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Potential Field Based Navigation for Planetary Rovers Using Internal States

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ABSTRACT

The work in this paper aims to introduce analysis and applications for the internal state model which is a new model for a swarm of rovers interacting via pair-wise attractive and repulsive potentials. The internal state model updates the state of the art in overcoming the local minima problem through solving the problem with comparatively lower computation cost than other methods. The simulations results show that using the internal state model, a swarm of planetary rovers, rather than moving in a static potential field, are able to manipulate the potential according to their estimation of whether they are moving towards or away from the goal, which allows them to escape from and maneuver around a local minimum in the potential field to reach a goal. An application of a swarm of rovers to solve the problem for different shaped obstacles is introduced to show the efficiency of the model. The model proves stable convergence to a goal and provides similarities with the behaviour of real groups of animals.

INTRODUCTION

Swarm robotics is a new and promising approach to the design and control of multi-agent robotic systems. It has a wide range of applications in numerous fields from space exploration to the deployment of teams of robots in maintenance[1]. Specific features of aggregations are striking in natural systems whose members have high rates of information exchange such as animal herds, insect swarms, bird flocks, and fish schools[2]. This leads us to use one of the most important phenomena in natural systems, which is the collective behaviour, to enhance the performance of a team of planetary rovers during operation.

In this paper we use a simple model of self-propelled rovers, which experience some dissipative frictional force. The swarm consists of N_p individuals with mass m_i, position r_i and relative distance $|\mathbf{r}_{ij}|$ between the i^{th} and j^{th} rover. A dissipative friction force with coefficient β is added to control the motion of the rovers. The rovers interact by means of a two-body generalized Morse potential, which decays exponentially at large distances and represents a realistic description of natural and artificial swarming robots. The equations of motion of the N_p rovers are defined as:

$$\mathbf{v}_i = \dot{\mathbf{r}}_i \tag{1}$$

$$m_i \dot{\mathbf{v}}_i = -\beta_i \mathbf{v}_i - \nabla_i V_{global}(\mathbf{r}_i) \tag{2}$$

$$V_{global}(\mathbf{r}_i) = V_{interaction}(\mathbf{r}_i) + V_{goal}(\mathbf{r}_{ig}) + V_{obstacles}(\mathbf{r}_{io}) \tag{3}$$

The generalized Morse potential defines the interactions amongst the swarm rovers $V_{interaction}(\mathbf{r}_i)$, the attraction potential of the goal

$V_{goal}(\mathbf{r}_{ig})$ and the repulsive potential of the N_o obstacles $V_{obstacles}(\mathbf{r}_{io})$. Then, the global potential $V_{global}(\mathbf{r}_i)$ is defined as

$$V_{global}(\mathbf{r}_i) = \sum_{j \neq i}^{N_p} \left(C_{r_j} e^{-\left|\mathbf{r}_i - \mathbf{r}_j\right|/l_{r_j}} - C_{a_j} e^{-\left|\mathbf{r}_i - \mathbf{r}_j\right|/l_{a_j}} \right) + \sum_{z=1}^{N_o} C_{io_z} e^{-\left|\mathbf{r}_i - \mathbf{r}_{o_z}\right|/l_{io_z}} - C_g e^{-\left|\mathbf{r}_i - \mathbf{r}_g\right|/l_g} \tag{4}$$

where C_{ig}, l_{ig}, C_{io_z} and l_{io_z} are the strength and range constants of the goal attraction potential and the z^{th} obstacle point repulsive potential that affects i^{th} rover, respectively.

PROBLEM DEFINITION

In recent years new assumptions about architectures 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. The local minima problem has been a serious issue for potential field methods for robot path planning[3]. The problem of local minima, shown in fig(1), has been discussed by many researchers[4,5]. Our motivation is that most of these attempts are not suitable for real time applications[5]. The problem can be defined such that an artificial potential field at G induces the rovers' motion towards a goal. In order to prevent collision with a static obstacle, an additional repulsive potential field is required. In general, a local minimum may form due to the superposition of the goal potential and that of the obstacles, resulting in a group of rovers, becoming partially or globally trapped in a state other than the goal.

