Group Coordination in Multi-Agent Systems: Is it a necessity or an overhead?

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ABSTRACT

Traditionally, defence analysts adopted what are known as Lanchester Equations to model and theorise about combat attrition, such as ELAN, JANUS, CASTFORME, ModSAF and OneSAF. With the recognition of the limitations of Lanchester Equations, the idea that combat can be modelled as a complex adaptive system has widely been accepted recently. This has led to the emergence of a number of multi-agent combat systems, or agent-based distillation systems (ABDs), such as ISAAC (Ilachinski 2000), EINSTein (Ilachinski 1999; Ilachinski 2004), MANA (Lauren and Stephen 2002), BactoWars (White 2004) and CROCADILE (Barlow and Easton 2002). These ABDs have facilitated the analysis and understanding of combat. However, these ABDs adopted the reactive agent architecture, where agents only react to their environment; (i.e. there is no coordination mechanism among the agents). The lack of planning and coordination limited the capacity of these ABDs to study group behaviours in combat.

The concept of fitness landscape was first introduced by Wright (1932) in biology to represent adaptive evolution as the population navigates on a mountainous surface where the height of a point specifies how well the corresponding organism is adapted to its environment. The structure and property of the fitness landscape play a major role in determining the success of the search method and the degree of problem difficulty (Horn and Goldberg 1999; Kallel et al. 2001; Teo and Abbass 2003; Vassilev and Miller 2000; Stadler 2002). In this paper we analyse the fitness landscapes generated by ABD with coordination mechanism and compare those with those from ABD without coordination mechanism to identify if group coordination is a necessity in agent-based combat modelling.

We adopt version II of WISDOM (the Warfare Intelligent System for Dynamic Optimisation of Missions) (Yang et al. 2005; Yang et al. 2006; Yang et al. 2006b) as a simulation platform. It is built on a novel multi-agent architecture, called NCMAA (Network Centric Multi-Agent Architecture) (Yang et al. 2005) which allows the analyst to easily model group coordination in multi-agent system. Three scenarios: Goal Oriented (GOL), Aggressive (AGG) and Defensive (DEF) are created as in (Yang et al. 2006a). The configurations of the environment, initial position and the number of agents are the same as in (Yang et al. 2006a). Each scenario involves repeating the simulation 100 repeats, each for 500 time steps. The same objective function and fitness function are adopted as in (Yang et al. 2006a). And ten different random walks are taken, each of length 10,000 solutions using two fitness functions (average and normalized). Each stochastic neighbourhood in the search space was obtained by adding a random number drawn from a Gaussian distribution with zero mean and 0.1 standard deviation to each variable in the genotype. If the value of any personality is out of the range $[-1, 1]$, the value is truncated. The generated fitness landscape associated with each scenario is then analysed by using information analysis approach proposed by Vassilev, Fogarty, and Miller (2000) to characterise the search space. The results are compared with those from WISDOM-I which does not have a coordination mechanism (Yang, Abbass, and Sarker 2006a). The difference conforms that modelling group coordination is crucial in ABDs.

Although the findings are based on an analysis in the defence domain, it can also be extended and applied into other domains. For example, in water resource management, if each end user is modelled as an agent, coordination among agents in the same state, same city or same suburb should be modelled and interactions between states, cities and suburbs can then be studied.

1 INTRODUCTION

Simulation has been used to study combat for a very long time with both human-based and computer-based systems. Although human-based simulation is more realistic, it is extremely expensive and does not allow defence analysts to investigate all aspects of combat. Recently, complex adaptive systems (CAS) and multi-agent systems (MAS) have widely been accepted as two valuable tools in military analysis. The idea that combat can be modelled as a CAS has widely been accepted and adopted in the field. This has led to the emergence of a number of multi-agent combat systems, or agent-based distillation systems (ABDs), such as ISAAC (Ilachinski 2000), EINSTein (Ilachinski 1999; Ilachinski 2004), MANA (Lauren and Stephen 2002), BactoWars (White 2004) and CROCADILE (Barlow and Easton 2002). These ABDs have facilitated the analysis and understanding of combat. However, these ABDs adopted the reactive agent architecture, where agents only react to their environment; (i.e. there is no coordination mechanism among the agents). The lack of planning and coordination limited the capacity of these ABDs to study group behaviours in combat.

