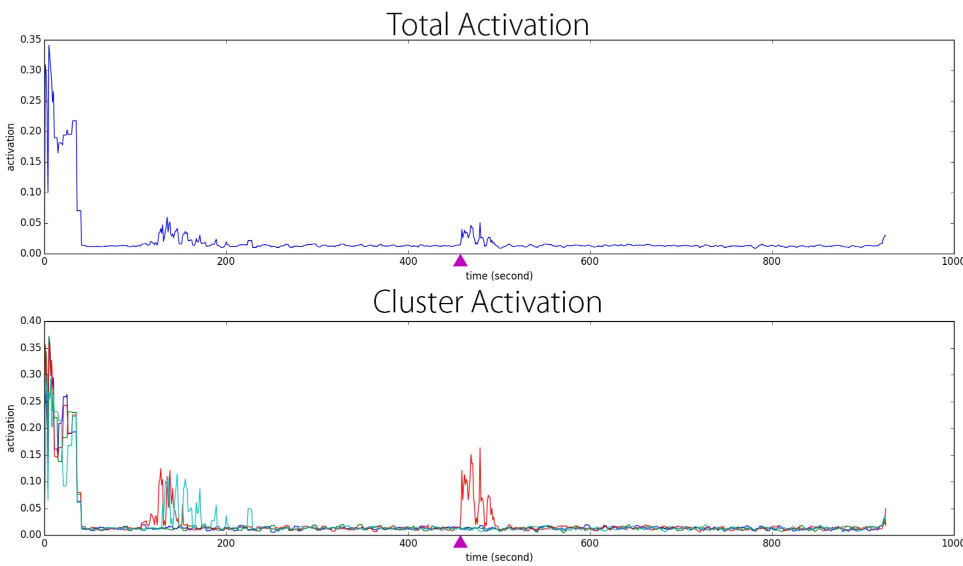
Figure 5.7: Average total activation and average cluster activations bar graphs for Spatial Mode and Random Mode of the multi-cluster experiment.

In addition, as expected, with the low sensitivity setting, the activation levels tend to be lower than with the high sensitivity setting. It is interesting to note that the sensitivity setting seems to make a much more significant difference in Random Mode than in Spatial Mode. It may again be attributed to the larger number of unidirectional links which seems to allow the activations to spread quicker and further. With the high sensitivity setting, the Random Mode CBLA system may simply be triggered by ambient noise, which causes the chain reactions of activations, much more frequently. Nevertheless, both settings detected the trigger as the activation values of Single Trigger trials were always larger than their No Trigger counterparts.

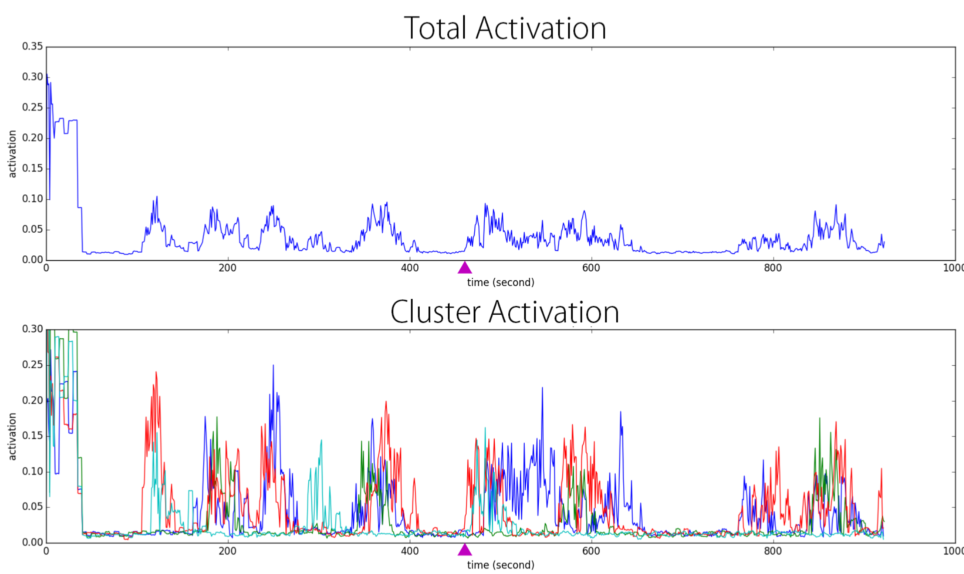
The total activation and the cluster activations over time for Trial 1 and 2, which were in Spatial Mode under the Single Trigger procedure, are shown in Figure 5.8. The initial high levels of activation were due to the initial model learning.

Near $t = 450$s, when the object was presented in front of a sensor in Cluster 3, the activation level at the cluster (red) shot up for both cases. However, for the low sensitivity case (Figure 5.8a), the trigger didn't manage to trigger the neighbouring Nodes. On the other hand, for the high sensitivity case (Figure 5.8b), activations in other clusters trail soon after. It is also interesting to point out that the magnitudes of activations for the other clusters were actually similar or even higher than Cluster 3. In our formulation, the maximum output level is mapped to the relative action value and virtual inputs are treated just like any other inputs. This means that Nodes that were not directly detecting the event could still register high knowledge gain potential. This means that CBLA Nodes in a cluster were indeed responding to and learning about an event happening in a neighbouring cluster.

Meanwhile, high sensitivity settings led to spontaneous activations occurring much more frequently. This is expected as systems with high sensitivity setting would respond to ambient noise and external events much more readily than ones with low sensitivity setting. Figure 5.9 compares the spontaneous activation patterns of Spatial Mode and Random Mode with high sensitivity setting when there was no trigger during the entire trial.

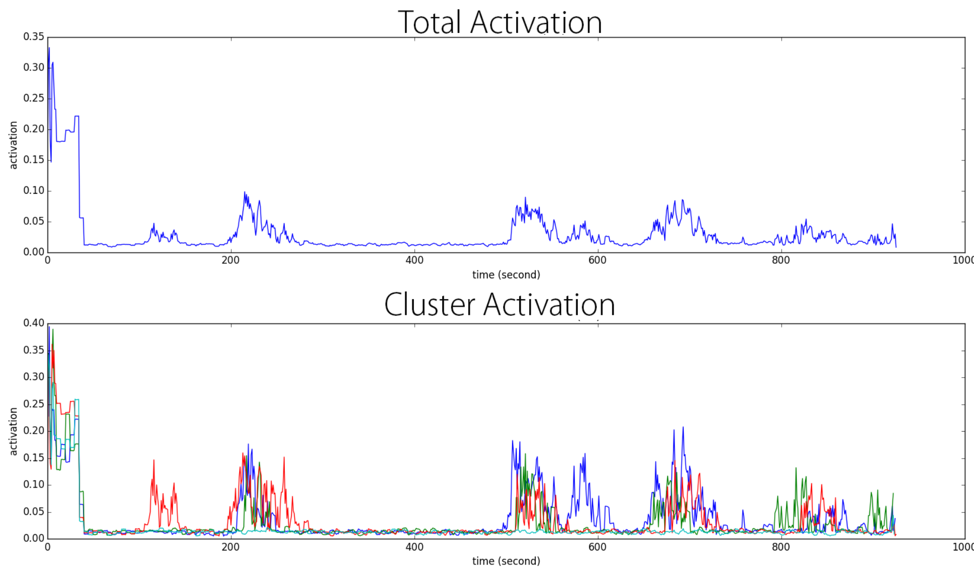


(a) Trial 1 - Single Trigger for Spatial Mode with low sensitivity setting

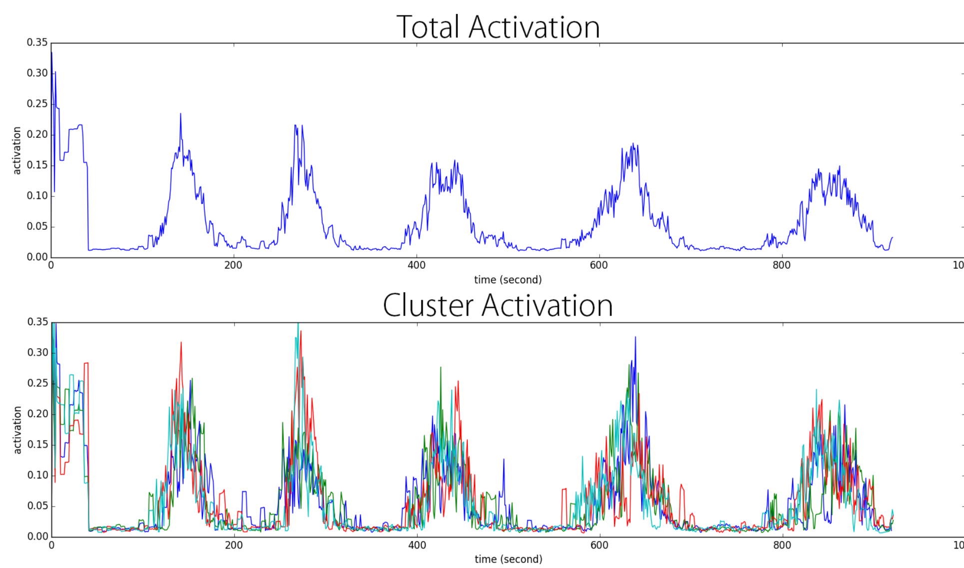


(b) Trial 2 - Single Trigger for Spatial Mode with high sensitivity setting

Figure 5.8: Average total activation and average cluster activations over time plots for Trials 1 and 2 of the multi-cluster experiment. The magenta triangle indicates the trigger point. In the Cluster Activation plot (bottom), the blue line represents Cluster 1; the green line represents Cluster 2; the red line represents Cluster 3; and the cyan line represents Cluster 4.



(a) Trial 4 - No Trigger for Spatial Mode with high sensitivity settings



(b) Trial 8 - No Trigger for Random Mode with high sensitivity settings

Figure 5.9: Average total activation and average cluster activations over time plots for Trials 4 and 8 of the multi-cluster experiment. In the Cluster Activation plot (bottom), the blue line represents Cluster 1; the green line represents Cluster 2; the red line represents Cluster 3; and the cyan line represents Cluster 4.

For Random Mode (Figure 5.9b), the spontaneous activation pattern was much more uniform than the one for Spatial Mode (Figure 5.9a). All clusters activated at around the same time with similar level of intensity. On the other hand, for Spatial Mode, there were disparate periods of activations when only one cluster activated or dominated. The irregularities in spontaneous activations were likely caused by the more localized nature of the links in Spatial Mode. Disturbances introduced by ambient noise were less likely to spread to other Nodes. In addition, spontaneous activations emerge in a Node after a prolonged period of low action values which causes the relative activation value to rise. The more localized activations in Spatial Mode may have disrupted the periodicity of spontaneous activations seen in Random Mode. As a result, the pattern of spontaneous activations of a Spatial Mode system was more irregular and non-uniform compared with those of a Random Mode system.

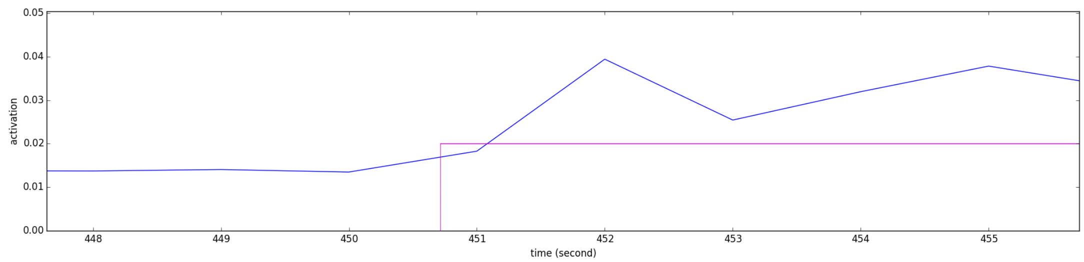
To illustrate the response time of the system to the trigger, we compared the result that we obtained in Trial 1 with the result from an identical experiment on a system running the Prescripted Engine. Figure 5.10 shows the total activations for both CBLA Mode and Prescripted Mode in the time interval close to the time of trigger. The magenta line on each graph indicates the time period when an object is placed in front of the sensor. Note that Total Activation values are calculated in time intervals of 1s. This means that, for instance, activations between 450s and 451s would be included in the activations at 450s.

In Prescripted Mode, the system activated immediately after the trigger. This is shown as the small increase in Total Activation at the 450s point, which included the trigger point. On the other hand, for CBLA Mode, there was an approximately a 1 second lag before the system responded to the trigger. This shows that while a CBLA system does respond to external interference, there is a noticeable delay in comparison to Prescripted Mode.

