Obstacle detection, identification and sharing on a robotic soccer team

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Abstract. When building a representation of the environment for a robot in a multi-agent application, as is the case of robotic soccer, sensor and information fusion of several elements of the environment are an important task. To build an increasingly better world model, one of the aspects that one should consider is the treatment of obstacles. This paper gives an insight of the general steps necessary for a good obstacle representation in the robot world model. A first step is the visual detection of the obstacles in the image acquired by the robot. This is done using an algorithm based on radial search lines and colour-based blobs detection, where each obstacle is identified and delimited. After having the visually detected obstacles, a fusion with a-priori known information about the obstacles characteristics allows the obstacle separation and filtering, so that obstacles that don't fill the criteria are discarded. With the position information shared by team mates, the matching of the obstacles and the team mates positions is also possible, thus identifying each of them. Finally, and with the purpose of having a team world model as coherent as possible, the robots are able to share the obstacle information of each other. The work presented in this paper was developed for the CAMBADA robotic soccer team. After achieving the 1st place in the Portuguese robotics open Robótica2008 and in the Robocup2008 world championship, the correct treatment of obstacles was one of the new challenges proposed among the team to improve the performance for the next competitions.

1 Introduction

Nowadays, there are several research domains in the area of multi robot systems. One of the most popular is the robotic soccer. RoboCup[1] is an international joint project to promote artificial intelligence, robotics and related fields. Most of the RoboCup leagues have soccer as platform for developing technology, either at software or hardware levels, with single or multiple agents, cooperative or competitive [1].

Among RoboCup leagues, the Middle Size League (MSL) is one of the most challenging. In this league, each team is composed of up to 5 robots with maximum size of 50x50cm base, 80cm height and a maximum weight of 40Kg, playing in a field of 18x12m. The rules of the game are similar to the official FIFA rules, with required changes to adapt for the playing robots [2].

1 http://www.robocup.org/

Each robot is autonomous and has its own sensorial means. They can communicate among them, and with an external computer acting as a coach, through a wireless network. This coach computer cannot have any sensor, it only knows what is reported by the playing robots. The agents should be able to evaluate the state of the world and make decisions suitable to fulfil the cooperative team objective.

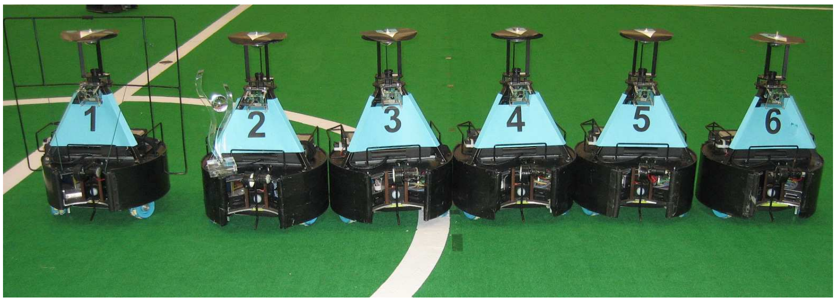


Fig. 1. Picture of the team robots used to obtain the results presented on this paper.

CAMBADA, *Cooperative Autonomous Mobile roBots with Advanced Distributed Architecture*, is the Middle Size League Robotic Soccer team from the University of Aveiro. The project started in 2003, coordinated by the IEETA[2] ATRI[3] group and involves people working on several areas for building the mechanical structure of the robot, its hardware architecture and controllers and the software development in areas such as image analysis and processing, sensor and information fusion, reasoning and control.

While playing soccer, the robots have the need to navigate around the field effectively, which means they have to reposition themselves or dribble the ball avoiding the obstacles on the field, that can be either team or opponent robots, or eventually the referee.

An increasing necessity felt by the team, to improve its performance, is the need for a better obstacle detection and sharing of obstacle information among team mates. This need is important to ensure a global idea of the field occupancy, since the team formation usually keeps the robots spread across the field. With a good cover of field obstacles, pass lines and dribbling corridors can be estimated more easily allowing improvements on team strategy and coordination.

This is essentially an information fusion problem, as the information available from the sensors of each robot and the shared information must be matched and refined. The final result of this fusion is a representation of the state of the surrounding world. In the CAMBADA team, there is an integration process responsible for that task. It is a step executed after image analysis and is responsible to take raw information from

[2] Instituto de Engenharia Electrónica e Telemática de Aveiro - Aveiro's Institute of Electronic and Telematic Engineering

[3] Actividade Transversal em Robótica Inteligente - Transverse Activity on Intelligent Robotics

the vision and other robot sensors and make a sensor fusion of all sources. For that, it may use the values stored in the previous representation, the current sensor measures (eventually after pre-processing) that has just arrived, the current actuator commands and also information that is available from other robots sensors or world state.

