MOONHOPPERS COLONY

Rubén Martínez-Cantín

Departamento de Informática e Ingeniería de Sistemas, Universidad de Zaragoza
Zaragoza, Spain
rmcantin@unizar.es

ABSTRACT

This paper is a first approach to a robotic exploration mission in low gravity environments. A colony of cooperative hopping robots has been proposed as an efficient solution based on the biological analogy of insects. The problem has been divided in three levels of behaviour: robot, team and colony. A survey about current devices, sensors and algorithms are presented in order to solve each of the levels. For the first level of behaviour I also introduce several experimental results using a multi-robot simulator.

INTRODUCTION

The Mars Pathfinder mission with the autonomous vehicle Sojourner[7], proved that mobile robots, especially microrovers, are a good solution for planetary exploration mission. The dual mission Spirit/Opportunity to Mars has continued with this tendency.

The use of robots reduces costs in missions because they are lighter than humans, they do not need life support systems, and, for exploration tasks, they do not need to be recovered.

On the other side, considering their reduced size, insects are especially gifted to explore great surfaces. However, their ability comes from three basic and simple principia: redundancy, efficiency and specialization.

A colony of insects is a global system composed by hundreds of units dedicated to one common task. This makes the global system immune to local failures. If an insect dies, his fellows finish the task without problems[8].

The morphology of insects is more efficient than that of other bigger animals. Their muscles are incredibly more powerful, their skin is more resistant, their wings are faster and they can climb over a smooth wall or walk over the water. These skills allow them to survive in extreme conditions. This efficiency increases exponentially in cooperative works.

The last advantage is specialization which is closely related with efficiency. Each species of colonial insects (bees, ants…) has several types of workers. Each type is specialized, and so more efficient, in one simple task (bring food, lay eggs…).

These principia may be applied to robotics. Recent studies with robots show that cooperative work with some little and cheap units is more efficient than work with a single expensive robot. Furthermore, if a malfunction happens in a unit, the process can continue.

Continuing with the biological analogy, hoppers may be the most efficient locomotion system in low-gravity environments, especially for little robots. As a robot gets smaller, obstacles the size of the robot come along much more frequently. But in planetary environments, all the obstacles are on the floor. The solution is to travel long distances staying as time as possible far away from the surface.

The behaviour of the hoppers will be structured in three levels: robot level, working team level and colony level. The paper presents an overview of techniques and algorithms for the three levels. A simulation of the behaviour of the robot level implemented in MATLAB is also presented.

In this paper, these principia will be oriented to a simulation of an exploration mission of the Moon for a base building. However, the concepts presented can be adapted to other robotics missions in low gravity environments.

MISSION CONCEPTS

The building of a base in the Moon has some interesting applications. It can be used to broaden the knowledge of the Moon and the Solar System. In addition, the base can be used to develop some scientific research in unusual conditions (low gravity, absence of atmosphere, seismically stable terrain, etc). These conditions are especially useful for radioastronomic observation.

The first step in base building includes a complete exploration of the possible emplacements[1]. The main characteristics that the elected emplacement must have, are:

1. Flat terrain for assuring landing manoeuvres and deployment.
2. Compactness of the terrain to hold up the buildings and installations.
3. Proximity to interesting points of the Moon.
4. Continuous communications with Earth.
5. Good observation of the sky.
6. Chemical composition of the ground suitable for extraction of necessary substances (oxygen, water, etc).

Some of these conditions can be analyzed using artificial satellites, but others need a surface exploration. A cooperative team of hopping robots (called hoppers) can inspect these constraints on every emplacement and choose the best.

In each robots' team, there will be a first group of hoppers, called active robots, with sensors to help navigation, localization and map building (stereo cameras, omnidirectional or panoramic cameras, laser rangefinder, etc)[2]. The other group, known as passive robots, will be equipped with mission tools:

1. Non navigational sensors: underground sonar, microscopic camera, spectrometer, chemical sensors,
2. Small tools for mining and ground prospecting
3. High performance CPUs for high level computing, real-time map building and data distribution.

First, the hopper's team could be deployed from a low orbit to the desired point as the mobility system of the robots include a structure resistant to impacts and have an automatic self-righting system. Secondly, active hoppers would launch their sensors to localize all robots, nearest obstacles and environment features. Then, one by one, each robot will jump to the next position according to the global and local planning. In every jump, active hoppers will launch the sensors to recompute the localization of every robot and feature using probabilistic approaches.

HOPPING ROBOTS

The paradigm of mobility systems is the wheeled vehicle (like Sojourner) because it is the most studied and tested device. However, the low gravity of the Moon and other celestial bodies such as small planets, satellites or asteroids require to think in new concepts of mobility systems which may seem inefficient in Earth.

