2010 IEEE International Conference on Robotics and Automation
Anchorage Convention District
May 3-8, 2010, Anchorage, Alaska, USA

Explicit Coordinated Localization Using Common Visual Objects

J.M. Peula, J. Cebolla, C. Urdiales and F. Sandoval

Abstract— **Localization in multi-robot systems is a key problem in multi agent systems. In many cases, specially involving legged robots, like the Robocup soccer competition, it relies on predefined landmarks at known locations. However, when several objects are in motion, vision occlusions due to agents in the field of view make this kind of localization unfeasible for mild time periods. This also happens if landmarks are not within the field of view. This paper presents a technique to let a robot estimate its position with respect to objects or robots by sharing whatever visual data it has with its teammates. Shared data is used to estimate the relative positions of robots watching the same object via stereoscopy. The rest of the robots can be localized via triangulation and acquire information on the position of hidden or unknown objects that other members of the team can see. The system has been tested with two Aibo ERS 7 robots from Sony and an Aiball.**

I. Introduction

Multiagent systems (MAS) have been deployed in the last decade in a variety of scenarios, and applied to several tasks. The use of multiple robots allows completion of a given task faster and more effectively [1] as multiple robots can be in different places at the same time, can perform concurrent and cooperative actions and, in general, allow the decomposition of a complex task into simpler ones. Areas in which MAS have proven to be useful are: self-organized robots [2] [3], biologically-inspired robot coordination [4], surveillance and exploration [5], military [6], etc.

Navigation in robotics can be defined as the problem of reaching a target in a safe way. This requires the robot to know its relative position with respect to the target and obstacles in the way (localization). In MAS, the trajectory of an agent is not defined only by its relative position with respect to a target, but also by the relative positions of the other agents with respect to itself, since they act as obstacles. In these cases, the environment is highly dynamic, so maps of the environment are difficult to keep updated and most systems work at reactive/hybrid level. Hence, localization of team members and/or rivals must be as fast as possible.

Depending on the environment, there are many different localization algorithms. They may rely on laser [7], sonar [8], vision [9] or a combination of sensors [10]. Also, they may work with artificial landmarks [11] or natural ones extracted from the environment [12]. Anyway, despite the sensors used, most approaches work with odometry corrected via *Kalman Filters* [12] [8] or *Particle Filters* [9] to better estimate the robot position. In absence of odometry, triangulation based on active or visual landmarks has been used [13] [14] to estimate the position of one robot with respect to its reference system.

J.M. Peula, C. Urdiales and F. Sandoval are with Department of Tecnología Electrónica, E.T.S.I, Telecomunicación, Universidad de Málaga, Campus de Teatinos S/N, 29071 - Málaga (Spain). peula, acurdiales, fsandoval@uma.es

In our case, our environment will be a typical test one for MAS: the RoboCup robot league. In RoboCup, specially when legged robots are involved, localization is mostly visual rather than based on dead-reckoning. Indeed, the soccer fields typically include color landmarks at known positions that the robot may use for global localization. Landmark based localization, though, presents two major drawbacks. First, robots may locate themselves with respect to the landmark, but do not know the positions of the others. Second, these systems are very prone to occlusions, specially when there are many robots in the field. Naturally, it is possible to take advantage of communication with other team members, so that the field of view of the team is larger than that of a robot alone.

In this paper we proposed a technique for cooperative localization in a MAS. Specifically, we use AIBO ERS-7 from Sony in our tests. Our system is based on the properties of stereo vision: given two cameras, the depth of an object in both fields of view can be estimated e.g. via disparity. In our case, robots have a single camera each, so we use a different property: given two robots capturing the same landmark, we can estimate the separation between their cameras and, hence, their relative position to each other. If we know the relative positions of enough agents/objects, we can estimate the locations of the rest by triangulation. Thus, the difference with other triangulation approaches (such as [13]) is that we do not use just information from beacons, but we use information from other robots to localize through triangulation. E.g. if a robot sees the ball and two team members are seeing this robot, we can estimate the relative positions of all 4 elements. This is explained in section II.