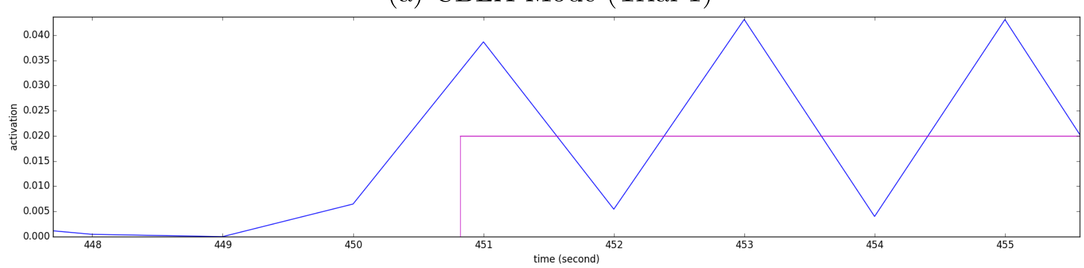
5.3.5 Conclusions

In this experiment, we showed that the activations in response to a triggering event were more likely to begin and concentrate near the source of the trigger when the network is configured in Spatial Mode. Since we hypothesized that the users would find activations in close proximity to be more relevant and interesting, Spatial Mode seems to be a more promising network configuration. Therefore, in the user study described in Section 5.4, the CBLA system was configured in Spatial Mode.

In addition, spontaneous activations were observed in the experiment. Fundamentally, this pattern is caused by the system's sensitivity to ambient sensor noise and can be



(a) CBLA Mode (Trial 1)



(b) Prescripted Mode

Figure 5.10: Total Activation in response to trigger. The blue line represents the Total Activation value over time. The magenta line indicates the period when an object was placed in front of the sensor

adjusted by changing the sensitivity constant, ν. Trials with low sensitivity setting were shown to have lower total activations. Although a lower sensitivity setting can indeed eliminate this spontaneous activations pattern as shown in Figure 5.8a, it would also make the sculpture to appear less responsive to users and to the external environment due to the dampened level of activation. We believe that a higher activation levels would be preferable for an interactive art sculpture, as it may better engage the visitors' attention. Therefore, in the user study described in Section 5.4, the high sensitivity setting was used.

Although the spontaneous activations may overlap with user-induced activations, nevertheless, the sculptural system was shown to be responsive as it always activated in response to the users' interaction if it was not already activated.

When compared with Prescripted Mode, there is a short but noticeable delay in response time. This may have an effect on the users' perceived responsiveness.

5.4 User Study

The CBLA system is designed to automatically generate interactive behaviours on interactive art sculptures. This user study aimed to determine whether the behaviours generated through this method can make the experience of interacting with the sculpture more interesting, compared with prescripted behaviours similar to those used in previous generations of the sculpture.

In this study, the test subjects reported their levels of interest at several points in time as they interacted with sculpture, which had two versions of behaviours. Afterwards, a short exit questionnaire was given to assess the subjects' overall experience. The results of this study may be used by designers to design more engaging and interesting interactive art sculptures.

5.4.1 Objectives

This study aimed to investigate the users' responses to the behaviour of the CBLA system in an interactive art sculpture under different configurations. In addition, the relationships between the intensities and types of activations and users' level of interest as they interact with the sculpture were examined.

The user study aimed to answer the following three questions.

1. Does the use of the CBLA increase users' interest level over prescripted behaviours?
2. Do people perceive CBLA as non-random?
3. Are certain behaviours more interesting than others?

Hypotheses

Prior to the user study, a hypothesis was made for each of the research questions raised.

1. The CBLA works by continuously generating new behaviours in order to improve its internal mathematical model of the sculpture and its sensed environment. The behaviours are adaptive and analogous to how animals and human beings learn. The users will find this kind of behaviour more interesting than prescripted behaviours.

2. Although the CBLA continuously generates new behaviours, it is not random. The users will not perceive the CBLA-generated behaviours as random.

3. The users categorize some types of behaviours as being more interesting than others.

5.4.2 Set-up

The multi-cluster test bed described in Section 4.5 was used in this user study as the interactive art sculpture that the participants interact with. In addition, the floor was lined with a grid numbered from 1 to 12 as shown in Figure 5.11. This grid allowed the participants to specify their locations within the sculpture during the experience sampling procedure.

Figure 5.11: Photograph of the floor grid underneath the multi-cluster test bed.

In addition, a screen was set up next to sculpture to display the sample number. A laptop running the software was set up facing away from the sculpture beside the screen.

5.4.3 Recruitment

Participants were recruited from the researchers' contact lists. All participants were healthy, physically able adults within the age range of 18 to 65 years old, male and female. Potential participants who were blind were excluded because they would be unable to perceive many of the behaviours, which were visually-manifested. Potential participants who were wheelchair users were excluded because they would not be able to access the studio, which had no elevator access.

In addition, participants had little prior knowledge about the workings of the CBLA system to avoid the subject-expectancy effect. This is a form of bias in which the test subject expects a particular result and this unconsciously affects the outcome.

In total, ten people participated in this study.

5.4.4 Procedures

Each participant was provided with the same information about the procedures of this user study. Only one participant was interacting with the sculpture at a time. No other participants were present during the entire trial.

Before the Trial

The test participant was invited to interact with an interactive art sculpture installed in the Toronto studio of Philip Beesley Architect Inc. (PBAI). The participant was then informed about the procedures of the study as described in the Information and Consent Form (Appendix D.1) and was asked to sign the attached consent form before he or she began participating in the trial.

After that, the participant was given a pen and an envelope with a stack of 8 identical business-card-sized questionnaire cards shown in Figure 5.12. He or she was asked to fill out one card every time a long tone was heard. The first question on the card asks the subject to write down the current sample number as shown on the screen. The second asks for his or her subjective interest level regarding the behaviour of the sculpture at that moment. The third question asks the subject to mark his or her location at that moment by looking down on to the grid on the floor. He or she was told to make a mark between the boxes if he or she was standing in between those boxes.

Right before the start of the trial, the researcher ran through the study procedures with the participant one last time. The participant was told that he or she was free to walk

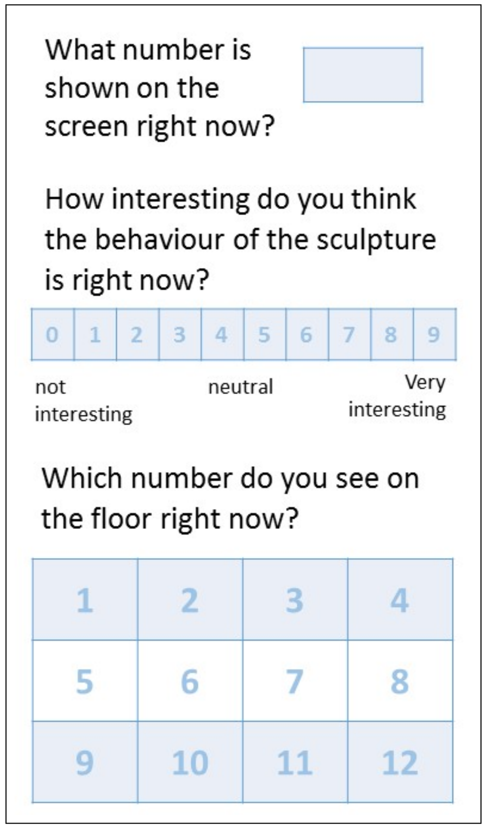


Figure 5.12: Questionnaire card for the user study.

around the space and interact with the art sculpture in any way and that there were not any prescribed interactions. The subject was also told that the entire trial would last for 20 minutes and he or she may request to terminate the study at any time.

During the trial

The test participant was free to roam around the space and interact with the art sculpture. A distinct long tone went off periodically at a 2.5 minute interval. Each time the tone went off, the participant would take out an empty questionnaire card, and answer the questions on the card. The trial would go on for 20 minutes which was equivalent to 8 cards.

There were two versions of interactive behaviours: Prescripted Mode and CBLA Mode. The Prescripted Mode was powered by the Prescripted Engine and is described in Section 4.5.5. The CBLA Mode was powered by the CBLA Engine and is described in detail in Chapter 3. Its network configuration was set to Spatial Mode with high sensitivity. Moreover, the CBLA Mode for each trial began at a previously saved state in which the CBLA system had run uninterrupted for approximately 575s.

The participants were not informed about the versions of the behaviours that they were interacting with nor the fact that there were two different versions of interactive behaviours. Both versions of the behaviours were run for approximately the same amount of time. After the fourth tone (which was half-way through the trial), the researcher would switch to the other version manually after the participant had finished filling in the questionnaire card and resumed interacting with the sculpture.

Since the experience of interacting with the sculpture was new to the test subjects, the order that the two types of behaviours was presented can make a big difference. The subjects may simply find the novelty of interacting with the sculpture interesting irrespective of the type of behaviour. In addition, since the exit questionnaires were given after the trials, the behaviours that the subjects experienced near the end of the trials may have more profound effects than the ones that they experienced earlier in the trials. Therefore, half of the participants were exposed to Prescripted Mode first and the other half were exposed to CBLA Mode first.

After the trial

After a participant had filled out the eighth questionnaire card, he or she was informed that the trial was completed. He or she then returned the questionnaire cards in the envelope given to him or her prior to the trial. The participant then filled out an exit questionnaire, shown in Appendix D.2, which has the following five questions.

1. How interesting was your overall experience while interacting with the art sculpture?

2. How responsive was the sculpture to your presence? Do you think its behaviour was totally random, or do you think it was responding directly to you?

3. How familiar are you with machine learning algorithms?

4. How would you describe the behaviour of the sculpture?

5. Additional comments

Question 1 elicits the participant's general opinions about how interesting it was interacting with the sculpture. Question 2 can provide insights on research question 2. Both questions 1 and 2 were rated on a scale from 0 to 9. Question 3 allows us to gauge whether or not the participant's prior exposure to machine learning had any effect of his or her perceptions of the behaviours of sculpture and it was rated on a scale from 0 to 4. Questions 4 and 5 are open-ended questions that can give us some qualitative information about the participant's experience that we might not capture otherwise.

After that, the participant was provided with the debriefing letter shown in Appendix D.3, which has more information about the learning algorithm, the interactive behaviours, and the purpose of this study. In addition, the interactive behaviours that he or she interacted with were explained verbally after all questionnaires were collected.

5.4.5 Results and Data

A total of 10 participants were recruited. There were three main sets of data collected in each trial: the set of 8 questionnaire cards, the exit questionnaire, and the states of the CBLA system during the entire trial.

The questionnaire cards recorded each subject's levels of interest and locations at the 8 sample points. The levels of interest data enabled us to compute the subject's overall interest level in each of the two segments, Prescripted Mode and CBLA Mode. We further separated the data into two groups based on the trial started with Prescripted Mode first or CBLA Mode first and they are presented in Table 5.2. On the other hand, the location data enabled us to examine the relationships between the activations near the test subject and his or her reported interest level.

The exit questionnaires provided information about the participants and their overall opinions and thoughts on their experience before any additional information about the user study was revealed. In addition, observations of the participants' behaviours and interesting comments made in verbal conversations with were noted to provide further insights.

The input, output, and internal variables of the CBLA Nodes and non-CBLA Nodes during the entire trial were collected. The activation levels of each CBLA Node were extracted at 1.0s time intervals for analyzing the correlations between activations and interest levels. A time interval of 1.0s was chosen to give sufficient granularity to the data.

Table 5.2: Self-reported interest levels at the sample points collected in the user study.

Trial #	**Sample Interest Level**								**Mean**	
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**[1:4]**	**[5:8]**
1	6	4	6	3	7	6	4	7	4.75	6
3	1	4	2	3	5	3	3	2	2.5	3.25
5	4	4	5	5	3	3	5	4	4.5	3.75
7	7	6	7	5	5	6	5	6.5	6.25	5.625
10	9	9	7	5	5	3	3	2	7.5	3.25

(a) Prescripted-first trials. The values in Trials 1 to 4 are the values during Prescripted Mode. The values in Trials 5 to 8 are the values during CBLA Mode.

Trial #	**Sample Interest Level**								**Mean**	
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**[1:4]**	**[5:8]**
2	7	6	8	6	8	7	6	7	6.75	7
4	7	9	2	0	0	4	6	9	4.5	4.75
6	2	2	1	1	5	5	5	5	1.5	5
8	5	3	2	6	8	3	6	8	4	6.25
9	7	7	4	5	5	8	8	7	5.75	7

(b) CBLA-first trials. The values in Trials 1 to 4 are the values during CBLA Mode. The values in Trials 5 to 8 are the values during Prescripted Mode.

5.4.6 Analysis I – Average Interest Levels between Prescripted Mode and CBLA Mode

We first separated the levels of interest data on the questionnaire cards (Tables 5.2a and 5.2b) into four groups: Prescripted Mode (first half), Prescripted Mode (second half), CBLA Mode (first half), and CBLA Mode (second half). The "Prescripted Mode" or "CBLA Mode" indicates the version of the behaviours that was running when the samples were recorded, and "(first half)" or "(second half)" indicates whether the samples were taken during the first or the second half of the trial. We then took the average across all trials for each sample point, which resulted in four sets of data with five elements each.