Recent studies in the field of hopping robots had shown the efficiency of this kind of locomotion in low gravity environments. This efficiency comes from two facts: the low rate of *energy cost per meter covered* and the capability to cross over high obstacles, i.e. big rocks, without needing to go around it. A comparative between a wheeled nanorover and a hopper is presented in Schell et al.[30].

Main studies in hopping robots are focused in two fields based upon the hopping mechanism: those in which the robot make little hops to maintain its equilibrium, like a man in an elastic bed; and those in which the robot makes long jumps for travelling, like a grasshopper or a frog. In this work, I have focused on those prepared long jumping.

There are two prototypes for this kind of robot which can be used for planetary exploration. The first has been developed in the Jet Propulsion Laboratory, California Institute of Technology, in USA and is the third generation of hoppers for planetary exploration[30]. The second has been developed in Sandia National Laboratories, in USA[29]. The characteristics of these two robots are compared in table 1 with the characteristics

chosen for the hopper in the simulations of this paper.
For the robot used in the simulations, I have chosen worse characteristics than those of the prototypes, except for the payload, as we assume each robot will carry independent equipment according to its role. The weight of the tool or sensor is not considered.

	Caltech Hopper	Sandia Hooper	Simulated Hopper
Weight	1 - 1.5 kg	1.25 kg	-
Max. high jump on 1g	~1 m	~3 m	1 m
Max. length jump on 1g	~2 m	~3 m	1 m
Energy source	Solar-panel charged batteries	Fuel tank (including oxidizer)	-
Energy life	Battery life (1 hop = 125 Jules)	~1000 hops	-
Adjustable jump	Yes	Yes	Yes
On-board control	Yes	Yes	Yes
On-board comms.	Yes	Yes	Yes
On-board sensors	Camera	No	-
Wheels	Yes	No	-
Payload	No	1.25 kg	1 tool or sensor

Table 1: Comparison between hoppers. Data extracted from Jet Propulsion Laboratory, California Institute of Technology[29] and Sandia National Laboratories[30].

MULTI-ROBOT NAVIGATION PROBLEM IN MOON

Many possible solutions have been studied to solve the navigation problem with one or more robots. Most of them are focused in less restrictive conditions (structured environments, flat floor movement, etc). The especial traits of the exploration mission in the Moon (unstructured and unknown environment, unknown starting position, GPS not available, etc) make navigation a complex issue that must be approached by separating it in more simple tasks. In this work the problem has been divided in two groups of tasks.

The first group are computations needed to be accomplished in each hop: localization of the hoppers, obstacle avoidance and formation control. These algorithms depend on the motion system of the robot and must be computed with the systems on-board to avoid time delays due to communication lag with Earth.
The tasks of the second group (goal planning, data processing, etc) can be computed on Earth with more complex algorithms and do not depend on the motion system of the robot (hopping, wheeled, etc).

Environment-based localization

The problem with exploration missions is that as the environment is completely unknown, the current localization is relative to the last known position. The extraterrestrial concept of the mission prevents us from using Global Position Systems (GPS) or magnetic compasses.
Usually, exploration missions require the building of an environment map. So, the Simultaneous Localization and Map-Building (SLAM) is one of the best solutions for localization during exploration[4].
This algorithm uses environment features (landmarks) to build a map while moving. The localization of the robot is based on continuous map matching. Furthermore, multi-robot platforms often use a common map to increase the accuracy of the computations.
Landmarks are difficult to be found in unstructured environments like Moon, so it is necessary to use complex landmark extraction and matching procedures. In the last years, the tendency for landmark detection is to use laser rangefinders, stereo vision[20] or omnidirectional-panoramic cameras[12,25]. The coordinates of the landmark can be related to a global or local reference system. Global reference systems are the best solution for centralized processing and map matching between robots. Local reference systems are used in distributed processing and they are not affected by singularities.
The weakness of the SLAM problem using hoppers is that the measures have to be made

between two points far away; increasing the difficulty of the matching problem (the length of the hop in some prototypes can reach more than 3 meters on Earth, which is approximately equivalent to 18 meters on Moon).
Consequently, another localization method with a higher frequency of measures would be useful. This conduces to dead-reckoning techniques (odometry, accelerometers, gyroscopes, etc.). But most of them do not work on hoppers.
Odometry works in wheeled vehicles or similar, because it requires a continuous contact between the robot and the ground. Accelerations-decelerations in the beginning-end of the jump are too high for an accelerometer. However, in hoppers, the rotation movement and the linear movement are separated in time, so a combination of gyroscopes can give good results for Euler angles computation[26].