The system has been tested with a navigation layer based on the Potential Field Algorithm (PFA). Once the robots share information about significant items in their field of view, they calculate their relative position and the ball's, and try to reach their goal in a reactive way. Our coordination mechanism is explained in section III. Experiments using Aibo-ERS7 legged robots, equipped with videocameras, are shown in section IV. Finally, section V presents our conclusions and future work proposal.

II. Landmark based visual localization

As commented, Robocup localization may be based in artificial landmark visual localization. Artificial landmarks are used because they are easier to detect than natural landmarks [15][16]. The position, size, shape and color of these artificial landmarks are usually known *a priori* to ease

978-1-4244-5040-4/10/$26.00 ©2010 IEEE

detection and also to allow size based distance estimation using a single camera. In a Robocup field, typical landmarks are beacons, goals and field lines [17][18], but field lines crossing can also be used [19], as well as the center circle and corner poles [20].

A typical problem in Robocup is that landmarks are symmetrical with respect to the floor plane. This means that if a single landmark is detected and no information at all on localization is available, the robot may know how far from the landmark is, but not from which direction it is seeing it. The same can be applied to the ball. This uncertainty can be reduced if two or more landmarks are detected, as triangulation allows correct positioning with respect to them both. Besides, since robots are moving, statistical tools like Markov Fields can be used to remove uncertainty as well. This is particularly important when landmarks are not unique, like fields lines, and must be disambiguated. Hoffmann [21], for example, uses negative information to improve self-localization. Each time the system expects to find a landmark, and does not find it, it weights as negative information. This negative information makes probability distribution in Markov localization converges more quickly.

Assuming that a robot can be correctly located if it sees an artificial landmark with respect to that landmark, there are still cases where visual landmark localization is challenging:

- When the robot can not see any landmark in its field of view and, hence, does not know its own position.
- When it knows its position with respect to a landmark but ignores the location of other robots and/or the ball.
- When robots know their position with respect to a moving landmark -e.g. ball, other robots-, but not respect to an absolute one -e.g. color beacons-.

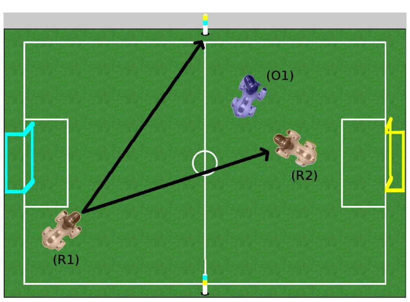

Fig. 1. Robot R2 Estimation of position with information of R1 (R2 cannot see the beacon due to O1) .

These problems could be solved if robots in a team talk with each other to share localization information. In Fig. 1, for example, robot R2 can not see any beacon due to occlusion by robot O1. Robot R1 can see both a beacon and R2. Hence, they can communicate to calculate their relative positions via triangulation. However, in many cases landmarks are partially occluded and their distance to the robot can not be well estimated from a single image. Furthermore, it is difficult to keep two of them within the field of view of a single robot to triangulate.

We propose, instead, to estimate the position of agents in the environment using information of objects seen at the same time by different robots. Each image provides information -correct or not- about the distance from the object to the watcher. A pair of images provide information via stereo vision about the location of the watchers with respect to the perceived object or with respect to each other. Finally, triangulation is used as an additional equation to the system to remove degrees of freedom and/or detect errors if necessary. The larger the number of robots with common perception, the more precise localization of agents is.

Stereo based depth calculation is based on the fusion of two slightly different views of a common scene. Depth is a function of the distance between cameras, their angle, focal distance, and, mainly, difference between both images in terms of Disparity. Specifically:

$$f * B = Z * d \tag{1}$$

Being f the focal distance, B the distance between the cameras, Z the distance to the object localize and d the disparity between the two images. If no information is available about possible objects in the field of view, disparity can be calculated via correlation. If objects are defined, though, like landmarks, it is only necessary to calculate their shifting in pixels from one image to the other.

