Experimental Scenarios in Colour Space

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***Abstract*-A general colour space domain was previously defined for investigating immunologically based adaptive models. This work defines a number of specific optimization and classification scenarios in colour space inspired by the general improvement properties of clonal selection, and the tolerance and self non-self discrimination properties of problems faced by the biological immune system. Previously defined immunologically inspired adaptive models are discussed in the context of the six colour space scenarios highlighting general implementation, performance, and behaviour measurement concerns that must be addressed before the intersection of such models and scenarios may be investigated meaningfully.**

Keywords-Experiment, Scenario, Artificial Immune System, Design, Adaptive Model

I. INTRODUCTION

What are some scenarios that may be proposed in colour space, and how might the various previously proposed immunologically inspired adaptive models be considered in the context of these scenarios?

Colour space, as defined by Brownlee [1], is a problem domain for investigating immunological inspired adaptive systems, such as [2,3]. This work elaborates on general optimization and classification scenarios using colour space that may be used to investigate aspects of single repertoire, multiple-repertoire, and multiple system adaptive models.

Section II defines a series of three optimization scenarios inspired by the general improvement (optimization) properties of the clonal selection adaptive plan. Section III defines a series of three classification scenarios inspired by the general properties of tolerance to self and the self non-self discrimination problem. Section IV discusses the two classes of problem scenario (all six scenarios) in the context of the three classes of adaptive model: base, discrete repertoire, and multiple system models. General behaviour expectations, performance measures, and implementation concerns are highlighted. Section V reviews some of the work that is required going forward concerning the evaluation of the adaptive models in the context of the defined colour space scenarios. Finally, insightful comment regarding the primary concerns of each of the three model classes is provided.

II. OPTIMIZATION SCENARIOS

These are scenarios in which a system must minimise distance to a defined colour coordinate in colour space. The objective coordinate(s) is not known to the optimizing system, rather an oracle objective function scores coordinates offered by the system, returning a distance from the offered coordinate to the objective coordinate. These scenarios are a simplification of the immune systems improvement (or optimization). The complexities encoded in the scenarios is intended to refect some of the general complexities faced by the immune system in differing antigenic environments.

Scenario	Summary
OS1 – One Colour	Single pathogen environment
OS2 – Multiple Colours	Multiple pathogen environment
OS2 – Dynamic Colours	Changing pathogen environment

Table 1 - Summary of optimization scenarios

OS1 – One Colour

A coordinate is selected (perhaps randomly). The system offers points to an oracle objective function, which returns the distance from the offered coordinate to the goal coordinate. This is an simplification of a single pathogen in the antigenic environment.

Term	Description
G	A goal coordinate in colour space. Has a distinct colour.
O	Objective function, oracle that returns a distance scoring from an offered coordinate to the goal coordinate (G). Distance may be Euclidean in the shape space.
N	Noise that may be added to the objective function. Noise may be uniformly random or Gaussian with respect to the goal coordinate.

Table 2 - Summary of terms used in the OS1

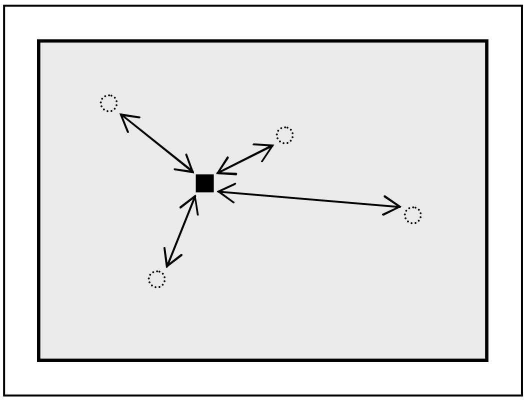

Figure 1 - Example depiction of a two-dimensional OS1

OS2 – Multiple Colours

This is an extension of OS1 where the single goal coordinate (G) is expanded to a set of parallel goal coordinates. Thus the performance of the system is to simultaneously minimise distance to all goal coordinates. This is a simplification of multiple pathogens in the antigenic environment.

Term	Description
G^n	Set of *n* goal objectives that the system must minimise distance to in parallel.
O^n	Objective function that scores offered coordinates in terms of the their distance from a single goal coordinate. Thus, O is extended to O^n and system performance is an aggregation of performance with regard to all goal coordinates.
N	Noise that may be added to the objective function. Noise may be uniformly random or Gaussian with respect to a given goal coordinate.