Multi robot-based localization

Multi-robot systems open the gates to new paradigms for more accurate localization and with fewer constraints than the classical ones. This theory is based on two concepts:

a) A robot can be used as an artificial feature, which is more easy to be extracted and matched than environment ones.
b) Multi-robot platforms allow several measures from different points of view of the same feature. So the position of features (and the position of the robot based on features) can be estimated more accurately.

The first point allows us to calculate the localization of passive robots, which would be impossible with environment localizations. For the robot identification, some authors use retroreflective totems for laser rangefinders positioning[15,16,17] and colour patterns for camera positioning[10].
The second point is especially relevant in multi-robot and multi-sensor platforms and not only for the localization problem. Each observation generates an information gain over the last observations, which produces more accuracy in the final measures (see figure 1).

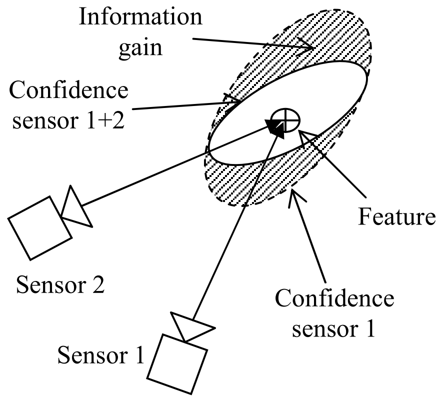

Fig. 1. Dependence between two observations. First, Sensor 1 observes the feature within a confidence interval (dashed ellipse). Finally, Sensor 2 observes the same feature with a confidence interval inside the last one (solid ellipse). The marked area shows the information gain.

The problem of data fusion has been developed from different points of view. The classical methods are based on centralized Kalman Filter (KF) and Extended Kalman Filter (EKF)[28]. Some authors present a decentralized version of this filter which substitutes the system state for the information state[13]. Fox et al. use a sampling method of Markov localization, the Monte Carlo Localization (MCL), for multi-robot localization. Finally, Howard et al. present techniques using particle filter[16] and maximum likelihood estimation[15].
At the end, all the robots use the data fusion results on a local or global reference depending of the method used.
There is also the possibility of building a graph, capturing the neighbourhood relations among the robots and its relative position[9]. This graph can be solved with feature matching or using active beacons[2]. The active beacon signal must be triangulated (or trilaterated) to obtain a global measure. In this case, the graph is used to build a system of equations to solve the relative positions of all robots. However, other method is needed due to the symmetry indeterminations in the localizations. On the other hand, the graph

could be a solution for computing the orientation of the robots.
The robot based localization presents some advantages in planetary environments:

1. The environment features are easily differentiable from retroreflective or coloured totems.
2. The robots themselves are the most dangerous obstacle, as they need to be near the rest of the group and because of their mobility.

Path planning and obstacle avoidance

Especially for outdoor navigation, both obstacle avoidance and path planning has to afford the concept of *traversability*.
For obstacle avoidance, traversability is called *obstacle negotiation* (ON), and it is the ability to decide if the obstacle should be traversed or circumnavigated[34]. This concept is extremely important in hoppers.
For path planning, Howard and Seraji[18] quantify the traversavility of the terrain based on fuzzy rules. The parameter includes terrain roughness and slope which are computed with stereo vision. The planning of the trajectory is also implemented using fuzzy rules.
Laubach and Burdick[21] present other path planning algorithm based on the experience with Mars Pathfinder mission. The planer works in a 2D environment model detecting obstacle boundaries inside an angular wedge of stereo vision. The position of the boundary determines the direction of the next step.
In fact, the most studied method for reactive navigation is based on potential fields. In this case, the obstacles generate a repulsive force as the goal generates an attractive one. These forces are generated with a discretization of the terrain using characteristic points or cells. Haddad et al. give an example using stereo vision with a projective discretization.
Normally, these approaches only work with obstacles with positive elevation (rocks), because in environments like Moon or Mars those are the more frequent. However, some authors are considering also negative elevations (craters) where classical stereo vision is unreliable. A good solution for this could be the multi-sensor platform[31].

