# Swarm Potential Fields with Internal Agent States and Collective Behaviour


**Mohamed H. Mabrouk** **Colin R. McInnes**
Department of Mechanical Engineering
University of Strathclyde
Glasgow,G1 1XJ
{mohamed.mabrouk, colin.mcinnes}@strath.ac.uk



### *Abstract*

Swarm robotics is a new and promising approach to the design and control of multi-agent robotic systems. In this paper we use a model for a system of self-propelled agents interacting via pair-wise attractive and repulsive potentials. We develop a new potential field method using dynamic agent internal states, allowing the swarm agents' internal states to manipulate the potential field. This new method successfully solves a reactive path planning problem that cannot be solved using static potential fields due to local minima formation. Simulation results demonstrate the ability of a swarm of agents that use the model to perform reactive problem solving effectively using the collective behaviour of the entire swarm in a way that matches studies based on real animal group behaviour.


## 1 Introduction

The design and control of artificial swarms has become a topic of growing interest. Swarm robotics has a range of applications in both civilian and military fields from space and subsea exploration to the deployment of teams of interacting artificial agents in disposal systems (Leonard and Fiorelli, 2001). The study of agent-based systems begins with a definition of the term agent (Maes, 1994). An individual agent may be programmed to be fully autonomous, but its abilities may be limited according to resource and physical constraints. On the other hand, swarms of self-organizing agents that exchange information may have a greater functionality than the individual members. Natural examples of interacting swarms of agents can be found in ants, bees, birds and schools of fish in the way that they create complex patterns with new and useful group properties (Camazine *et al.,* 2003). In recent years, an understanding of the operating principles of natural swarms has proven to be a useful tool for the intelligent design and control of artificial robotic agents (Bonabeau *et al.,* 1999); (Gazi and Passino, 2003).

Swarming robotic systems are often modelled as a two-dimensional collection of point agents in which members may interact with one another through attractive-repulsive pair-wise interactions. Specific choices of potential field lead agents to self-organize into coherent patterns (Levine *et al.,* 2000); (Gazi and Passino, 2002). More recently swarm stabilization or collapse with increasing constituent number in different zones of the *H*-stability diagram, shown in Fig. 1, has been predicted. Many swarming systems have been investigated and complex behaviour such as phase transitions and emergent patterns have been observed Fig. 2, (D'Orsogna *et al.,* 2006); (Mabrouk and McInnes, 2007). In these studies, the connection between the so-called *H*-stable nature of the interaction potential and resulting aggregating patterns have been found using tools from statistical mechanics. Virtual leaders (Chuang *et al.,* 2007); (Mabrouk and McInnes, 2007) and structural potential functions (Olfati-Saber, 2006) have also been introduced to provide provable group behaviour to ensure vehicles can avoid obstacles or form desired patterns. The actual realizations of self-propelled vehicles interacting according to virtual Morse potentials have been investigated (Nguyen *et al.,* 2005).

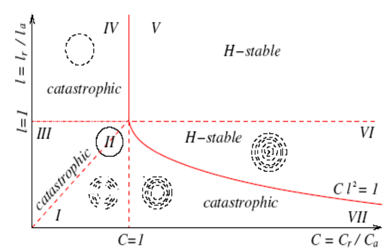


**Fig. 1**. *H*-stability phase diagram of the Morse potential (D'Orsogna et al., 2006a)

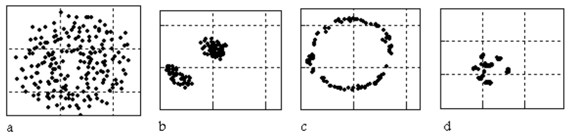


**Fig. 2**. Patterns of swarm of agents in different $H$-stability diagram catastrophic regions and different interaction parameters (Mabrouk and McInnes, 2007). (a) Vortex, region VII, $N_p$ =200, $l_r$ =0.5, $l_a$ =2, $C_r$ =1, $C_a$ =0.5, $\alpha$ =1.6, $\beta$ =0.5 (b) Clumps, region I, $N_p$ =100, $l_r$ = 0.5, $l_a$ =1, $C_r$ =0.6, $C_a$ =1, $\alpha$ =1, $\beta$ =0.5 (c) Ring, region II , $N_p$ =100, $l_r$ =0.5, $l_a$ =1, $C_r$ =0.5, $C_a$ =1, $\alpha$ =1, $\beta$ =0.5 (d) Ring clumping, region IV, $N_p$ =100, $l_r$ =1.2, $l_a$ =1, $C_r$ =0.6, $C_a$ =1, $\alpha$ =1, $\beta$ =0.5