All the information available from the sensors in the current cycle is kept in specific data structures (Fig. 2), for posterior fusion and integration, based on both the current information and the previous state of the world.

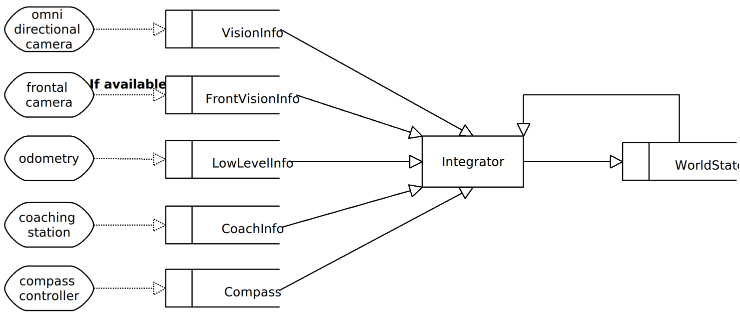


Fig. 2. Integrator functionality diagram.

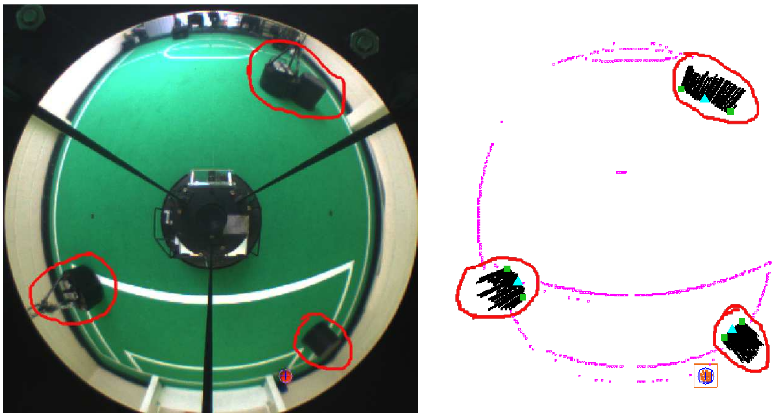
This paper focuses on the description of the obstacle treatment in the CAMBADA team. In Section 2 a general description of how the obstacles are detected by the vision process is presented, also describing how the raw information is passed to the integration process. Section 3 describes how the raw information is read and, based only on the local robot information, how the identification is processed. Section 4 presents how the sharing and acceptance of team mates obstacles is made. Section 5 concludes this document.

Note that most of the figures presented in this paper, after this point, are images acquired by the omni-directional camera of the robots. To ensure the comprehension of the figures, in most of them, lines were made around the areas of interest of the image. Also, the triangles and squares representing the obstacle centres and limits inside that areas of interest were increased in size and intensity, since the original image capture squares are more difficult to see in images of the presented size.

2 Visual obstacle detection

The first step for obstacle avoidance is its detection. The CAMBADA robots gather their information about the surroundings by means of a robotic vision system. Currently, only the omni directional camera gathers information about obstacles, as no frontal camera is being used at this time.

According to RoboCup rules, the robots are mainly black. Since in game robots play autonomously, all obstacles in the field are the robots themselves (occasionally the referee, which is recommended to have black/dark pants). The vision algorithm takes advantage of this fact and detects the obstacles by evaluating blobs of black colour inside the field of play [3]. Through the mapping of image positions to real metric positions [4], obstacles are identified by their centre (triangle on the image captures) (Fig. 3b)) and left and right limits (squares on the image captures) (Fig. 3b)). This is done by creating, from the centre of the image (the centre of the robot), radial sensors around the robot, each one representing a line with a given angle, which are then analysed for the search of black regions. These are called *scanlines* [5].



a) **b)**

Fig. 3. Captures of an image acquired by the robot camera and processed by the vision algorithms, areas of interest were surrounded. Left **a)**: the image acquired by the camera; Right **b)**: the same image after processing. It is visible how the obstacles are identified by their centre (triangle), left and right limits (squares). It is also visible that the 2 obstacles aligned are detected as a single bigger obstacle (top right of the frames).

