We are IntechOpen,
the world's leading publisher of Open Access books
Built by scientists, for scientists

6,900
Open access books available

186,000
International authors and editors

200M
Downloads

Our authors are among the

154
Countries delivered to

TOP 1%
most cited scientists

12.2%
Contributors from top 500 universities

BOOK CITATION INDEX
CLARIVATE ANALYTICS
INDEXED

WEB OF SCIENCE™

Selection of our books indexed in the Book Citation Index
in Web of Science™ Core Collection (BKCI)

Interested in publishing with us?
Contact book.department@intechopen.com

Numbers displayed above are based on latest data collected.
For more information visit www.intechopen.com

Analysing the Difficulty of Learning Goal-Scoring Behaviour for Robot Soccer

Jeff Riley and Vic Ciesielski
RMIT University
Australia

1. Introduction

This work describes a method of analysing fitness landscapes and uses the method to analyse the difficulty of learning goal-scoring behaviour for robot soccer – a problem that is considered to be very difficult for evolutionary algorithms. Learning goal-scoring behaviour can be made easier or harder by varying the amount of expert knowledge provided to the evolutionary process. Expert knowledge can be varied by changing the innate player behaviours available, providing an *a priori* problem decomposition (that is, breaking the problem into a series of smaller, easier problems) or by providing a composite fitness function that effectively guides the search.

The concept of fitness landscapes, and the idea that the process of evolution could be studied by visualizing the distribution of fitness values across the population as a landscape, has been long-established in the field of evolutionary biology, having been first proposed by Sewell Wright (Wright, 1932). Later the landscape analogy was revived with the development of formal methods to handle optimization problems in complex physical systems (Frauenfelder et al., 1997). A major area of concern with fitness landscapes is that there is no generally accepted definition of what constitutes a fitness landscape. There is not much agreement in the field as to what a fitness landscape is and how it should be arranged - whether a neighbourhood relation is required to describe it, and much less agreement as to what the neighbourhood relation should be. This work addresses these shortcomings by describing a simple, "black-box" neigbourhood relation that defines the fitness landscape generated by an evolutionary search. The efficacy of the method is shown by applying an evolutionary technique to a difficult search problem (learning goal-scoring behaviour), and using *autocorrelation* and *information content* landscape measures to analyse features of the resultant fitness landscape to explain how the difficulty of the problem is changed by injecting human expertise. The analysis reveals that when only basic skills are available to the player the fitness landscape is very flat and contains only a few thin peaks. As more human expertise is injected, more gradient information becomes apparent on the landscape and genetic search is more successful.

Evolving soccer-playing skills for robot soccer players is a well-known difficult problem for evolutionary algorithms. A wide variety of approaches and technologies have been used in attempts to construct good robot soccer players. These include hand-coding, genetic

algorithms, genetic programming, reinforcement learning, neural networks, behaviour-based and deliberative agents, and various combinations of those. In the early years of the RoboCupSoccer competition (Kitano et al., 1995) a few researchers attempted to fine tune, or learn incrementally, some low-level skills using AI machine learning techniques (Stone, 1998; Stone & Sutton, 2001), but nearly all entrants used hand-coded skills and strategies (Luke, 1998). Even today hand-coded players, or players with hand-coded skills, generally continue to outplay players whose skills have been entirely learned or developed automatically (Lima et al., 2005). For example, the 2005 RoboCupSoccer 2D simulation league winner used hand-coded strategies which employed a mixture of hand-coded skills and skills developed using machine learning techniques (Riedmiller et al., 2005). There has been only limited success when applying standard machine learning techniques to this problem. Much of the work to date has been characterised by researchers beginning their work with high expectations, then ratcheting down their expectations as the work progresses, and finally adjusting their goals (and the soccer playing behaviours and skills of the players being developed) to align with the progress being made.

The size of the robot soccer search space and the paucity of solutions that lead to good soccer-playing behaviour tend to suggest that, in the extreme case, the problem resembles a *needle-in-a-haystack* problem (Jones & Forrest, 1995a; Langdon & Poli, 1998a; Right et al., 2002), indicating a possible cause for the difficulty of the problem for evolutionary algorithms. Previous work in the area of evolutionary learning for robot soccer has focussed on the learning, and what parameters and controls need to be manipulated in order to produce acceptable soccer-playing behaviour, but there has been no systematic investigation of the difficulty of the problem. Understanding why problems are difficult for evolutionary algorithms is a critical step not only in solving the particular problem under investigation, but also in advancing the field and improving the potential usefulness of evolutionary algorithms. The goal of this work is to describe a method for analysis of the fitness landscape generated by the problem of learning goal-scoring behaviour for robot soccer, and to use the analysis to better understand the difficulty of the problem and how progress might be made.

2. Evolving Goal-Scoring Behaviour for Robot Soccer

For this work a messy-coded genetic algorithm (Holland, 1975; Goldberg et al., 1989) is used to evolve a single robot soccer player in the SimpleSoccer simulated soccer environment (Riley, 2003). The behaviour of the player is governed by a fuzzy inferencing system (Zadeh, 1965; Jang et al., 1997) with the ruleset for the fuzzy inferencing system being evolved by the genetic algorithm.

The player being evolved is endowed with a configurable subset of soccer-playing skills taken from a rich set of basic and hand-coded skills and default actions. The player executes one of the skills or performs the default action available to it in response to some external stimulus; the specific response being determined by the fuzzy ruleset and the fuzzy inferencing system. The external stimulus used as input to the fuzzy inference system is the visual information supplied by the soccer simulator.

A full description of the method used to evolve the soccer player is given in the previous chapter.

3. Fitness Landscapes

Wright's original diagram, reproduced in Fig. 1, is a two-dimensional depiction of the relative "adaptiveness" of all possible combinations of allelic states for genes on a particular chromosome. The diagram is effectively a contour map with the contour lines representing levels of adaptiveness. This original diagram included no labels for the axes, and no indication was given as to how the various gene combinations should be arranged on the landscape - no notion of "neighbourhood" was defined or discussed by Wright. In landscape terms, the neighbourhood relation defines which points, or individuals, are arranged as immediate neighbours on the landscape, and so is extremely important in defining the landscape.
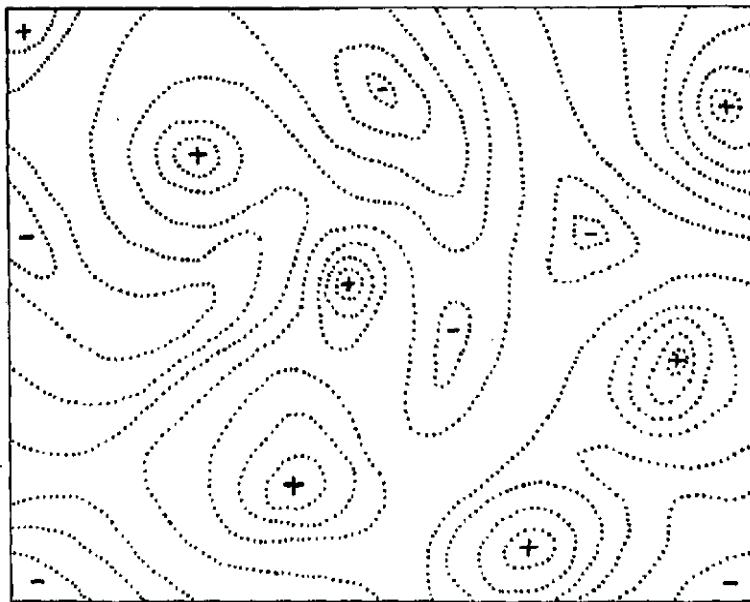

Fig. 1. Diagrammatic representation of the field of gene combinations in two dimensions instead of many thousands. Dotted lines represent contours with respect to adaptiveness. *Reproduced from (Wright, 1932)*

Much of the work involving fitness landscapes avoids a rigorous definition of the landscape under analysis (Jones, 1995a), and where it is mentioned or implied at all the landscape is usually assumed to be the single-bit mutation landscape: the landscape generated by arranging all single-bit mutations of a chromosome represented as a string of binary digits such that chromosomes that differ by only a single bit are neighbours, then plotting the fitness of each chromosome on a separate axis. On such landscapes, genetic operators such as crossover are assumed to take hypersteps over the fitness landscape described by mutation. There have been attempts to overcome this deficiency, and following is a description of some of major recent work in the field.

The NK fitness landscape model (Kauffman, 1989; Kauffman & Levin, 1987) was proposed as a means to study how epistasis - the dependency of fitness upon the interaction of the allelic state of multiple genes (Lush, 1935) - affects the ruggedness of the fitness landscape. An NK fitness landscape is defined by a fitness function which can be tuned in order to alter the ruggedness of the resultant fitness landscape. The fitness function is defined by two parameters: the number of genes (N), and the number of epistatic links, or interactions, between genes (K). In the most common implementations each gene has two possible alleles, thus the genotype can be represented by a bit string of length N. Each gene in a chromosome contributes to the fitness of the chromosome based on K+1 values: its own and those of the K genes to which it is linked. The three-dimensional fitness landscape is constructed by arranging chromosomes in two dimensions on the landscape such that bit strings that differ in the value of only one bit are neighbours, then using the fitness of the chromosomes as the third dimension. The NK landscape is widely used by the evolutionary computation community to generate epistatic landscapes as test functions for search and optimisation techniques (De Jong et al., 1997; Heckendorn et al., 1999; Skellett et al., 2005; Smith & Smith, 2001).
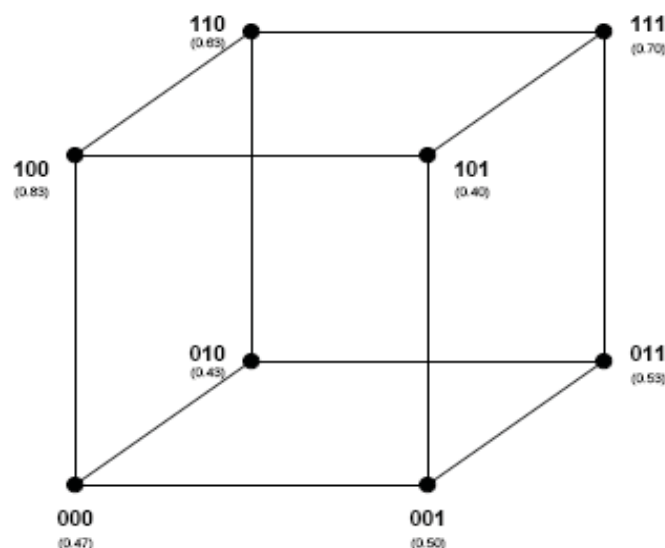

Fig. 2. An example of a fitness landscape for bit strings of length three, where the neighbourhood relation is defined by point mutation. Fitness values (randomly assigned) are shown in parentheses. *Reproduced from (Hordijk, 1996)*

Weinberger (1990a; 1991a) proposed a fitness landscape model in which the landscape is represented as a graph on which the vertices correspond to individuals and have associated fitness values, and traversing the edge of the graph corresponds to the action of a genetic operator (mutation, crossover etc.) and so taking a step on the landscape. Jones (1995a; 1995b), Culberson (1994), and later Hordijk (1996) describe similar fitness landscape models in which the landscape is represented as a graph (e.g. Fig. 2). Reidys and Stadler (2002) analyse a similar fitness landscape topography, focussing on the geometry of the moves

from one vertex to another and provide a mathematical treatment of the edge traversals and the resultant complex topographies.