In our case, each robot has only one camera and if it perceives a known landmark -robot, ball or beacon- it can estimate its distance to that landmark because their sizes are known *a priori*. We use equation 1 to estimate instead where are robots with respect to each other when they are watching the same object (beacon, ball or other robot). In this case, we know about Z, extracted from the presumedly known distances of robot 1 and 2 to the object. For an Aibo, we heuristically estimated f to be equal to 190 pixels. Disparity (d) can be easily extracted from the object shifting in the images captured by both robots. Hence, B can be obtained via Eq. 1.

For example, Fig. 2 shows a situation in which robots R1 and R2 see two objects in common. Specifically, an opponent (blue) and the the ball (pink). In this case, R1 does not know where it is, because robot O1 hides the beacon. Hence, the only solution to estimate R1 location is to estimate it from the objects they see. Each robot knows at what distance is each object (they know the size of the ball and the opponent) and they know the angle between them, so applying stereo, R2 can estimate the position of R1.

This differs from classic triangulation in the sense that each robot may be, in fact, watching a single landmark, which can be moving (e.g. Aiball). If robots perceive two landmarks at known positions at the same time, triangulation is feasible. For example, Fig. 3 shows a situation in which there are two robots of the same team (R1 and R2) and two opponents (O1 and O2). R2 cannot see the beacon due to occlusion by O1, and R1 due to occlusion by O2, so they can not localize themselves correctly. However, R1 can see both the ball and R2. Using the law of the cosine (Eq. 2), R1 can estimate the positions of the ball and opponents O1 and O2 with respect to robocentric coordinates of R2.

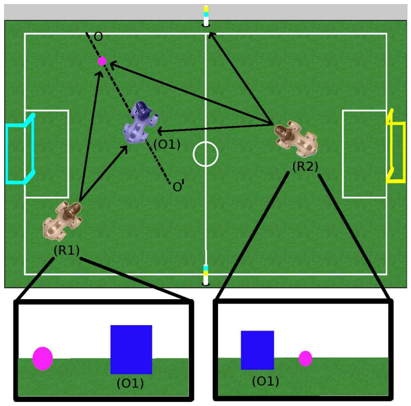

Fig. 2. Example of stereo based distance estimation.

$$C^2 = A^2 + B^2 - 2ABcos(\alpha) \quad (2)$$

Hence, although R1 and R2 do not know their position in the field, they can establish a coordinated strategy, since they have information about the target, their team mates and their opponents. In any case, in order to reduce degrees of freedom in equation systems conformed by stereo pairs or to detect errors provoked by wrong size based distance estimation from single images, triangulation can be applied to threesome of elements located in the field to check if results are coherent. Naturally, when there are more agents, there are more unknown factors, but also they cover a larger field of view, so there are more equations and it is possible to remove uncertainty.

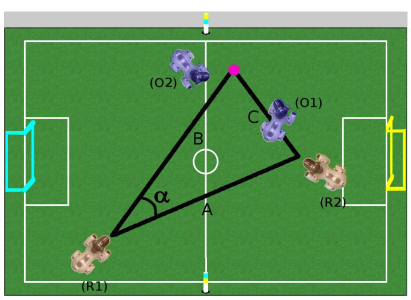

Fig. 3. Example of triangulation.

III. Coordination

In order to check how the proposed localization system works, we have implemented a coordinated navigation mechanism with Sony Aibo ERS 7 robots. It is important to note that MAS do not necessarily imply coordination. Robots could have different agendas or even be competitive. Most coordination mechanisms, though, fit into one of the following categories:

- Explicit coordination. In this category, agents communicate explicitly with each other and the actions of each agent in the group are calculated by deliberative planning. In explicit coordination team actions can be calculated in parallel to determine the best individual action for reducing duplication of effort and furthering the goals of the team. This approach can be strongly centralized [22], weakly centralized [23] or distributed [24]. In any case, there is a process that takes into account all different individuals's targets, position and skills to choose a course of action.
- Implicit coordination. This technique relies on the dynamics of interaction among robots and the environment in order to achieve the desired collective performance, often in the form of designed emergent behaviors. In these methods, agents do not explicitly work together, but simply act on their own behalf, taking into account the existence of the others either to modulate their actions or simply to avoid getting in their way. Their acts generate an emergent combined action [25], which is accepted as cooperative, such as in insect colonies [26], for example. This mechanism is typical in animals and it is quite efficient when all robots are similar.