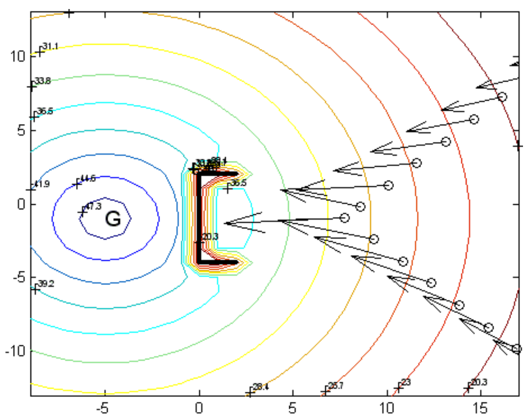

Fig. 1: t=0

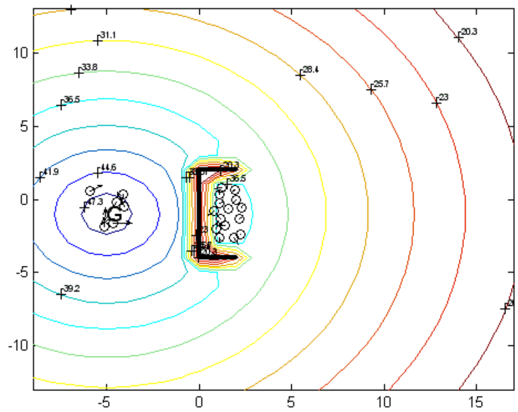

Fig. 1: t=36

Fig. 1: Classical reactive problem for a swarm of rovers with trapping in a local minimum

For the scenario in fig(1), the swarm center velocity will increase as the swarm approaches the goal and decreases as an obstacle repels the swarm, while the swarm is again trapped if it enters a local minimum of the potential field. According to the local minimum survey[4], forward chaining is indeed an efficient technique to solve the local minimum problem. The forward chaining technique development can be summarised in the following stages. The early version of forward chaining allows the potential surface to be manipulated so that the goal is temporarily replaced by a local subgoal[6]. By chaining the local subgoals in a sequence until eventually reaching the original goal, and then breaking the resulting path into steps, the agent can be gradually led to the original goal location. The method's main disadvantage was the failure of the agent to reach the goal if the agent comes to a standstill. Therefore, the method was developed by introducing the forward chaining technique[7] to keep the agent in motion through selection of the next subgoal target state to be the lowest potential value point on a circle whose center is at the current state. Although the disadvantage is covered, this transforms the local minimum problem into a local oscillation problem of various step lengths. To overcome the local oscillation problem, the back and forth motion was eliminated through restricting subgoal selection to the forward semi-circle corresponding to the last direction of movement. While this enables the agent to move forward along the obstacle boundary, for shallow C-shaped boundaries, further modifications that include more computations were made to overcome more curvature in difficult obstacle shapes.

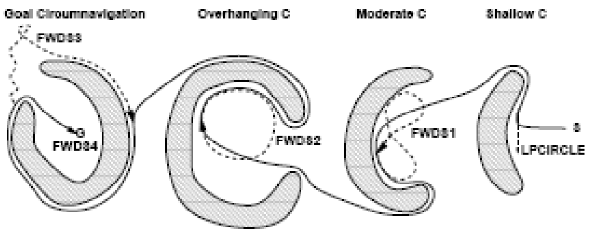

Fig. 2: path of an agent uses the forward chaining technique for successive different types of C-shape obstacles[7]

From the development of the method, it can be seen that the early version of the algorithm has been enhanced. A sample path using the final FWDS4 subgoal placement heuristic algorithm is shown in fig(2), together with the oscillatory path, shown in dashed line, according to one of the algorithm's earlier versions for a single agent.