Culberson's model described a landscape defined by a crossover operator rather than mutation, and in which the graph vertices represented a population of points. Jones presents a similar model, and expands it further to include the concept that each genetic operator defines its own separate landscape (Jones 1995a). In Jones' "one operator, one landscape" model, an evolutionary algorithm which implements the genetic operators selection, mutation and crossover makes transitions on three separate landscapes (Fig. 3). According to Jones' model the evolutionary algorithm takes steps on the mutation landscape, after which individuals are paired to form vertices on the crossover landscape and further steps are then taken on that landscape, and then the population is gathered into a vertex on the selection landscape for a further step there. The neighbourhood relation in Jones' model is therefore simply defined by the genetic operator for each landscape.
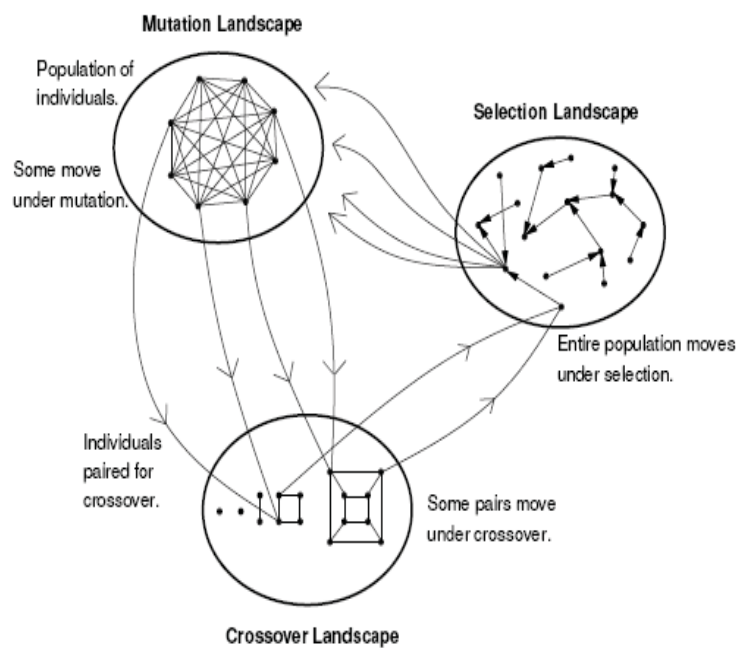

Fig. 3. A simplified view of an evolutionary algorithm operating on three landscapes.
Reproduced from (Jones 1995a)

More recently Moraglio and Poli (2004) presented a new topological framework for evolutionary algorithms and as part of that framework redefine the mutation and crossover operators to be more tightly linked to the fitness landscape. In the model proposed by Moraglio and Poli the genetic operators are defined by the fitness landscape upon which they operate – the genetic operators are a natural consequence of the neighbourhood relation and distance metric of the fitness landscape. For example, under what Moraglio and

Poli call topological uniform crossover, offspring are defined as those individuals that lie between the parents on the fitness landscape. Similarly, under topological ε-mutation, offspring are defined as those individuals that lie ε steps away from the parent on the fitness landscape.

In essence, the fitness landscape is a metaphor – a metaphor in which the landscape is often thought of as a 3-dimensional terrain, where the peaks (hills or mountains) represent areas of high fitness and the valleys between the peaks low fitness. A fitness landscape which depicts the fitness values of a population that varies greatly in fitness will likely display many local high peaks surrounded by deep valleys. Such a landscape is said to be rugged. Similarly, if many individuals in the population have a similar fitness, the landscape will vary little and is said to be flat. Search on some landscapes is notionally easier than search on others – search on a predominantly flat landscape is likely to be difficult, as is search on a rugged landscape with peaks and valleys randomly distributed.

In evolutionary biology the proliferation of an individual's genetic material is considered the ultimate objective of life, and the success or failure of a particular genotype, or its phenotypic expression, is most often measured by the number of progeny it produces – so for evolutionary biology, the fitness of an individual is a function of the number of progeny produced by that individual. For evolutionary optimisation the objective is usually less nebulous, and the success or failure of a particular genotype, or phenotype, is measured by a well-defined fitness function, and typically the number of progeny produced by an individual is a function of the fitness of that individual. Fitness landscapes are used in evolutionary biology and evolutionary optimisation to show the correlation between genotypes, or phenotypes, as a measure of success or failure and search difficulty (Jones & Forrest, 1995b; Kauffman, 1989; Kauffman & Levin, 1987; Langdon & Poli, 1998b; Vassilev, 1997).

4. Which Fitness Landscape?

As discussed in the previous section there are several possible definitions of, and representations for, fitness landscapes, and choosing the definition and representation which best describes the combination of the problem being studied and the algorithm being used to study it is extremely important.

A fitness landscape is most often defined by three basic attributes:

- a search space
- a relation that defines which points are neighbours in the search space
- a fitness function that assigns a fitness value to each point in the search space

A significant problem with this definition of fitness landscapes is the specification of the neighbourhood relation. The neighbourhood relation and its specification is extremely important because any discussion of landscapes invariably involves the terms "peaks" and "valleys", and no peak or valley can exist without the notion of neighbourhood – a peak is only a peak because it is higher than its neighbours.

Often the neighbourhood relation is defined in simple terms, such as the hamming distance for bit strings, or by defining all single bit mutations of a bit string as neighbours. This potentially ignores an important ingredient in the evolutionary processes: evolutionary algorithms are usually governed by some combination of several operators. A definition of

the neighbourhood relation in terms of the actual mix of genetic operators (for example, selection, mutation and crossover) being used by the algorithm would seem to be more relevant and useful to an analysis of the performance of the algorithm. Since the search is for individuals of good fitness, the individuals which comprise the search space and their associated fitness values should ideally be arranged as a fitness landscape which has individuals of better fitness clustered together so that the landscape contains peaks and valleys representing the fitness extremes. The issue is how to represent the fitness landscape to achieve that, and a critical question is: what attributes of an individual should determine the locality of that individual on the fitness landscape?

If the neighbourhood relation is not defined correctly in terms of describing the actions of the algorithm being used to perform the search, then the fitness landscape is not the landscape searched by the search algorithm, and so not necessarily indicative of the difficulty of the search. On a physical landscape points are neighbours, or next to each other, because (for example) a person walking on that landscape can traverse the distance between those points in a single step. The corollary is that if a searcher walking on a landscape is not able to traverse the distance between two points in a single step, then those points are not next to each other and so, by definition, are not neighbours on the landscape defined by that searcher and the associated granularity of search (a single step). Simply plotting attributes of the members of the search space against fitness – for example chromosome length in the case of a genetic algorithm, or program length for genetic programming – while possibly useful for visualising the fitness distribution of the search space, may not be sufficient to describe the fitness landscape traversed by the search algorithm, since there may be no reason to expect that the search algorithm could traverse the distance between neighbouring points on that landscape with a single step.

As discussed earlier, a fitness landscape is a metaphor and an aid to the visualisation of the operation of a search algorithm, but for anything other than the actual landscape traversed by the search algorithm the metaphor is flawed and the visualisation is misleading. For example, the analogy of the search algorithm to a short-sighted explorer wandering over a (possibly rough) terrain (Langdon & Poli, 2002) is only valid for the actual fitness landscape searched by the algorithm, and anything else gives a misleading view of the complexity, or ruggedness, of the landscape. For the explorer analogy to be useful, the neighbourhood relation must reflect the notion that an individual's neighbour on the fitness landscape is any individual in the search space which can be reached in a single step of the explorer. In the case of an evolutionary algorithm, the explorer is the algorithm, and the single step is the combination of whichever genetic operators are implemented by that algorithm: selection, mutation and crossover. It should also be remembered that during the search the explorer may not be able to see all its theoretical neighbours. This is because, for an evolutionary algorithm using crossover, the individuals reachable in a single step from one parent depend upon the other individuals selected for mating, and while an individual can theoretically mate with any other individual in the search space, in reality the individuals available for selection are restricted by the size of the population. So to continue the analogy of the short-sighted explorer, not only is the explorer short-sighted, but also lacks peripheral vision.

While it should be remembered that the 3-dimensional fitness landscape is just a metaphor, since in most cases the surface being traversed by the searcher will be multi-dimensional and so complex that there will be no landscape that could actually be visualised, the analogy

of the searcher on a 3-dimensional landscape is a useful aid to imagining how a search algorithm might use the available attributes of the search space.

It is important to understand that the (metaphoric) fitness landscape is defined by a number of attributes, which include the search algorithm, and not solely by the specification of the problem. It is not valid to visualise a fitness landscape without reference to a search algorithm, and then decide what algorithm will best search the landscape – the operation of the search algorithm defines the neighbourhood relation, and so the shape, of the landscape. Previous work with fitness landscapes recognises the need to refer to the search algorithm when characterising the landscape (Hordijk, 1996; Jones & Forrest, 1995b; Reeves, 1999; Vassilev et al., 2000). Jones and others (Hordijk, 1996; Jones & Forrest, 1995a) further suggest that each operator employed by a search algorithm (e.g. selection, mutation and crossover for a genetic algorithm) should be viewed as operating on its own landscape. The notion that search operators define and act on separate landscapes may be useful for studying the effect of individual operators, but the combined effect of each move on each landscape needs to be considered. If the algorithm employs multiple operators, then the output of the algorithm is some combination of those operators, so it is not reasonable to consider a move on the "mutation landscape" without considering how that then affects a subsequent move on the "crossover landscape".

A further problem with the "one operator, one landscape" approach is determining what constitutes an operator. Jones (1995a) has, in the case of evolutionary algorithms, suggested that selection, mutation and crossover should each define and operate on separate landscapes, but none of those operators are necessarily atomic. Is an operator considered to define its own landscape simply because it has a well-known label? The breakdown of the evolutionary operation into the three operators of selection, mutation and crossover seems somewhat arbitrary.

5. Landscape Measures

Early work on the characterisation of landscapes involved analysing structural parameters such as the number and distribution of local minima (Edwards & Anderson, 1975; Sherrington & Kirkpatrick, 1975; Tanaka & Edwards, 1980). More recently, several methods for measuring and analysing landscapes for search algorithms have been proposed. The methods proposed can be categorised into two broad streams: statistical measures (Altenberg, 1995; Hordijk, 1996; Jones & Forrest, 1995b; Lipsitch, 1991; Manderick et al., 1991; Weinberger, 1990b; Weinberger, 1991b) and information measures (Borenstein & Poli, 2005a,b,c; Vassilev, 1997; Vassilev et al., 2000). Borenstein and Poli have extended the information measure to include a measure of the performance of the algorithm and so define a "performance landscape" which may prove useful but does not yet have sufficient history to gauge its efficacy. All the methods proposed have in common the notion that the points in the search space are arranged according to some neighbourhood relationship, and a measure of fitness, performance or information content associated with the points defines the ruggedness of the landscape.