Deployment and formation control

The planning of multi-robot configuration requires taking a new step in the navigation.
Some authors have developed algorithms for formation control of wheeled vehicles in unstructured environments than can be translated to a hoppers colony.
Desai et al.[6] offer a leader-follower method. T A robot takes the role of the leader and follows the path planning like a single robot. The algorithm uses a graph with some behavioural rules for formation control. The formation is recomputed, changing the distance-orientation of the followers related to the predecessors and based on local sensor feedback. With this system, the formation can avoid obstacles and change their shape without changing the graph.
In contrast, other authors focus in adaptative control to formation-keeping, considering also the effect of actuator saturation in some robots[19]. In this case, the whole formation follows the path planed.
Finally, other cooperative method for multi-robot navigation is the use of a landmark trail as navigation waypoints. The first robot sets the waypoints related to relevant environment features common to all robots. The rest of the group has to follow the trail to reach the goal[32]. Moreover, this trail can be also built using active robots to track the passive robots along the path (see figure 2). Some algorithms based on incremental deployment can be adapted to this purpose[17]. The single condition of the robot trail is that every active robot must be in the field of view of the next robot. Thus the distance covered in each step is:

$$d = \sum_{N_{ar}} R_i = N_{ar} \cdot R$$

where N_{ar} is the number of active robots and R_i is the maximum reliable range of the sensor i. If the robots' team is homogeneous R_i is a constant value (R) for all the robots.

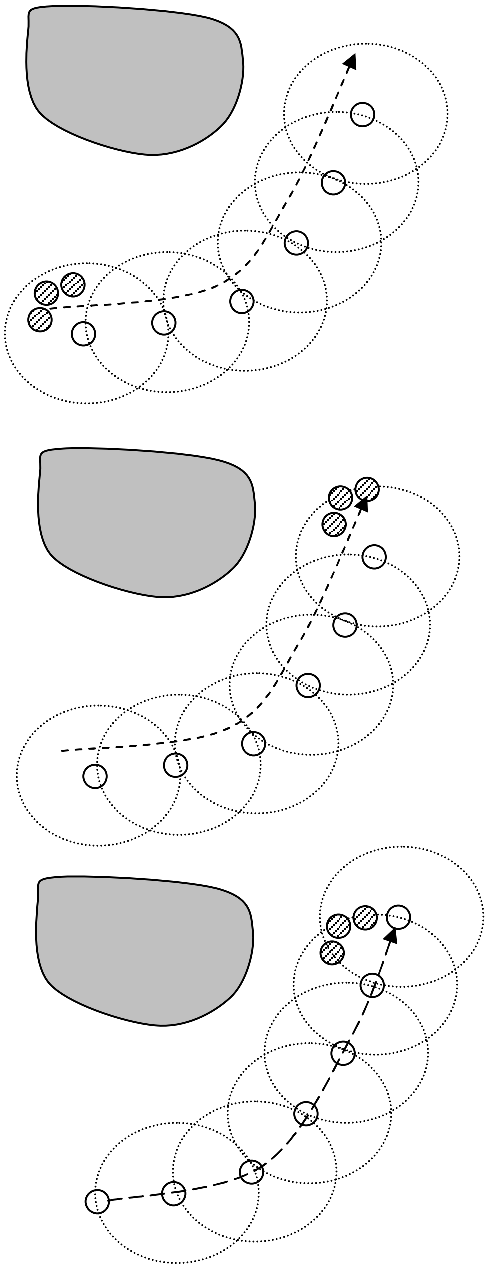

Fig. 2. Trail of active robots. First, the active robots (white circles) are deployed along the path. Then the passive robots (dashed circles) travel along the path with the tracking of the active robots. If the number of active robots is not enough to cover all the distance, the process is repeated from the first point since the goal is reached. The dotted circles show the range of sensors.

EXPLORATION IN THE MOON

Exploration is probably the broadest studied application for single and cooperative robots. It is based on the information gain about the knowledge of the environment. However, in this work the concept of exploration includes ground prospecting, chemical analysis and other mission objectives.

Furthermore, some authors have created the concept of integrated exploration which joins the main problems of mobile robotics: localization (where I am), mapping (where I was) and motion control (where I go). Since other authors focus on the information gain for the exploration, Makarenko et al. [22] weight the concepts of information gain U_I (new knowledge of the environment), navigability U_N (less distance travelled to build the map) and localizability U_L (density of known features to an accurate localization). The integration allows adding a new concept: the mission goals U_G. The final decision of the next goal will be the highest values of the total utility U^{TOT}:

$$U^{TOT} = w_I \cdot U_I + w_N \cdot U_N + w_L \cdot U_L + \sum w_G \cdot U_G$$

The relative weights (w) depend on the mission and must be adjusted according to the priorities of the goals and the estimations of the structure of the environment.