In this paper, we adopt version II of WISDOM (the Warfare Intelligent System for Dynamic Optimisation of Missions) (WISDOM-II) (Yang et al. 2005; Yang et al. 2006; Yang et al. 2006b) as a simulation platform. three scenarios are created and the fitness landscape associated with each scenario is analysed to characterise the search space. The results is then compared with those in (Yang et al. 2006a), which are generated from version I of WISDOM, which mimics MANA where there is not group coordination. The difference shows that the results obtained from ABDs where there is no coordination among agents can be misleading and cannot be generalized. In the rest of the paper, we first briefly review the basic concepts and methodologies of fitness landscape analysis adopted in this study followed by a description of the scenarios and experiments, then the analysis of the results. Finally conclusions are drawn.

2 METHODOLOGY - FITNESS LANDSCAPE ANALYSIS

The concept of fitness landscape was first introduced by Wright (1932) (Wright 1932) in biology to represent adaptive evolution as the population navigates on a mountainous surface where the height of a point specifies how well the corresponding organism is adapted to its environment. The landscape is usually perceived as mountains with a number of local peaks, valleys, and flat areas representing solutions with equal fitness values. The fitness landscape is rugged when there are many local peaks surrounded by deep valleys. Vassilev (Vassilev et al. 2000) proposed an approach to analyse fitness landscape, where a fitness landscape is picturised as a set of basic objects each of which is represented by a point and the possible outcomes that may be produced by the corresponding evolutionary operators at that point. Four measures (Vassilev et al. 2000) were proposed for characterizing the structure of a fitness landscape $\mathcal{L}$ through analyzing the time series of fitness values $\{f_t\}_{t=1}^n$, which are real numbers taken from the interval $\mathcal{I}$ and obtained by a random walk on this fitness landscape : Information content $H(\varepsilon)$, Partial information content $M(\varepsilon)$, Information stability (ε^*) and density-basin information $h(\varepsilon)$.

Information content ($H(\epsilon = 0)$) approximates the variety of shapes in the fitness landscape, thus it evaluates the ruggedness of the landscape path with respect to the flat area in the path. The modality encountered during a random walk on a fitness landscape can be characterized by partial information content ($M(\epsilon = 0)$). When the partial information content is zero, there is no slope in the path and the landscape is flat. If the partial information content is one, the landscape path is maximally multi-modal. The information stability (ϵ^*) is defined as the smallest value of ε for which the fitness landscape becomes flat. The higher the information stability is, the flatter the fitness landscape. The density-basin information evaluates the density and the isolation of the peaks in the landscape. Thus it is an indication of the variety of flat and smooth areas of the fitness landscape. Higher density-basin information means a number of peaks are within a small area while lower density-basin information means isolated optima.

3 EXPERIMENTAL SETUP

In Yang, Abbass, and Sarker (2006a), we identified three classes of scenarios: Goal Oriented (GOL) and Balanced (BAL), Defensive (DEF) and Coward (COW), and Aggressive (AGG) and Very Aggressive (VAG) based on the characteristics of the fitness landscape. In this paper, three strategies, one from each group, (see Table 1) are chosen for the red team while the strategy (a vector of personalities) of the blue team is allowed to vary.

Table 1. Strategies for the red team used in the experiments

Scenario	Friend	Enemy	Goal
Goal Oriented (GOL)	Neutral	Neutral	Target
Aggressive (AGG)	Neutral	Attack	Neutral
Defensive (DEF)	Cluster	Neutral	Neutral

In order to identify the role of group coordination, all unique features of WISDOM-II are turned off except two decision making mechanisms: "strategic"