The methods used to measure and analyse the structure of fitness landscapes in this work are the autocorrelation method suggested by Weingberger (1990b; 1991b), and the information content approach suggested by Vassilev et al. (Vassilev, 1997; Vassilev et al., 2000). These methods were chosen because they are different methods of measuring the

structure of landscapes and, while there seems to be no generally accepted standard approach, both methods have gained some favour and are commonly cited as reasonable landscape characterisation methods (Hordijk, 1996; Merz & Freisleben, 1999; Smith et al., 2002; Stadler, 1996). Jones' *Fitness Distance Correlation* (Jones & Forrest, 1995b) is an interesting landscape measure but requires that the solution be known in order to calculate the metric, so is not applicable to this work.

5.1 Autocorrelation and Correlation Length

Correlation measures are the most commonly used means of characterising fitness landscapes and are seen as good indicators of ruggedness. A landscape is characterised as rugged when it contains multiple local maxima (minima). Typically, the more rugged the landscape the lower the average fitness correlation between neigbouring points on the landscape. Autocorrelation refers to the correlation of a time series with its own past and future values, and is also known as serial correlation, referring to the correlation between members of a series of numbers arranged in time. Autocorrelation is a correlation coefficient, but instead of measuring the correlation between two different variables, autocorrelation measures the correlation between two values of the same variable at times X_i and X_{i+k}, where k is the number of time steps, or lag, between the two values.

Autocorrelation definition (Hordijk, 1996; Weinberger, 1990b; Weinberger, 1991b):

Given measurements Y_1, Y_2, …, Y_N, at time X_1, X_2, …, X_N, where N is the number of measurements, and

$$\overline{Y} = \frac{1}{N}\sum_{i=1}^{N} Y_i, N > 0$$

the time lag autocorrelation function is defined as

$$r_k = \frac{\sum_{i=1}^{N-k}(Y_i - \overline{Y})(Y_{i+k} - \overline{Y})}{\sum (Y_i - \overline{Y})^2}, N > k \tag{1}$$

Note that from Equation 1, if $|r_k| \approx 1.0$ there is much correlation between the points k steps apart in the series, whereas if $|r_k| \approx 0.0$ there is little correlation.

Weinberger proposed that a random walk be generated on the fitness landscape, where each step on the walk is taken between neighbouring points but the neighbour to which the step is taken is selected randomly, and the fitness values for each point visited during the random walk form a time series of numbers. The autocorrelation function can then be used as a measure of the ruggedness of the landscape described by the random walk.

The correlation length of a series of numbers is the largest distance, or time lag, between points for which some correlation exists. Hordijk (1996) defines the correlation length of a time series as one less than the first time lag for which the autocorrelation falls inside the region bounded by the two-standard-error bound (i.e. one less than the first time lag at which the autocorrelation becomes statistically equal to zero, making the correlation length

the largest time lag for which the correlation between two points is still statistically significant). This is the method used for calculating the correlation length in this work. The two-standard-error bound e for a series of N points is defined as

$$e = \pm \frac{2}{\sqrt{N}}, N > 0$$

so the correlation length l is defined in this work as the first lag for which

$$|r_k| < \left| \frac{2}{\sqrt{N}} \right|, N > 0 \qquad (2)$$

5.2 Information Content

An alternative to the statistical autocorrelation measure proposed by Weinberger is Vassilev's information content method, based on both classic and algorithmic information theory (Chaitin, 1987; Shannon, 1948). Vassilev et al. propose three information measures that characterise the structure of a fitness landscape from a series of points generated by a random walk over the landscape (Vassilev, 1997; Vassilev et al., 2000) :

- Information Content – characterises the ruggedness of the landscape.
- Partial Information Content – measures the modality of the landscape.
- Information Stability – the sensitivity of the information content measures.

These measures are calculated by generating a random walk of length n on the fitness landscape, with the aim being to extract information by characterising the series of points as an ensemble of objects. To calculate the information content, a string $S(\varepsilon)$ is constructed representing a group of objects generated from a random walk over the fitness landscape, where

$$S(\varepsilon) = S_1, S_2, ..., S_n, S_i \in \left\{ \overline{1}, 0, 1 \right\}$$

and $S(\varepsilon)$ is enumerated according to the function

$$S_i = \psi_{f_i}(i, \varepsilon), t = 1..n$$

and

$$\psi_{f_i} = \begin{cases} \overline{1} & if \quad f_i - f_{i-1} < -\varepsilon \\ 0 & if \quad |f_i - f_{i-1}| \leq \varepsilon \\ 1 & if \quad f_i - f_{i-1} > \varepsilon \end{cases}$$

Thus the string $S(\varepsilon)$ defines a sequence of objects where each object is represented by a substring $S_i S_{i+1}$ being a sub-block of length two of the string $S(\varepsilon)$.

The parameter ε is a real number taken from the interval [0.0, 1.0] (in this case) which defines neutral fitness and determines the accuracy with which the string $S(\varepsilon)$ is defined. If the absolute fitness difference between neighbouring points is less than ε, the points are

considered to be of equal fitness. This means that as ε increases from 0.0 to the maximum possible fitness difference between points along the walk (1.0), the amount of fitness change (entropy), and the sensitivity of ψ_{f_i}, decrease to zero.

The information content $H(\varepsilon)$ is defined as the entropic measure of the group of sub-blocks of length two of string $S(\varepsilon)$, and is given by

$$H(\varepsilon) = -\sum_{p \neq q} P_{[pq]} \log_6 p_{[pq]} \tag{3}$$

$P_{[pq]}$ are frequencies of the possible blocks pq of elements from the set $\left\{\overline{1}, 0, 1\right\}$ given by

$$P_{[pq]} = \frac{n_{[pq]}}{n}$$

where n[pq] is the number of occurrences of pq in $S(\varepsilon)$ and n is the length of $S(\varepsilon)$.

The partial information content $M(\varepsilon)$ is a measure of the modality (the number or frequency of local optima) of the landscape, and is calculated by filtering out elements of the string $S(\varepsilon)$ which are not essential for measuring modality to create a new string $S'(\varepsilon)$, then measuring the length μ of the new string. The string $S'(\varepsilon)$ is defined as

$$S'(\varepsilon) = S_{i_1}, S_{i_2}, ..., S_{i_k}, S_{i_j} \neq 0, S_{i_j} \neq S_{i_{j-1}}, j > 1$$

Thus the string $S'(\varepsilon)$ has the form $\overline{1}\, 1\, \overline{1}\, 1\, \overline{1}\, ...$, representing the slopes of the path taken by the random walk over the landscape, and so is empty if $S(\varepsilon)$ contains only 0s.

The partial information content $M(\varepsilon)$ is given by

$$M(\varepsilon) = \frac{\mu}{n} \tag{4}$$

Note that when $M(\varepsilon) = 1.0$, the path taken by the random walk over the landscape is considered to be maximally multimodal, and when $M(\varepsilon) = 0.0$, the path is flat.

The information stability ε^* is defined as the smallest value of ε for which the landscape becomes flat (i.e. for which $S'(\varepsilon)$ is empty). Since ε governs the sensitivity of the information content and partial information content measures, ε^* is a measure of the difference in fitness between neighbouring points on the random walk.

6. Fitness Landscape Definition

As discussed in sections 3 and 4, there has been much previous work done with regard to fitness landscapes, and there is a variety of views and some disagreement. The previous sections of this work have presented a discussion of the issues. For the purposes of this work it is critical that the fitness landscape being analysed be formally defined, and that the definition be related to the search algorithm used to search the landscape.

Genetic algorithms are typically thought of as performing a search on a landscape described by single-bit mutation, where mutation performs a *local* search and the crossover operation is depicted as a *hyperstep* on the mutation landscape, allowing mutation to perform a local

search on a different, usually distant part of the landscape. For this work however, the fitness landscape is considered to be defined by the overall operation of the genetic algorithm.

The autocorrelation and information content measures used in this work to characterize the fitness landscape provide an analysis of a series of numbers: in the case of the autocorrelation measures, the analysis indicates how well correlated numbers in the series are. Of significance is not so much how the numbers in the series are collected or generated, but that the series be representative of the entity – in this case the fitness landscape – being measured. The random walk proposed by Weinberger is a good means to generate a representative series of points for the single-bit mutation landscape (provided that the walk is sufficiently long or that the landscape is statistically isotropic), but is not directly applicable to the landscape defined by the overall operation of the genetic algorithm.

Consider an observer watching a genetic algorithm searcher perform a *random walk* on a fitness landscape and assume that although the observer is able to discern the granularity of the search (the genetic algorithm's single steps), the means by which the GA determines where each step takes it is hidden from the observer.

The observer sees the searcher walking randomly over the landscape and considers points on the landscape one step apart to be neighbours. The definition of the neigbourhood relation is of no consequence to, and is not required by, the observer since the searcher is defining neigbouring points by performing the walk. If the random walk performed by the genetic algorithm searcher was sufficiently long, and the "altitude" (fitness) at each step recorded for the observer, the entire fitness landscape would be determined by observation. The landscape so determined would be the precise fitness landscape defined by the search algorithm.

A random walk of *s* steps is conducted as follows:

- An individual i_0 is randomly selected from the search space

- For each step *s, s = 1 .. maxsteps*

- i_{s-1} undergoes mutation with probability $P_{mutation}$

- Another individual *i, i ≠ i_{s-1},* is randomly selected from the search space

- Crossover is performed between *i* and i_{s-1} with probability $P_{crossover}$, resulting in two new individuals i'_1 and i'_2, both of which are neighbours of (a single step from) i_{s-1}

- Set $i_s = i'_1$ and step to i_s

This "black box" view of the genetic algorithm operation and consequential determination of the neighbourhood relation and fitness landscape doesn't change the actual operation of the genetic algorithm or the conceptual notion of the algorithm conducting a parallel search of different areas of the fitness landscape. What this view does is change the notion of the step size of the genetic algorithm from the result of a single genetic operator to the amalgamation of the genetic operators used by the algorithm, so the perception of the topography of the landscape is changed accordingly. This view of the fitness landscape satisfies the requirement that the landscape neigbourhood relation be defined by the search algorithm and is the definition used for the robot soccer problem addressed by this work.

7. Search Space and Fitness Landscape Analysis

Since the skills with which a player is endowed will undoubtedly affect the ability of the player to learn goal scoring behaviour, a key question is *"How does changing the skills available to the soccer player affect, or change, the fitness landscape?"* It would seem to be somewhat intuitive that changing the skills available to the players in some way alters the fitness landscape over which the search is conducted. In fact the fitness landscape is altered by changing the skills available to players, but it changes because the underlying search space is different for each set of skills: the chromosomes are interpreted differently for each skillset, and in fact may take on different values for each skillset depending upon the range of skills available in the skillset, so the individuals (players) that comprise the search space are different for each skillset. Since changing the skills available to the players defines a new search space it also defines a new fitness landscape.