Since our goal is to check how MAS coordinated localization works, we rely on implicit coordination. It is interesting to note that agents do communicate, but just to localize each other rather than to make decisions together. Specifically, each robot relies on a Potential Field Approach (PFA) [27], where the goal is set depending on the relative positions of robots and ball and agents in the environment are simply modelled as moving obstacles. PFA is one of the best known reactive algorithms due to its simplicity and easy implementation. PFA simply models the robot as a free particle moving in a potential field, where the obstacles have the same charge as the robot (and hence, generate an repulsion force), and the goal has a different charge (attracts the robot). All in all, the robot tends to move towards the goal, avoiding obstacles in the way and preserving smoothness. The easiest PFA formulation simply consists of:

$$U(q) = U_g(q) + \sum U_o(q) \quad (3)$$

where the attractor $U_g(q)$ and repulsors $U_o(q)$ are calculated as:

$$U_g(q) = k_1 dist(q, goal)^2 \quad (4)$$

$$U_o(q) = k_2 \cdot \frac{1}{dist(q, obstacle)} \quad (5)$$

k_1 and k_2 being constants to tune how fast we approach to the goal and how close we get to obstacles, respectively. All described forces are presented in Fig. 4.

Coordination works as follows. Communication between AIBOs uses *Telepathy*. *Telepathy* is a communication class included in last version of Tekkotsu, an useful programming framework for AIBO. The telepathy class of Tekkotsu let an AIBO subscribe to events in other AIBO if they are wirelessly connected. Thus, a subscribed AIBO can process remote events and its own events. The class let the AIBO know if an event is remote or not and, if remote, it can know which AIBO detected it. This class translates communication

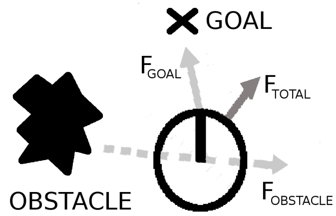

Fig. 4. Example of forces (F) over robot using PFA.

to events, simplifying communication, and making it easier to manage.

In our case, Aibos are subscribed to color detection events, where each color is associated to a different item, e.g. the pink ball, orange for a robot in a rival team, yellow for a robot in our team, etc. Whenever an Aibo$_i$ receives an event ($E_i(t)$) calculates its distance ($d_{iC}(t)$ if local or $d_{kC}(t)$ if remote) to the object and it checks if it is local. If local it adds it to PFA of the robot ($U(t)$). After that, it checks for all previous distances ($d_{jC}(t)$) calculated (local or remote) associated to this color object in last 2 seconds. If any, it calculates the distance ($d_{ij}(t)$ if local or $d_{kj}(t)$ if remote), using disparity. The more color events a robot has, the more precise the position. This estimations are added to PFA. Localization can be still ambiguous after checking all distances associated to color events. In this case, triangulation is used to reduce ambiguity. Finally, next movements of the robots are added to PFA. Fig. 5 shows the flow diagram of event processing.

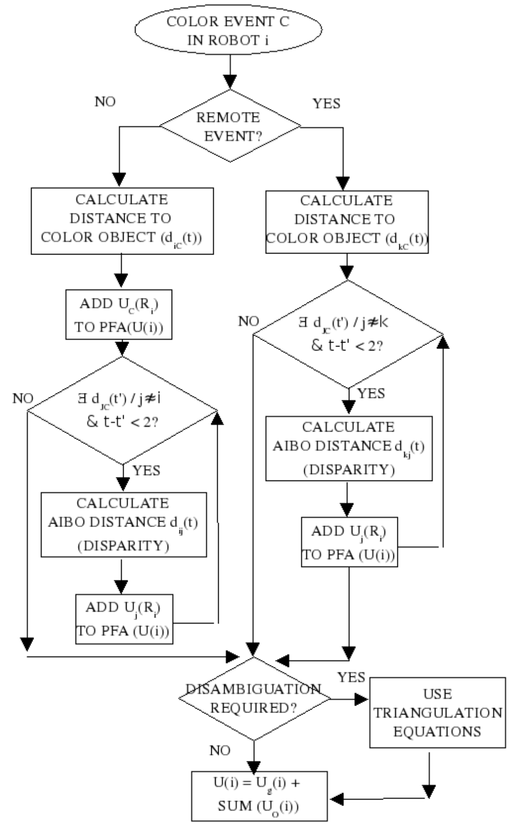

Fig. 5. Event processing flow diagram.