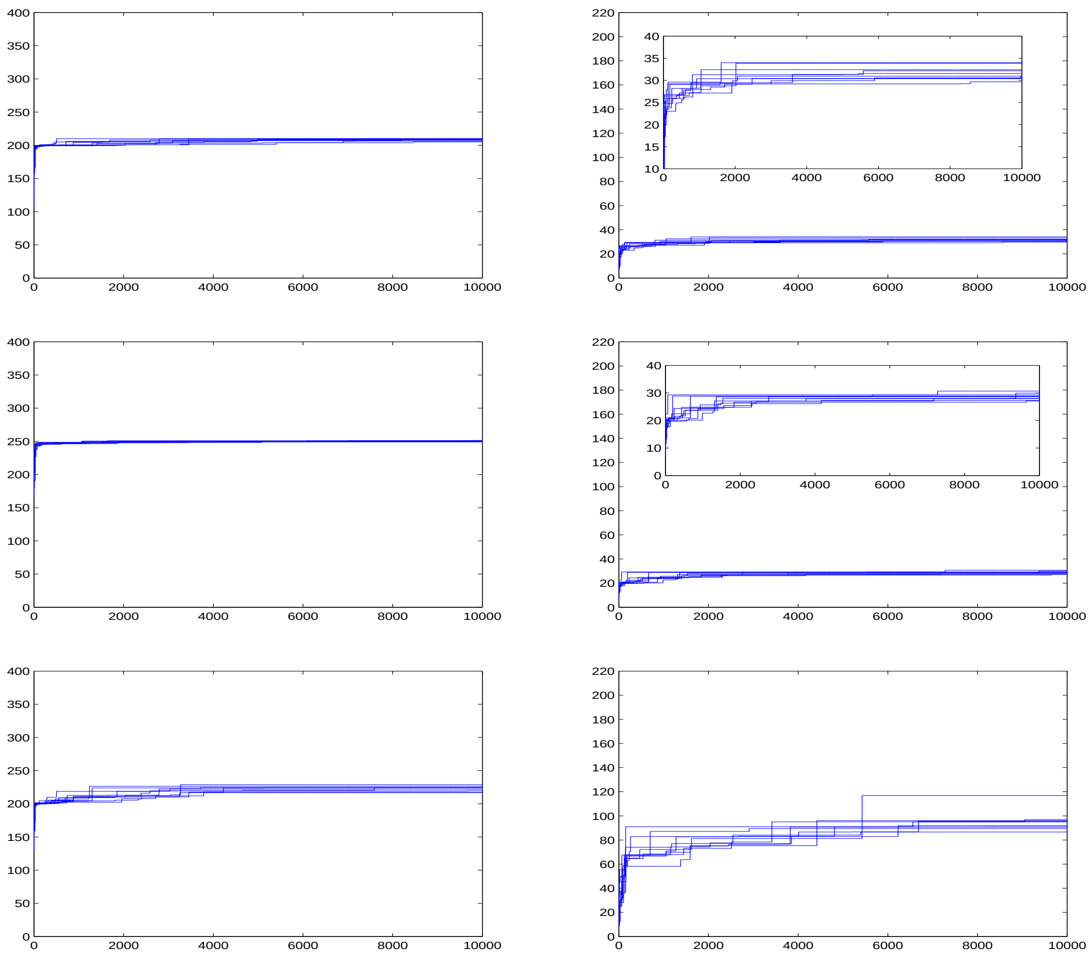

Figure 1. The best solution found over time by using the average fitness (on left) and normalized fitness (on right) for random walk. The order for top to bottom is: GOL, AGG, and DEF

which guides the movement of the whole group, and "tactical" which guides the movement of each individual. In WISDOM-II, the decision variables are represented with a vector of 18 real numbers representing different characteristics of personalities (Yang et al. 2005). All personalities (decision variables) are real numbers in the range of $[-1, 1]$.

The configurations of the environment, initial position and the number of agents are the same as in (Yang et al. 2006a). For each scenario, ten different random walks are taken, each of length 10,000 solutions using two fitness functions (average and normalized). Each stochastic neighbourhood in the search space was obtained by adding a random number drawn from a Gaussian distribution with zero mean and 0.1 standard deviation to each variable in the genotype. If the value of any personality is out of the range $[-1, 1]$, the value is truncated. A single evaluation of the game involves repeating the simulation 100 repeats, each for 500 time steps. The same fitness functions (Equation 1 and 2) are adopted as in (Yang et al. 2006a). F_2 has a strong bias for stable solutions.