These prior studies assume that the free parameters of the potential field are fixed a priori. In (Mabrouk and McInnes, 2007) the parameters were assumed to be internal states for each agent through which the agent can manipulate the potential field. The dynamics of these internal states are defined through sets of first order differential equations. The behaviour observed was similar to the behaviour of honey bees, where the individuals that sense a threat release a pheromone which stimulates an alarm response in other bees in the colony to gather around those individuals.

In this paper we develop our work to introduce a simpler model of driven self-propelled agents, which also experience some dissipative frictional force. The model consists of $N_P$ agents with mass $m_i$, position $\vec{r}_i$ and relative distance $|\vec{r}_{ij}|$ between the $i^{th}$ and $j^{th}$ agents. For simplicity, we will consider unit mass agents and to prevent the agents from reaching large speeds, a dissipative frictional force with coefficient $\beta$ is added (D'Orsogna *et al.,* 2006). The agents interact by means of a two-body generalized Morse potential $U(\vec{r}_i)$, which decays exponentially at large distances and represents a comparatively realistic description of natural swarming agents. The potential is characterized by attractive and repulsive potential fields of strength $C_a$ and $C_r$ with ranges $l_a$ and $l_r$ respectively. The equations of motion for $N_p$ agents are then defied by:

$$\vec{v}_i = \partial \vec{r}_i / \partial t \tag{1}$$

$$m_i . \partial \vec{v}_i / \partial t = -\beta_i . \vec{v}_i - \vec{\nabla}_i U(\vec{r}_i) \tag{2}$$

$$U(\vec{r}_i) = \sum_{j \neq i} (C_r . e^{-|\vec{r}_{ij}|/lr} - C_a . e^{-|\vec{r}_{ij}|/la}) \tag{3}$$

## 2. Problem Definition:

In recent years new assumptions about the architecture needed for intelligence have emerged. These approaches attempt to emulate natural, rather than artificial intelligence and are based on, or at least inspired by, biology. In an attempt to build a control system for autonomous agents, Balkenius presented a general architecture for behaviour-based control (Balkenius, 1994). He proposed a number of architectural principles which make it possible to combine reactive control with problem solving in a coherent way. He used the term behaviour to denote the system internal to the agent that is responsible for the externally observed behaviour.

The problem of local minima (trapped states), shown in Fig. 3, was discussed by Balkenius. The reactive problem for an agent, or swarm of agents, attracted to a goal point at position $G$ can be defined such that an artificial potential field at $G$ induces motion towards the goal. When the agent, or swarm of agents, moves towards the goal the velocity of each individual agent rises, and the agents translate to the goal along the gradient of the potential field. However, in order to prevent collision with a static obstacle, an additional repulsive potential field is required. These two potential fields are then superimposed to form a global potential field which describes the workspace of the problem. In general however, a local minimum may form due to the superposition of the goal potential and that of the obstacles, resulting in the agent, or swarm of agents, becoming trapped in a state other than the goal $G$.

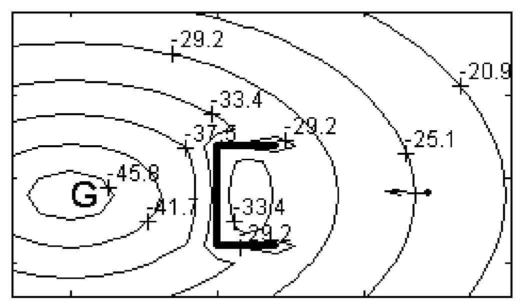


**Fig.3** Classical reactive problem for a single agent

Considering this problem, the entire swarm, or part of the swarm will be trapped at the obstacle since the agents trapped inside the obstacle will experience two virtual forces; the first force is the attraction to the goal while the other will be the repulsion from the obstacle. Moreover in most cases there will be no opportunity for the swarm members to escape from the local minimum due to the pair-wise interaction potential - particularly when the goal potential is of large amplitude. This problem motivates the use of the collective swarm behaviour to avoid such trapping in local minima; further discussion of the problem is given in appendix.