The problem of choosing which robot must reach each goal is known as the multi-robot task allocation. This is a classical mathematical problem (multi traveller salesman problem, MTSP) which has been evaluated in different situations, missions and environments[5,11,24]. The main objective for each step is to get the combination robot-frontier points that maximizes utility (U) while minimizes the travelling-time cost (V) (like market economy problems[35])

$$\forall\ i \in frontier,\ j \in robots$$
$$\max \sum U_{i,j} \ \therefore\ \min \sum V_{i,j}$$

There are also some algorithms that focus on the problem from the point of view of

mapping and exploration. These methods add some concepts like information overlapping[3].
Multi-robot exploration algorithms are based on active robot teams. Rekleitis et al.[27] offer some algorithms which are useful in open spaces with low obstacle density. They are based on robot tracking and strict formation control. The algorithm has low information gain which is compensated with a high accuracy of the localizability. They use similar hypothesis to those presented in this paper.
In contrast, recent works are founded on the frontier-based exploration using occupancy grids[33]. On those papers, each robot is focused on a different part of the environment and, usually, one robot is separated from the others. These hypotheses introduce a different point of view compared to those in our paper.
The solution studied here is a multi-team algorithm. Each team of robots (actives and passives) is considered like a single unity for the exploration of the environment, but all the robots are part of the same network.

SIMULATIONS

I have simulated the first level of behaviour presented in this paper. This includes the problems of localization (single and multi-robot), map-building and obstacle avoidance.
The experiments have been implemented in a MATLAB multi-robot simulator. For simplicity, the simulator only considers 2D movement, because the possible emplacements for a moon base have the constraint to be flat terrains. Furthermore, the obstacles implemented are equivalent to medium-high rocks which are the most frequent obstacle for a hopping robot on the Moon. The features considered for the Simultaneous Localization And Map-building, SLAM algorithm are the peaks of the rocks, which are an invariant feature taking into account the heterogeneous sensors (laser rangefinder and stereo panoramic cameras). The robots are detected and identified using a retro-reflective coloured totem. The range of view of the camera has been limited to 200 meters and the laser to 20 meters. All the matches are supposed correct.

The data fusion is solved using an extended Kalman Filter (EKF)[23]. It is based on the general nonlinear system and measurement model, where **x**, **u** and **z** represent the state, action and measurement vectors and **v**, **w** are the state and measurement noises:

$$\begin{aligned}\mathbf{x}_k &= \mathrm{f}(\mathbf{x}_{k-1}, \mathbf{u}_k; \mathbf{v}_{k-1}) \\ \mathbf{z}_k &= \mathrm{h}(\mathbf{x}_{k-1}; \mathbf{w}_{k-1})\end{aligned}$$

The system and measurement noises are assumed to be Gaussian with zero mean and are represented by their covariance matrices **Q** and **R**. In the simulation the values for these covariance matrices are:

$$\mathbf{Q} = \begin{bmatrix} (0.25 \cdot d)^2 & 0 \\ 0 & 2.7 \cdot 10^{-3} \end{bmatrix}$$

$$\mathbf{R}_{camera} = \begin{bmatrix} 625 & 0 \\ 0 & 1.6 \cdot 10^{-5} \end{bmatrix}$$

$$\mathbf{R}_{laser} = \begin{bmatrix} 10^{-4} & 0 \\ 0 & 2.5 \cdot 10^{-5} \end{bmatrix}$$

where d is the distance travelled in a jump by the robot.
The optimal state estimate is propagated from state k-1 to state k by the relation:

$$\begin{aligned}\hat{\mathbf{x}}_k^- &= \mathrm{f}(\mathbf{x}_{k-1}, \mathbf{u}_k; 0) \\ \mathbf{P}_\mathbf{k}^- &= \mathbf{A}_{\mathbf{k-1}}\mathbf{P}_{\mathbf{k-1}}\mathbf{A}_{\mathbf{k-1}}^\mathbf{T} + \mathbf{B}_{\mathbf{k-1}}\mathbf{Q}_{\mathbf{k-1}}\mathbf{B}_{\mathbf{k-1}}^\mathbf{T}\end{aligned}$$

At state k, the measurement $\mathbf{z}_k$ becomes available. The estimate is updated by the kalman filter gain $\mathbf{K}_\mathbf{k}$ in both the mean and covariance relations:

$$\begin{aligned}\mathbf{K}_\mathbf{k} &= \mathbf{P}_\mathbf{k}^- \mathbf{H}_\mathbf{k}^\mathbf{T} \left(\mathbf{H}_\mathbf{k}\mathbf{P}_\mathbf{k}^-\mathbf{H}_\mathbf{k}^\mathbf{T} + \mathbf{R}_\mathbf{k}\right)^{-1} \\ \hat{\mathbf{x}}_k^+ &= \hat{\mathbf{x}}_k^- + \mathbf{K}_\mathbf{k}\left(\mathbf{z}_k - \mathrm{h}(\hat{\mathbf{x}}_k^-)\right) \\ \mathbf{P}_{\mathbf{k+1}}^- &= (\mathbf{I} - \mathbf{K}_\mathbf{k}\mathbf{H}_\mathbf{k})\mathbf{P}_\mathbf{k}^-\end{aligned}$$