$$F_1 = \frac{\sum(InitHealth_b + Dmg_r - Dmg_b)}{100} \quad (1)$$

$$F_2 = \frac{F_1}{1 + standard\ deviation} \quad (2)$$

4 RESULTS

Figure 1 depicts the time series of the best solution found so far for random walk by using the average fitness and the normalized average fitness. According to the average fitness, one may see that the best solution found in the AGG scenario is higher than that in the GOL scenario or DEF scenario. As discussed in (Yang et al. 2006a), in the scenario when the red team would always like to attack its enemy, it may lose coordination among the red agents, for example, in the AGG scenario. Therefore the blue team may easily damage the red team. However, the result from WISDOM-II shows the normalized average fitness

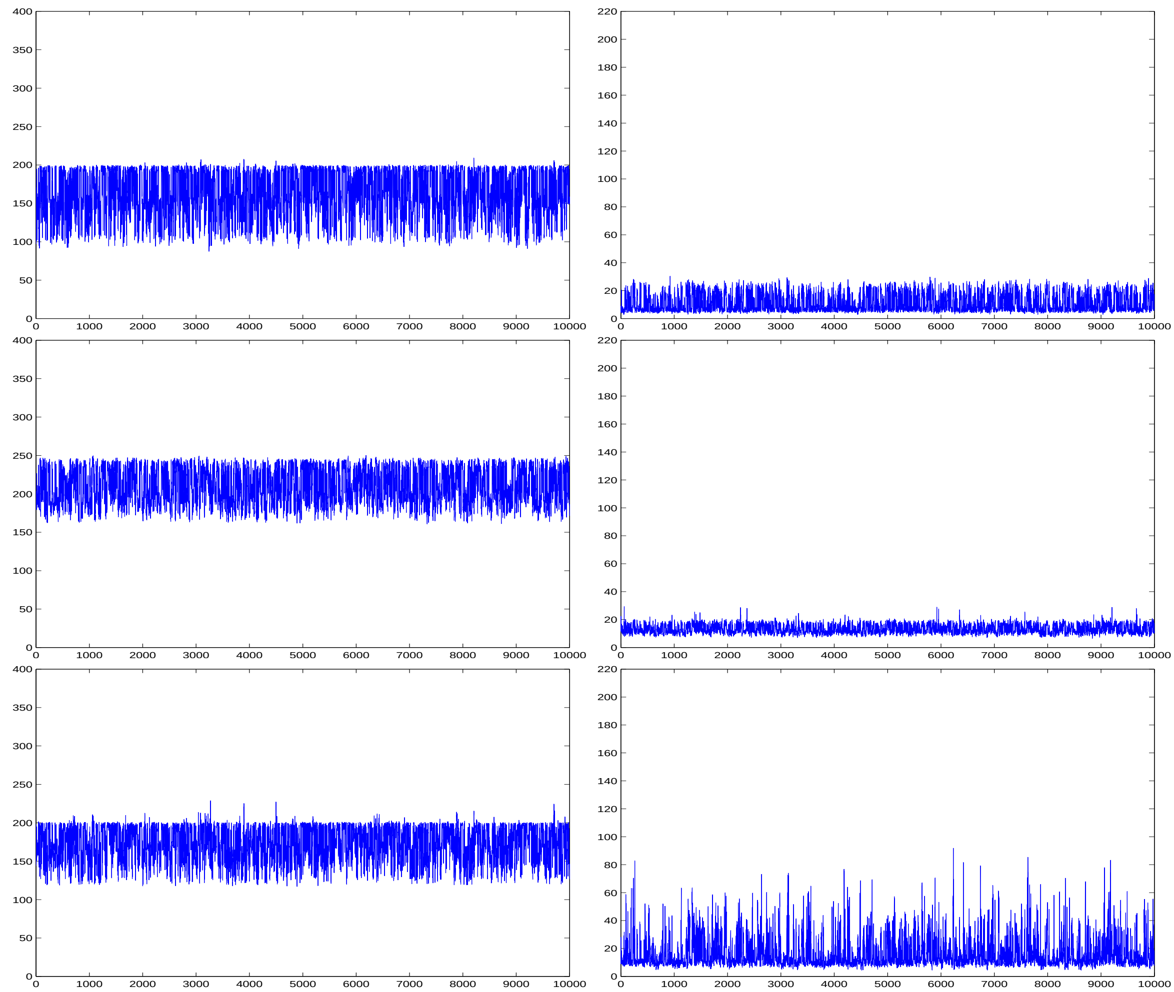

Figure 2. The fitness value over time for random walk using average fitness (on left) and normalized average fitness (on right). The order from top down is: GOL, AGG, DEF, respectively

value of the best solution found in the DEF scenario is the highest among these three scenarios. The very low value of the normalized average fitness in the GOL and AGG scenario suggests that the searching process in both scenarios involves a large amount of variations. The stochasticity plays a critical role in both GOL and AGG scenarios.