IV. Experiments and Results

In this section we present some tests of the proposed localization system. Since behavior coordination is not our main goal, tests are simple, in plain environments. As commented, we have used two AIBO ERS-7 and an Aiball. In the first experiment both AIBOs have to coordinate to catch the ball without crashing by sharing their visual data to localize each other, even though they are focusing on the ball and, hence, most of the time out of the other's field of view. The second test adds a new object, an orange obstacle. The two AIBOs see the ball and the obstacle. The objective of this test is to estimate the position of both AIBOs using information of the objects and to catch them. Each AIBO has its own goal. The AIBO that is nearest to the orange box have to catch it, so the other AIBO has to catch the rose ball. The third test is similar, but the obstacle prevents one of the AIBOs from seeing the ball. Thus the other AIBO has to send this information, and then cooperate to catch its own goal and not to crash meanwhile.

As commented, in our experiments we had only two Aibos, so it was fairly easy to know where information came from. If we have more than two robots wearing the same team color, it would be harder to disambiguate which one is which one. Usually, since they share information not only about what they see, but also about previous estimated positions, this issue is not a problem. E.g. a lost robot not seeing landmarks can use information from localized member of its team to estimate where it is if any of them is watching it. In absence of such information, though, all robots should share what they see at the same time. Resulting equations would conform an equation system where where only a single solution is feasible.

A. Experiment 1

In the first experiment we have two AIBOs, and a ball in front of them. We placed them close to each other on purpose, so that they could collide when moving towards the ball. Their only goal here is to catch the ball in a safe way. To estimate the position of the AIBOs, we rely on the proposed stereo technique. We are assuming that there is only one ball in the environment.

Fig. 6.a shows the initial position of the AIBOs and the progress of the test when no position estimation is used. It can be observed that the two AIBOs crash in the middle of the experiment, and they go on crashing till they catch the ball. The objective of this test is to show that they cannot avoid each other without position estimation.

Fig. 6.b shows the same test but using position estimation. It can be observed that they correctly estimate their position. Thus they avoid crashing and finally they catch the ball from opposite sides. The information that they are sharing is the position of the ball respect to each AIBO, and the angle of the neck. With this information, they can estimate the position of the other AIBO and avoid themselves.

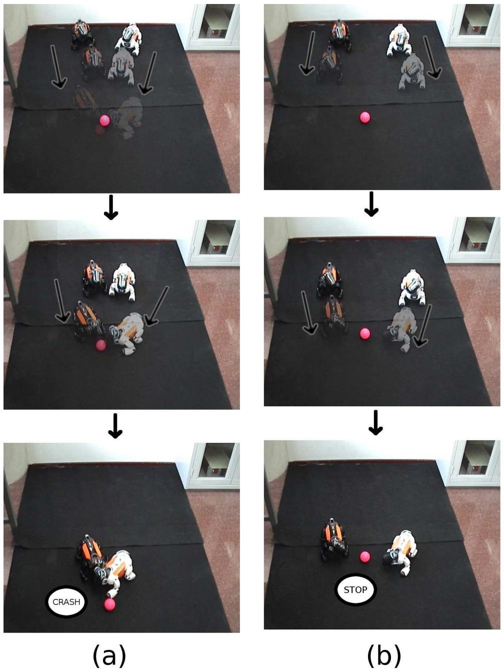

Fig. 6. (a) Implicit coordination between AIBOs without communication. (b) Explicit coordination between AIBOs with communication of position estimation.