INTERNAL STATE MODEL

Inspired from escape from complex workspaces[8], which can be seen in many natural systems, the use of dynamic internal states (potential field free parameters) is considered as a means of allowing rovers to manipulate the potential field in which they are manoeuvring to solve the local minimum problem.
The repulsion potential range affecting the i^{th} rover (l_{io}) is represented as a function of an obstacle constant (l_o), which characterizes the physical nature of the obstacle, and the rover repulsion potential range (l_{ri}) which characterizes the rover internal state, while the repulsion potential strength affecting the i^{th} rover (C_{io}) is represented as the obstacle constant (C_o). The attraction potential range of the goal affecting the i^{th} rover (l_{ig}) is also represented as the goal constant (l_g), which characterizes the physical nature of the goal, while the attraction potential strength of the goal affecting the i^{th} rover (C_{ig}) is represented as the goal constant (C_g) such that

$$C_{io} = C_o \tag{5}$$

$$l_{io} = l_o + l_{ri} \tag{6}$$

$$C_{ig} = C_g \tag{7}$$

$$l_{ig} = l_g \tag{8}$$

For the problem scenario shown in fig(1), the swarm will never attempt to manoeuvre around the fixed obstacle simply because the rovers never know that they are trapped. The speed of the centre-of-mass of the swarm is used as an effective mechanism for the swarm to increase its perception about its progress through the workspace, and so avoid trapping in local minima. The function Q_c is used to increase the perception of the group of rovers inspired from reward or punishment based perception in real biological systems[9,10]. The function is defined such that if the swarm is being repelled away from the goal, Q_c will have a negative value that is viewed as punishment indicating that a part of or the entire swarm is moving away from the goal. If $Q_c \geq 0$, which is viewed as reward, the swarm senses collectively that it is moving towards the goal.
The following set of first order differential equations are now used to express the internal states of the i^{th} rover[5]

$$\dot{C}_{ri} = \begin{cases} A_r e^{-\lambda_q Q_c} - \lambda_r C_{ri} & \text{if } Q_c < 0 \\ 0 & \text{if } (Q_c \geq 0) \text{or} \, |\mathbf{r}_c - \mathbf{r}_g| \leq \varepsilon \end{cases} \tag{9}$$

$$\dot{l}_{ri} = \begin{cases} B_r e^{-\lambda_q Q_c} - \lambda_r l_{ri} & \text{if } Q_c < 0 \\ 0 & \text{if } (Q_c \geq 0) \text{or} \, |\mathbf{r}_c - \mathbf{r}_g| \leq \varepsilon \end{cases} \tag{10}$$

$$\dot{C}_{ai} = \begin{cases} A_a e^{\lambda_v |\mathbf{v}_i|} - \lambda_a C_{ai} & \text{if } Q_c < 0 \\ 0 & \text{if } (Q_c \geq 0) \text{or} \, |\mathbf{r}_c - \mathbf{r}_g| \leq \varepsilon \end{cases} \tag{11}$$

$$\dot{l}_{ai} = \begin{cases} B_a e^{\lambda_v |\mathbf{v}_i|} - \lambda_a l_{ai} & \text{if } Q_c < 0 \\ 0 & \text{if } (Q_c \geq 0) \text{or} \, |\mathbf{r}_c - \mathbf{r}_g| \leq \varepsilon \end{cases} \tag{12}$$

$$\dot{\beta}_i = \begin{cases} \dfrac{A_\beta}{1 + e^{-|\mathbf{v}_i|}} - \lambda_\beta \beta_i & \text{if } Q_c < 0 \\ 0 & \text{if } Q_c \geq 0 \end{cases} \tag{13}$$

where coefficients A_r, B_r, A_a, B_a, A_β, λ_q, λ_r, λ_v, λ_a, λ_β are employed to scale the dynamics of the internal states.
The swarm of rovers should be guaranteed to maintain a cohesive swarm for two reasons (1) to magnify the effect of the speed of the center-of-mass of the swarm on the global perception of the swarm and (2) to ensure that the swarm aggregates to face the problem collectively and then acts as a flock, as noted in studies of real biological systems[11]. Equation (9) – equation (12) express the repulsion amplitude and range and the attraction amplitude and range of the i^{th}