The same is not true of changing the function used for the fitness evaluation. Different fitness functions alter the fitness landscape, not the underlying search space, because the individuals that comprise the search space remain the same. Furthermore, since only the means by which the individuals are evaluated is changed, the change to the fitness landscape is not in the neighbourhood relation but only in the fitness values of the individuals. For this reason, changing the fitness function has the potential to significantly change the fitness landscape, and so affect the effectiveness of the search process. Some fitness functions could make "mountains out of molehills" – teasing gradient information out of otherwise flat landscapes. Sometimes this is valid, but sometimes the definition of the fitness function effectively solves the problem for the search algorithm.

The difficulty of learning goal-scoring behaviour is evidenced by the size of the search spaces defined by the different skillsets of the players. These search spaces range in size from 1.55×10^{158} different chromosomes for the base skillset of {Turn, Kick, Dash} to 7.4×10^{161} for the complete skillset. The calculation of search space size is described in detail in (Riley, 2005).

7.1 Experiments Performed

A number of experiments were performed in order to examine how the fitness landscape, and the performance of the resulting search over it, is affected by varying the player skillset (refer to the full list of available skills shown in Table 1 of the previous chapter), the default action (previous chapter, Table 2) and the fitness function (discussed below). In addition to the evolutionary search, five random walks (as described in section 6) were conducted for each experiment, each walk starting at a randomly selected point on the fitness landscape and continuing for a duration of 100,000 steps. The statistics gathered during the walks are also analysed.

7.2 Fitness Functions Evaluated

Two fitness functions were compared: a composite fitness function and a simple, goals-only fitness function. For both fitness functions implemented the fitness values range from 0.0 to 1.0, with 1.0 being the worst fitness possible, and optimal fitness values approaching 0.0.

The simple, goals-only fitness function rewards a player for goals scored only – the greater the number of goals scored the greater the reward. The goals-only fitness function was implemented as:

$$f = \begin{cases} 1.0 & , goals = 0 \\ \dfrac{1.0}{2.0 \times goals} & , goals > 0 \end{cases} \qquad (5)$$

where *goals* is the number of goals scored by the player.

The composite fitness function rewards, in order of importance:

- the number of goals scored in a trial
- minimising the distance of the ball from the goal

This combination was chosen to reward players primarily for goals scored, while players that do not score goals are rewarded on the basis of how close they are able to move the ball to the goal on the assumption that a player which kicks the ball close to the goal is more likely to produce offspring capable of scoring goals. This decomposes the original problem of evolving goal-scoring behaviour into the two less difficult problems:

- evolve ball-kicking behaviour that minimises the distance between the ball and goal, and
- evolve goal-scoring behaviour from the now increased base level of skill and knowledge

The composite fitness function was implemented as:

$$f = \begin{cases} \begin{cases} 1.0 & , kicks = 0 \\ 0.5 + \dfrac{dist}{2.0 \times fieldLen} & , kicks > 0 \end{cases} & , goals = 0 \\ \dfrac{1.0}{2.0 \times goals} & , goals > 0 \end{cases} \qquad (6)$$

where *goals* is the number of goals scored by the player
      kicks is the number of times the player kicked the ball
      dist is the minimum distance of the ball to the goal
      fieldLen is the length of the field

Note that both the simple and composite fitness functions represent the problem as a minimisation problem, so a lower fitness value is a better result than a higher fitness value.

7.3 Genetic Algorithm Parameters

The genetic algorithm parameters used in the experiments were chosen empirically after some experimentation. The population size and number of generations were chosen to provide reasonable population diversity and search space coverage. The GA parameters are shown in Table 1. Each player was allowed a fixed time in which to score as many goals as possible.

Skill	Description
Maximum Chromosome Length	64 genes
Population Size	500
Maximum Generations	500
Selection Method	Elitist: *a percentage of the best players is retained, with the remainder selected using the Roulette Wheel method.*
Elitist Retention Percentage	2.5
Crossover Method	Single Point Cut and Splice
Crossover Probability	0.95
Mutation Rate	10%
Mutation Probability	0.15

Table 1. GA parameters

7.4 Results and Analysis

For each experiment the following information is presented for analysis and comparison:

- Data from the evolutionary search:
  - Line graphs showing the population average fitness and individual best fitness for generations 1 to 500. Note that a *lower* fitness is a better fitness.
  - A bar chart showing the cumulative fitness distribution for all individuals evaluated during the 500 generations, showing the percentage of all individuals evaluated which failed to kick the ball (denoted by "nm" on the graph x-axis), moved the ball closer to the goal (graduated), kicked one goal, two goals, three goals etc.
- Data from the random walks:
  - A correlogram showing the autocorrelation data for time lags 1 to 100 for the five random walks and the two-standard error bounds.
  - A graph showing the information content data for $0 \le \varepsilon \le 1.0$ for the five walks.
  - A table showing:
    - the mean fitness and fitness variance of the points visited in the random walks.
    - the fitness distribution for all individuals evaluated during the random walks.
    - the average autocorrelation for the first time lag (i.e. for immediate neighbours).
    - the average correlation length.
    - the average information content $H(\varepsilon)$ and average partial information content $M(\varepsilon)$ for selected ε.
    - the average information stability $\varepsilon*$.

7.4.1 Experiment 1: Composite Fitness; All Skills; Default Action = Hunt Action 1

Experiment 1 is the problem for which the search algorithm has been given the most help in the form of initial player skills, default action, and a composite fitness function to guide the search. The data shown on the graph of population average fitness (Fig. 4) tend to indicate that the population as a whole ceases to improve after 30 to 40 generations though, as evidenced by the graph of best fitness values, individuals of good fitness continue to be found beyond that point. The percentage of the population exhibiting ball-kicking or goal-scoring behaviour is reasonably high, as shown by the frequency distribution (Fig. 5).

From the data presented in Table 2 it is apparent that although the mean fitness of the 100,000 individuals evaluated during the random walk is close to 1.0 (indicating no ball movement) and the variance small, the random walk did find individuals which exhibited goal-scoring behaviour, and in fact found more than 100 individuals which scored multiple goals.

The autocorrelation data shown in Fig. 6 and the correlation length given in Table 2 indicate that the fitness landscape for this problem (as described by the random walk) offers a reasonable amount of gradient information that the search algorithm can use to guide the search. With an autocorrelation of ~0.32 for points on the random walk a single step apart and a fairly steep descent for points further apart, the correlation between next and near neighbours on this fitness landscape is not so high that a search algorithm is led unerringly to a solution, but with a good correlation and a long correlation length the problem, in this form, should be readily solved by a search algorithm able to take advantage of the landscape features.

Random Walk Statistics (Average over 5 walks)								
Mean Fitness	0.98283							
Fitness Variance	0.00669							
Individual Fitness	**No Movement**	**Ball Movement**	**Goals**					
			1	**2**	**3**	**4**	**5**	**>5**
Number of Individuals	95974	3462	434	99	26	4	1	0
Autocorrelation $r(1)$	0.31716							
Correlation Length	41							
ε	**Information Content** $H(\varepsilon)$				**Partial Information Content** $M(\varepsilon)$			
0.0	0.12447				0.03266			
0.2	0.09770				0.03020			
0.4	0.06179				0.01269			
0.6	0.00754				0.00098			
0.8	0.00229				0.00025			
0.885	0.00000				0.00000			

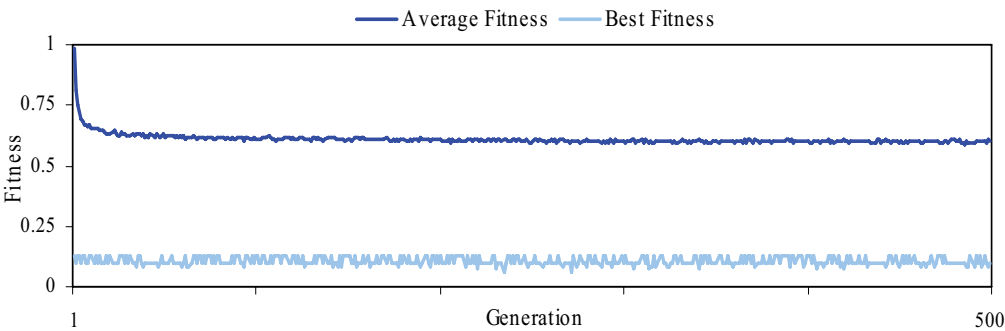Table 2. Experiment 1: Random walk statistics

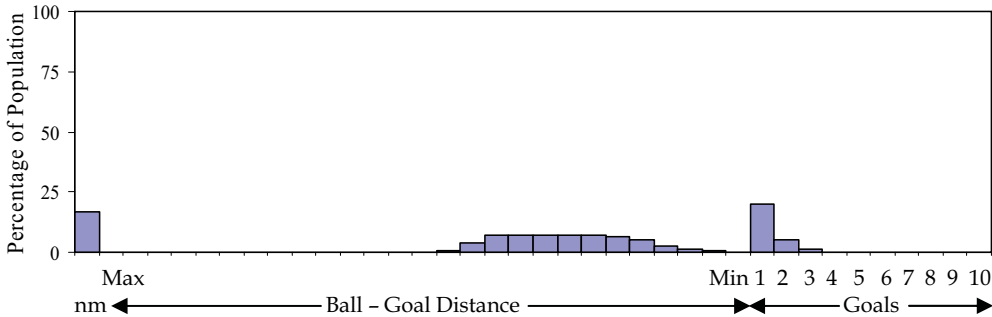Fig. 4. Experiment 1: Average and best fitness

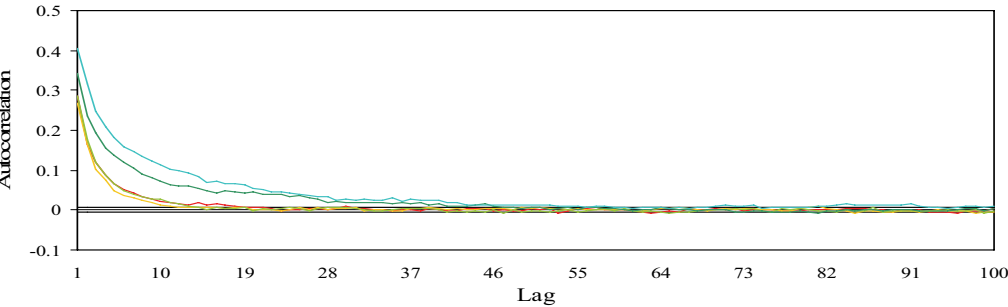Fig. 5. Experiment 1: Ball movement and goals scored

Fig. 6. Experiment 1: Autocorrelation

The information content graph shown in Fig. 7 supports the autocorrelation data for this experiment. Information stability is quite high at 0.885, indicating a high difference in fitness among neighbouring points, so pointing to some good gradient information being present in the landscape. $H(0.0)$ is not particularly large, indicating that the diversity of shapes on the landscape is not high. Similarly $M(0.0)$ is relatively small, indicating that the degree of modality of the landscape is low.
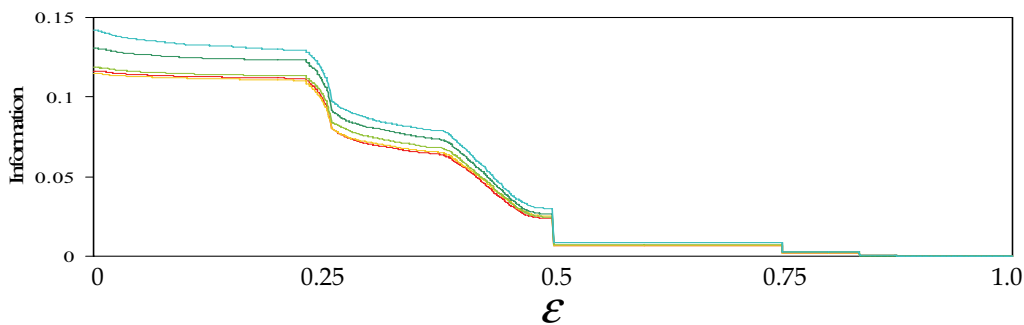
Fig. 7. Experiment 1: Information content

7.4.2 Experiment 2: Composite Fitness; Base Skills; Default Action = Hunt Action 1

The difference between this experiment and experiment 1 is that instead of the player being endowed with all available skills, the player in this experiment has only the base skills of turn, kick and dash. The player has hunt action 1 configured as the default action. The fitness function is the composite fitness function.