where **I** is an identity matrix and system (**A**), input (**B**) and measurement (**H**) matrices are

computed as the Jacobians of the system (f(x,u)) and measurement (h(x)) functions respectively.
For the initial covariance, the value chosen is several times higher than any distance on the map.
The state of the system includes position (*x*, *y*) from the robots and the features. The orientation of the robots is assumed to be calculated by other methods like triangulation or coded totems.
For obstacle avoidance, the path planer has been implemented based on simple potential fields, because the discrete movement of the hoppers do not need accurate adaptations. Therefore, the attractive and repulsive forces are defined as

$$\mathbf{F}_a = \frac{d_{goal}}{K_a}$$

$$\mathbf{F}_r = 1 - \frac{d_{obstacle}}{K_r}$$

where Ka and Kr are the respective weighting constants. Finally, the total force applied to the robot is

$$\mathbf{F}^{TOT} = \mathbf{F}_a - \sum_{obs} \mathbf{F}_r$$

This force shows the direction of the next jump and is proportional to its length.
The weights of the potential fields have been calibrated to keep the robots close to each other.

Simulation with a simple far obstacle

According to the characteristics presented to the terrains for a base building in the Moon, the obstacles and the landmarks are few and far from the working area of the robots. As a result, these features are out of range of the laser rangefinders and only the cameras can build a map.
This fact has been simulated in an environment with a single far obstacle/landmark (see figure 3). The results of the experiments with different teams of robots are presented in table 2. The combination of multiple robots increases the accuracy of the measures (even though some of the robots are passive). The conjuction of laser and camera offers the best solution because it mixes a wide range measure (camera) for the obstacles/landmarks with an accurate short range measure (laser rangefinder) for the robots.

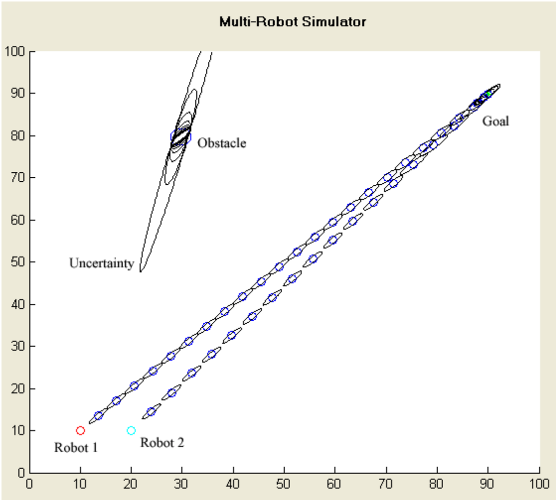

Fig 3: Experiment with far obstacle

	Robot 1	Robot 2	Obstacle
Passive	12.9791	-	-
Camera	11.6760	-	7.8734
Camera & Camera	7.0822	7.2479	4.8756
Camera & Laser	2.5771	2.5771	2.5049
Camera & Passive	8.4589	9.1673	5.6345
Laser & Passive	5.1807	5.1807	-

Table 2: Maximum uncertainties (in meters) at the end of the experiments with single far obstacle.

Simulation with several obstacles

I have developed some experiments with a higher density of features in all the range of distances from the robots' team. In this case, the simulation represents a more general environment with some obstacles in the trajectory of the robots. Figure 4 shows the effect of potential fields in the trajectory of a camera robot. The simulation presents also the effects of adding new robot/features to the environments. Again, a good combination is camera-laser. However, adding new passive robots offers similar or better results.

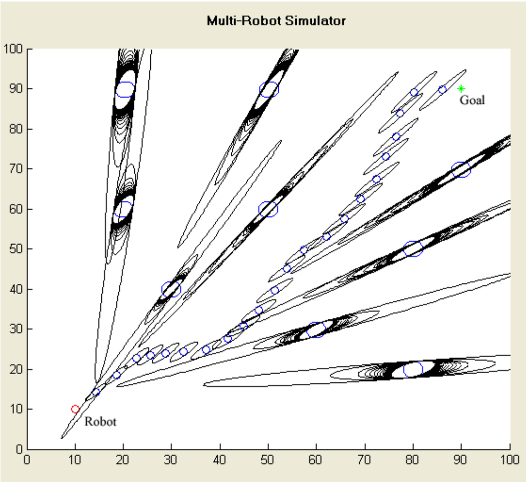

Fig 4: Experiment with several obstacles

			Robots	Obstacles		
Cam	Las	Pass	Mean	Mean	Max	Min
1			6.9921	4.8309	6.3934	3.4764
	1		6.3640	-	-	5.1533
2			4.1949	3.1861	3.8826	2.6678
1	1		2.4928	2.4923	2.4931	2.4918
2	1		2.4899	2.4898	2.4900	2.4896
1	1	3	2.4877	2.4877	2.4880	2.4875
2	2	3	2.4856	2.4856	2.4857	2.4855

Table 3: Maximum uncertainties (in meters) at the end of the experiments with several obstacles.