## 3. Agent Internal State Model:

Escape from complex workspaces can be seen in many natural systems in which the system consists of a number of agents enclosed in a trap. An example is a system of gas molecules which are enclosed in a single-exit container while the molecules experience a change in their state, due to a rise in temperature for example. The change of the internal state of the system simply changes the trap region from a local minimum into a region of maximum potential from which all the agents are emitted as if squeezed out. The repulsive interaction potential of each agent increases, leading both to an increase in repulsion between agents and between the walls of the trap (Mabrouk and McInnes, 2007).

The use of agent internal states (potential field free parameters) will now be considered as a means of allowing agents to manipulate the potential field in which they are maneuvering. This concept will be used for a swarm of agents maneuvering towards a goal in a potential field which contains a local minimum. The agents' internal states will now be defined through a set of differential equations which will allow the swarm of agents to manipulate the potential field in which it is maneuvering and so escape from a local minimum.

For a fixed obstacle, the repulsion potential range affecting the $i^{th}$ agent ($l_{oi}$) can be represented as a function of an obstacle constant ($l_o$), which characterizes the physical nature of the obstacle, and the particle repulsion potential range ($l_{ri}$) which characterizes the agent internal state while the repulsion potential strength affecting the $i^{th}$ agent ($C_{oi}$) can be represented as the obstacle constant ($C_o$). The attraction potential range of the goal affecting the $i^{th}$ agent ($l_{gi}$) can also be represented as a function of a goal constant ($l_g$), which characterizes the physical nature of the goal, and the particle attraction potential range ($l_{ai}$) which characterizes the agent internal state while the attraction potential strength of the goal affecting the $i^{th}$ agent ($C_{gi}$) can also be represented as the goal constant ($C_g$) such that:

$$C_{oi} = C_o \tag{4}$$

$$l_{oi} = l_o + l_{ri} \tag{5}$$

$$C_{gi} = C_g \tag{6}$$

$$l_{gi} = l_g + l_{ai} \tag{7}$$

When an agent approaches an obstacle it suffers an elastic collision which pushes the agent away from the goal. The goal then attracts the agent back and the agent will never attempt to maneuver around the obstacle simply because it never knows it is trapped. Therefore if a swarm of agents enters a local minimum of the potential field it will be under the two forces; repulsion from the obstacles and attraction to the goal; this will cause in that the swarm center speed to increase as it approaches the goal and decreases as it is repelled.

The swarm center speed, which is the mean of all individuals' velocities, is now used as a means to increase the perception of the swarm about the environment to avoid trapping in local minima. The following differential equations are now used to express the internal states of the agents:

$$\partial C_{ri} / \partial t = \frac{A_r}{1 + e^{|\vec{v}_c|}} - \lambda_r . C_{ri} \tag{8}$$

$$\partial l_{ri} / \partial t = \frac{B_r}{1 + e^{|\vec{v}_c|}} - \lambda_r . l_{ri} \tag{9}$$

$$\partial C_{ai} / \partial t = A_a . e^{|\vec{v}_i|} - \lambda_a . C_{ai} \tag{10}$$

$$\partial l_{ai} / \partial t = B_a . e^{|\vec{v}_i|} - \lambda_a . l_{ai} \tag{11}$$

$$\partial \beta_i / \partial t = \frac{A_\beta}{1 + e^{-|\vec{v}_c|}} - \lambda_\beta . \beta_i \tag{12}$$

Equations (8-11) express the repulsion amplitude and range and the attraction amplitude and range of the $i^{th}$ agent, according to the speed of each agent as well as swarm center. Moreover, Eq. (12) ensures a smooth maneuver around obstacles by slowing agents, which are moving away from the obstacle by linking the dissipation coefficient $\beta$ of each agent to the swarm center speed. The damping terms in Eq. (8-12) ensure that the deviation of the agent internal state is minimized and the internal states can return to an equilibrium value. The coefficients ($A_r$, $B_r$, $A_a$, $B_a$, $A_\beta$, $\lambda_r$, $\lambda_a$, $\lambda_\beta$) are employed to manipulate these terms. The benefit of using this model is that when the agents are repelled the swarm center speed is decreased, $l_{oi}$ takes higher values which turns the workspace in the neighbourhood of the obstacles into a zone of maximum potential. This then leads to escape from the local minima (Mabrouk and McInnes, 2007), while the potential field relaxes after escape due to the damping terms in the differential equations for the internal states. The swarm leader concept, generated by Eq.(10,11), is used to make the swarm aggregate together simulating the behaviour of real animals (Shettleworth 1998) as well as increase the attraction potential of those agents who have found a path around the obstacles towards the goal.