Figure 1 also shows that the improvement mostly occurs at the start of the search stage for both average fitness and normalized average fitness. The improvement almost stops for both AGG and GOL scenarios after 2000 steps. However better solutions can still be found in the DEF scenario after 2000 steps, especially when using the normalized average fitness.

When compared with the corresponding table in (Yang et al. 2006a), similar patterns can be observed except that the normalized average fitness is lower in WISDOM-II than in WISDOM-I for the GOL scenario. This implies that the influence of the stochasticity is higher in WISDOM-II than in WISDOM-I.

Figure 2 presents some representative examples of the time series of fitness value for random walk. Obviously the fitness landscape is quite rugged for both average fitness and normalized average fitness. In this chapter, a good solution is defined as that the blue damage is less than the red damage. That is, the fitness value of the average fitness is larger than 200. It is very hard to find a good solution for both GOL and DEF scenario. Only few good solutions can be found and are highly separated by a number of bad solutions. For the AGG scenario, lots of solutions found are good solutions.

The low fitness value of the normalized average fitness in all three scenarios in Figure 2 suggests that all the solutions found in all three scenarios, especially in the GOL and DEF scenario, are unstable. This is consistent with the above findings about the role of the stochasticity.

When compared with the corresponding figure in (Yang et al. 2006a), one may easily see the difference. The signal-worst solutions, as defined in (Yang et al.