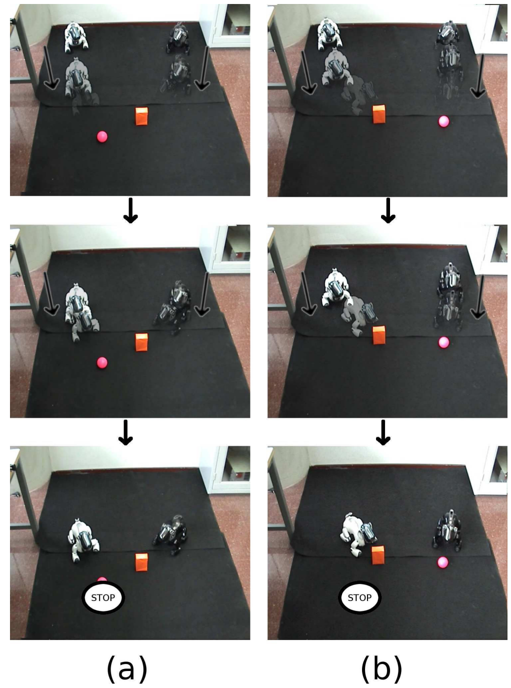

Fig. 7. Explicit coordination of two AIBOs seen two objects in common and using position estimation. (a) Black AIBO nearer to obstacle. (b) White AIBO nearer to obstacle.

B. Experiment 2

This experiment is similar to the first one, but in addition to the ball, there is an obstacle. Both AIBOs can see the obstacle and the ball. So the experiment consists on estimating the position of the other robot and catching the obstacle or the ball. The nearest AIBO to the orange obstacle have to catch it. The other AIBO has to catch the ball.

Fig. 7 shows the initial position of the AIBOs and the objects they can see (both the obstacle and the ball). It can be seen that they correctly estimate where they are to avoid crash and that they catch the correct objective. The black AIBO (Fig. 7.a) catches the orange obstacle (black AIBO is the nearest) and the white one have to catch the ball. Fig. 7.b shows the same scenario but the goals are changed (ball for black AIBO and obstacle for the white one).

C. Experiment 3

This experiment is similar to the last one, but in this case, the obstacle prevents white AIBO from seeing the ball. Thus only black AIBO can see the ball at first. The experiment consists, first of all, in estimating the position of the other robot. Then, the AIBO that can see the ball, has to send this information to the other AIBO, and after that, they establish their goals depending on their distance to the obstacle and to the ball.

Fig. 8 shows the initial position of the AIBOs and the progress of the test. It can be seen that they correctly estimate where they are to avoid crash. It can be seen too that they establish their goals correctly. In Fig. 8.a black AIBO is nearer to the obstacle (so this is its goal) and white one has to catch the ball. In Fig. 8.b obstacle is nearer to white AIBO, so goals are changed. This shows that they have correctly shared information about the estimated position of the ball. Otherwise, they cannot establish and catch their goals.

V. Conclusions and Future Works

This paper has presented an approach to visually estimate the localization of multiple objects and robots by sharing data extracted from the images they capture with a single camera. Artificial landmarks are used to this purpose. Relative distances between them are estimated by building an equation set from different estimations: i) monocular size based distance estimation; ii) stereo based distance estimation for robots sharing perception of an object; iii) triangulation to reduce degrees of freedom in the test. As a result, robots may estimate where they are with respect to each other or where objects occluded or out of their fields of view are located at each time instant and without need of keeping an absolute coordinate system. Since the method is reactive in nature, speed compensates for lack of precision and/or punctual errors.

The system has been tested using Aibo ERS7 robots in a Robosoccer like environment, where objects have pure colors and their size is known *a priori*. No lines or field beacons have been used in the present experiments. These tests have proven that the proposed method is valid to deal with situations where robots can not see each other or their target by sharing visual data via a telepathy mechanism supported by the Tekkotsu architecture. Localization information has been used to set targets and repulsors in a very simple PFA in order to coordinate the robots reactively. Even though