The data shown on the graph of population average fitness (Fig. 8) indicate that improvement of the population stops at about generation 150, and although the graph of best fitness values indicates that individuals exhibiting goal-scoring behaviour continue to be found, terminating the search after generation 150 would not have adversely affected the result. Fig. 9 shows that the percentage of the population exhibiting goal-scoring behaviour is extremely small, with a very large proportion of the population not kicking the ball at all.

| Random Walk Statistics (Average over 5 walks)								
Mean Fitness	0.99947							
Fitness Variance	0.00014							
Individual Fitness	No Movement	Ball Movement	Goals					
			1	2	3	4	5	>5
Number of Individuals	99776	224	0	0	0	0	0	0
Autocorrelation $r(1)$	0.10724							
Correlation Length	9							
ε	Information Content $H(\varepsilon)$			Partial Information Content $M(\varepsilon)$				
0.0	0.01268			0.00180				
0.1	0.01258			0.00178				
0.2	0.01256			0.00178				
0.3	0.00202			0.00022				
0.371	0.00000			0.00000				

Table 3. Experiment 2: Random walk statistics
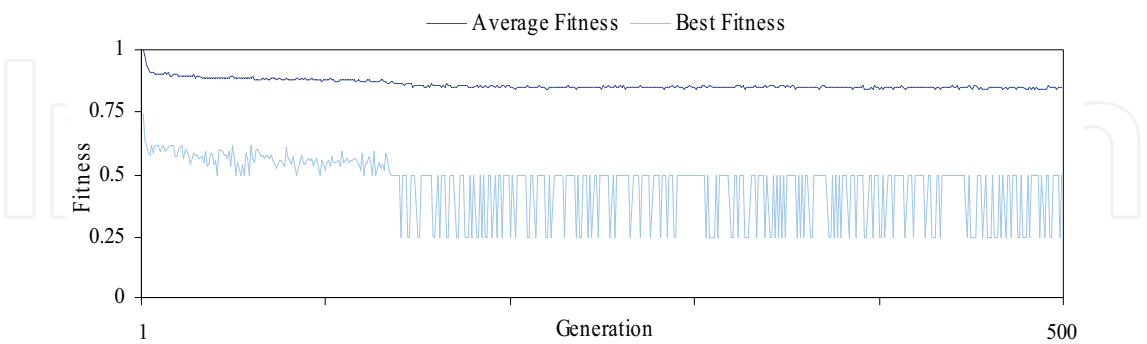
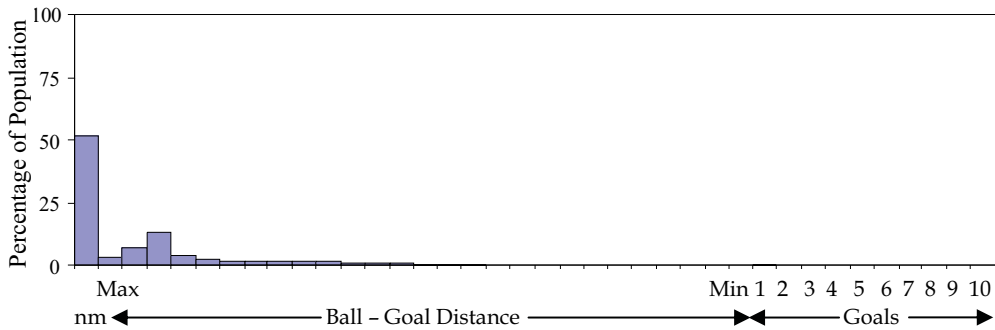Fig. 8. Experiment 2: Average and best fitness

Fig. 9. Experiment 2: Ball movement and goals scored

These results show clearly the effect of removing from the players a range of mid-level hand-coded skills, and raise the question of what effect removing those skills has on the structure of the fitness landscape and how that affects the search.

The autocorrelation graph (Fig. 10) and correlation length (Table 3) indicate that the fitness landscape for this problem offers only a limited amount of useful gradient information the search algorithm can use to guide the search. With an autocorrelation of ~0.1 for points on the random walk a single step apart and falling to zero for points just a few steps further apart, the correlation between next and near neighbours on this fitness landscape indicates that the structure of the fitness landscape is close to random and not as conducive to search as was the fitness landscape of experiment 1, thus increasing the difficulty of the problem.

Similar to experiment 1, the data presented in Table 3 show the mean fitness of the 100,000 individuals evaluated during the random walk is close to 1.0 (indicating no ball movement) and the variance very small, but in this case no individuals exhibiting goal-scoring behaviour were found during the random walk.

The information content graph for this experiment (Fig. 11) supports the autocorrelation data. Information stability is relatively low at 0.371, indicating a low difference in fitness among neighbouring points. With the autocorrelation data indicating a near random landscape, and information stability indicating a low fitness variation among neighbouring

points, there is almost no useful gradient information in the landscape to guide the search. *H(0.0)* is very small, indicating that the diversity of shapes on the landscape is very low. Similarly *M(0.0)* is extremely small, indicating that the landscape lacks any real degree of modality. Both values further indicate the lack of useful landscape data to guide the search. The data presented all indicate that the removal of a set of mid-level, hand-coded skills has changed the relative difficulty of the problem, and that this is a result of the structure and features of the fitness landscape being altered by the problem representation – what was a landscape reasonably rich in features that helped guide the search has become a relatively barren landscape lacking in information useful for search.
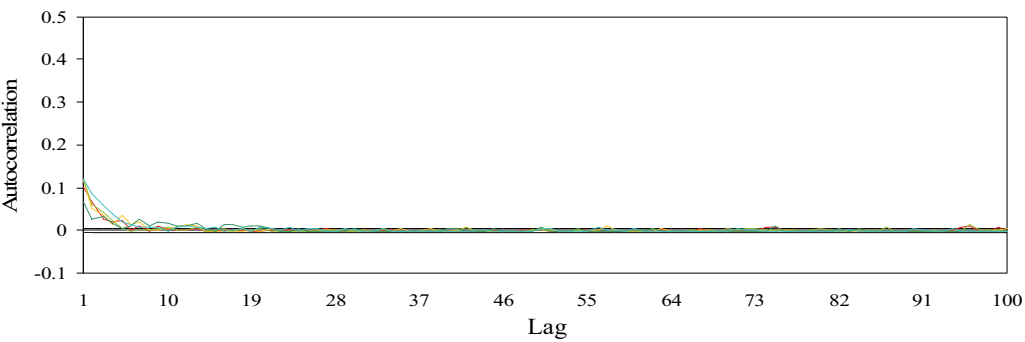
Fig. 10. Experiment 2: Autocorrelation
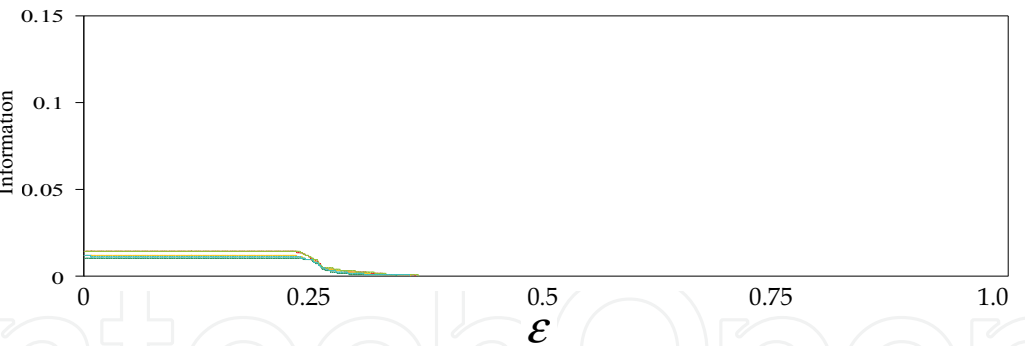
Fig. 11. Experiment 2: Information content

7.4.3 Experiment 3: Composite Fitness; All Skills; Default Action = Hunt Action 3

For experiment 3 the player is again given access to all available skills. The difference between experiment 3 and experiment 1 is that the default hunt action for experiment 3 is limited to a 90° turn in a randomly chosen direction.

The graphs of population average and best fitness (Fig. 12) indicate that while the evolutionary search was able to find individuals which scored multiple goals, the overall population hardly improved for the duration of the search. The percentage of the

population exhibiting ball-kicking or goal-scoring behaviour is low, as shown by the frequency distribution (Fig. 13). From the data presented in Table 4 it is evident that the random walk found very few individuals which exhibited goal- scoring behaviour – significantly fewer than in experiment 1.
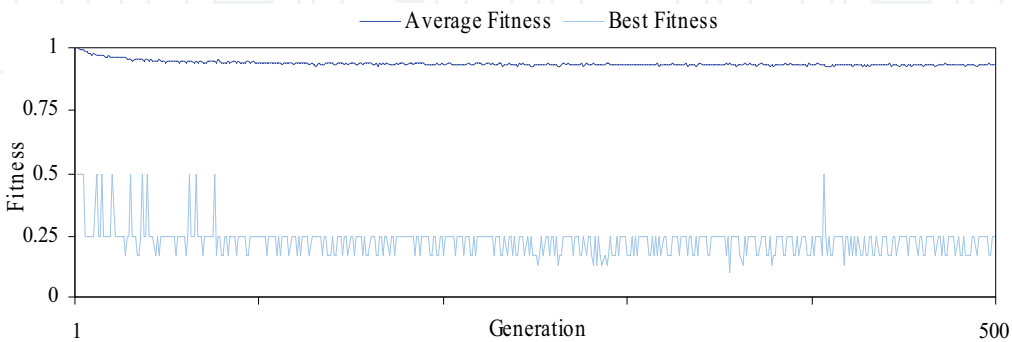