Prescripted Mode (first half):	(4.75, 2.5, 4.5, 6.25, 7.5)
Prescripted Mode (second half):	(7.0, 4.75, 5.0, 6.25, 7.0)
CBLA Mode (first half):	(6.75, 4.5, 1.5, 4.0, 5.75)
CBLA Mode (second half):	(6.0, 3.25, 3.75, 5.625, 3.25)

We then performed Welch's T-Tests for unequal variance on different combinations of these four sets of data as described below. For each test from Test 1 to Test 6, the two-tails P-value must be below 0.1 in order for the null hypothesis (H0) to be rejected in favour of the alternate hypothesis (H1).

1. Prescripted Mode: on during first half vs on during second half

   Data Set 1: Prescripted Mode (first half)

   Data Set 2: Prescripted Mode (second half)

   — H0. Average interest level for prescripted mode is the same regardless if it is on first or second.

   — H1. Average interest level for prescripted mode is different depending on whether it is on first or second.

2. CBLA Mode: on during first half vs on during second half

   Data Set 1: CBLA Mode (first half)

   Data Set 2: CBLA Mode (second half)

   — H0. Average interest level for CBLA mode is the same regardless if it is on first or second.

   — H1. Average interest level for CBLA mode is different depending on whether it is on first or second.

3. Either Mode: on during first half vs on during second half

   Data Set 1: Prescripted Mode (first half) + CBLA Mode (first half)

   Data Set 2: Prescripted Mode (second half) + CBLA Mode (second half)

   — H0. Average interest level is the same regardless if it is on first or second.

   — H1. Average interest level is different depending on whether it is on first or second.

4. CBLA Mode vs. Prescripted Mode: on during first half

Data Set 1: CBLA Mode (first half)

Data Set 2: Prescripted Mode (first half)

— H0. Average interest level for CBLA mode is the same as Prescripted mode when it is on first.

— H1. Average interest level for CBLA mode is different from Prescripted mode when it is on first.

5. CBLA Mode vs. Prescripted Mode: on during second half

   Data Set 1: CBLA Mode (second half)

   Data Set 2: Prescripted Mode (second half)

   — H0. Average interest level for CBLA mode is the same as Prescripted mode when it is on second.

   — H1. Average interest level for CBLA mode is different from Prescripted mode when it is on second.

6. CBLA Mode vs. Prescripted Mode: on during either half

   Data Set 1: CBLA Mode (first half) + CBLA Mode (second half)

   Data Set 2: Prescripted Mode (first half) + Prescripted Mode (second half)

   — H0. Average interest level for CBLA mode is the same as Prescripted mode.

   — H1. Average interest level for CBLA mode is different from Prescripted mode.

Out of the six Welch's T-Tests, only Test 5, which compared the levels of interest between CBLA Mode and Prescripted Mode when they were on during the second half of the trial, was able to reject the null hypothesis with a two-tailed P-value of 0.0684. The average interest level of Prescripted Mode and CBLA Mode were 6.0 and 4.375 respectively. This means that Prescripted Mode was more interesting than CBLA Mode by approximately 37% when they were on during the second half of the trial with a 96.58% confidence. We did not find any significant differences in reported levels of interest between CBLA Mode and Prescripted Mode in any other cases.

Furthermore, we were interested in finding out if an average participant would find Prescripted Mode more or less interesting than CBLA Mode. Since each participant had seen both versions of behaviours, we compared their responses by performing Paired T-Tests.

We first compared each test subject's average levels of interests in CBLA Mode and Prescripted Mode, irrespective of which halves the behaviours were presented.

7. CBLA Mode vs Prescripted Mode

   Data Set 1: CBLA Mode (first half) + CBLA Mode (second half)

   Data Set 2: Prescripted Mode (second half) + Prescripted Mode (first half)

   — H0. Participants find that CBLA Mode is equally as interesting as Prescripted Mode.

   — H1. Participants find that CBLA Mode is not equally as interesting as the Prescripted Mode.

In Test 7, we found that CBLA Mode was in fact less interesting than Prescripted Mode with a 96.16% confidence. An average participant who had interacted with both kinds of behaviours gave Prescripted Mode a rating of 5.55 and a CBLA Mode a rating of 4.44. This means that Prescripted mode was approximately 25% more interesting than CBLA Mode irrespective of the order that they were presented.

Taking a closer look, we wanted to see if the orders that the two versions were presented had any significance.

8. CBLA Mode vs. Prescripted Mode when Prescripted Mode is on first

   Data Set 1: CBLA Mode (second half)

   Data Set 2: Prescripted Mode (first half)

   — H0. Participants find that CBLA Mode is equally as interesting as Prescripted Mode when Prescripted Mode is on first.

   — H1. Participants find that CBLA Mode is not equally as interesting as the Prescripted Mode when Prescripted Mode is on first.

9. CBLA Mode vs Prescripted Mode when CBLA Mode is on first

   Data Set 1: CBLA Mode (first half)

   Data Set 2: Prescripted Mode (second half)

   — H0. Participants find that CBLA Mode is equally as interesting as Prescripted Mode when CBLA Mode is on first.

   — H1. Participants find that CBLA Mode is not equally as interesting as the Prescripted Mode when CBLA Mode is on first.

In Test 8, we could not find any significance difference in ratings between CBLA Mode and Prescripted Mode when Prescripted Mode was on first. On the other hand, in Test 9, we found that CBLA Mode was rated lower at an average of 4.5 compared to Prescripted Mode at an average of 6.0 with a 96.32% confidence when CBLA Mode was on first. This translates to a 33% increase in interest level when the behaviour was switched from CBLA Mode to Prescripted Mode. This is quite surprising as we expected the initial curiosity of the participants would boost the interest level of the behaviour presented first.

5.4.7 Analysis II – Correlations between Activation level and Interest Level

This analysis aims to determine if there were any correlations between the participants' reported levels of interest to the activation levels of the sculpture. In this analysis, we did not consider which version of the behaviours was running at the sample point and focused on the actual activation levels of the sculpture.

The extracted activation levels for each CBLA Node were the output levels of each node averaged over 1.0s windows. For each trial, there were 8 sample points which correspond to the times when the participant filled out questionnaire cards and reported his or her levels of interest and locations. For each sample point, the time interval containing it and 30 time intervals (which translates to 30 seconds) preceding it were considered as activations related to the sample point. A time interval of 30s was chosen in order to include prior activations that were likely to be associated with the participant's response at that a sample point.

Two metrics were developed to quantify activation levels. The first metric is "average sample average activation", $\overline{\overline{\alpha}}$. It is computed by taking the average of the output values in the 30 time intervals preceding and at the sample point and then taking the average of that value across all the Nodes under consideration as formulated in (5.5).

$$\overline{\overline{\alpha}} = \frac{1}{N} \sum_{j=0}^{N} \frac{1}{31} \sum_{t=t_{s-30}}^{t_s} \overline{m}_{jt} \tag{5.5}$$

where $\overline{\overline{\alpha}}$ is the average sample average activation level among all CBLA Nodes being considered; N is the number of CBLA Nodes being considered; t_s is the time interval that the sample point is in. t_{s-30} is the time interval that is 30 time intervals before t_s; and $\overline{m}_{jt}$ is the output level of CBLA Node j at time interval t.

The second metric is the "average sample peak activation", $\overline{\widehat{\alpha}}$. It is computed by taking the maximum output values in the 30 time intervals preceding and at the sample point and then taking the average of that value across all the nodes under consideration as formulated in (5.6).

$$\overline{\widehat{\alpha}} = \frac{1}{N}\sum_{j=0}^{N} \max(\overline{m}_{jt_{s-30}}, ..., \overline{m}_{jt_s}) \tag{5.6}$$

where $\overline{\widehat{\alpha}}$ is the average sample peak activation level among all CBLA Nodes being considered; N is the number of CBLA Nodes being considered; $\overline{m}_{jt_{s-30}}$ and $\overline{m}_{jt_s}$ are the output levels of the CBLA Node j at time intervals t_{s-30} and t_s respectively.

These two particular metrics were selected because we did not know if the duration of the activations would have any effect on the users' interest levels. By using both the peak activations and average activations, both cases can be covered.

We examined if there were any correlations between interest levels and different types of activation levels using these two metrics. One type of activation level is the system wide activation which was captured by computing the metrics among all CBLA Nodes. The other type is device type activation, which was captured by computing the metrics among just Half-Fin Nodes, Light Nodes, or Reflex Nodes.

In addition, proximities of the activations to the participant were considered. We formulated a modified version of $\overline{\overline{\alpha}}$ and $\overline{\widehat{\alpha}}$ that are weighted by the inverse proximities of the Nodes to the participant. They are called "average sample proximal average activation", $\overline{\overline{\rho}}$, and "average sample proximal peak activation", $\overline{\widehat{\rho}}$. The proximity was measured in relative distance unit as only the relative proximities among Nodes were considered in this metric.

$$\overline{\overline{\rho}} = \frac{1}{N}\sum_{j=0}^{N} \frac{1}{31 \cdot d_j} \sum_{t=t_{s-30}}^{t_s} \overline{m}_{jt} \tag{5.7}$$

where $\overline{\overline{\rho}}$ is the average sample proximal average activation level among all CBLA Nodes being considered; N is the number of CBLA Nodes being considered; d_j is the relative distance between the CBLA Node j and the subject; t_s is the time interval that the sample point is in; t_{s-30} is the time interval that is 30 time intervals before t_s; and $\overline{m}_{jt}$ is the output level of CBLA Node j at time interval t.

$$\overline{\widehat{\rho}} = \frac{1}{N}\sum_{j=0}^{N} \frac{1}{d_j} \max(\overline{m}_{jt_{s-30}}, ..., \overline{m}_{jt_s}) \tag{5.8}$$

where $\overline{\widehat{\rho}}$ is the average sample proximal peak activation level among all CBLA Nodes being considered; N is the number of CBLA Nodes being considered; d_j is the relative distance between the CBLA Node j and the subject; $\overline{m}_{jt_{s-30}}$ and $\overline{m}_{jt_s}$ are the output levels of the CBLA Node j at time intervals t_{s-30} and t_s respectively.

Since we were interested in the correlations between activation levels of the sculpture and the interest level of an average user, we combined the data for all 10 trials and computed metrics described above. We then computed the Pearson correlation coefficients, r, between each of those metrics and the user's level of interest in Table 5.3.

Table 5.3: Correlations between activation levels and user's interest level

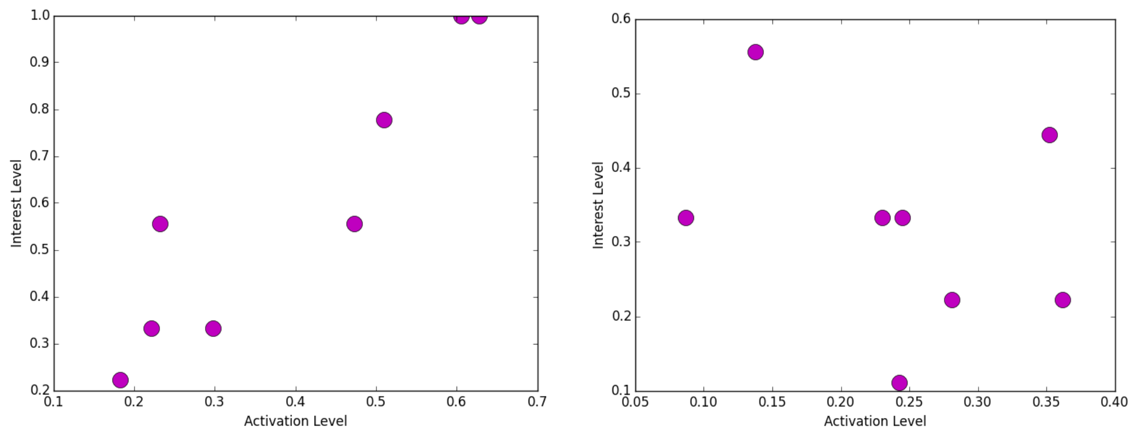
Metric	**Nodes**	r	**P-value**
$\overline{\overline{\alpha}_{all}}$	all CBLA Nodes	0.366304	0.000833
$\overline{\overline{\alpha}_{hf}}$	Half-Fin Nodes	0.357302	0.001139
$\overline{\overline{\alpha}_{l}}$	Light Nodes	0.395201	0.000286
$\overline{\overline{\alpha}_{rfx}}$	Reflex Nodes	-0.083434	0.461854
$\overline{\widehat{\alpha}_{all}}$	all CBLA Nodes	0.317221	0.004143
$\overline{\widehat{\alpha}_{hf}}$	Half-Fin Nodes	0.374608	0.000618
$\overline{\widehat{\alpha}_{l}}$	Light Nodes	0.322380	0.003541
$\overline{\widehat{\alpha}_{rfx}}$	Reflex Nodes	0.021213	0.851844
$\overline{\overline{\rho}_{all}}$	all CBLA Nodes	0.345267	0.001709
$\overline{\widehat{\rho}_{all}}$	all CBLA Nodes	0.317167	0.004149

Over the whole system, there was a weak positive correlation between interest level and both average sample average activation levels, $\overline{\overline{\alpha}_{all}}$, and average sample peak activation levels, $\overline{\widehat{\alpha}_{all}}$, with over 99% confidence.