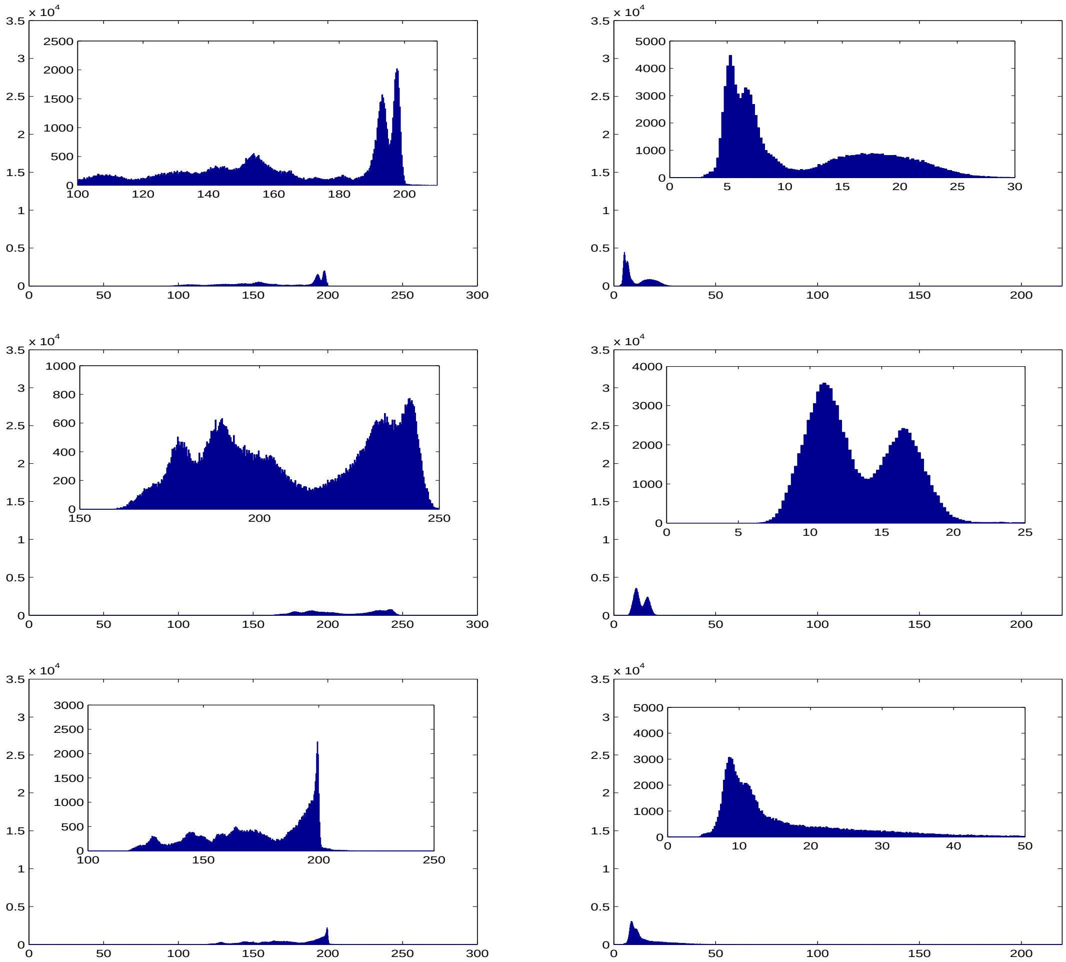

Figure 3. Histogram for random walk by using the average fitness (on left) and normalized fitness (on right). The order for top to bottom is: GOL, AGG, and DEF

2006a), are lower (and therefore better) in both average fitness and normalized average fitness for all three scenarios in WISDOM-II than in WISDOM-I. This is because WISDOM-II has a strategic decision making mechanism to coordinate the behaviours of the agents. Since WISDOM-I does not have this kind of coordination mechanism, the fitness value of the worst solution searched is higher in WISDOM-II than in WISDOM-I.

The tit-for-tat situation also does not appear in WISDOM-II. As discussed in (Yang et al. 2006a), the tit-for-tat behaviour is common when the game is symmetric. However, the game is no longer symmetric in this study by using WISDOM-II. The red team can not take advantage of the strategic decision making mechanism while the blue team can.

Figure 3 is the histogram of the fitness value by two fitness functions for the random walk. In order to facilitate the comparison between WISDOM-I and WISDOM-II, the figures use the same scale as in (Yang et al. 2006a). For the average fitness function, the fitness value of most solutions found in the GOL scenario is between 100 and 200, in the DEF scenario it is between 120 and 200, and in the AGG scenario it is between 170 and 245. Only few solutions are GOOD solutions in either GOL or DEF scenario. For the GOL and DEF scenario, peaks around the point with the fitness value of 200 shows that there is a high probability to find a solution with the fitness value of 200. However in the AGG scenario, there are two small peaks with the fitness value of 190 and 240 respectively and with similar height. It suggests that it is more likely to find a solution with the fitness value of either 190 or 240 than any other values in the AGG scenario.

For the normalized average fitness function, the fitness value of most solutions found in all three scenarios is less than 20. In the GOL scenario, there is a big peak at the point with the fitness value of 10 and a small peak around the point with the fitness value of 20. It suggests that the fitness value of the solution found in the GOL scenario is more likely to be around 10. In the AGG scenario, almost all solutions fall into

Table 2. The information theoretic measures using both fitness functions for random walk

		ϵ^*	$H(\epsilon = 0)$	$M(\epsilon = 0)$	Exp. # of Optima
Average Fitness	GOL	105.00 ± 5.27	0.41 ± 0.00	0.59 ± 0.00	2969.40 ± 13.44
	AGG	80.00 ± 0.00	0.41 ± 0.00	0.58 ± 0.01	2887.00 ± 29.40
	DEF	89.00 ± 9.94	0.42 ± 0.00	0.59 ± 0.01	2949.60 ± 27.10
Normalized Average Fitness	GOL	23.70 ± 1.49	0.41 ± 0.00	0.61 ± 0.01	3048.00 ± 32.19
	AGG	16.80 ± 1.32	0.41 ± 0.00	0.62 ± 0.00	3081.30 ± 18.99
	DEF	73.00 ± 3.50	0.40 ± 0.00	0.60 ± 0.00	3012.10 ± 15.27