## 4. Model Analysis:

Using the dynamic internal states defined in Eq. 8-12, the potential field is now a function of four parameters for each agent. The generalized Morse potential function is defined as:

$$U_i = \sum_{j\neq i} (C_{r_j}.e^{-|\vec{r_{ij}}|/l_{r_j}} - C_{a_j}.e^{-|\vec{r_{ij}}|/l_{a_j}}) \tag{13}$$

Assuming no obstacles and no goals at present, the system energy will then be defined as follows:

$$\phi = \sum_{i}^{Np} (\frac{1}{2} m_i \vec{v_i}^2 + U_i) \tag{14}$$

where $U_i$ is the potential energy of the $i^{th}$ agent. Then:

$$\mathring{\phi} = \sum_{i}^{Np} (m_i \vec{v_i}.\mathring{\vec{v}}_i + \nabla_i U.\vec{v_i}) + \sum_{i}^{Np}\sum_{j\neq i}^{Np} \mathring{C}_{r_j}.e^{-|\vec{r_{ij}}|/l_{r_j}} - \mathring{C}_{a_j}.e^{-|\vec{r_{ij}}|/l_{a_j}} + C_{r_j}.\frac{\mathring{l}_{r_j}.|\vec{r_{ij}}|}{l^2_{r_j}} e^{-|\vec{r_{ij}}|/l_{r_j}} - C_{a_j}.\frac{\mathring{l}_{a_j}.|\vec{r_{ij}}|}{l^2_{a_j}} e^{-|\vec{r_{ij}}|/l_{a_j}}) \tag{15}$$

where the ($^{o}$) notation stands for time derivative. Substituting from Eq.2 it can be seen that:

$$\mathring{\phi} = -\sum_{i}^{Np} (\beta_i.\vec{v}^2_i) + \sum_{i}^{Np}\sum_{j\neq i}^{Np} \mathring{C}_{r_j}.e^{-|\vec{r_{ij}}|/l_{r_j}} - \mathring{C}_{a_j}.e^{-|\vec{r_{ij}}|/l_{a_j}} + C_{r_j}.\frac{\mathring{l}_{r_j}.|\vec{r_{ij}}|}{l^2_{r_j}} e^{-|\vec{r_{ij}}|/l_{r_j}} - C_{a_j}.\frac{\mathring{l}_{a_j}.|\vec{r_{ij}}|}{l^2_{a_j}} e^{-|\vec{r_{ij}}|/l_{a_j}}) \tag{16}$$

While the internal states now have their own dynamics, the damping terms in Eq. 8-11, ensure that these states return to their equilibrium values as shown in Fig.4. This ensures that $\mathring{C}_{r_j}, \mathring{l}_{r_j}, \mathring{C}_{a_j}, \mathring{l}_{a_j}$ tend to zero, which will yield:

$$\mathring{\phi} = -\sum_{i}^{Np} \beta_i.\vec{v_i}^2 \tag{17}$$

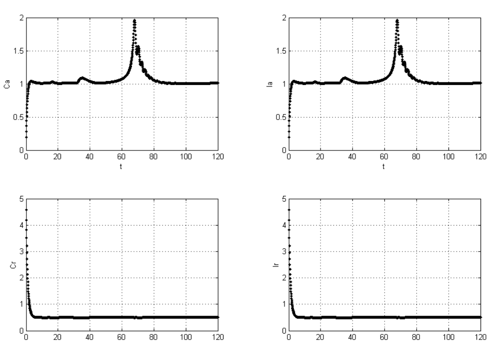


**Fig.4** Interaction parameters of one of the free swarm agents

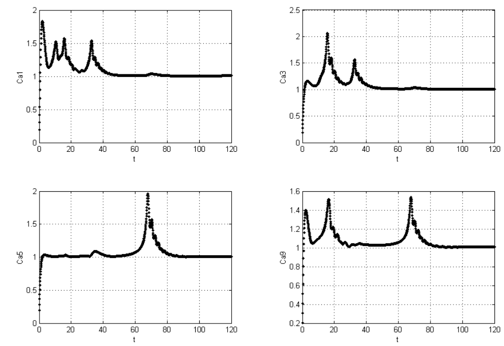


**Fig.5.** Attraction potential strength of different agents in the free swarm

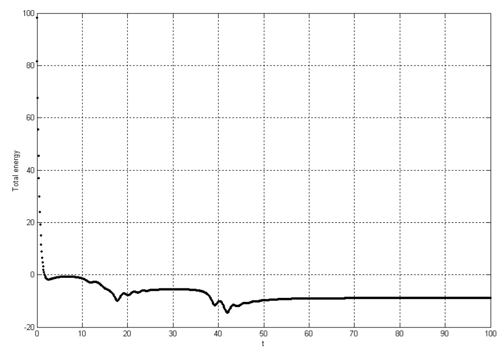


**Fig.6.** The free swarm system total energy versus time

Therefore the swarm will come to equilibrium. The dissipation coefficient $\beta$ while having a non zero value, results in Fig.6 show the swarm energy approaching a constant. We can also see in Fig.5 that the agents' attraction potential will reach equilibrium, so that the swarm agents prefer to remain as a group in a way that matches the studies based on real animal group behaviour.

## 5. Simulation Results:

First, the case of a swarm whose agents use fixed internal states will be considered. Here the free parameters describing the potential field, and so the potential field itself, are constant. The simulation results in Fig. 7 show a swarm of agents in which part of the swarm becomes trapped in the local minimum of the potential field while the rest of the swarm, according to their initial positions, reach the goal. This is typical of conventional implementations of the artificial potential field method to path planning problems.

For dynamic internal states the simulation results shown in Fig. 8 show that the swarm, which is given the same initial conditions as the swarm in Fig.7, enters the local minimum and when repelled the repulsion potential of the agents increases in a way that converts the obstacle to be a zone of maximum potential to the agents. As the agents escape from the local minimum the potential field relaxes due to the damping terms in Eqs. (8-12) and in addition, the dissipation coefficient $\beta$ ensures smooth maneuvering of the trapped agents. The goal potential field then drags the agents away from the obstacle zone and defines a gradient path that the agents follow directly to the goal. The comparison between the results in Fig. 7 and Fig. 8 clearly shows the effect of using the internal state dynamics to solve the reactive problem effectively.

Finally, we can see the use of the swarm leader concept in the simulation results Fig. 9 which show a swarm that splits into two groups. Group (a) whose individuals use the internal state dynamic model that manipulates the potential according to the agents' internal states and group (b) whose individuals still use the static potential. It can be seen that group (a) have a clear path to the goal while group (b) is trapped in a local minimum. Group (a) swarm individuals, according to the internal state model, acquire leader properties (large $C_a$ ) in a way that the individuals trapped in the local minimum are attracted to them rather than to the goal. The behaviour is similar to related work concerning pedestrian dynamics (Helbing and Molnar, 1995)