For device type correlation, we found a higher correlation for Light Nodes than the system-wide correlation when considering the average sample average activation levels. On the other hand, higher correlation was found for Half-Fin Nodes when considering the average sample peak activation levels. Interestingly, we did not find any significant correlation between the activation levels of Reflex Node to the user's interest level.

The proximities of the activations do not increase the correlation. The correlation coefficients for average sample proximal average activation $\overline{\overline{\rho}_{all}}$ and average sample proximal peak activation $\overline{\widehat{\rho}_{all}}$ are approximately the same as their system-wide counterparts. This might be attributed to the fact that the sculpture is relatively small.

Although the overall correlations across all ten studies were relatively weak, there were in fact large variations among different studies. For instance, the average total peak activations level, $\overline{\widehat{\alpha}_{all}}$, for Study 10 showed strong correlation with the subject's interest level. It had a Pearson coefficient, r, of 0.924443 with over 98% confidence. On the other hand, the same metric for Study 3 showed no significant correlation. The two cases are plotted in Figure 5.13 for a visual side-by-side comparison.



(a) Study 10 with strong correlation

(b) Study 3 with no significant correlation

Figure 5.13: Study-specific correlation between the average sample peak activation level, $\overline{\widehat{\alpha}_{all}}$, and user's level of interest.

This shows that different people responded and interacted very differently to the behaviours of the sculpture. For instance, some people might indeed be attracted by the activations and were engaged to interact with the sculpture, while some might be attracted to the sculpture due to other reasons, such as the aesthetic of the design. More samples would be needed to further categorize the different types of users.

5.4.8 Analysis III – Perceived Responsiveness

In the exit questionnaire, we asked the participants to rate their overall interest level and how responsive they thought the behaviour was. In Table 5.4, responses for the two questions and the average interest level reported on the questionnaire cards were tabulated. All three ratings were reported on a scale of 0 to 9.

The Pearson correlation coefficient, r, between responsiveness and overall interest level was 0.680 with over 96% confidence. Similarly, the r between responsiveness and the aver-

Table 5.4: User reported overall interest levels and responsiveness for each trial. The trials are further grouped into Prescripted First and CBLA First.

	Trial #	Q1. Overall Interest Level	Q2. Responsiveness	Average Interest Level on Questionnaire Cards
Prescripted First	1	6	4	5.375
	3	6	5	2.875
	5	6	6	4.125
	7	7	6	5.938
	10	9	7	5.375
CBLA First	2	8	8	6.875
	4	7	4.5	4.625
	6	6	6	3.250
	8	7	7	5.125
	9	8	9	6.375

age interest level reported on the questionnaire cards was 0.572 with over 91% confidence. This shows that responsiveness of the behaviours did have a moderate positive correlation to how interesting they were to the users.

On the other hand, there was moderate discrepancy between the overall interest level and the average interest level reported on the questionnaire cards. Taking the difference between the two revealed that, on average, the overall interest level rating was greater than average interest level reported on the questionnaire cards by 2.01 points. Their Pearson correlation coefficient is 0.682 with over 97% confidence. These results show that the participants' reported interest levels as they were interacting with the sculpture were significantly different from the ones reported afterwards. This is probably because some people tended to put more emphasis on their most recent experience when answering the questions on the exit questionnaires. In fact, if Prescripted Mode was on during the second half of the trials, the average responsiveness rating was 6.9 as opposed to 5.6 when CBLA Mode was on during the second half with confidence level over 89%. Since the CBLA Mode should be less responsive than Prescripted Mode, we can speculate that when subjects reported on their impressions on the responsiveness of the sculpture after the trials, they disproportionately emphasized their most recent interactions.

5.4.9 Conclusions

In this user study, we attempted to answer the three research questions raised in Section 5.4.1.

First, does the use of the CBLA increase user's interest level over prescripted behaviours? In the analyses done in Section 5.4.6, we showed that CBLA Mode was in fact less interesting than Prescripted Mode by 25%. This effect was even more pronounced when the trial started with CBLA Mode first and switched to Prescripted Mode halfway. Prescripted Mode was on average 33% more interesting that CBLA Mode. This is contrary to our hypothesis as we did not find any significant evidence that the use of CBLA increased the users' interest levels.

Second, do people perceive CBLA as non-random? It is more difficult to answer this question since we did not ask the participants to rate the sculpture's responsiveness for each type of behaviour. In fact, based on question 4 of the exit questionnaire in Appendix E, most participants did not realize that there were two distinct sets of behaviours that were switched over midway. This wasn't asked since we couldn't reveal the type of behaviours that they should expect during the trials. However, we did find a positive correlation between interest level and responsiveness rating. Since CBLA Mode was considered less interesting when we tried to answer research question 1, this might indicate that CBLA Mode was considered less responsive. In addition, we speculate that test subjects would emphasize the later half of the trials when answering the exit questionnaires. On that front, we also found that the responsiveness ratings were lower when CBLA Mode was on in the second half. In addition, in question 4, when the participants were asked to described the behaviours of the sculpture, they often described the CBLA portion using words like "random", "totally random", "somewhat random", or "unresponsive". This shows that many participants did think that CBLA Mode was indeed random and perceived to be unresponsive. This is also contrary to our hypothesis that the participants will perceive the learning behaviours as non-random. This might explain why the participants did not find the CBLA Mode behaviours more interesting.

Finally, are certain behaviours more interesting than others? In the analysis done in Section 5.4.7, we found that there was a weak positive correlation between the overall activation levels and the user's interest level. In other words, the participants found that more actuation is more interesting than less actuation. On the other hand, we did not find that any specific device had a significantly stronger positive correlation. However, we found that activations of the Reflex Node, which actuates either a pair of LEDs or a vibration motor, showed no correlation with the user's interest level. Similarly, we did not find that proximity of the actuations influenced the user's level of interest much either. This may be because the size of the sculpture was relatively small and the participants could easily see, hear, and walk to anywhere in the space relatively quickly, in comparison to the time required to fill out the questionnaire cards. In sum, we show that activations do tend to increase user's level of interest but, contrary to our hypothesis, we could not find any particular categories of behaviours that were more interesting than the others.

5.5 Discussion

This project is motivated by the desire to generate life-like behaviours automatically. However, we in fact don't know if being life-like is interesting to all people. Gaver et al. [34] suggested that ambiguity can be used as a tool to create interactive arts that are more engaging and thought-provoking by posing questions without providing solutions. However, without the balance between ambiguity and consistency, the work can also appear to be confusing and meaningless. Indeed, research has shown that people find events that are new and comprehensible interesting [35]. Novelty and complexity alone are not enough to make the behaviours interesting. The user may also need to understand it. A participant that was in a trial with CBLA Mode presented first described the behaviours of the system as follows:

> "The sculpture changes lighting, creates sound, and moves to attract user. It responds to human presence, gestures, and hand claps. It seemed to generate random movements at the beginning, but a pattern was repeated as the experiment goes on."

This quote shows that when the behaviours went from CBLA Mode to Prescripted Mode, without knowing that there were two distinct behaviours, the participants may have thought that they have began to understand the behaviour of the system. On the other hand, when switched from Prescripted Mode to CBLA Mode, the users' understanding of the behaviours decrease. A participant in a trial which Prescripted Mode was presented first described the behaviours as follow:

> "...Parts that used to do something with straightforward motion/presence became unresponsive on one pillar - could not figure out the pattern. Behaviour changed a bit with time but slightly seemingly random as to how it changed."

This quote shows that the participant went from understanding how the system works, to thinking that it was random. This effect might have contributed to the significant increase in level of interest when the behaviour was switched from CBLA Mode to Prescripted Mode, but not the other way around.

For a CBLA Node to activate, its CBLA Engine has to first accumulate prediction errors, which then provide it the opportunities to improve its prediction models. This process requires the CBLA Node to perform some actions and acquire feedbacks from the environments. Since each action takes time to perform, it would inevitably require a longer time to respond in comparison to a system that only reacts to its sensory inputs. Therefore, the delays in response time may have played a role in reducing the sculpture's perceived responsiveness. Participants might have looked away or lost interest before the sculpture was able to respond.

On the other hand, though noticeable, the delays seem to be rather short, as shown in Figure 5.10a. Therefore, delay in response alone might not be sufficient to explain the low responsiveness rating. Another probable factor is the predictability of the response. Unlike the Prescripted Mode, the responsive behaviours of the CBLA Mode are much less consistent. For instance, the type, the intensity, and the timing of the actuations are often different when given the same kinds of trigger. In addition, there are far more spontaneous activations as well. A participant commented on his or her experience as follows:

> "...Sometimes the responses I got from the sculpture were not what I was hoping for. For example, when I held up my hand to the leaf, the leaf itself was not really moving towards me as much as the two other leaves that were a bit farther away...."

Since what was described in the quote above is different from the prescripted behaviours, it is very likely that the quote describes the subject's experience during the CBLA Mode portion of the trial. This suggests that the CBLA system was responsive but in ways that were less predictable. The unpredictability of the response makes it difficult for the users to recognize the causal relationship between the response of the sculpture and their actions. Thus, this factor might have contributed to the lower responsiveness ratings.

In addition, the participants recruited may be very different from the typical visitors to art exhibitions, where the interactive art sculptures are typically displayed. People who frequent art exhibitions are probably interested in arts in the first place. Those visitors would also have the opportunity to read about the work prior to their interactions with the sculpture. Indeed, [38] showed that an abstract poem would appear more interesting when hints about its meaning were given. In this user study, the participants didn't necessarily have any interest in arts and were not given any information about the behaviours of the sculpture. [35] suggested that concepts that are confusing to novices can be interesting to experts. Knowledge in arts and the philosophy behind the Hylozoic Series sculptures might enable the users to appreciate the complex and subtle patterns of the CBLA system that aren't immediately obvious. Thus, the simplicity and comprehensibility of Prescripted behaviours might seem more interesting to a person who has not been exposed to this kind of interactive arts before.

In fact, from written responses on the exit questionnaires and the informal conversations after the studies, we realized that people had very different interests, and different expectations about the behaviours of the sculpture. Some expected much more coordinated, fast-pace movements, while some found the slow and organic-looking movements appealing. Some expected the sculpture to be very responsive, while some did not even know that there were sensors that could detect their presence at first. Some participants took figuring out the exact mechanism of the sculpture's behaviours as a challenge; some were enjoying it and some were frustrated by their inability to figure out the patterns. Moreover, there were also participants who enjoyed looking at the design of the sculpture and some were interested in the design of the circuit boards and actuators. They spent a great deal of time examining the details of the sculpture itself rather than interacting with the sculpture. Furthermore, the ways in which the participants interacted with the sculpture varied greatly. Some mainly stood back and observed, while some walked around the space rapidly and touched many parts of the sculpture at great frequency. In fact, one participant was taking apart the sculpture in order to better examine the parts and how those alterations change the activation patterns of the sculpture. Perhaps by informing the users about the behaviours of the sculpture, the users can understand its behaviours better and prevent the negative feeling of disappointment when what they expect is absent.

Interest level may be related to the user's curiosity, rather than their enjoyment of the experience. There are many theories that attempt to explain the existence and mechanism of human curiosity [36]. Berlyne [37] theorized that human curiosity stems from the natural drive to answer questions, whether raised by the subject or by others. If an answer can be quickly retrieved from existing knowledge, the drive is quickly reduced. On the other hand, if the answer is unknown, explorations through various means would be conducted in order to resolve the conflicts between existing knowledge and novel experience. Curiosity emerges from the process of resolving conflicts and reducing the dissonance. Indeed, this is similar to the implementation of CBLA. Nevertheless, it is unclear whether observations and interactions with a system that mimics curiosity can induce curiosity. Other approaches that maximize the user's learning progress, instead of the system's learning progress, may be necessary.

Moreover, we hypothesize that, over a long period of time, prescripted behaviour would become repetitive and less interesting. In this user study, the participants were only interacting with the prescripted behaviours for 10 minutes and perhaps that was insufficient for them to realize that it was repetitive and lose interest. In fact, one participant (quoted above) thought it was responsive to sound, and was making noise and still trying to figure out its non-existent response to sound until the end. Indeed, the set up of this interactive art sculpture was also very different from a typical set-up. Typically, this kind of sculpture is set up in a public space. Visitors are free to enter or leave the space as they like. In cases of a permanent installation, the sculpture forms the background for some other daily activity. This is very different from the one-on-one, timed interactions that we tested in this user study. In addition, typically, visitors would be accompanied by other people and the effect of multiple occupants in the same space was not covered.