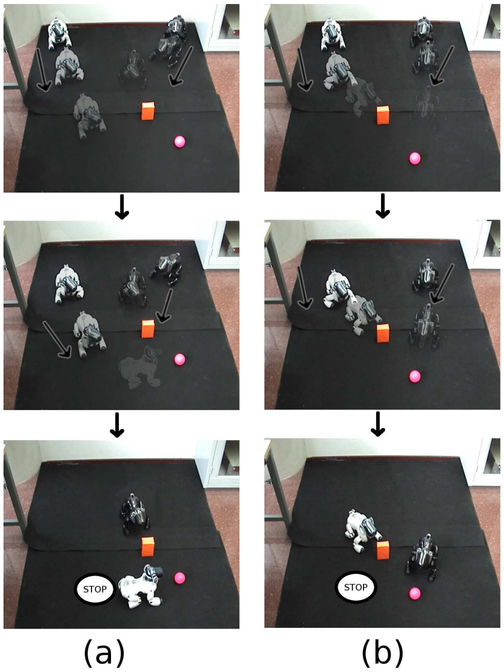

Fig. 8. Explicit coordination of two AIBOs using position estimation. White AIBO does not see the ball. (a) Black AIBO nearer to obstacle. (b) White AIBO nearer to obstacle.

results have been successful in all cases, these tests are still preliminary and it would be necessary to include a larger number of robots so that uncertainty is larger. If any problem arises in those cases, localization beacons in Robocup environment should be useful to reduce it. Future work will focus on testing the system with a larger team and more opponents.

VI. Acknowledgements

This work has been partially supported by the Spanish Ministerio de Educacion y Ciencia (MEC), Project n. TEC2008-06734 and by the Junta de Andalucia, SIAD Project No. TIC-3991.

References

[1] R. C. Arkin, *Behaviour based robotics*, Cambridge, 1998.

[2] S. Nolfi, "Behaviour as a complex adaptive system: On the role of self-organization in the development of individual and collective behaviour," *Complexus*, vol. 2, pp. 195 – 203, 2005.

[3] G. Baldassarre, A. V. Trianni, A. M. Bonani, A. F. Mondada, A. M. Dorigo, and A. S. Nolfi, "Self-organised coordinated motion in groups of physically connected robots," *IEEE Transactions on Systems, Man and Cybernetics - Part B: Cybernetics*, vol. 37, no. 1, pp. 224 – 239, 2007.

[4] R. Vaugham, A. N. Sumpter, A. J. Henderson, A. A. Frost, and A. S. Cameron, "Experiments in automatic flock control," *Robotics and Autonomous Systems*, vol. 31, no. 1, pp. 109 – 117, 2000.

[5] M. B. Dias and A. A. Stentz, "A free market architecture for distributed control of a multirobot system," vol. 11, no. 3, Venice (Italy), 2000, pp. 115 – 122.

[6] K. Konolige, C. Ortiz, R. Vincent, A. Agno, B. Limketkai, M. Lewis, L. Briesemeister, D. Fox, J. Ko, B. Stewart, and L. Guibas, "Centibots: Large scale robot teams," *Proocedings of the 2003 NRL Workshop on Multi-Robot Systems*, vol. 2, 2003.

[7] J.-H. Tzou and K. L. Su, "High-speed laser localization for a restaurant service mobile robot," *Artificial Life and Robotics*, vol. 14, no. 2, pp. 252 – 256, Nov. 2009.

[8] D. Navarro, G. Benet, and M. Martinez, "Line based robot localization using a rotary sonar," in *Proceedings of the 12th IEEE Conference on Emerging Technologies and Factory Automation ETFA07*. Patras (Greece): AAAI Press, Sep. 2007, pp. 25 – 28.

[9] J. Wolf, W. Burgard, and H. Burkhardt, "Robust vision-based localization by combining an image-retrieval system with monte carlo localization," *IEEE Transactions on Robotics*, vol. 21, no. 2, pp. 208–216, 2005.

[10] K. Hara, M. Inoue, S. Maeyama, and A. Gofuku, "Navigation using one laser source for mobile robot with optical sensor array installed in pan and tilt mechanism," in *Proceedings of the IEEE/ASME International Conference on Advanced Intelligent Mechatronics (AIM'08)*, Xian, Jul. 2008, pp. 257 – 262.