The detection of black colour on the scanlines is analysed both in angular intervals and length intervals, to define the limits of each black blob. Since the vision system is a non-SVP hyperbolic catadioptric system [4], the sizes of objects on the image vary with the distance to the robot. Due to an inverse distance map calculation, by exploring a back-propagation ray-tracing approach and the mathematical properties of the mirror surface, the relation of distances in the image and the real world is known (Fig. 4).

Through the function represented in Fig. 4, it is possible to create a normalised relation of blobs widths and lengths with the distance. Sometimes an obstacle is separated in several blobs, mainly due to the noise in the image and problems in colour classification, which leads to fails in the detection of black regions in the scanlines. To avoid these situations, an offset is considered to decide when the angular space between blobs is considered enough to represent a real obstacle separation. The same principle is considered concerning the position of the black area in consecutive scanlines.

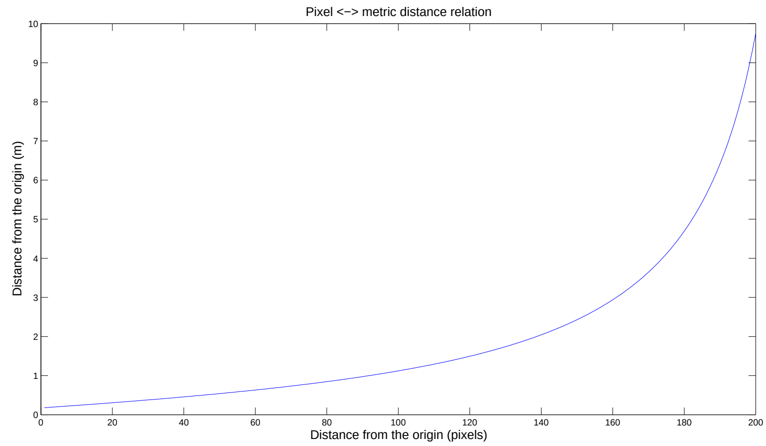


Fig. 4. Relation between pixels and metric distances. The centre of the robot is considered the origin and the metric distances are considered on the ground plane.

The separation offsets of a blob close to the robot are bigger than the ones at a high distance, to maintain coherent precision. The angular separation offset is considered for situations where robots are side-by-side, at the same distance, but there is no visual contact between each blob; the length separation offset is checked for situations where, on sequential scanlines, there are blobs with visual contact but the robots are actually at different distances. Both situations are depicted in Fig. 5.

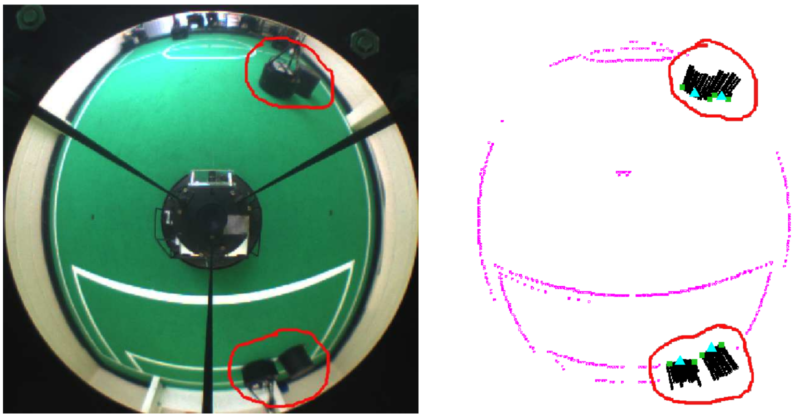
For each detected blob, their pixel sizes are calculated and an estimation of the obstacles left and right limits, as well as their centres, is made. This information is made available for the integration process to filter and treat.

Note that the work described in the remaining of this paper is independent of the vision algorithm, as long as the described information is available. Several approaches exist concerning obstacle identification. The work presented in [6] describes an approach for a similar application but with a non omni-directional vision system. In [7,8], visual colour and edge based detection algorithms are described, but both with times too high for use in the MSL environment. Other applications use several other sensors like laser range, stereo cameras or offline setup, but the financial and space costs of such solutions is much higher [9,10].

3 Obstacle selection and identification

With the objective of refining the information of the obstacles, and have more meaningful and human readable information, the obstacles are selected and a matching is attempted, in order to try to identify them as team mates or opponents.