Our observations of the variety of user behaviours and responses suggest that the data could be further categorized based on the type of user. Different people expected different things out of this experience, and analyzing the different groups separately may reveal more useful information about user response to the different types of behaviours. In addition, the user study should be done in a more realistic setting over a longer period of time to reveal whether CBLA can indeed be more interesting in the long run.

Nevertheless, these results may be sensitive to the parameters used in the experiment. For instance, when calculating the activation values in Section 5.4.7, we considered the activations in the 30s time interval prior to a sample point to be relevant to the response of the user at that sample point. It is unclear whether this choice reflects the actual behaviour of a human user. Further experiments should be conducted to examine how recent the activations have to be to affect the user's response. Indeed, this system may also be sensitive to many of the internal parameters of the CBLA Nodes such as the sensitivity setting, loop period, the type of prediction model, the sizes of the averaging windows, and thresholds of the split criteria. This study simply offers a demonstration of how a CBLA system may behave. Future research should study the effects of the values of these parameters on the interactive behaviours of the sculpture.

Chapter 6

Conclusions and Future Work

The work presented in this thesis was driven by the desire to create interactive art sculptures that possess the characteristics of living things [2]. In previous generations of the Hylozoic Series interactive art sculptures [5], complex behaviours emerged from the superpositions of a set of simple prescripted responsive behaviours. In this thesis, we introduced an autonomous behaviour generation system by applying a reinforcement learning algorithm that mimics curiosity. In addition, we examined the interactions between the CBLA system and the human users and how it compared with prescripted behaviours.

6.1 CBLA System

The CBLA builds on the Intrinsic Adaptive Curiosity (IAC) algorithm [7] created for developmental robots. CBLA enables the sculptural system to select actions that lead to maximum potential knowledge gains. In order to implement the CBLA on a distributed sculptural system with hundreds of sensors and actuators, a novel formulation that uses a network of CBLA Nodes, with each representing a subset of the sculptural system, was developed. Each CBLA Node runs its own copy of the CBLA and constructs prediction models that model the relationships between its states and actions, and the consequences. The multi-Nodes approach enables each Node to operate at a rate that is appropriate for its associated actuators and sensors. In addition, this reduces the dimension of the state space which in turn reduces the number of samples required to acquire the model. These Nodes are then connected via shared inputs and virtual inputs. These links allow information from one Node to propagate to other parts of the system.

Furthermore, a mechanism that relates the maximum activation levels based on the relative action value of the system was developed to give a visual indication of the CBLA Node's appraisal of the knowledge gain potentials in its associated regions. The behaviours of the system under different network configurations and action selection policies when an external trigger is applied were examined. Using the Spatial Mode network configuration, which connects Nodes based on their spatial proximities, enables the CBLA system to respond with a higher level of activation near the source of the trigger immediately after the triggering event. In addition, using a high sensitivity setting enables a higher level of activation to both ambient noise and deliberate triggers. These settings were selected for the user study conducted in this thesis.

In future work, experiments should be conducted using different parameters and settings to examine their effects on the behaviour of the system. Parameters such as the sensitivity setting, the loop period of each CBLA Node, and the thresholds of the split criteria; and settings such as the network configuration, region splitting mechanism, action selection policy, and type of the prediction models may all have profound effects on the behaviours of the system. For instance, while a smaller loop period may shorten the response time, it will require that new action selection policies or controllers for the actuators to be developed. While using Lasso has the advantage of reducing the dimensionality of the model, it may inadvertently decouple the links between CBLA Nodes.

In addition, even though mechanisms were put in place to control the number of regions in a CBLA Engine, it would still continue to grow indefinitely under the current implementation. New mechanisms, such as merging similar regions, and removing obsolete regions, should be investigated and developed to facilitate long term operation of the CBLA system.

6.2 Interactive Control System

Implementation of a CBLA system requires the control and sampling of a larger number of sensors and actuators and at a higher frequency than what the previous generations of the interactive control system could handle. Therefore, a new set of electronic hardware and control software was developed. This new interactive control system enables the interfacing of hundreds of actuators and sensors and the capability of high speed communication with a computer through USB. This simplified the implementation of a computationally intensive and multi-threaded CBLA system by running it on a standard computer instead of an embedded platform. A four-cluster experimental test bed was built for the experiments involving human users.

In future work, the interactive control system should be implemented on a distributed platform. This reduces the risk of system-wide failure caused by the problems at the central computer. In addition, it would enable the system to support an even larger number of Nodes that require more computational power and a larger number of connection ports than are available to a single computer. Furthermore, a more robust database and data logging module should be developed to allow long term data collection and real-time data retrieval.

6.3 User Interaction

A study that involved the users interacting with the sculpture one at time was conducted. During the interaction, the users reported their interest levels periodically. By drawing connections between the users' responses and the type of behaviours, it was shown that when the sculpture was switched from CBLA Mode to Prescripted Mode, the users' levels of interest increased. This means that under the circumstances of this user study, behaviours generated by the CBLA system were less interesting than the prescripted behaviours. Furthermore, the proximity of the activations did not seem to influence the users' level of interest. We also did not find a particular type of Node to be more interesting than the overall system. However, though unclear why, we did find the activation levels of the Reflex Node to be uncorrelated to the users' levels of interest.

Weak to moderate positive correlations were found between activation levels, perceived responsiveness of the system, and the users' levels of interest. This suggests that systems with activations that are more prominent and with more comprehensible relationships with the users' actions may engage the users better, at least during the short term interaction investigated in this study. The less predictable behaviours generated by a CBLA system are perhaps one of the reasons why its behaviours was reported to be less interesting than the simple and highly responsive prescripted behaviours.

In future work, the effects of response time and predictability of the sculptural system's responsive behaviour on the users' perceived responsiveness should be further investigated. More experiments should be conducted to model the response time of a CBLA Node to different kinds of triggers, under different configurations. In addition, the repeatability of the behaviours should be quantified to enable comparisons of the users' perceptions under different levels of predictability. After all, if an user cannot predict the response of the sculpture repeatedly, he or she would have difficulty to associate the responsive behaviours to his or her actions.

Although a positive correlation was found between activation levels and the users' level of interest, there is no evidence of causation. It is possible that users who were more interested in the sculpture, due to other reasons, interacted with the sculpture more and caused higher levels of activation. In future work, the hypothesis that activations promote higher user engagement should be tested by studying the responses of the users to a system that ignores all sensory inputs and activates at different level of intensity autonomously. The results from that study would improve our understanding of the importance of the interactive aspect relative to the performative aspect of system.

Through observations and the responses from the exit questionnaires, we observed that different participants in the study interacted with the sculpture in very different ways, and had very different expectations about their experience. This suggests that, in future work, more meaningful correlations may be revealed by categorizing the different types of users. Alternatively, to align participants' expectations, the expected behaviours and meanings behind the concepts of the sculpture can be explained to the participants prior to the study. This is similar to how visitors may read and learn about the sculptures prior to interacting with them in a museum setting. Therefore, in future work, studies should be conducted to investigate the effects of prior knowledge on the users' appraisal of their experience.

In addition, though the test bed resembled a typical interactive art sculpture, there were also significant differences. For instance, the small size of the test bed means that the proximity of the activation became less of a factor since all Nodes were close to the user. In addition, in a public exhibition, users' interactions with a sculpture might be secondary to their primary activities such as socializing with friends, or simply passing by to get from one location to another. Users may find the experience more interesting as an augmentation to their primary activities in comparison to the more focused, one-on-one experience tested in this thesis. Therefore, in future work, user studies that better reflect the actual use cases should be designed and conducted to further examine the users' experience in interacting with the sculpture.

Indeed, the advantage of using CBLA, which generates complex and changing behaviours, may only be apparent in a longer study. From the written responses of the questionnaires (Appendix E), the participants had a tendency to want to learn to "play" the system and understand the its interactive behaviours. Therefore, simple and easily predictable behaviours may had been preferable. However, we hypothesize that as novice users become experts, those simple behaviours may become boring, while the more complex and evolving behaviours of a CBLA system may become more interesting. In future work, longer studies on the same users that span over a few days, or even months, should be conducted to test this hypothesis.

References

[1] M. T. K. Chan, R. Gorbet, P. Beesley, and D. Kulić, "Curiosity-Based Learning Algorithm for Distributed Interactive Sculptural Systems," in *2015 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, Hamburg Germany, 2015, pp. 3435–3441.

[2] R. Gorbet, M. Memarian, M. Chan, D. Kulić, and P. Beesley, "Evolving Systems within Immersive Architectural Environments: New Research by the Living Architecture Systems Group," *Next Generation Building*, 2015.

[3] P. Beesley and C. Macy, *Kinetic Architectures & Geotextile Installations*. Toronto, Ontario, Canada: Riverside Architectural Press, 2010.

[4] P. Beesley, R. Gorbet, P. Ohrstedt, and H. Isaacs, *Hylozoic Ground: Liminal Responsive Architecture*. Toronto, Ontario, Canada: Riverside Architectural Press, 2010.

[5] P. Beesley, *Sibyl: New Responsive Immersive Architecture Projects 2010-12*, 1st ed. Kitchener, Ontario: Riverside Architectural Press, 2012.

[6] "MMCA Epiphyte Chamber," 2013. [Online]. Available: http://philipbeesleyarchitect.com/sculptures/1312_MMCA_Epiphyte-Chamber/index.php [Accessed: 2016-01-15]

[7] P.-Y. Oudeyer, F. Kaplan, and V. V. Hafner, "Intrinsic Motivation Systems for Autonomous Mental Development," *IEEE Transactions on Evolutionary Computation*, vol. 11, no. 2, pp. 265–286, 2007.

[8] E. Edmonds, G. Turner, and L. Candy, "Approaches to interactive art systems," in *Proceedings of the 2nd international conference on Computer graphics and interactive techniques in Austalasia and Southe East Asia GRAPHITE 04*, 2004, pp. 113–117.

[9] J. Drummond, "Understanding Interactive Systems," *Organised Sound*, vol. 14, no. 02, p. 124, 2009.

[10] E. Edmonds, L. Muller, and M. Connell, "On creative engagement," *Visual Communication*, vol. 5, no. 3, pp. 307–322, 2006.

[11] B. Wands, "Variations : An Interactive Musical Sculpture," in *C&C '05 Proceedings of the 5th conference on Creativity & cognition*. ACM, 2005, pp. 306–309.

[12] B. Costello, L. Muller, S. Amitani, and E. Edmonds, "Understanding the experience of interactive art: Iamascope in Beta_space," *IE '05 Proceedings of the second Australasian conference on Interactive entertainment*, pp. 49–56, 2005.

[13] Hangar.org, "Interactive Environment." [Online]. Available: https://www.hangar.org/docs/docs_lab/IA.pdf [Accessed: 2016-01-12]

[14] M. Fox and M. Kemp, *Interactive architecture*. Princeton Architectural Press Princeton, 2009, vol. 1.

[15] K. Oosterhuis and N. Biloria, "Interactions with Proactive Architectural Spaces: The Muscle Project," *Communications of the ACM*, vol. 51, no. 6, pp. 70–78, Jun. 2008.

[16] Metabody, "Metatopia," Nov. 2014. [Online]. Available: http://metabody.eu/metatopia/ [Accessed: 2016-01-20]

[17] Philip Beesley Architect Inc, "Aurora." [Online]. Available: http://philipbeesleyarchitect.com/sculptures/1115_Simons-Aurora/ [Accessed: 2016-01-19]

[18] A. D. Dragan, S. Bauman, J. Forlizzi, and S. S. Srinivasa, "Effects of Robot Motion on Human-Robot Collaboration," in *Proceedings of the Tenth Annual ACM/IEEE International Conference on Human-Robot Interaction - HRI '15*, vol. 1, 2015, pp. 51–58.

[19] A. Dragan, R. Holladay, and S. Srinivasa, "An Analysis of Deceptive Robot Motion," in *Robotics: Science and Systems*, 2014, p. 10.

[20] M. J. Gielniak, K. Liu, and A. L. Thomaz, "Generating human-like motion for robots," *The International Journal of Robotics Research*, vol. 32, no. 11, pp. 1275–1301, 2013.

[21] M. A. Bedau, J. S. McCaskill, N. H. Packard, S. Rasmussen, C. Adami, D. G. Green, T. Ikegami, K. Kaneko, and T. S. Ray, "Open problems in artificial life," *Artificial life*, vol. 6, no. 4, pp. 363–376, 2000.

[22] Minimaforms, "Petting Zoo FRAC Centre." [Online]. Available: http://minimaforms.com/petting-zoo-frac [Accessed: 2016-01-05]

[23] T. Ikegami, "A design for living technology: Experiments with the mind time machine," *Artificial Life*, vol. 19, no. 3/4, pp. 387–400, 2013.