[11] Z. Liu, N. Jiang, , and L. Zhang, "Self-localization of indoor mobile robots based on artificial landmarks and binocular stereo vision," in *Proceedings of the 2009 International Workshop on Information Security and Application (IWISA09)*, Nov. 2009, pp. 226–231.

[12] A. Georgiev and P. Allen, "Localization methods for a mobile robot in urban environments," *IEEE Transactions on Robotics*, vol. 20, no. 5, pp. 208– 216, Oct. 2004.

[13] F. Calabrese and G. Indiveri, "An omni-vision triangulation-like approach to mobile robot localization," in *Intelligent Control, 2005. Proceedings of the 2005 IEEE International Symposium on, Mediterrean Conference on Control and Automation*, June 2005, pp. 604 – 609.

[14] J. M. Font-Llagunes and J. A. Batlle, "Consistent triangulation for mobile robot localization using discontinuous angular measurements," *Robotics and Autonomous Systems*, vol. 57, no. 9, pp. 931 – 942, 2009.

[15] E. Celaya, J.-L. Albarral, P. Jiménez, and C. Torras, "Visually-guided robot navigation: From artificial to natural landmarks," in *FSR*, 2007, pp. 287–296.

[16] A. C. Murillo, J. J. Guerrero, and C. Sagues, "Robot and landmark localization using scene planes and the 1d trifocal tensor," in *Intelligent Robots and Systems, 2006 IEEE/RSJ International Conference on*, 2006, pp. 2070–2075.

[17] T. Röfer and M. Jüngel, "Vision-based fast and reactive monte-carlo localization," in *in The IEEE International Conference on Robotics and Automation*. IEEE, 2003, pp. 856–861.

[18] T. Röfer, T. Laue, and D. Thomas, "Particle-filter-based self-localization using landmarks and directed lines," in *RoboCup*, 2005, pp. 608–615.

[19] I. Herrero, C. Urdiales, J. M. Peula, I. Sanchez-Tato, and F. Sandoval, "A guided learning strategy for vision based navigation of 4-legged robots," *AI Commun.*, vol. 19, no. 2, pp. 127 – 136, 2006.

[20] H. Strasdat, M. Bennewitz, , S. Behnke, and S. Behnke, "Multi-cue localization for soccer playing humanoid robots," in *In Proceedings of 10th RoboCup International Symposium*. Springer, 2006.

[21] J. Hoffmann, M. Spranger, D. Göhring, and M. Jüngel, "Exploiting the unexpected: Negative evidence modeling and proprioceptive motion modeling for improved markov localization," in *RoboCup*, 2005, pp. 24–35.

[22] A. Barrett, G. Rabideau, T. Estlin, and S. Chien, "Coordinated continual planning methods for cooperating rovers," *Aerospace and Electronic Systems Magazine, IEEE*, vol. 22, no. 2, pp. 27–33, 2007.

[23] M. B. Dias and A. A. Stentz, "Opportunistic optimization for market-based multirobot control," vol. 3, 2002, pp. 2714 – 2720.

[24] R. Murphy, C. Lisetti, R. Tardif, L. Irish, and A. Gage, "Emotion-based control of cooperating heterogeneous mobile robots," *IEEE Transactions on Robotics and Automation*, vol. 18, no. 5, pp. 744–757, 2002.

[25] R. Rocha, A. J. Dias, and A. A. Carvalho, "Cooperative multi-robot systems:: A study of vision-based 3-d mapping using information theory," *Robotics and Autonomous Systems*, vol. 53, no. 3-4, pp. 282 – 311, 2005.

[26] S. Garnier, A. C. Jost, A. R. Jeanson, A. J. Gautrais, A. M. Adadpour, A. G. Caprari, and A. G. Theraulaz, "Aggregation Behaviour as a Source of Collective Decision in a Group of Cockroach-Like-Robots," vol. 3630, 2005, pp. 169 – 178.

[27] O. Khatib, "Real-time obstacle avoidance for manipulators and mobile robots," *International Journal of Robotic Research*, vol. 5, no. 1, p. 60, 1986.