Consequently, the best solution for a working team is a combination of laser robots that covers all the positions of the other robots (especially passive robots), complemented with a pack of camera robots for a complete knowledge of the environment, solving the problem of visual occlusions (not considered in the simulations).
Furthermore, multi-robot platforms are especially useful to avoid singularity errors.

CONCLUSION

In this paper, I have introduced an approach to the problem of planetary exploration, in low gravity environments.
The solution has been oriented to an exploration mission in the Moon, but it could be adapted to other satellites or planets like Mars, with new mission parameters (search of life or water, crater exploration, etc).
Future work includes an accurate model of the environment and robots for the simulator (3D movement, visual occlusion, landmark extraction and matching, etc.) and the implementation of the next levels of behaviour (formation control and autonomous deployment and exploration).

ACKNOWLEDGMENTS

I wish to thank the disinterested collaboration of the people of the Robotics, Perception and Real Time Group of the University of Zaragoza (J.J. Guerrero, J.A. Castellanos, C. Sagüés, J.M.M. Montiel and L. Montano). I wish to thank also B.L. Spletzer from Sandia National Laboratories for providing the technical details of his hopper. Special thanks to ESA Educational Office for sponsoring during the IAF Congress 2003.

REFERENCES

1. M. Bautista Aranda, En las Puertas del Espacio. Camino al infinito: una apasionante aventura científico-técnica, McGraw-Hill, 2001.
2. J. Borenstein, H.R. Everet, L. Feng, D. Wehe. Mobile Robot Positioning: Sensors and Techniques, Journal of Robotic Systems, 14(4), pp. 231-249, 1997.
3. W. Burgard, M. Moors, D. Fox, R. Simmons, S. Thrun, Collaborative Multi-Robot Exploration, In Proc. of the IEEE International Conference on Robotics and Automation, 2000.
4. J.A. Castellanos, J.M.M. Montiel, J. Neira, J.D. Tardos, The SPmap: A Probabilistic Framework for Simultaneous Localization and Map Building, IEEE Transactions on Robotics and Automation, pp. 948-952, vol 15(5), Oct. 1999.
5. S.A. Chien, A. Barrett, T.A. Estlin, G. Rabideau, A comparison of coordinated planning methods for cooperating rovers.. In Proc. of the Fourth International Conference on Autonomous Agents, 2000.
6. J.P. Desai, J.P. Ostrowski, V. Kumar, Modelling and Control of Formations of Nonholonomic Mobile Robots, IEEE Trans. on Robotics and Automation, pp. 905-908, vol 17(6), Dec. 2001.
7. G.N. DeSouza., A.C. Kak., Vision for mobile robot navigation: A survey. IEEE Trans. on Pattern Analysis and Machine Intelligence, 24(2): 237-267, 2002.
8. M. Dorigo, V. Maniezzo, A. Colorni, The ant system: Optimization by a colony of cooperating

agents, IEEE Transactions on Systems, Man and Cybernetics – Part B, pp. 26(1):29-41, 1996.