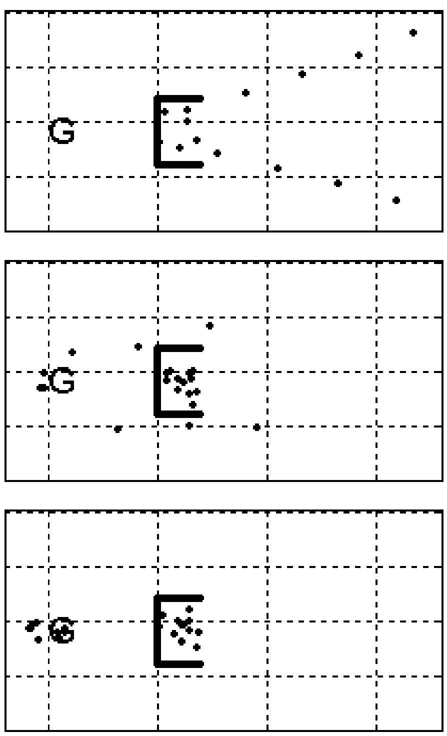


**Fig. 7.** Behaviour of a swarm with fixed internal states

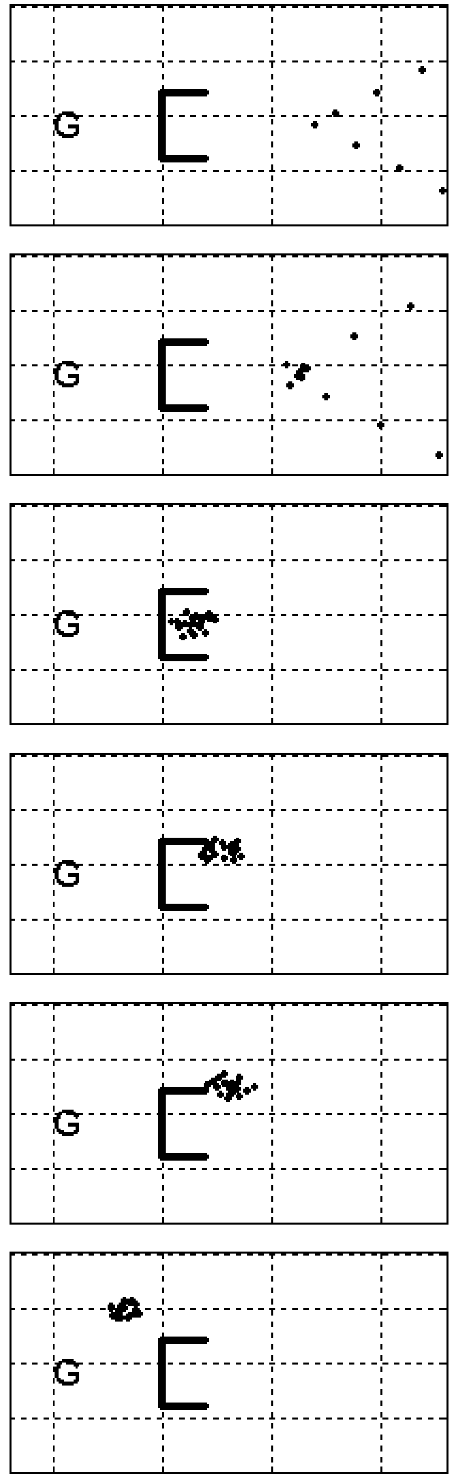


**Fig.8.** Swarm solving a reactive problem using the internal state model

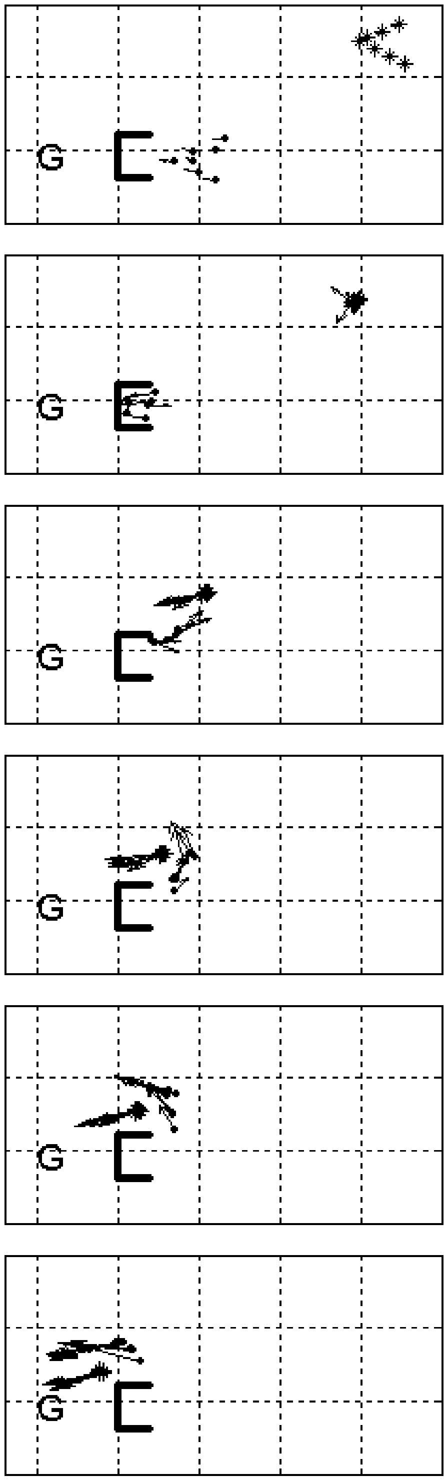


**Fig.9.** Part of swarm uses the internal state model (*) while the rest of the swarm uses fixed internal states.

## Conclusions:

A new model for a system of self-propelled agents interacting via pair-wise attractive and repulsive potentials is presented. The model proves to be stable and provides similarities with the behaviour of real groups of animals. Using the model, along with a potential field method which uses the concept of agent internal states to allow agents to manipulate the potential field in which they maneuver, allows a swarm of agents to escape from and maneuver around a local minimum in the potential field to reach a goal. Rather than moving in a static potential field, the agents are able to manipulate the potential according to their estimation of whether they are moving towards or away from the goal.