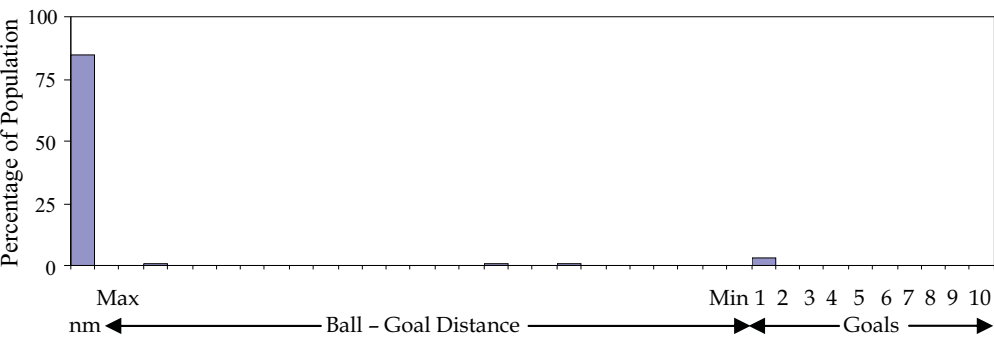Fig. 12. Experiment 3: Average and best fitness
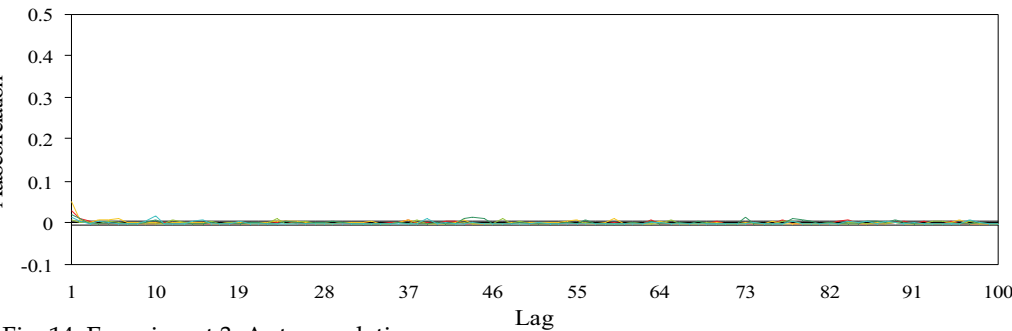

Fig. 13. Experiment 3: Ball movement and goals scored
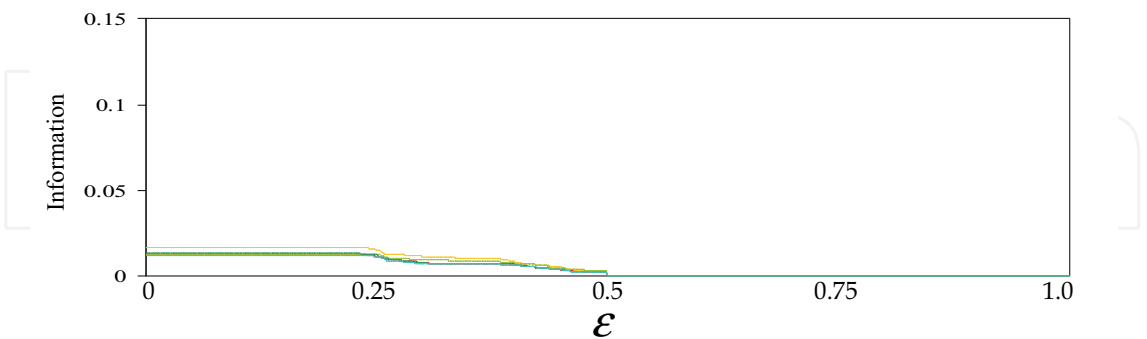

Fig. 14. Experiment 3: Autocorrelation

Fig. 15. Experiment 3: Information content

Random Walk Statistics (Average over 5 walks)								
Mean Fitness	0.99927							
Fitness Variance	0.00029							
Individual Fitness	No Movement	Ball Movement	Goals					
			1	2	3	4	5	>5
Number of Individuals	99801	168	31	1	0	0	0	0
Autocorrelation $r(1)$	0.02546							
Correlation Length	3							
ε	Information Content $H(\varepsilon)$				Partial Information Content $M(\varepsilon)$			
0.0	0.01344				0.00193			
0.1	0.01344				0.00193			
0.2	0.01344				0.00193			
0.3	0.00899				0.00120			
0.4	0.00703				0.00090			
0.5	0.00000				0.00000			

Table 4. Experiment 3: Random walk statistics

The autocorrelation and information content data shown in Fig. 14, Fig. 15 and Table 4 paint a similar picture – from the data it is clear that the fitness landscape lacks much of the gradient information evident in experiment 1, and is even closer to random than in experiment 2. Information stability at 0.5 indicates a reasonable difference in fitness among neighbouring points, but with an autocorrelation of 0.025 for points on the random walk a single step apart and a correlation length of only 3, this fitness landscape offers the searcher virtually no assistance. *H(0.0)* and *M(0.0)* are both extremely small, indicating that the diversity of shapes and the degree of modality on the landscape are very low, further indicating the lack of any useful landscape data to guide the search. This is entirely due to the removal of any sort of intelligence from the default hunt action.

7.4.4 Experiment 4: Goals-only Fitness; All Skills; Default Action = Hunt Action 1

In experiment 4 the player is given all available skills and the default action is hunt action 1. The fitness function used for this experiment is the goals-only fitness function, so the player is rewarded only for scoring goals.

The results for experiment 4 are very similar to those for experiment 1, with the major difference being the autocorrelation and information content data (Fig. 18, Fig. 19 and Table 5). The population average fitness is higher for experiment 4, but this is expected for a goals-only fitness function - since players are not rewarded for moving the ball close to the goal players not actually scoring goals are assigned the worst possible fitness of 1.0. The best fitness and fitness frequency graphs (Fig. 16 and Fig. 17) are almost identical (for goal-scoring behaviour in the case of the fitness frequency graph), indicating that the evolutionary search was almost not affected by the change in fitness evaluation.

The autocorrelation and information content graphs (Fig. 18 and Fig. 19) indicate that the fitness landscape has somewhat less gradient information useful for search, but still sufficient to facilitate a successful search. In fact, the data from Table 5 show that the random walk for experiment 4 found more players which scored goals than did the random walk for experiment 1. This is further indication that when the players are given the full complement of hand-coded skills the number of solutions in the search space increases, and so the difficulty of the problem and the importance of the fitness evaluation are both reduced significantly.

From Table 5 it can be seen that as for experiment 1, information stability is quite high at 0.882, indicating a high difference in fitness among neighbouring points and the existence of good gradient information on the landscape. $H(0.0)$ is much lower than for experiment 1, indicating that the diversity of shapes on the landscape is much lower.

Random Walk Statistics (Average over 5 walks)								
Mean Fitness	0.99672							
Fitness Variance	0.00189							
Individual Fitness	**No Movement**	**Ball Movement**	**Goals**					
			1	2	3	4	5	>5
Number of Individuals	99417	n/a	456	104	19	3	1	0
Autocorrelation *r(1)*	0.09497							
Correlation Length	20							
ε	**Information Content** $H(\varepsilon)$				**Partial Information Content** $M(\varepsilon)$			
0.0	0.03028				0.00520			
0.2	0.03028				0.00520			
0.4	0.03020				0.00519			
0.6	0.00868				0.00116			
0.8	0.00229				0.00025			
0.882	0.00000				0.00000			

Table 5. Experiment 4: Random walk statistics

Similarly *M(0.0)* is very small, and much smaller than for experiment 1, indicating that the degree of modality of the landscape is much lower. These are expected results for the goals-only fitness evaluation compared to the composite fitness function.
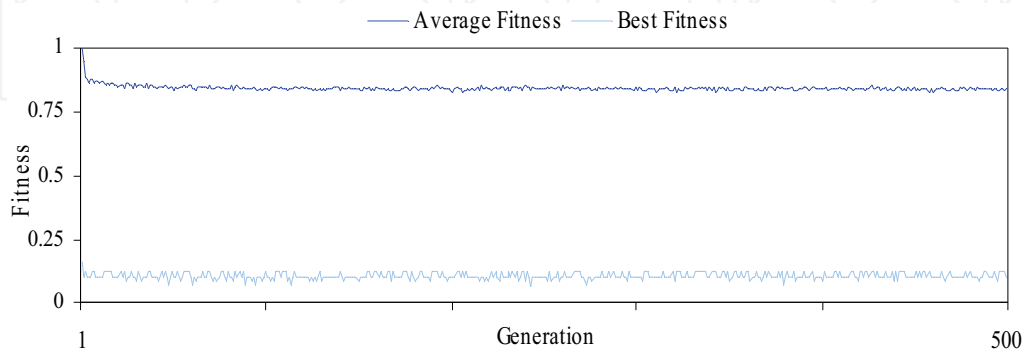

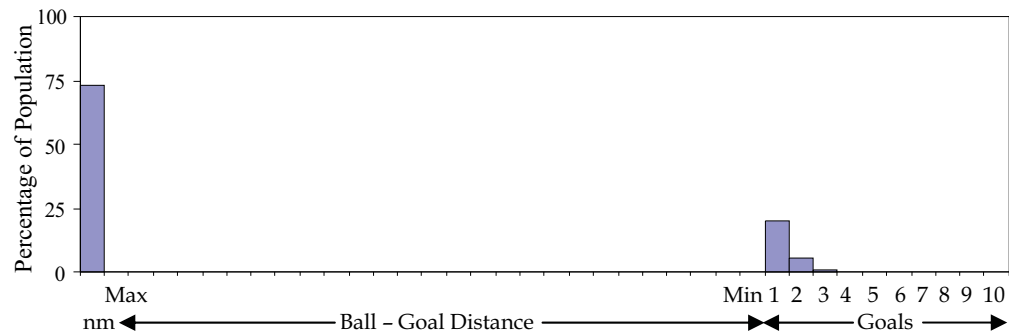Fig. 16. Experiment 4: Average and best fitness

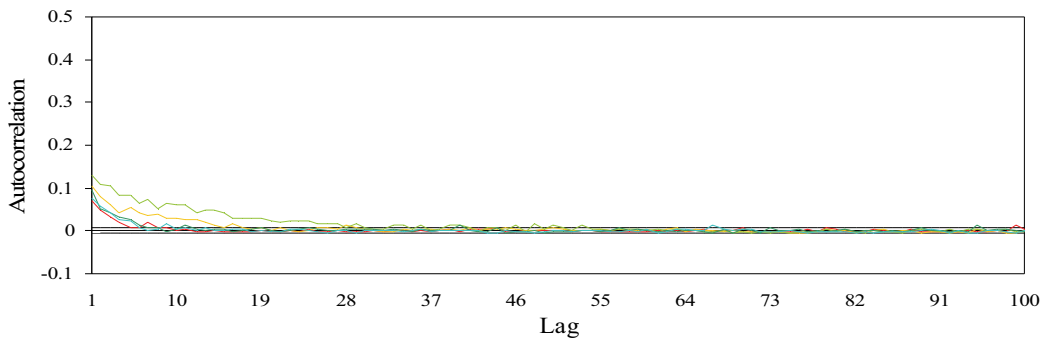Fig. 17. Experiment 4: Ball movement and goals scored