9. G. Dudek, M. Jenkin, E. Milios, D. Wilkes, Robust Positioning with a Multi-Agent Robotic System, In Proc. of the International Joint Conference of Artificial Intelligence (IJCAI-93) Workshop on Dynamically Interacting Robots, pp. 118-123, 1993.
10. D. Fox, W. Burgard, H. Kruppa, S. Thrun, A probabilistic Approach to Collaborative Multi-Robot Localization, Autonomous Robots, 8(3), 2000.
11. B.P. Gerkey, M.J. Matarić, Multi-Robot Task Allocation: Analyzing the complexity and Optimality of Key Architectures, In Proc. of the IEEE International Conference on Robotics and Automation, 2003.
12. J.J. Gonzalez-Barbosa, S. Lacroix, Rover localization in natural environments by indexing panoramic images, IEEE Internacional Conference on Robotics & Automation, 2002.
13. B. Grocholsky, A. Makarenko, H. Durrant-Whyte, Information-Theoretic Coordinated Control of Multiple Sensor Platforms. In Proc. of IEEE International Conference on Robotics and Automation, 2003.
14. H. Haddad, M. Khatib, S. Lacroix and R. Chatila. Reactive Navigation in Outdoor Environments using Potential Fields. In Proc. of IEEE International Conference on Robotics and Automation, pp. 1232-1237, 1998.
15. A. Howard, M.J. Matarić, G.S. Sukhatme, Localization for Mobile Robot Teams Using Maximum Likelihood Estimation, In Proc. of IEEE International Conference on Robotics and Automation, 2003.
16. A. Howard, M.J. Matarić, G.S. Sukhatme, Putting the 'I' in 'Team': An Ego-Centric Approach to Cooperative Localization, In Proc. of IEEE International Conference on Robotics and Automation, 2003.
17. A. Howard, M.J. Matarić, G.S. Sukhatme, An Incremental Deployment Algorithm for Mobile Robot Teams, In Proc. of IEEE International Conference on Robotics and Automation, 2002.
18. A. Howard, H. Seraji, Real-Time Assessment of Terrain Traversability for Autonomous Rover Navigation, In Proc. of IEEE/RSJ International Conference on Intelligent Robots and Systems, 2000.
19. S. Joshi, Multilevel adaptation for autonomous mobile robot formations, AIAA-200-4167, Session on Robotics, UAV, and Autonomous Systems, AIAA Guidance, Control, and Navigation Conference, 2000.
20. S. Lacroix, A. Mallet, R. Chatila, L. Gallo, Rover Self Localization in Planetary-like Environments, International Symposium on Artificial Intelligence, Robotics and Automation in Space, 1999.
21. S. Laubach and J. Burdick, An Autonomous Sensor-Based Path-Planner for Planetary Microrovers, In Proc. of IEEE Conference on Robotics and Automation, 1999.
22. A.A. Makarenko, S.B. Williams, F. Bourgault, H.F. Durrant-Whyte, An Experiment in Integrated Exploration. In Proc. of the IEEE/RSJ International Conference on Intelligent Robots and Systems, 2002.
23. P.S. Maybeck, Stochastic Models, Estimation and Control (Vol. 1), Academic Press, 1979.
24. M.J. Matarić, G.S. Sukhatme, E.H. Østergaard, Multi-Robot Task Allocation in Uncertain Environments, Autonomous Robots, 14, pp. 255-263, 2003.
25. E. Menegatti, E. Pagello Toward a topological Mapping with a multi-robot team, In Proc. of Workshop on Cooperative Robotics, IEEE/RSJ Int. Conf. on Intelligent Robots and Systems (IROS2002-WS7), 2002.
26. L. Ojeda, J. Borenstein, FLEXnav: Fuzzy Logic Expert Rule-based Position Estimation for Mobile Robots on Rugged Terrain, In Proc. of IEEE International Conference on Robotics and Automation, pp. 317-322, 2002.
27. I.M. Rekleitis, G. Dudek, E.E. Milios, Multi-Robot Collaboration for Robust Exploration, In Proc. of IEEE International Conference on Robotics and Automation, 2000.
28. S.I. Roumeliotis, G.A. Berkey, Distributed Multi-Robot Localization, IEEE Transactions on Robotics and Automation, pp. 781-795, vol 18(5), Oct. 2002.
29. Sandia National Laboratories, USA: http://www.sandia.gov/
30. S. Schell, A. Tretten, J. Burdick, S.B. Fuller and P. Fiorini, Hopper on Wheels: Evolving the Hopping Robot Concept, In Proc. of the Field and Service Robotics, pages 379-384, 2001.
31. R. Simmons, L. Henriksen, L. Chrisman, G. Whelan, Obstacle Avoidance and Safeguarding for a Lunar Rover, In Proc. of AIAA Forum on Advanced Developments in Space Robotics, 1996.
32. R.T. Vaughan, K. Stoy, G.S. Sukhatme, M.J. Matarić, Exploiting Task Regularities to Transform Between Reference Frames in Robot Teams, In Proc. of IEEE International Conference on Robotics and Automation, 2002.
33. B. Yamauchi, Frontier-based Exploration using Multiple Robots, In Proc. of the Second International Conference on Autonomous Agents, 1998.
34. C. Ye, J. Borenstein, A new terrain mapping method for mobile robots obstacle negotiation, In Proc. of UGV Technology Conference, SPIE AeroSense Symposium, 2003.
35. R. Zlot, A. Stentz, M.B. Dias, S. Thayer, Multi-Robot Exploration Controlled by a Market Economy, In Proc. of the IEEE International Conference on Robotics and Automation, 2002.