rover, according to the speed of each rover as well as the value of the function Q_c, which depends on the speed of the center-of-mass of the swarm. When the rovers are repelled from an obstacle, the swarm center velocity decreases, I_{io} then increases due to equation (6) and equation (10), 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 because the potential field relaxes due to the damping terms in the differential equations for the internal states defining a gradient path which the aggregated swarm follows directly to the goal.
The cohesion generated by equation (9) – equation (10) ensures aggregation amongst the swarm's rovers to face the local minimum problem. The net effect is then that the trapped swarm is forced to simultaneously explore escape paths. The damping terms in equation (9) – equation (12) ensure that the deviation of the rover internal state relaxes and returns to an equilibrium value as soon as the local minimum problem is solved.
Moreover, equation (13) ensures smooth manoeuvres around obstacles by linking the dissipation coefficient of each rover to its speed.

MODEL PERFORMANCE ANALYSIS

We compare our model performance with the most updated technique to solve the local minimum problem; the forward chaining technique[7], by comparing the results obtained by the internal state model fig(3) to the published results[7] obtained by forward chaining fig(2), for the same environment. In addition to single rover, we also consider cooperation amongst multiple rovers. It is shown that the swarm aggregation concept is used and the rovers prefer to aggregate when facing a problem in a way that matches the studies based on real animal group behaviour.
The three disadvantages that have motivated the development of the forward chaining method are covered in the internal state model by using the perception function Q_c along with the use of the squeeze effect[8], which guarantee keeping the rovers in motion until reaching the global potential minimum position through emitting the rovers away from any obstacle region and ensure eliminating the oscillation problem (back and forth motion) by defining a gradient path around the obstacles through which the rovers are led directly to the goal.

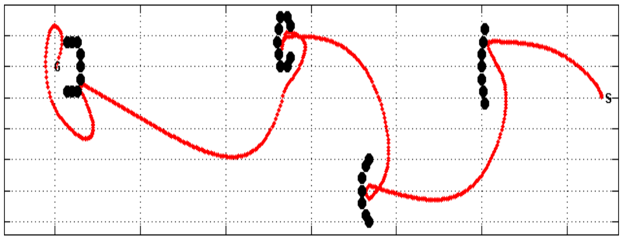

Fig. 3: Path of a rover using the internal state model to escape from local minima for different types of C-shape obstacles

SIMULATION RESULTS

Using the new dynamic internal states for the same problem as used earlier, when a part of the swarm is repelled the function Q_c switches to a negative value. Therefore, the attraction potential equations in the algorithm are activated such that as the rovers' speed increases, the inter-rover attraction potential increases and they gather to form a cohesive swarm. This has the advantage of magnifying the effect of the function Q_c and making the swarm aggregate to solve the problem for the entire swarm. Weak aggregation may lead to part of the swarm remaining trapped in the local minimum. In addition, a cohesive swarm is required to ensure that the position and velocity of the centre-of-mass remains meaningful. Goal and obstacle interaction parameters used for the problem scenario are used again for the simulation results shown in fig(4).