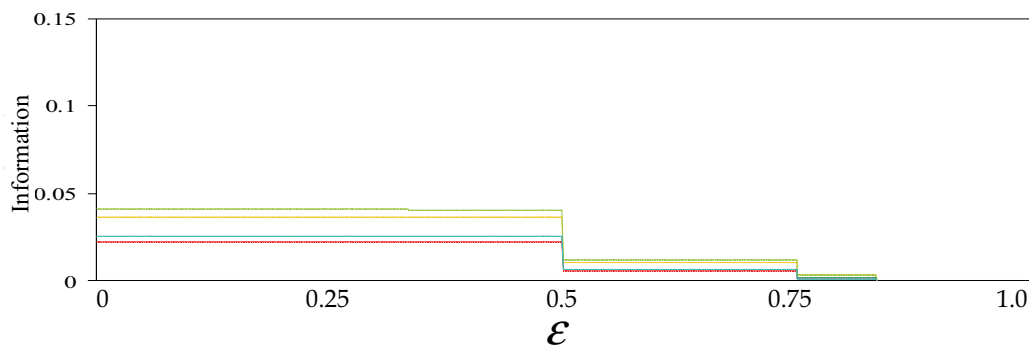Fig. 18. Experiment 4: Autocorrelation

Fig. 19. Experiment 4: Information content

8. Conclusions and Further Work

This work has presented a method for the analysis of the fitness landscape described by the problem of learning goal-scoring behaviour using a genetic algorithm. The method described uses landscape measures to examine features of the fitness landscape such as the degree of correlation between, or randomness of, points on the landscape, the modality of the landscape, and the ruggedness of the landscape. These landscape features are used to better understand the reasons for the difficulty of the problem, especially for evolutionary algorithms. The *autocorrelation* and *information content* measures are indicative of the ease with which the searcher will be able to identify the most productive areas of the landscape and in which direction (on the landscape) the search should proceed.

Also presented in this work is an analysis of the fitness landscape for the robot soccer problem using the landscape measures described, showing how the measures can be used to assess how varying different attributes (e.g. initial player skills, player default action and the fitness function) changes problem difficulty. The analysis indicates that as more human expertise and expert knowledge is injected into an evolutionary search algorithm via hand-coded innate skills, smart default actions and a composite fitness function to guide the search, the problem of learning goal-scoring behaviour for robot soccer becomes more solvable. In the case of the experiments performed for this work, the genetic algorithm is able to evolve individuals which display goal-scoring behaviour to the extent that they are able to consistently score multiple goals in the tests conducted. This is an expected result, and the focus of this work is on using the fitness landscape analyses to explain the results and the difficulty of the problem.

The fitness landscape analysis further indicates that as human expertise and expert knowledge is removed from the algorithm by restricting the hand-coded innate skills and smart default actions available to the players, or by using a simple goals-only fitness function, at some threshold the problem becomes intractable for the evolutionary algorithm. This suggests that while there may be gradient information in the fitness landscape, as the human expertise is reduced the density of solutions in the search space becomes very low, the "mountain ranges" in the landscape begin to become isolated from each other, and the landscape begins to appear as a flat plain, sparsely populated by individual peaks – so the problem begins to resemble a *needle-in-a-haystack* problem. In this case the genetic algorithm is not able to locate the sparsely distributed gradient information any way other than by

randomly sampling the search space and it performs little or no better than random search - confirmed by a small number of tests performed comparing genetic and random search. This is an indication that the injection of human expertise and expert knowledge acts like a magnifying glass to the searcher - as more expertise and knowledge is injected the fitness landscape features conducive to search are magnified, and as the expertise and knowledge is removed those landscape features become less discernible. As the granularity of the injected knowledge is decreased (e.g. a less rich set of skills) the modality of the landscape decreases and the gradients between peaks become smoother.

This is one of the underlying causes of the difficulty of the robot soccer problem for evolutionary algorithms, and the analysis presented in this work suggests that with a difficult problem such as robot soccer an evolutionary algorithm will only find a reasonable solution if one of:

- a rich skill set (placing the initial population closer to the desired solution)
- a composite fitness function (providing a solution recipe)

is present - if both of those components are absent the problem becomes very difficult for evolutionary algorithms.

Varying player skills changes the search space of the problem – a different set of players is being searched for each skillset. It is therefore not surprising that changing the innate skills of the players has a significant effect on the outcome of the search – searching the set of players which have essentially been pre-coded to exhibit good soccer-playing skills is almost guaranteed to find more players exhibiting better goal-scoring behaviour than searching the set of players which have no pre-coded soccer-playing skills. This is akin to searching for good goal-scoring behaviour in an assembled group of premier league soccer players, and then searching an assembled group of randomly selected people off the street – every now and then a person from the street will score a goal, but the premier league players will do it more often and more consistently.

The default player action was shown to be a very significant determinant of performance for the robot soccer problem. This was also seen in the results presented by Luke (1998). For this work the default action was almost always invoked when the ball could not be seen. The importance of the default action tends to suggest that while some basic skills such as kicking, dribbling, perhaps even passing, can be somewhat readily learned, learning subtle tactics and strategies is difficult.

Similarly, it was shown through experiments that compared the effectiveness of a simple goals-only fitness function against that of a composite fitness function that a composite fitness function can better guide the search. A well-designed composite fitness function can effectively act as a recipe for solving a problem. A great deal of human expertise and expert knowledge can be injected into a composite fitness function, and in effect the problem can virtually be solved by the fitness function before the algorithm begins the search.

Further work to ascertain the best balance between the two components identified as being necessary for successful evolutionary search (a rich skill set or a composite fitness function) would be useful, as would work to determine if there is a limit in the level of initial skills at which a difficult problem becomes intractable.

Within the evolutionary computation community there are several definitions and variations of the fitness landscape traversed by an evolutionary algorithm. This work proposed a definition of the fitness landscape described by the combination of the genetic

algorithm and the problem being investigated, but further work needs to be done to develop a consistent definition of the fitness landscape, or landscapes, described by the operation of an evolutionary algorithm. With a consistent landscape definition, more work can be done to develop measures that will aid researchers in tuning algorithms and search methods based on landscape analysis.

The fitness landscape definition used for this work is based on the assumption that the combination of the genetic operators implemented defines the neighbourhood relation of the landscape, and that the fitness function defines the height of the landscape at each point. Given this definition the shape, ruggedness, and indeed the searchability of the landscape, will be affected by changes to any of the genetic operators and the fitness function. This suggests that it would be advantageous to experiment with various combinations of those parameters in order to determine if a search might be successful or what combination would improve the chance of a successful search, prior to launching into an exhaustive search. A useful avenue of further work is to develop a framework for this prior analysis so that a description of the means by which the analysis should be conducted can be determined (for example, the number and size of random walks conducted over the landscape in order to calculate the landscape measures), as well as quantifying the desired values for the landscape measures.

9. References

Altenberg, L. (1995). The Schema Theorem and Price's Theorem. In: *Foundations of Genetic Algorithms 3*, D. Whitley & M. Vose, (Ed.), pp. 23-49, Darrell Whitley and Michael Vose, San Francisco CA.

Borenstein, Y. & Poli, R. (2005a). Information Landscapes, *Proceedings of the 2005 Conference on Genetic and Evolutionary Computation*, pp. 1551-1522, Washington DC, June 2005, The ACM Press, NY.

Borenstein, Y. & Poli, R. (2005b). Information Landscapes and Problem Hardness, *Proceedings of the 2005 Conference on Genetic and Evolutionary Computation*, pp. 1425-1431, Washington DC, June 2005, The ACM Press, NY.

Borenstein, Y. & Poli, R. (2005c). Information Landscapes and the Analysis of Search, *Proceedings of the 2005 Conference on Genetic and Evolutionary Computation*, pp. 1287-1294, Washington DC, June 2005, The ACM Press, NY.

Chaitin, G.J. (1987). *Information, Randomness & Incompleteness: Papers on Algorithmic Information Theory*, World Scientific, ISBN 9971-50-479-0, Singapore.

Culberson, J.C. (1994). Mutation-Crossover Isomorphisms and the Construction of Discriminating Functions. *Evolutionary Computation*, Vol. 2, No. 3, 1994, pp. 279-311.

De Jong, K.A.; Potter, M.A. & Spears, W.M. (1997). Using Problem Generators to Explore the Effects of Epistasis, *Proceedings of the Seventh International Conference on Genetic Algorithms*, pp. 338-345, East Lansing MI, July 1997, T. Bäck, (Ed.), Morgan Kaufmann, San Francisco CA.

Edwards, S.F. & Anderson. P.W. (1975). Theory of Spin Glasses. *Journal of Physics F: Metal Physics*, Issue 5, May 1975, pp. 965-974.

Frauenfelder, H.; Bishop, A. R.; Garcia, A. & Perelson, A., eds. (1997). Landscape Concepts in Physics and Biology. *Special Issue of Physica D*, Vol. 107, 1997, pp. 2-4, Elsevier Science, Amsterdam Holland.

Goldberg, D.; Korb, B. & Deb, K. (1989). Messy Genetic Algorithms: Motivation, Analysis, and First Results. *Complex Systems*, Vol. 3, No. 5, 1989, pp. 493-530.

Heckendorn, R.B.; Rana, S. & Whitley, D.L. (1999). Test Function Generators as Embedded Landscapes, In: *Foundations of Genetic Algorithms 5*, W. Banzhaf & C. Reeves, (Ed.), pp. 183-198, Morgan Kaufmann, ISBN 1558-60-559-2, San Francisco CA.

Holland, J. (1975). *Adaptation in Natural and Artificial Systems.* The University of Michigan Press, Ann Arbor: MI.

Hordijk, W. (1996). A Measure of Landscapes, *Evolutionary Computation*, Vol. 4, No. 4, 1996, pp. 335-360.

Jang, J.-S.; Sun, C.-T. & Mizutani, E. (1997). *Neuro-Fuzzy and Soft Computing*, Prentice Hall, ISBN 0-13-261066-3, Upper Saddle River NJ.

Jones, T. (1995a). One Operator, One Landscape, *Technical Report 95-02-025*, Santa Fe Institute, Santa Fe NM.

Jones, T.C. (1995b). Evolutionary Algorithms, Fitness Landscapes and Search, PhD Thesis, 1995, University of New Mexico, Albuquerque NM.

Jones, T. & Forrest, S. (1995a). Genetic Algorithms and Heuristic Search, *Technical Report 95-02-021*, Santa Fe Institute, Santa Fe NM.

Jones, T. & Forrest, S. (1995b) Fitness Distance Correlation as a Measure of Problem Difficulty for Genetic Algorithms, *Proceedings of the Sixth International Conference on Genetic Algorithms*, pp. 184-192, ISBN 1-55860-370-0, Pittsburgh PA, July 1995, L. J. Eshelman, (Ed.), Morgan Kaufmann, San Francisco CA.