Table 3 - Summary of terms used in the OS2

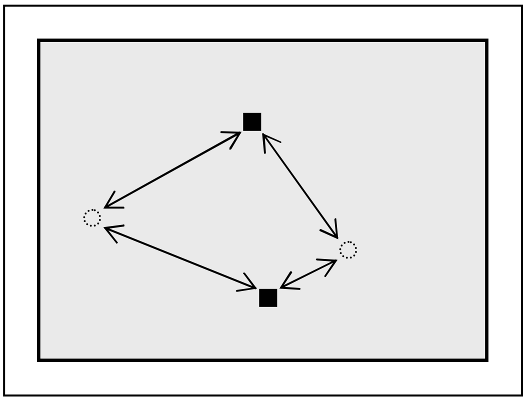

Figure 2 - Example depiction of a two-dimensional OS2

OS3 – Dynamic Colours

This is an extension of OS2, although the coordinates are dynamic, subjective to movements in coordinate space (are not fixed or static). Movement may be varied in a number of ways such as step changes, which may be random or cyclic, or iterative changes resulting in slowly migrating coordinates that the system must track. This is a simplification of a dynamic antigenic environment.

Term	Description
G^n	Set of *n* dynamic goal objectives that the system must minimise distance to in parallel.
B	Dynamic behaviour of the goal coordinates. This may include a random step change. A cyclic step change where *d* sets of goal coordinates must be selected as well as the order of the sets, and the periodicity of the set change. An iterative coordinate migration behaviour may be employed requiring a coordinate migration scheme to be defined.
O^n	Objective function that scores offered coordinates in terms of the their distance from a single goal coordinate. Thus, O is extended to O^n and system performance is an aggregation of performance on all goal coordinates.
N	Noise that may be added to the objective function. Noise may be uniformly random or Gaussian with respect to the goal coordinate.

Table 4 - Summary of terms used in the OS3

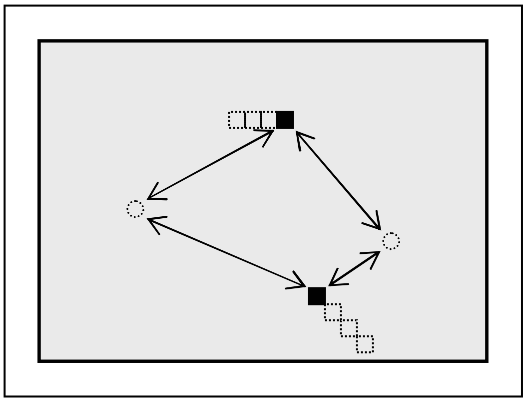

Figure 3 - Example depiction of a two-dimensional OS3

III. Classification Scenarios

This section describes scenarios in which a system must discriminate between coordinates of differing classes. The class boundaries are withheld from the system, although a sample of coordinates from the domain are provided *a priori* to seed the model. These scenarios are simplified version of the discrimination of antigen in the immune system, for example the tolerisation of self and the differentiation of self-molecules from non-self molecules.

Scenario	Summary
CS1 – Two Classes	Discriminate known from unknown
CS2 – Multiple Classes	Discriminate between known classes
CS3 – Dynamic Classes	Discriminate between changing classes

Table 5 - Summary of optimization scenarios

CS1 – Two Classes

In this scenario, the system must discriminate between coordinates from two classes, given a priori examples of coordinates from one class. This is a simplification of the classical self non-self discrimination problem. The geometry is fixed, and performance is a measure of miss-classifications.

Term	Description
G	Geometry used to separate the colour space into concave regions. In this scenario regions are allocated the class label 'A' or 'B' corresponding to self, and non-self classes.
S	Sample of *a priori* coordinates from the domain, only of class 'A' in this scenario. The samples may be drawn from different distribution schemes, such as uniformly random or Gaussian.

Table 6 - Summary of terms used in the CS1

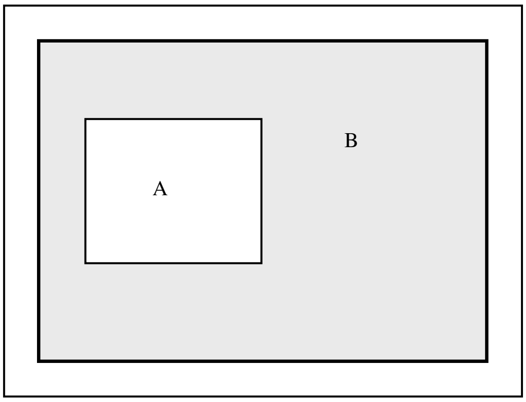

Figure 4 - Example depiction of a two-dimensional CS1

CS2 – Multiple Classes

This scenario is an extension of CS1, although the number of classes is extended to *n*, thus the geometry of the domain must support the number of classes. This is a simplification of different types of self and non-self material that the system must differentiate.