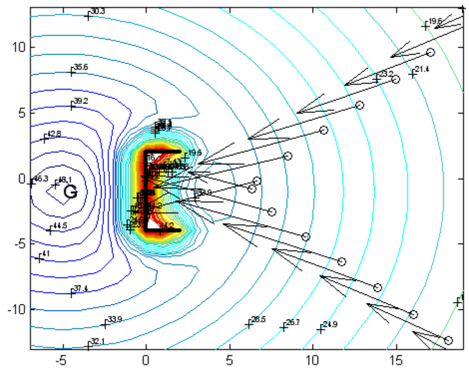

Fig. 4: t=2

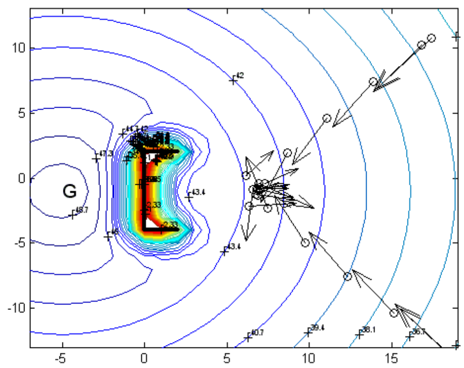

Fig. 4: t=8

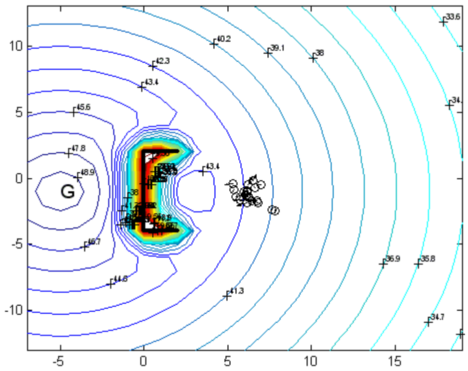

Fig. 4: t=30

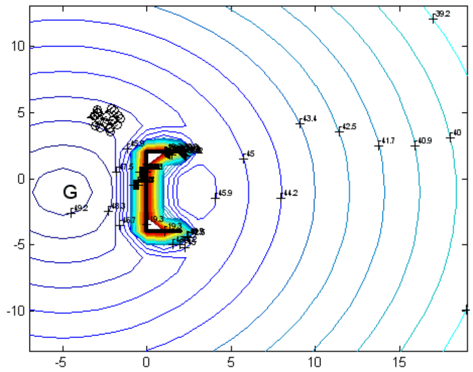

Fig. 4: t=62

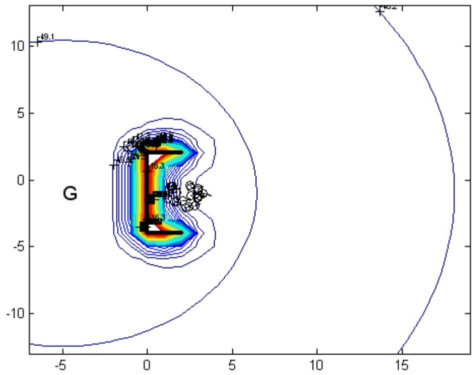

Fig. 4: t=37

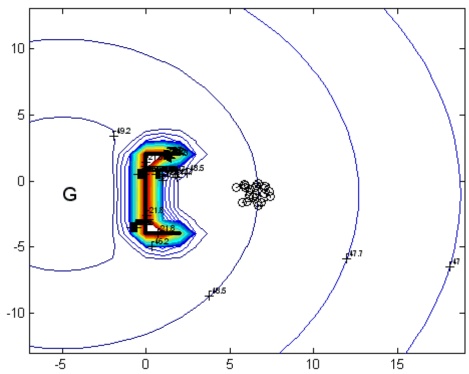

Fig. 4: t=47

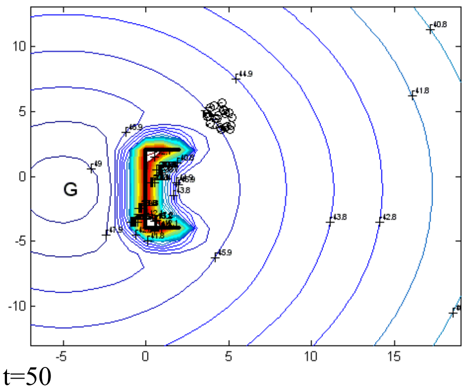

Fig. 4: t=50

Fig. 4: Path of a rover using the internal state model to escape from local minima for different types of C-shape obstacles[5]

A Multiple goals application is now presented. A group of rovers are to move together in a multi-obstacle environment to visit three goals G_1, G_2, and G_3 and switching off each goal they visit. In this case, the robots are required to reach the goals with obstacle avoidance, and to move in a group without colliding with each other. The rovers during the mission are shown in fig(5), while fig(6) shows the swarm center path during the mission. The goal and obstacle interaction parameters are C_o =4, C_{g1} =70, C_{g2} =50, C_{g3} =20, l_o =0.25 and l_g =60, the rover's initial interaction parameters are C_a =0.5, l_a =1, C_r =0.5, l_r =1, β =0.5 and the control parameters used are unit except A_r =0.6, B_r =0.6, A_β =1.3, ε =0.5, where ε is the goal proximity which if visited by any rover the goal will be switched off.