[24] M. Lungarella, G. Metta, R. Pfeifer, and G. Sandini, "Developmental robotics: a survey," *Connection Science*, vol. 15, no. 4, pp. 151–190, 2003.

[25] M. Asada, K. Hosoda, Y. Kuniyoshi, H. Ishiguro, T. Inui, Y. Yoshikawa, M. Ogino, and C. Yoshida, "Cognitive Developmental Robotics : A Survey," *IEEE Transactions on Autonomous Mental Development*, vol. 1, no. 1, pp. 12 – 34, 2009.

[26] C. Prince, N. Helder, and G. Hollich, "Ongoing emergence: A core concept in epigenetic robotics," 2005.

[27] V. R. Kompella, M. F. Stollenga, M. D. Luciw, and J. Schmidhuber, "Explore to see, learn to perceive, get the actions for free: SKILLABILITY," in *2014 International Joint Conference on Neural Networks (IJCNN)*, 2014, pp. 2705–2712.

[28] M. Luciw, V. Kompella, S. Kazerounian, and J. Schmidhuber, "An intrinsic value system for developing multiple invariant representations with incremental slowness learning," *Frontiers in neurorobotics*, vol. 7, 2013.

[29] M. H. Lee, Q. Meng, and F. Chao, "Staged competence learning in developmental robotics," *Adaptive Behavior*, vol. 15, no. 3, pp. 241–255, 2007.

[30] P.-Y. Oudeyer, F. Kaplan, V. V. Hafner, and A. Whyte, "The playground experiment: Task-independent development of a curious robot," in *In Proceedings of the AAAI Spring Symposium on Developmental Robotics*, Stanford, California, 2005, pp. 42–47.

[31] B. Bridgeman, "Efference copy and its limitations," *Computers in Biology and Medicine*, vol. 37, no. 7, pp. 924–929, 2007.

[32] M. Tokic, "Adaptive -greedy exploration in reinforcement learning based on value differences," in *33rd Annual German Conference on AI*, Karlsruhe, Germany, 2010, pp. 203–210.

[33] R. Tibshirani, "Regression Shrinkage and Selection via the Lasso," *Journal of the Royal Statistical Society. Series B (Methodological)*, vol. 58, no. 1, pp. 267–288, 1996.

[34] W. W. Gaver, J. Beaver, and S. Benford, "Ambiguity as a resource for design," in *Proceedings of the SIGCHI conference on Human factors in computing systems*. ACM, 2003, pp. 233–240.

[35] P. J. Silvia, "Interest - The curious emotion," *Current Directions in Psychological Science*, vol. 17, no. 1, pp. 57–60, 2008.

[36] G. Loewenstein, "The psychology of curiosity: A review and reinterpretation." *Psychological bulletin*, vol. 116, no. 1, p. 75, 1994.

[37] D. E. Berlyne, "A theory of human curiosity," *British Journal of Psychology. General Section*, vol. 45, no. 3, pp. 180–191, 1954.

[38] P. J. Silvia, "What Is Interesting? Exploring the Appraisal Structure of Interest," *Emotion*, vol. 5, no. 1, pp. 89–102, 2005.

[39] D. Beazley, "Understanding the Python GIL," in *PyCON Python Conference 2010*, Atlanta, Gerogia, USA, 2010.

[40] "Joule's law," 2016. [Online]. Available: http://www.britannica.com/science/Joules-law [Accessed: 2016-01-05]

[41] Dynalloy Inc., "Technical Characteristics of Flexinol Actuator Wires (Rev. 12)." [Online]. Available: http://www.dynalloy.com/pdfs/TCF1140.pdf [Accessed: 2016-01-05]

[42] L. C. Burmeister, *Convective Heat Transfer*. John Wiley & Sons, 1993.

[43] Cree Inc., "Cree 5mm Round LED Product Family Data Sheet," 2011. [Online]. Available: http://www.cree.com/~/media/Files/Cree/LED-Components-and-Modules/HB/Data-Sheets/C503C-WAS-WAN-1098.pdf [Accessed: 2016-01-05]

APPENDICES

Appendix A

Design of the Control Module

At the heart of a Control Module, shown in Figure A.1, there is a Teensy 3 USB-based development board. It controls each device through the Device Port and communicates with the computer through USB as a human interface device (HID). Each Device Port has four output pins capable of pulse-width modulation (PWM), two input pins connecting to the Teensy's on-board analogue-to-digital converter (ADC), and two lines for digital serial communication over Inter-Integrated Circuit bus (I2C). It is designed to provide a convenient and fast interface to commonly used analogue actuators and sensors, and a digital bus for added flexibility. The on-board SPI and UART port are reserved for future expansion.

In order to increase the number of PWM pins beyond what is provided natively on the Teensy, an I2C bus controlled PWM controller[1] was used. This does not affect the I2C buses on the Device Ports since it is using the other one of Teensy's two I2C buses. The I2C bus for the Device Ports is further multiplexed into six. This makes each Device Port more independent, and devices may have the same addresses as long as they are on different Device Ports. By having virtually six independent I2C buses, it simplifies the configuration of the Device Modules as they can all be configured the same way.

[1] PCA9685 16-channel, 12-bit PWM Fm+ I^2C-bus LED controller: www.nxp.com/documents/data_sheet/PCA9685.pdf

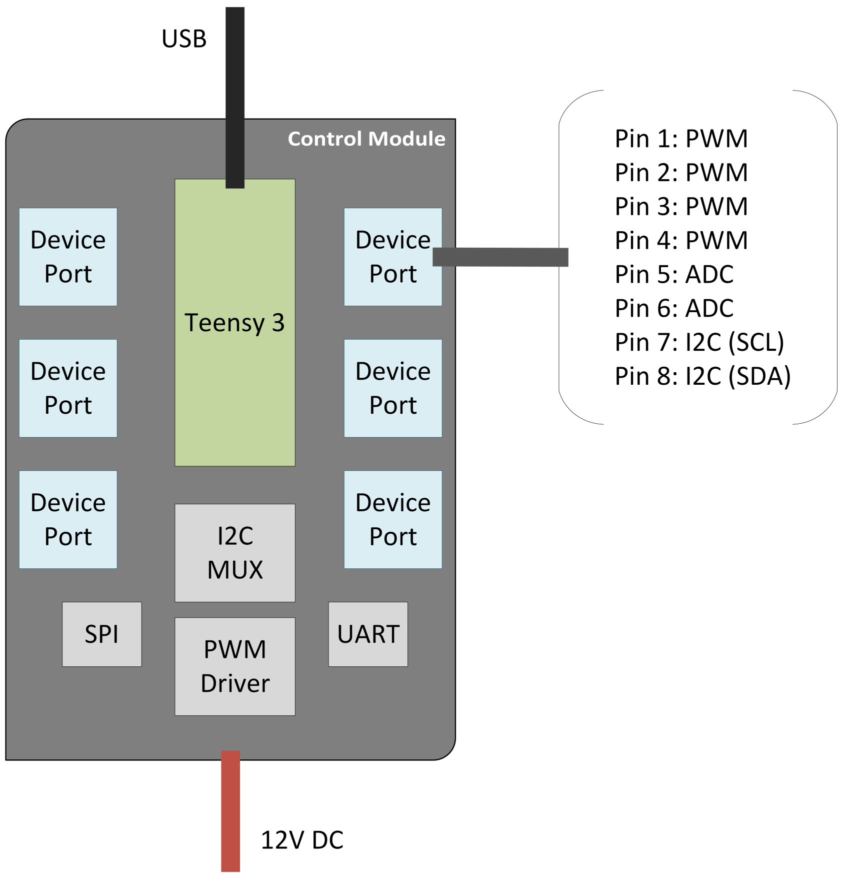


Figure A.1: A Control Module consists of a Teensy 3, 6 Device Ports, a SPI port, and a UART port. Each Device port has 8 wires and they carry the signals that are commonly used in our system.

Appendix B

Design of the Data Logging Module

The data generated by the Nodes are in many different types, such as integer, floating point, string, list, tuple, and other custom object types. In addition, objects such as the CBLA Learner are continuously expanding and its hierarchy gets deeper over time. Moreover, each type of data packet gets generated at different non-constant time cycles. This makes simply saving them in a table or a relational database impractical. In our implementation, a simple key-value type NoSQL database based on Python's shelve[1] module was used. In shelve, the data are stored as serialized Python objects using the pickle[2] module. This type of database gives the flexibility of storing an assortment of data types without the need to predefine them. However, since the data are not stored as plain text, a special script is required to extract the data in the desired formats for offline analysis.

B.1 Database Structure

Each time the CBLA System is run, a new shelve database is created for the session. This is to ensure that data from previous sessions does not get corrupted accidentally. In addition, in order to restart from a previous session, one only has to remove the database files of the succeeding sessions. If there are previous sessions, the CBLA system will access an index file to locate the database file of the most recent session and retrieve information regarding the previous state of the system. Information about the start time, end time, and the configurations of the system can also be found in the index file. Figure B.1 illustrates the structure of the database created by the Data Logger.

[1] Python shelve documentation: https://docs.python.org/3.4/library/shelve.html
[2] Python pickle documentation: https://docs.python.org/3.4/library/pickle.html

```
Session 1
 |__Node A
 |   |__Info Type
 |   |   |__S names:  (IR Sensor 0, IR Sensor 1, ...)
 |   |   |__M names:  (LED, Vibration Motor, ...)
 |   |   |__CBLA State
 |   |   |   |__Step Count:  245
 |   |   |   |__Experts
 |   |   |   |   |__Expert IDs:  (0, 3, ...)
 |   |   |   |   |__Mean Errors:  (0.1, 0.001, ...)
 |   |   |   |   |__Prediction Models:  (linreg obj 1, linreg obj 2, ...)
 |   |   |   |   |__...
 |   |   |   |__Robot:  reflex_robot obj
 |   |   |   |__...
 |   |   |__...
 |   |__Packet Type
 |       |__t = 1.00s
 |       |   |__packet (t = 1.001s)
 |       |   |   |__S: (10, 1024, 20, ...)
 |       |   |   |__M: (0, 140, 255, ...)
 |       |   |   |__Relative Action Value:  10
 |       |   |   |__...
 |       |   |__packet (t = 1.002s)
 |       |   |__...
 |       |__t = 1.01s
 |       |__...
 |__Node B
 |__...
Session 2
...
```

Figure B.1: Example showing the structure of the database created by the Data Logger .

For each Node, there are two main types of data: Packet Type and Info Type. Each Packet Type data has a timestamp which indicates when the data block is generated. These data blocks are generated continuously and they must all be stored. They contain information about the sensor readings, actuator outputs, and the internal parameters of the CBLA Engine such as its current mean error, number of regions, and relative action values. Packet Type data are mainly used for secondary analysis purposes. On the other hand, Info Type data describes the system and does not have a timestamp. When new versions of Info Type data arrive, the old ones can be overwritten. Information like the names and order of the sensor and actuator variables, which do not change over the runtime of the system, are Info Type data. In addition, the state of the CBLA Engine, which is needed for recovering from a later time, is also an Info Type data. Over the long term, while it is desirable for the state to be saved frequently, the size of the data that describes it would become too large to allow multiple copies of it to be stored. By saving it as an Info Type, the old version can simply be overwritten by a newer version.

B.2 Data Logging Process

Due to the large amount of data that are being generated at high frequencies, saving each block of data directly would require too much time and introduce significant lag in the system. Therefore, a multi-stage process as illustrated in Figure B.2 is used to improve data logging efficiency.

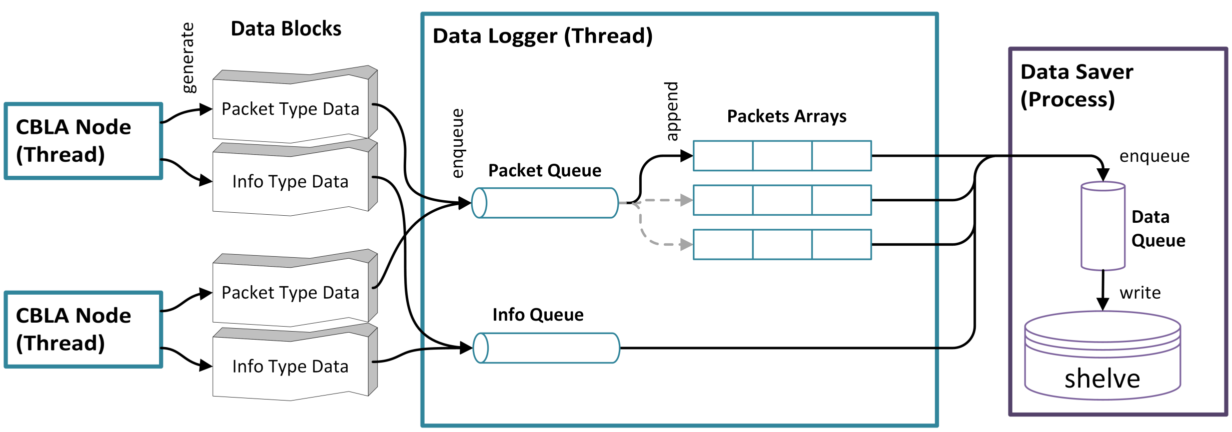


Figure B.2: Flowchart of the data logging process from data generation to writing to the disk.