Term	Description
G	Geometry used to separate the colour space into concave regions. The number of regions may or may not equal the number of classes
N	The number of classes the system must differentiate.
S	Sample of *a priori* coordinates from the domain. The sample is drawn from across the entire colour space, from all classes

Table 7 - Summary of terms used in the CS2

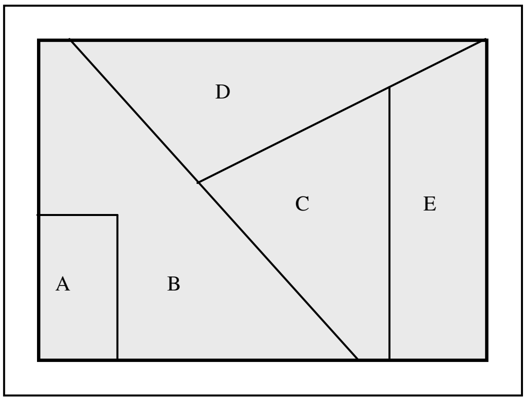

Figure 5 - Example depiction of a two-dimensional CS2

CS3 – Dynamic Classes

This scenario is an extension of CS2, although the geometry is not fixed. In the simplest case (two classes), the class boundaries between self and non-self change either in a stepwise, or iterative manner. The system must track the changes of the class boundaries by continuously sampling the domain. Performance may be a trade-off between on-going accuracy and number of samples (effort).

Term	Description
G	Geometry used to separate the colour space into concave regions. The number of regions may or may not equal the number of classes
N	The number of classes the system must differentiate.
B	Dynamic behaviour of the class boundaries. Class boundaries may change in a stepwise manner or may change slowly over time.
S	Sample of *a priori* coordinates from the domain. The sample is drawn from across the entire colour space, from all classes

Table 8 - Summary of terms used in the CS3

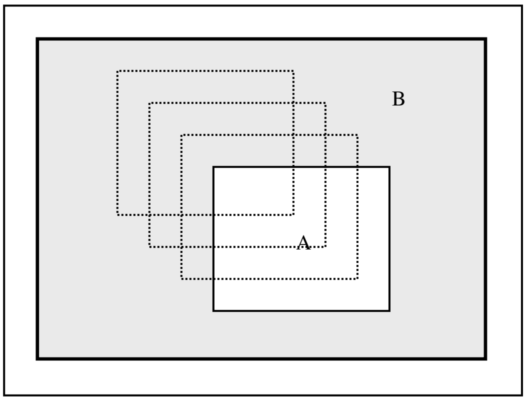

Figure 6 - Example depiction of a two-dimensional CS3

IV. Discussion

This section comments on the proposed optimization and classification scenarios in the context of the immunologically based adaptive models proposed by Brownlee in [2,3]. In particular, the types of behaviours and expectations of performance for base models, multiple repertoire models, and multiple system models. The intension of this discussion is to highlight some obvious and potential research questions regarding the intersection of previously proposed models and the various colour space scenarios.

Base Model Scenarios

The base models are representative of the fundamental clonal selection adaptive strategy. The scenarios may be used to demonstrate basic learning, memory, and adaptation properties.

Scenario	Comment
OS1	Adaptation from a random repertoire to a single objective. Noise may be used to demonstrate robustness of adaptation
OS2	Location and maintenance of multiple objectives. Addressing multiple overlapping and conflicting goals in parallel.
OS3	*Step-wise change*: adaptation from a biased starting position to a new position *Cyclic change*: demonstrate and effective application memory of past antigenic exposures *Iterative change*: tracking of one or multiple pathogens as they change their characteristics through time
CS1	Unlike one-goal optimization scenarios, all classification scenarios depend on the entire repertoire representing the solution (rather than perhaps a single cell). The system must learn and internally represent the class boundaries using cells as exemplars. A critical model property will be its ability to generalize from example coordinates to class boundaries.
CS2	Multiple classes requires more complex geometry and finer classification capabilities by the models.
CS3	Moving class boundaries will require models to track the class boundaries. Unlike tracking single coordinates in OS3, tracking class boundaries will require a lot of trial and error using a clonal selection strategy. Further, unlike OS3, regardless of the change type, memory may not be an efficient solution.

Table 9 - Summary of general expected base model behaviour on scenarios

Discrete Repertoire Scenarios

The distinguishing difference between base models and discrete repertoire models is the spatially distributed nature of the models. With this in mind, the primary concern is that of information sharing or mixing. Exposure to information in the scenario may not be uniform across the spatial structure of the system, thus knowledge learned at one geographic location may be required at another geographic location at some unknown time in the future.