Table 3. Comparison of the fitness landscape generated by WISDOM-I and WISDOM-II

	WISDOM-I	**WISDOM-II**
Influence of stochasticity	high	
Signal-worst	high	low
Tit-for-Tat	common	not common
Attractor	at the fitness of 200	No
Information content	similar in both systems	
Partial information content	low	high
Information stability	high	low
# of expected optima	low	high
Progress of search	most improvements occurs at the beginning	

the fitness range of 10 to 20. That means it is almost impossible to find a solution with fitness value above 20. However for the DEF scenario, although there is a big peak between 10 and 20, there are a lot of solutions found between 20 and 40. There are two peaks in both GOL and AGG scenarios while there is only one peak in the DEF scenario. This implies that the effect of stochasticity is higher in both GOL and AGG scenario than that in the DEF scenario.

When compared with the corresponding figure in (Yang et al. 2006a), one can see that only in the AGG scenario can a good solution be easily found for both WISDOM-I and WISDOM-II. For both GOL and DEF scenarios, there is an attractor at the point with the fitness value of 200 in WISDOM-I while there is no such attractor in WISDOM-II. Looking at the normalized average fitness, for both WISDOM-I and WISDOM-II, there are many solutions found with fitness value less than 20. This implies that the solutions in all scenarios are very unstable for both systems.

Table 2 lists the results of the fitness landscape analysis using the information content approach. It is clear that the landscapes using both average fitness and normalized average fitness are very similar, and the landscapes of all three scenarios are also very similar in terms of $H(\epsilon = 0)$, $M(\epsilon = 0)$ and expected number of optima. This means the degree of ruggedness and modality of the landscape in these three landscapes is almost the same. However, in terms of ϵ^*, the landscapes are different. The highest information stability is obtained in the GOL scenario when using average fitness while the highest information stability is observed in the DEF scenario when using normalized average fitness. That is, the highest difference between two neighbouring peaks is observed in the GOL scenario using average fitness while the highest difference between two neighbour peaks is observed in the DEF scenario using normalized average fitness. One may also notice that the information stability is similar between the landscapes using average fitness and normalized fitness in the DEF scenario. This suggests that there are higher peaks in the DEF scenario than that in the GOL and AGG scenario.

When compared with the corresponding table in (Yang et al. 2006a), $H(\epsilon = 0)$ is similar between WISDOM-I and WISDOM-II while $M(\epsilon = 0)$ is higher in WISDOM-II than that in WISDOM-I. That is, the ruggedness is similar while the modality is higher in WISDOM-II. It can also be reflected by the number of expected optima. ϵ^* in WISDOM-I is much higher than that in WISDOM-II according to the average fitness. This is caused by the same reason as the lower value of the fitness signal-worst in WISDOM-II. Since the fitness value of the worst solution found is higher in WISDOM-II than that in WISDOM-I, the difference between two neighbour solutions is obviously lower in WISDOM-II than in WISDOM-I. In terms of the normalized average fitness, it is consistent with the previous finding that there is no attractor in the GOL and DEF scenarios in WISDOM-II.

5 CONCLUSION

In this paper, a fitness landscape analysis based on WISDOM-II is used to study the effect of coordination. Three scenarios requiring different strategies are chosen for the red team: GOL, AGG and DEF while the strategy of the blue team is evolved. All the configurations are the same as in (Yang et al. 2006a).

For all three scenarios, the fitness landscapes are rugged and multi-modal. The difficulty of the blue team in finding a good solution (a combination of the personalities for the blue agents) to win the game is largely dependent on the strategy the red team takes. The characteristics of the fitness landscape change when the strategy of the red team changes. The degree of difficulty for the blue team to find a good solution increases in the order of: AGG, DEF and GOL. All these findings are consistent with those in (Yang et al. 2006a). However, there are also many differences between the fitness landscapes generated by WISDOM-I, which does not have group coordination and WISDOM-II, which has group coordination. Table 3 is a summary of these difference. As discussed above, the strategic decision making mechanism (group coordination) has been identified as the major cause leading to some differences between landscapes. Therefore, modelling group coordination is crucial in multi-agent systems. Although the findings are based on an analysis in the defence domain, it can also be extended and applied into other domains. For example, in water resource management, if each end user is modelled as an agent, coordination among agents in the same state, same city or same suburb should be modelled and interactions between states, cities and suburbs can then be studied.

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