Packet Type data blocks are being generated at a rate of approximately one block every 20 milliseconds per Node. This is relatively high given the hundreds of Nodes that a typical CBLA system has. On the other hand, Info Type data are being generated at a much slower rate at roughly one data block every two minutes per Node. Both types of data blocks would first get enqueued onto the Data Logger before being transferred to the Data Saver which is the module responsible for writing the data into the shelve database. This step is necessary to avoid slowing down the CBLA Nodes because Data Saver is a separate process, and transferring data to another Process takes significantly longer time than to another thread.

For the higher frequency Packet Type data blocks, instead of directly being sent to the Data Saver, they are first packed in Packet Arrays. This process decreases the total transfer time to the Data Saver by drastically lowering the number of enqueue calls which have non-trivial overhead. There is one Packet Array for each Node and they get enqueued to the Data Saver periodically.

The Data Saver is implemented as a process in order to avoid the GIL limitation imposed by Python [39]. This enables the system to make use of the parallel computing capability of a multi-core computer. Although transferring data to a process takes longer as it requires the copying of the actual data rather than just the pointers, it is still faster than writing the data onto the disk. Therefore, it is still more efficient to move the data and let a separate process load the data onto the database.

Nevertheless, depending on the number of Nodes in the system, there are situations when data are indeed being generated at a rate faster than it can be stored. Eventually, over the long term, the memory of the host computer will be full and the program will crash. In addition, a long wait time between data generation and data storage means that if the program crashes unexpectedly, a large amount of data would be lost. To avoid crashing and the loss of data, once the length of the queue has reached a certain threshold, a clean-up procedure is activated. It momentarily pauses all other threads, and allocates all the processing power for the purposes of data storage. Practically, this process only takes around 50 to 70 milliseconds. Since it happens only once every few minutes, it is generally not noticeable by the human viewer. In fact, the reason why it only takes so little time is because, by pausing all other threads, it eliminates the overhead of thread switching. This process ensures that the CBLA system can operate as long as there is sufficient storage space on the hard drive of the host computer.

Appendix C

Design of the Device Nodes

C.1 SMA Controller Node

Development of this model starts with the intuition that the temperature of the wire increases when the rate of heating is greater than the rate of cooling. The rate of heating is related to the voltage across the wire. On the other hand, the rate of cooling is related to the temperature of the wire since it is mainly driven by the wire's own natural convection.

We first calculate the heat transfer rate as a result of current passing through the SMA wire. According to Joule's Law [40],

$$q_1 = i^2 \cdot r \tag{C.1}$$

where q_1 is heat transfer rate in Watts; i is the current in Amperes; r is the resistance of the wire in Ohms.

According to Ohm's Law,

$$i = \frac{v}{r} \tag{C.2}$$

where i is the current; v is the voltage in Volts; and r is the resistance.

Substituting (C.2) into (C.4), we get

$$q_1 = \frac{v^2}{r} \tag{C.3}$$

In our case, although r is not actually a constant since the resistance of the SMA wire decreases as it shortens [41], the effect is sufficiently small that it can be treated as a constant. Therefore, we get,

$$q_1 = k_{heating} \cdot v^2 \tag{C.4}$$

where q_1 is the heat transfer rate in Watts.

Since our control signal, x, is proportional to the voltage, it can simply be absorbed into the $k_{heating}$ constant as

$$q_1 = k_{heating} \cdot x^2 \tag{C.5}$$

Then, we calculate the heat loss rate due to natural convection of the SMA wire. According to Newton's Law of Cooling [42],

$$q_2 = h_c \cdot A \cdot dT \tag{C.6}$$

where q_2 is the heat transfer rate in Watts; h_c is the convective heat transfer coefficient; A is the area of the heat transfer surface in m^2; and dT is the temperature difference between the air and the surface in Kelvin.

If we approximate h_c, A, and the air temperature T_{air} as constants, we get

$$\begin{aligned} q_2 &= k_{cooling} \cdot (T - T_{air}) && \text{(C.7a)} \\ &= k_{cooling} \cdot T - k_{cooling} \cdot T_{air} && \text{(C.7b)} \\ &= k_{cooling} \cdot T + k_{air} && \text{(C.7c)} \end{aligned}$$

where q_2 is the heat transfer rate in Watts; $k_{cooling}$ and k_{air} are constants; and T is the temperature of the SMA wire in Kelvin.

Combining (C.5) and (C.7c), we get the total heat transfer rate as

$$\begin{aligned} q &= q_1 - q_2 && \text{(C.8a)} \\ &= k_{heating} \cdot x^2 - k_{cooling} \cdot T + k_{air} && \text{(C.8b)} \end{aligned}$$

We can then calculate the kinetic energy generated during time interval Δt by multiplying (C.8b) by Δt.

$$KE = (k_{heating} \cdot x^2 - k_{cooling} \cdot T + k_{air}) \cdot \Delta t \tag{C.9}$$

Since temperature is directly proportional to kinetic energy, the proportionality constant can be absorbed into $k_{heating}$, $k_{cooling}$, and k_{air} as well.

$$\Delta T = (k_{heating} \cdot x^2 - k_{cooling} \cdot T + k_{air}) \cdot \Delta t \tag{C.10}$$

At each time step, Δt, the temperature is incremented by ΔT.

$$\begin{aligned} T_{t+1} &= T_t + \Delta T && \text{(C.11a)} \\ &= T_t + k_{heating} \cdot x^2 - k_{cooling} \cdot T_t + k_{air} && \text{(C.11b)} \end{aligned}$$

In this formulation, the actual unit of the temperature is not important. Instead, we define 0 as the temperature when the SMA wire is the longest and 1 when the SMA wire is the shortest. The steady-state temperature of the SMA wire should be 0 when the input, x, is 0. If we substitute 0 into T_{t+1}, T_t, and x into (C.11b), we get $k_{air} = 0$.

$$T_{t+1} = T_t + k_{heating} \cdot x^2 - k_{cooling} \cdot T_t \tag{C.12}$$

From the SMA wire's technical specifications[41], we identify the maximum current at which the SMA wire can operate continuously without heat damage. Using that value, we determine the maximum continuous output level, x_c. This means that when the desired temperature, T, is equal to 1, at steady-state, x should be at x_c. This means,

$$\begin{aligned} 0 &= k_{heating} \cdot x_c^2 - k_{cooling} && \text{(C.13a)} \\ k_{cooling} &= k_{heating} \cdot x_c^2 && \text{(C.13b)} \end{aligned}$$

The SMA wires would not be damaged due to over-heating as long as the relationship in (C.13b) holds. At the end, we get

$$T_{t+1} = T_t + k_{heating}(x^2 - x_c^2 \cdot T_t) \tag{C.14}$$

as the temperature model for the SMA Controller Node.

We then apply and tune a PI controller on this temperature model to track a desired temperature as shown in Figure C.1. A Node can specify a desired temperature, $T_{desired}$, between 0 and 1 and the SMA Controller tracks this temperature within its internal temperature model. The control signal generated by this PI Controller is applied to the actual SMA wire in parallel.

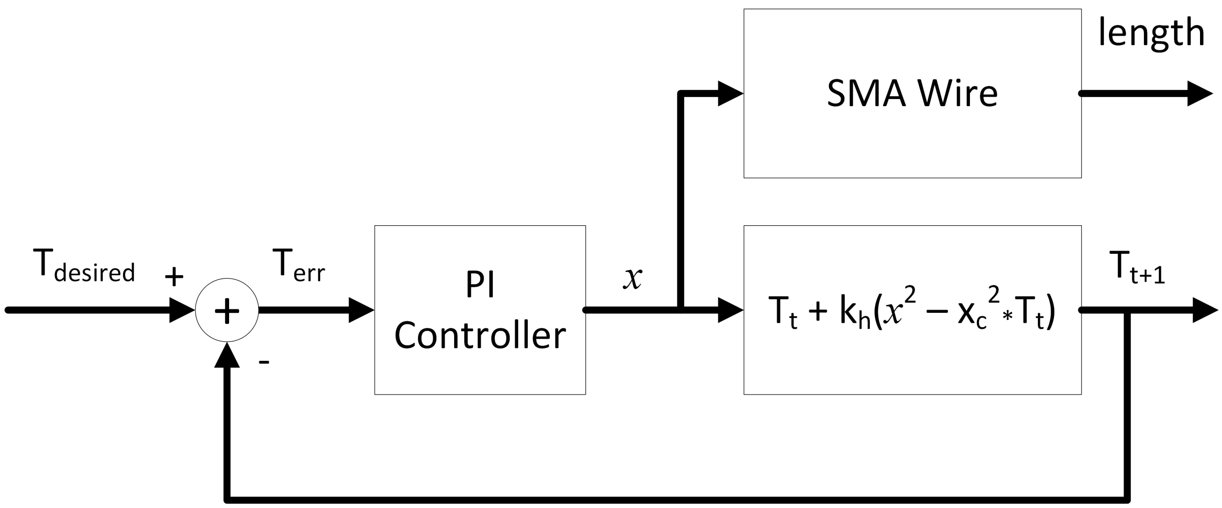


Figure C.1: Block diagram of the SMA Controller. k_h is equivalent to $k_{heating}$.

C.2 LED Driver Node

The LED Driver changes its output gradually to produce dimming effects. However, the relationship between brightness level of a typical LED and the input voltage is non-linear [43]. At low voltage levels, the brightness increases rapidly as input voltage increases. At higher voltage levels, a larger increase in voltage is needed to increase the brightness at the same rate. In order for the change in brightness to appear more linear, (C.15) is used to update the output level of an LED.

At every time step,

$$x_{t+1} = \begin{cases} 0.00001 & \text{if } x_t == 0 \text{ and } x_{desired} > 0 \\ x_t + k \cdot x_t, & \text{if } x_t < x_{desired} \\ x_t - k \cdot x_t, & \text{if } x_t > x_{desired} \\ x_t, & \text{otherwise} \end{cases} \tag{C.15}$$

where x_{t+1} is the output level in the next time step $t + 1$; x_t is the current output level at time t; $x_{desired}$ is the desired output level; and k is a constant that determines rate of change in brightness. $x_{desired}$ must be between 0 and 1.

Formulating second and third cases of (C.15) as a first-order ODE shows that it is an exponential function.

$$\frac{dx(t)}{dt} \pm k \cdot x(t) = 0 \tag{C.16}$$

Solving (C.16), we get

$$x(t) = x(0) \cdot e^{k} \cdot e^{\mp k \cdot t} \tag{C.17}$$

where $x(0)$ is the initial output level when the desired output level is changed.

This LED Driver enables the output level of the LED to increase at a faster rate in the higher brightness region.

Appendix D

User Study Materials

D.1 Information and Consent Form

Information & Consent Form

Date:

Title of Project:
Investigation of user's level of interest while interacting with the Sentient Canopy interactive art sculpture

Faculty Supervisors:

Dr. Dana Kulić
Department of Electrical and Computer Engineering
dana.kulic@uwaterloo.ca
519-888-4567 ext. 37260

Dr. Robert B. Gorbet
Department of Knowledge Integration
rbgorbet@uwaterloo.ca
519-888-4567 ext. 33489

Student Investigator:
Matthew Tsz Kiu Chan
Department of Electrical and Computer Engineering
matthew.chan@uwaterloo.ca

Study Overview

My name is Matthew Tsz Kiu Chan and I am a MASc student working under the supervision of Dr. Dana Kulic in the Adaptive Systems Laboratory in the Department of Electrical and Computer Engineering and Dr. Rob Gorbet in the Department of Knowledge Integration, at the University of Waterloo.

You are invited to participate in a study that investigates users' level of interest while interacting with the new series of interactive art sculptures named *Sentient Canopy*, which is produced in collaboration with the Philip Beesley Architect Inc. (PBAI) in Toronto, ON. This study is for my Master's thesis and is conducted in collaboration with PBAI. Similar sculptures have been displayed in many venues in different countries in the past. For a list of previous installations, please visit http://philipbeesleyarchitect.com/sculptures.

What You Will Be Asked to Do

Participation in this study involves interacting with the art sculpture. While you are interacting with the sculpture, you will be asked to fill out a short questionnaire regarding your interest level whenever you hear a signal. You are free to roam around the studio and interact with the sculpture as you like. There is not any specific prescribed interaction and you are free to choose how you want to interact with the sculpture. At the end of the study, you will return all the completed questionnaires in an envelope and you will be asked to fill out another short questionnaire about your overall experience. Please see attached “Study Procedures” sheet for details.