Kauffman, S.A. (1989). Adaptation on Rugged Fitness Landscapes, In: *Lectures in the Sciences of Complexity*, D. Stein, (Ed.), pp. 527-618, Addison-Wesley, ISBN 1-201-51015-4, Redwood City CA.

Kauffman, S.A. & Levin, S. (1987). Towards a General Theory of Adaptive Walks on Rugged Landscapes, *Journal of Theoretical Biology*, Vol. 128, No. 1, September 1987, pp. 11-45.

Kitano, H.; Asada, M.; Kuniyoshi, Y.; Noda, I. & Osawa, E. (1995). Robocup: The Robot World Cup Initiative, *Working Notes of the 1995 IJCAI Workshop on Entertainment and AI/Alife*, pp. 19-24, Montreal Canada, August 1995.

Langdon, W.B. & Poli, R. (1998a). Why "Building Blocks" Don't Work on Parity Problems, *Technical Report CSRP-98-17*, School of Computer Science, University of Birmingham.

Langdon, W.B. & Poli, R. (1998b). Why Ants are Hard, *Genetic Programming 1998: Proceedings of the Third Annual Conference*, pp. 193-201, Madison WI, July 1998, Koza, J.R.; Banzhaf, W.; Chellapilla, K.; Deb, K.; Dorigo, M.; Fogel, D.B.; Garzon, M.H.; Goldberg, D.E.; Iba, H. & Riolo, R.L. (Eds.), Morgan Kaufmann, San Francisco CA.

Langdon, W.B. & Poli, R. (2002). *Foundations of Genetic Programming* , Springer, ISBN 978-3540424512.

Lima, P.; Custódio, L.; Akin, L.; Jacoff, A.; Kraezschmar, G.; Ng, B.K.; Obst, O.; Röfer, T.; Takahashi, Y. & Zhou, C. (2005). RoboCup 2004 Competitions and Symposium: A Small Kick for Robots, a Giant Score for Science. *AI Magazine* 26(2), 2005, pp. 36-61.

Lipsitch, M. (1991). Adaptation on Rugged Landscapes Generated by Iterated Local Interactions of Neighboring Genes, *Proceedings of the Fourth International Conference on Genetic Algorithms*, pp. 128-135, San Diego CA, July 1991, Morgan Kaufmann, San Francisco CA.

Luke, S. (1998). Genetic Programming Produced Competitive Soccer Softbot Teams for RoboCup97, *Genetic Programming 1998: Proceedings of the Third Annual Conference*, Madison WI, July 1998, Koza, J.R.; Banzhaf, W.; Chellapilla, K.; Deb, K.; Dorigo, M.; Fogel, D.B.; Garzon, M.H.; Goldberg, D.E.; Iba, H. & Riolo, R.L. (Eds.), Morgan Kaufmann, San Francisco CA.

Lush, J.L. (1935). Progeny Test and Individual Performance as Indicators of an Animal's Breeding Value. *Journal of Dairy Science*, Vol. 18, 1935, pp. 1-19.

Manderick, B., de Weger, M. & Spiessens, P. (1991). The Genetic Algorithm and the Structure of the Fitness Landscape, *Proceedings of the Fourth International Conference on Genetic Algorithms*, pp. 143-150, San Diego CA, July 1991, Morgan Kaufmann, San Francisco CA.

Merz, P. & B. Freisleben, B. (1999). Fitness Landscapes and Memetic Algorithm Design. In: *New Ideas in Optimization*, Corne, D., Dorigo, M. & Glover, F. (Eds.), pp. 245-260, McGraw-Hill, ISBN 978-0077095062, London.

Moraglio, A. & Poli, R. (2004). Topological Interpretation of Crossover, *Proceeding of the 2004 Genetic and Evolutionary Computation Conference*, Part I, pp. 1377-1388, Seattle WA, June 2004, Deb, K., Poli, R., Banzhaf, W., Beyer, H.-G., Burke,E.K., Darwen, P.J., Dasgupta, D., Floreano, D., Foster, J.A., Harman, M., Holland, O., Lanzi, P.L., Spector, L., Tettamanzi, A., Thierens, D., Tyrrell, A.M. (Eds.), Springer.

Reeves, C.R. (1999). Landscapes, Operators and Heuristic Search. *Annals of Operational Research*, Vol. 86, 1999, pp. 473-490.

Reidys, C.M. and P.F. Stadler. (2002). Combinatorial Landscapes. *Society for Industrial and Applied Methematics, SIAM Review*, Vol. 44, No. 1, 2002, pp. 3-54.

Riedmiller, M.; Gabel, T.; Knabe, J. & Strasdat, H. (2005). Brainstormers 2D - Team Description 2005. In: *RoboCup 2005: Robot Soccer World Cup IX.*, Bredenfeld, A.; Jacoff, A.; Noda, I. & Takahashi, Y. (Eds.), Springer, Berlin.

Right, A.H., Row, J.E. & Neil, J.R. (2002). Analysis of the Simple Genetic Algorithm on the Single-peak and Double-peak Landscapes, *Proceedings of the 2002 Congress on Evolutionary Computation*, pp. 214-219, Hawaii, May 2002, IEEE Computer Society, Washington DC.

Riley, J. (2003). The SimpleSoccer Machine Learning Environment, *Proceedings of the First Asia-Pacific Workshop on Genetic Programming*, pp. 24-30, Canberra, Australia, December 2003, Cho, S-B.; Nguen, H.X. & Shan, Y. (Eds.).

Riley, J. (2005). Evolving Fuzzy Rules for Goal-Scoring Behaviour in a Robot Soccer Environment, *PhD Thesis*, RMIT University: Melbourne, Australia.

Shannon, C.E. (1948). A Mathematical Theory of Communication. *Bell System Technical Journal*, Vol. 27, 1948, pp. 379-423; 623-656.

Sherrington, D., & S. Kirkpatrick, S. (1975). Solvable Model of a Spin Glass. *Physical Review Letters*, Vol. 35, 1975, pp. 1792-1796.

Skellett, B., Cairns, B., Geard, N., Tonkes, B. & Wiles, J. (2005). Maximally Rugged NK Landscapes Contain the Highest Peaks, *Proceedings of the 2005 Genetic and Evolutionary Computation Conference*, pp. 579-584, Washington DC, June 2005, Beyer, H.-G., O'Reilly, U.-M., Arnold, D.V., Banzhaf, W., Blum, C., Bonabeau, E.W., Cantu-Paz, E., Dasgupta, D., Deb, K., Foster, J.A., de Jong, E.D., Lipson, H., Llora, X., Mancoridis, S., Pelikan, M., Raidl, G.R., Soule, T., Tyrrell, A.M., Watson, J.-P. & Zitzler, E., (Eds.), ACM Press.

Smith, R.E. & J.E. Smith, J.E. (2001). New Methods for Tunable, Random Landscapes. In: *Foundations of Genetic Algorithms 6*, Morgan Kaufmann, ISBN 978-1558607347, San Francisco CA.

Smith, T., Husbands, P., Layzell, P. & O'Shea, M. (2002). Fitness Landscapes and Evolvability. *Evolutionary Computation*, Vol. 10, No. 1, 2002, pp. 1-34.

Stadler, P. (1996). Landscapes and Their Correlation Functions. *Journal of Mathematical Chemistry*, Vol. 20, 1996, pp. 1-45.

Stone, P. (1998). Layered Learning in Multiagent Systems, *PhD Thesis*, Carnegie Mellon University, Pittsburgh PA.

Stone, P. & Sutton, R. (2001). Scaling Reinforcement Learning Toward RoboCup Soccer, *Proceedings of the Eighteenth International Conference on Machine Learning*, Williamstown MA, July 2001, Brodley, C.E. & Danyluk, A.P. (Eds.), Morgan Kaufmann, San Francisco CA.

Tanaka, F. & S. F. Edwards, S.F. (1980). Analytic Theoeries of the Ground State Properties of a Spin Glass. I. Ising Spin Glass. *Journal of Physics F: Metal. Physics*, Vol. 10, 1980 pp. 2769-2778.

Vassilev, V.K. (1997). Information Analysis of Fitness Landscapes, *Proceedings of the Fourth European Conference on Artificial Life*, pp. 116-124, Brighton, UK, July 1997, Husbands, P. & Harvey, I. (Eds.), The MIT Press.

Vassilev, V., T. Fogarty, and J. Miller. (2000). Information Characteristics and the Structure of Landscapes. *Evolutionary Computation*, Vol. 8, No. 1, 2000, pp.31-60.

Weinberger, E. (1990a). Fourier and Taylor Series on Fitness Landscapes. *Biological Cybernetics*, Vol. 65, 1990, pp. 321-330.

Weinberger, E. (1990b). Correlated and Uncorrelated Fitness Landscapes and How to Tell the Difference. *Biological Cybernetics*, Vol. 63, 1990, pp. 325-336.

Weinberger, E. (1991a). Measuring Correlations in Energy Landscapes and Why it Matters. In: *Information Dynamics*, Atmanspacher, H. & Scheingraber, H. (Eds.), Plenum Press, New York NY.

Weinberger, E. (1991b). Local Properties of Kauffman's N-K model: A Tunably Rugged Energy Landscape. *Physical Review A*, Vol. 44, No. 10, 1991, pp. 6399-6413.

Wright, S. (1932). The Roles of Mutation, Inbreeding, Crossbreeding and Selection in Evolution, *Proceedings of the Sixth International Congress on Genetics*, pp. 356-366, Ithaca NY, August 1932, Jones, D.F., (Ed.), Brooklyn Botanic Garden NY.

Zadeh, L. (1965). Fuzzy Sets. *Journal of Information and Control*, vol. 8, 1965, pp. 338-353.

Robotic Soccer

Edited by Pedro Lima

ISBN 978-3-902613-21-9

Hard cover, 598 pages

Publisher I-Tech Education and Publishing

Published online 01, December, 2007

Published in print edition December, 2007

Many papers in the book concern advanced research on (multi-)robot subsystems, naturally motivated by the challenges posed by robot soccer, but certainly applicable to other domains: reasoning, multi-criteria decision-making, behavior and team coordination, cooperative perception, localization, mobility systems (namely omni-directional wheeled motion, as well as quadruped and biped locomotion, all strongly developed within RoboCup), and even a couple of papers on a topic apparently solved before Soccer Robotics - color segmentation - but for which several new algorithms were introduced since the mid-nineties by researchers on the field, to solve dynamic illumination and fast color segmentation problems, among others. This book is certainly a small sample of the research activity on Soccer Robotics going on around the globe as you read it, but it surely covers a good deal of what has been done in the field recently, and as such it works as a valuable source for researchers interested in the involved subjects, whether they are currently "soccer roboticists" or not.

How to reference

In order to correctly reference this scholarly work, feel free to copy and paste the following:

Jeff Riley and Vic Ciesielski (2007). Analysing the Difficulty of Learning Goal-Scoring Behaviour for Robot Soccer, Robotic Soccer, Pedro Lima (Ed.), ISBN: 978-3-902613-21-9, InTech, Available from:
http://www.intechopen.com/books/robotic_soccer/analysing_the_difficulty_of_learning_goal-
scoring_behaviour_for_robot_soccer

INTECH
open science | open minds