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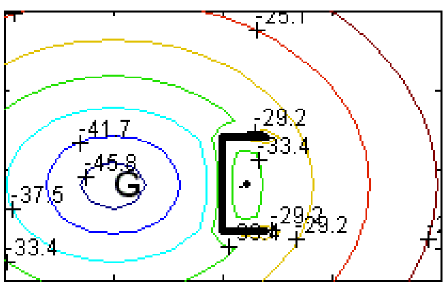
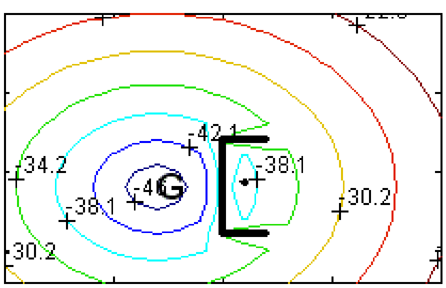
# Appendix

## A. The parameters on which the depth of the local minimum depends

The depth of the local minimum is affected by some parameters, such as strength of goal attraction potential, (goal – obstacles) separating distance and strength of obstacle repulsion potential. The following figures demonstrate further discussion of the problem:

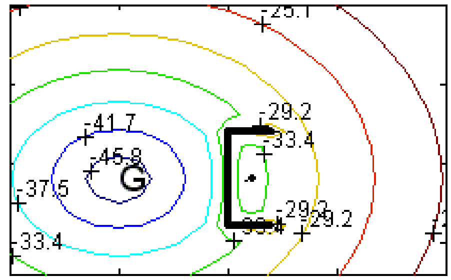



(a)

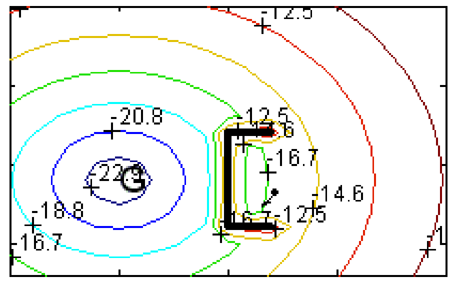



(b)

**Fig.A1** the depth of the local minimum increases as the (goal – obstacle) separating distance decreases

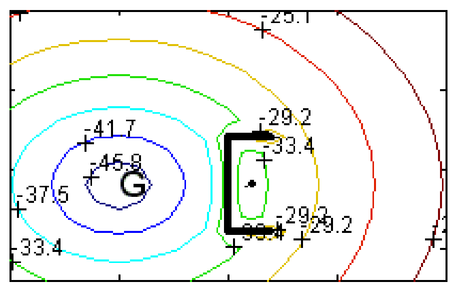



(a)

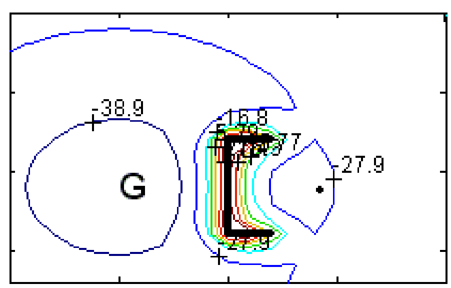



(b)

**Fig.A2** the depth of the local minimum increases as the goal attraction amplitude increases (a) *Cg*=50 (b) *Cg*=25




(a)




(b)

**Fig.A3** the depth and shape of the local minimum differs as the obstacle repulsion amplitude differs (a) *Co*=4, *lo*=0.05 (b) *Co*=7, *lo*=0.5