Participation

Participation in this study is voluntary and it will take approximately 30 minutes of your time. You may decline to answer any questions presented during the study if you so wish. Further, you may decide to withdraw from this study at any time by advising the researcher, and may do so without any penalty.

Personal Benefits of the Study

There are no personal benefits to participation.

Risks to Participation in the Study

There are no known or anticipated risks/stressors to the participants as a result of taking part in this study. The interactive art sculptures developed by Philip Beesley Architect Inc. have been exhibited in more than 10 countries where thousands of people have visited the art sculptures. The sculptures are made of soft and light-weight material and actuated with low power actuators. An actuator is a device that converts energy, such as electricity, into motion, light, and sound. This new series of interactive art sculptures does not pose greater risk of physical harm than what existed in previous installations.

Confidentiality

All information you provide is considered completely confidential; indeed, your name will not be included or in any other way associated, with the data collected in the study. Furthermore, because the interest of this study is in the average responses of the entire group of participants, you will not be identified individually in any way in any written reports of this research. Paper records of data collected during this study will be destroyed after they have been digitized. The converted electronic data will be kept for 20 years on a secure computer, to which only researchers associated with the Adaptive Systems Laboratory have access. This data may be additionally used for subsequent secondary data analysis comparing user responses to various interaction strategies, however, your name and identity will not be obtainable from the stored data.

Questions and Research Ethics Clearance

If after receiving this letter, you have any questions about this study, or would like additional information to assist you in reaching a decision about participation, please feel free to ask the student investigator or a faculty supervisor listed at the top of this sheet.

I would like to assure you that this study has been reviewed and received ethics clearance through a University of Waterloo Research Ethics Committee. However, the final decision about participation is yours. If you have any comments or concerns resulting from your participation in this study, please contact Dr. Maureen Nummelin, the Director, Office of Research Ethics, at 1-519-888-4567, Ext. 36005 or maureen.nummelin@uwaterloo.ca.

Thank you for your interest in our research and for your assistance with this project.

Consent of Participant

I have read the information presented in the information letter about the study being conducted by Matthew Tsz Kiu Chan under the supervision of Dr. Dana Kulic in the Adaptive Systems Laboratory in the Department of Electrical and Computer Engineering and Dr. Rob Gorbet in the Department of Knowledge Integration at the University of Waterloo in collaboration with Philip Beesley Architect Inc. in Toronto, ON.

I have had the opportunity to ask any questions related to this study, to receive satisfactory answers to my questions, and any additional details I wanted. I am aware that I may withdraw from the study without any penalty at any time by advising the researchers of this decision.

This project has been reviewed by, and received ethics clearance through a University of Waterloo Research Ethics Committee. I was informed that if I have any comments or concerns resulting from my participation in this study, I may contact the Director, Office of Research Ethics, at 1-519-888-4567, Ext. 36005.

With full knowledge of all foregoing, I agree, of my own free will, to participate in this study.

____

Print Name

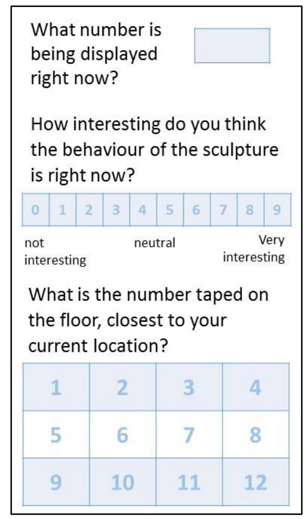
____

Signature of Participant

____

Date

Study Procedures


What number is being displayed right now?

How interesting do you think the behaviour of the sculpture is right now?

0	1	2	3	4	5	6	7	8	9

not interesting — neutral — Very interesting

What is the number taped on the floor, closest to your current location?

1	2	3	4
5	6	7	8
9	10	11	12

1. In the envelope that you have received, you will find a stack of questionnaire cards that look like the image to the right.
2. You are free to walk around the studio and interact with the art sculpture. Periodically, a tone will sound in the studio. When you hear the tone, please take one card out. You are expected to hear a sound around every 3 to 5 minutes.
3. When the tone sounds, the researcher will display a number; and write down the number in the first box.
4. Report how interesting you think the behaviour of the sculpture is at that moment by circling one of the numbers from 0 to 9 under the second question.
5. Look down to the floor. There should be a number right below or near where you are standing. Please circle the number that is closest to where you are standing under the third question.
6. After that, you can return the completed card to the envelope and continue walking around the studio and interacting with the sculpture.
7. When you leave or when the staff signal the end of the showing, please return the envelope containing the questionnaire cards to the desk where you got the envelope from.
8. You will then be asked to fill out a survey on your overall experience and your knowledge of machine learning.
9. At last, you will be given a debriefing letter with more information about the study.

D.2 Exit Questionnaire

Feedback Survey

1. How interesting was your overall experience while interacting with the art sculpture?

0	1	2	3	4	5	6	7	8	9

Not Interesting — Neutral — Very Interesting

2. How responsive was the sculpture to your presence? Do you think its behaviour was totally random, or do you think it was responding directly to you?

0	1	2	3	4	5	6	7	8	9

Totally Random — Unambiguous Response

3. How familiar are you with machine learning algorithms?

0	1	2	3	4
I've never heard of it	I've heard of the term but don't know what it is	I've a general idea of how it works	I've studied or done some work in machine learning	I'm an expert in machine learning

4. How would you describe the behaviour of the sculpture?

5. Additional comments

D.3 Debriefing Letter

DEBRIEFING LETTER

Adaptive System Laboratory

Department of Electrical and Computer Engineering, University of Waterloo

Project Title:
Investigation of user's level of interest while interacting with the Sentient Canopy interactive art sculpture

Student Investigator:
Matthew Tsz Kiu Chan
Department of Electrical and Computer Engineering
matthew.chan@uwaterloo.ca

Faculty Advisors:
Dr. Dana Kulić
Department of Electrical and Computer Engineering
dana.kulic@uwaterloo.ca
519-888-4567 ext. 37260

Dr. Robert B. Gorbet
Department of Knowledge Integration
rbgorbet@uwaterloo.ca
519-888-4567 ext. 33489

We appreciate your participation in our study, and thank you for spending the time helping us with our research!

In this study, you interacted with the *Sentient Canopy* interactive art sculpture and were asked to provide feedback on your interest level as you interacted with the sculpture, and on your overall experience after the session.

Two interactive behaviours were actually run on the sculpture during your visit. One was a pre-programmed version in which the automatic actuation and responses to sensory inputs were fixed. The other set of behaviours was based on a Curiosity-Based Learning Algorithm (CBLA), in which parameters that dictate the behaviours are generated automatically and change as the sculpture learns about itself and you. In the CBLA version, the sculpture will continuously learn to model the mapping between its inputs and outputs and select actions that will lead to greater learning. For example, it will attempt to learn if moving the Tentacle up and down will affect readings from the sensors. This is analogous to how animals and human beings learn. In this study, we hope to determine whether the behaviours generated through this method can make the experience of interacting with the sculptures more interesting. Simply put, we would like to know if behaviours generated using the CBLA are more interesting than those designed by human experts. The results of this study can enable designers to design more engaging and interesting art sculptures.

We hypothesized that the viewers will enjoy behaviours that are less predictable and changing. It is expected that since the CBLA continuously generates new interactive behaviours, viewers will find it more engaging and interesting. On the other hand, although the CBLA continuously generates new behaviours, it is not random. It tends to exhibit new behaviours that promote predictable response from the viewers and the environment. We think that the viewer will be able to recognize that its behaviours are not random. In addition, we hypothesized that certain sets of parameters may generate more interesting behaviours and this can be a systematic way to discover those behaviours. The results from this study will provide us with evidence allowing us to accept or reject these hypotheses.

We could not give you complete information about the study before your involvement because it may have influenced your perception during the study in a way that would make investigations of the research question invalid. Specifically, we did not tell you that there were two versions of the behaviours and what the expected behaviours of the sculpture are because we wanted to avoid the *subject-expectancy effect*. This is a form of bias in which the test subject expects a particular result and this unconsciously affects the outcome. We hope that you understand the need for this partial disclosure now that the purpose of the study has been more fully explained to you.

All information you provided is considered completely confidential; indeed, your name will not be included or in any other way associated, with the data collected in the study. Furthermore, because the interest of this study is in the average responses of the entire group of participants, you will not be identified individually in any way in any written reports of this research. Paper records of data collected during this study will be destroyed after they have been digitalized. The converted electronic data will be kept for 20 years on a secure computer, to which only researchers associated with the Adaptive Systems Laboratory have access. This data may be additionally used for subsequent secondary data analysis comparing user responses to various interaction strategies, however, your name and identity will not be obtainable from the stored data.

This project has been reviewed by, and received ethics clearance through a University of Waterloo Research Ethics Committee. In the event you have any comments or concerns resulting from your participation in this study, please contact Dr. Maureen Nummelin, the Director, Office of Research Ethics, at 1-519-888-4567, Ext. 36005 or maureen.nummelin@uwaterloo.ca.

Because the study involves some aspects that you were not told about before starting, it is very important that you not discuss your experiences with anyone who potentially could be in this study. If people come into the study knowing about our specific predictions, as you can imagine, it could influence the results, and the data we collect would be not be useable. Also, since you will be given a copy of this feedback letter to take home with you, please do not make this available to others.

If you think of some other questions regarding this study, please do not hesitate to contact Matthew T.K. Chan at matthew.chan@uwaterloo.ca.

We really appreciate your participation, and hope that this has been an interesting experience for you.

References (related studies that may be of interest to you):

P.-Y. Oudeyer, F. Kaplan and V. V. Hafner, "Intrinsic Motivation Systems for Autonomous Mental Development," *IEEE Transactions on Evoluntionary Computation,* vol. 11, no. 2, pp. 265-286, 2007.

Appendix E

User Study Exit Questionnaires Written Responses

Trial #	Q4. Descriptions of the Sculpture’s Behaviours	Q5. Additional Comments
1	Sometimes the sculpture seemed to be guiding me. It will flash lights on more and stop when I'm within range of the sensors. Sometimes it seemed to be following me. It would actuate behind me. Sometimes it is unresponsive, or totally random.	It's difficult to gauge "interest" on a moment to moment basis. Sometimes something very interesting will happen, but minutes will go by with no response.
2	It was (or appear to be) somewhat random at the beginning but became more & more predictable (still not perfect though) during the process. The sculpture was responding to my position and hand movements in the end. Good job!	I feel that it is also a learning process for me (i.e. I am learning to interact with the sculpture during the process as well). Sometimes the responses I got from the sculpture were not what I was hoping for. For example, when I held up my hand to the leaf, the leaf itself was not really moving towards me as much as the two other leaves that were a bit farther away. Overall, the sculpture's behaviour did appear to be more predictable as time went on. Yet the downside of this is that it becomes less exciting. I felt as if there was not much to explore further and my curiosity level went down accordingly. I was quite obvious where the sensors are in this case, which provided a convenient contact point for interaction. Had I not know where the sensors were, it would be a more interesting experience.
3	Somewhat random, because I tried to activate the sensors and it did not pick up my presence.	I tried to figure out how those movement of the leaves were accomplished. I did not see any motors or moving pulleys. I am very impressed that I found out that it was the shrinking wires.

4	It was random at first but then I'm sure it was responding to my presence; i.e. whenever I touched something that section would move.	Cool sculpture!
5	Motor feather: proximity based, when you get close to it, it starts responding; Wing: not sure, felt random; Brown liquid light: not sure, felt random.	I found motor feathers to be the most interesting, followed by the wing. The liquid lights were the least interesting. Towards the end of the experiment, the movements of all the components felt random. But some motor feathers were still responding to my hand waves.
6	It felt like walking around a forest with some bees around.	None
7	A "living" mechanical rainforest. I thought the movement in the canopy was random/pre-programmed at first, but then noticed that "leaves" would light up & move when I was in their proximity. I noticed this pattern became less strong eventually. Behaviour seemed related to mine, but not dependant on it.	Geometry of the canopy was very cool!
8	The sculpture changes lighting, creates sound, and moves to attract user. It responds to human presence, gestures, and hand claps. It seemed to generate random movements at the beginning, but a pattern was repeated as the experiment goes on.	None
9	The sculpture responds to where I am on the grid using motion sensors. For an example, when I am near the flanky leaf, it starts to respond. The lights on the ceiling respond to the motion sensors attached to the upper leaf structure with the motion sensor attached to it.	None

10	At first straightforward: doing something as long as I/my hand was in front of it. Lights at the top took more effort to light up. About halfway through some behaviours were more random, could not figure out the new pattern I needed to do to get another area of the sculpture to do things while I was away from it - but it seemed to do something regardless at random times. Parts that used to do something with straightforward motion/presence became unresponsive on one pillar - could not figure out the pattern. Behaviour changed a bit with time but slightly seemingly random as to how it changed.	Visually pleasing and great concept! Enjoyed the idea of incorporating sound with the vibrating "feathers" in addition to the lights and movement.