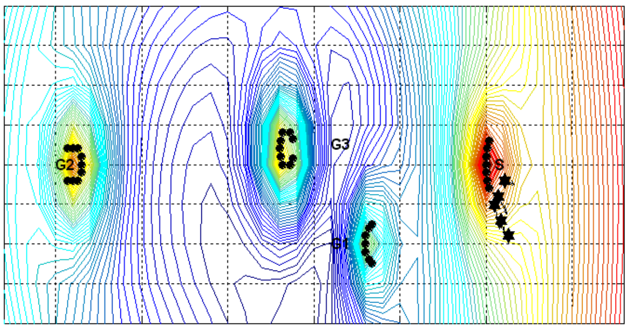

Fig. 5: t=1

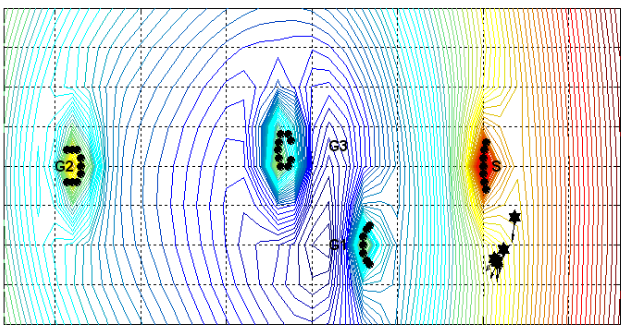

Fig. 5: t=2

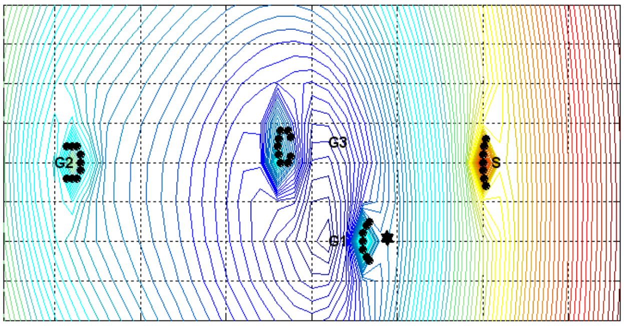

Fig. 5: t=8

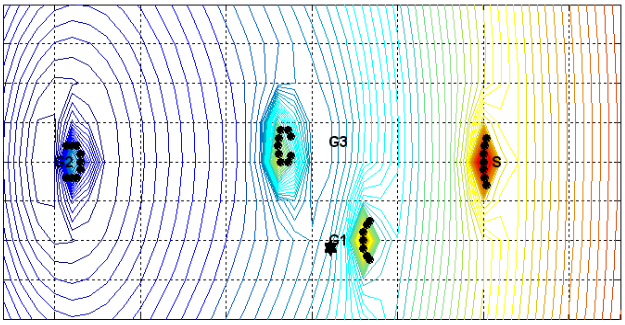

Fig. 5: t=17

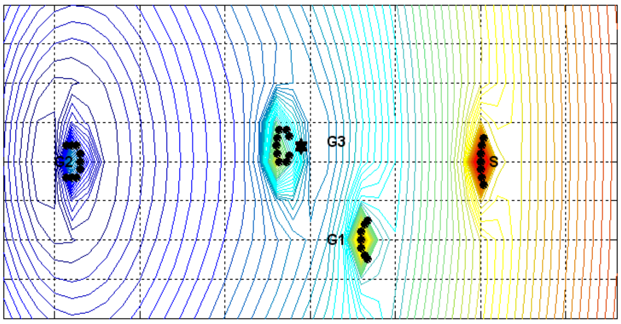

Fig. 5: t=21

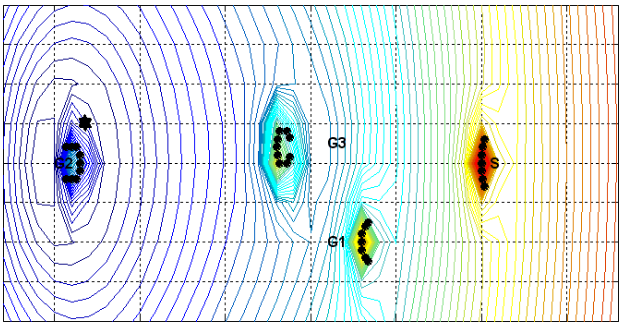

Fig. 5: t=53

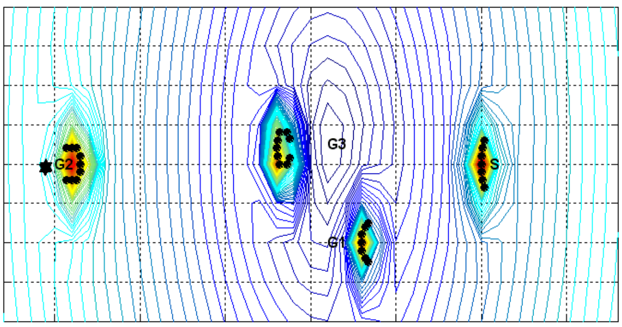

Fig. 5: t=66

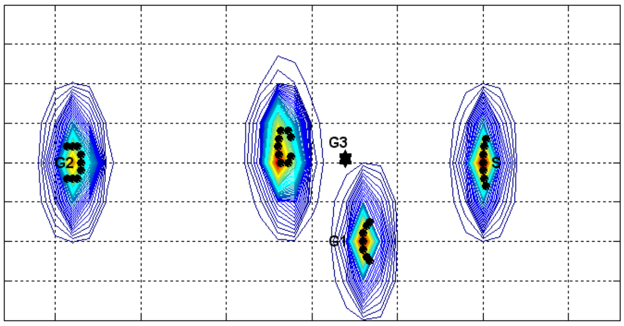

Fig. 5: t=97

Fig. 5: Path of swarm of rovers that aggregate during a mission

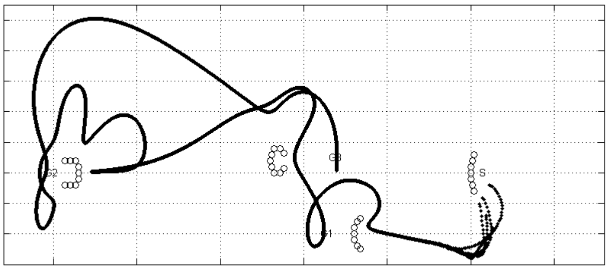

Fig. 6: Path of swarm of rovers that aggregate during a mission

The simulations results show that using the internal state model, a swarm of planetary rovers, rather than moving in a static potential field, are able to manipulate the potential according to their estimation of whether they are moving towards or away from the goal, which allows them to escape from and maneuver around a local minimum in the potential field to reach a goal. An application of a swarm of rovers to solve the problem for different shaped obstacles is introduced to show the efficiency of the model.

CONCLUSIONS

Using the internal state model, a swarm of planetary rovers, rather than moving in a static potential field, are able to manipulate the potential according to their estimation of whether they are moving towards or away from the goal, which allows them to escape from and maneuver around a local minimum in the potential field to reach a goal.
This work is considered a new technique to overcome the local minima, which might form in 2D artificial potential fields based navigation environments for a swarm of planetary rovers. We compare our model performance with the most updated technique to solve the local minimum problem; the forward chaining technique. The performance comparison results confirm that the internal state model is more suitable for real time application with high efficiency

in solving the problem along with comparatively lower computation cost.

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