Scenario	Comment
OS1	All repertoires or a subset of repertoires may be exposed to the objective function. In the latter case, an additional performance measure may be used to assess the latent performance of those repertoires that are not stimulated. Further, stimulation patterns may change with time in a stepwise, cyclic, or iterative fashion with a different effect on the learning properties of the system.
OS2	This scenario will have the same general concerns. The different goals may be exposed to the system with various distributions. Sets of repertoires may be explicitly 'optimized' with a specific objective function, and the latent capabilities may be assessed with all other repertoires not explicitly optimized with the specific objective function. This would facilitate measures of information dispersion, mixing, for features such as migration, recirculation, homing, and recruitment.
OS3	Evaluating performance in the context of dynamic goals is a logical extension to evaluating mixing properties outlined with the previous two scenarios. In step-wise and cyclic changes, it may be the distribution of antigenic exposure to the repertoire sets that change. Alternatively, different repertoire sets may be tracking the iterative changes of various pathogens in parallel, although with stepwise changes in the spatial exposure distribution.
CS1	The concern of the classification scenarios is that an summary of performance is the aggregation of many individual classification decisions. These decisions may be spread across sets of repertoires in a natural, random, or artificial partitioning of training and test samples. For example, spatial partitions of discrete repertoires may be trained of partitioned sets of the training data, and all evaluated on the same test data. Alternatively, all repertoires may be exposed to the same training data, and exposed to different partitions of the test data.
CS2	A natural progression of single-class partitioning, is multiple class portioning. This is where different sets of localities are trained on sets of class data and evaluated against all class data. Alternatively, all repertoires are exposed to the all class data and evaluated in a class-partitioned manner.
CS3	A final progression in difficulty is the movement of class boundaries. Like OS1, the stepwise or cyclic change may be with regard to sets of localities that are exposed to differing classes. Alternatively, different sets of localities may be tracking different classes, and evaluated in terms of their latent classification capabilities with non-tracked classes.

Table 10 - Summary of general discrete repertoire behaviour on scenarios

Multiple System Scenarios

The distinguishing feature between multiple system models and base or discrete repertoire models is that they subsume both of these model types. These models consist of populations of interacting immune systems.

Scenario	Comment
OS1	Different systems adapt to a single goal at different rates and with different precision. Of interest is information sharing amongst systems, and biasing of the initial repertoire to affect improved adaptation rates and precision.
OS2	Like different aspects of a discrete repertoire model being exposed to different goals, the same approach may be used to vary exposure to sets of complete systems. Rather than an exposure map to the geography of a system, this would result in a pathogen exposure distribution over a population of systems.
OS3	Given overlapping exposure maps outlined above, these exposure maps may change with time, both in terms of pathogen virulence (migrating goals), and geographic pattern (migrating goal exposure).
CS1	Different systems may have 'slightly' different definitions of self, resulting in slightly different understandings of non-self, although with high-commonality in terms of the external pathogenic environment. Sharing of information regarding knowledge of the pathogenic environment must be traded off with the adverse effects of trading attack systems that may destroy self.
CS2	In addition to the differing self and non-self classes in CS1, altered exposure maps causes different systems to have unique antigenic environments, thus sharing and biasing may have a neutral effect between different environments. Multiple classes of pathogen may drive sub-population specialisation.
CS3	Extending upon CS2, the differing pathogen classes and their geographic locations may move over time, requiring that the specialisation of sub-populations to track the distinctions between classes through time.

Table 11 - Summary of general multiple system model behaviour

V. EXTENSIONS

The scenarios provide a test-bed of simplified immunological-related problems in which to phrase adaptive systems. In phrasing the three levels of previously defined adaptive systems in the context of the two classes of scenarios (optimization and classification), many specialised model-related concerns have surfaced. These concerns are related to (1) implementation detail of models, (2) implementation detail of scenarios, (3) measures of scenario success, and (4) measures of model behaviour. All four of these areas must be considered prior to the investigation of scenario-model intersections.

In addition, general principles have been made apparent regarding the three classes of model, as follows:

Model Type	Primary Concerns
Base	Learning, memory, and adaptation
Discrete Repertoire	Spatial consistency, information capacity
Multiple System	Population survivability, robustness, diversity

Table 12 - Summary of the three classes of models and general concerns

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REFERENCES

[1] Jason Brownlee, "'Colour Space': A Contrived Problem Domain for Investigating Adaptive Models," Complex Intelligent Systems Laboratory (CIS), Centre for Information Technology Research (CITR), Faculty of Information and Communication Technologies (ICT), Swinburne University of Technology, Victoria, Australia, Technical Report ID: 070322A, Mar 2007.

[2] Jason Brownlee, "A Series of Adaptive Models Inspired by the Acquired Immune System," Complex Intelligent Systems Laboratory (CIS), Centre for Information Technology Research (CITR), Faculty of Information and Communication Technologies (ICT), Swinburne University of Technology, Victoria, Australia, Technical Report ID: 070302A, Mar 2007.

[3] Jason Brownlee, "A Series of Discrete Repertoire Models Inspired by Lymphocyte Migration," Complex Intelligent Systems Laboratory (CIS), Centre for Information Technology Research (CITR), Faculty of Information and Communication Technologies (ICT), Swinburne University of Technology, Victoria, Australia, Technical Report ID: 070320A , Mar 2007.