Due to the weak precision at long distances, a first selection of the obstacles is made by selecting only the obstacles closer than a given distance as available for identification



a) **b)**

Fig. 5. Example of an image acquired by the robot camera and processed by the vision algorithm. The areas of interest are surrounded. Left **a)**: the image acquired by the camera; Right **b)**: the same image after processing. It is visible the 2 possibilities of separation made: angular separation, on the bottom pair of obstacles; length separation, on the top pair of obstacles.

(currently 5 metres). Also, obstacles that are smaller than 10 centimetres wide or outside the field of play margin are ignored. This is done because the MSL robots are rather big, and in game situations small obstacles are not present inside the field. Also, it would be pointless to pay attention to obstacles that are outside the field of play, since the surrounding environment is completely ignorable for the game development.

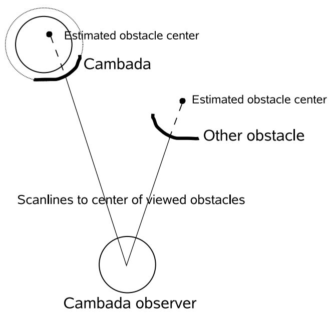
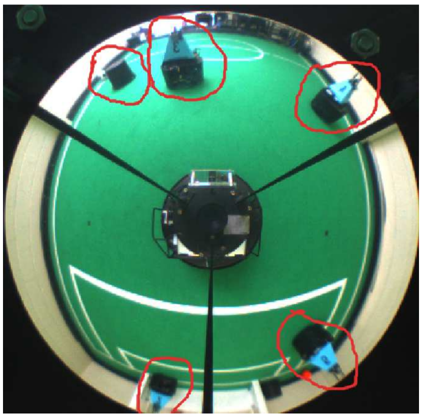
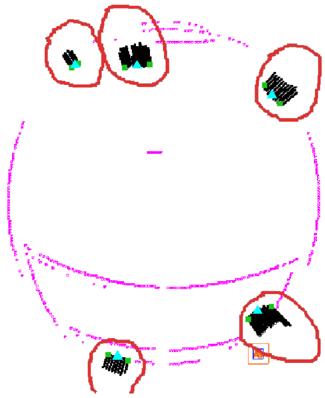


Fig. 6. When a CAMBADA robot is on, the estimated centres of the detected obstacles are compared with the known position of the team mates and tested if they are within the robot radius; the left obstacle is within the CAMBADA radius, the right one is not.

To be able to distinguish obstacles, to identify which of them are team mates and which are opponent robots, a fusion between the own visual information of the obstacles and the shared team mates positions is made. By creating a circle around the team mate positions with the robot radius plus an error margin, varying with the distance, a matching of the estimated centre of visible obstacle within the team mate area is made (Fig. 6), and the obstacle is identified as the corresponding team mate in case of a positive matching (Figs. 7c), 8c)).



a)



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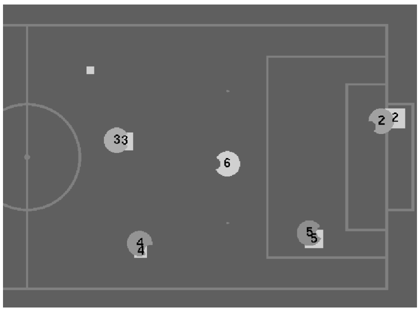

c)

Fig. 7. Illustration of single obstacles identification. Top Left **a)**: image acquired from the robot camera, denoting the single obstacles selected for identification (with lines surrounding them); Top Right **b)**: the same image after processing. The visual detection of the same obstacles are also denoted; Bottom **c)**: image of the control station, where each robot represents itself and robot 6 (the lighter grey) draws all the 5 obstacles in evaluation conditions (represented by squares with the same grey scale as itself). All the obstacles correspondent to team mates were correctly identified (marked by its corresponding number over the obstacle square) and the opponent is also represented with no number. Note that the positions of the robots visible in the image (each has its number on the body) is inverted due to the mirrored vision system.

Since the obstacles detected can be large blobs, the above described identification algorithm cannot be applied directly to the visually detected obstacles. If the detected obstacle fullfills the minimum size requisites already described, it is selected as candidate for being a robot obstacle. Its size is evaluated and classified as robot if it does not exceed the maximum size allowed for MSL robots [2] (Fig. 7a) and 7b)).

If the obstacle exceeds the maximum size of an MSL robot, a division of the obstacle is made, by analysing its total size and verifying how many robots are in that obstacle. This is a common situation, robots clashing together and thus creating a compact black blob, originating a big obstacle (Fig. 8a) and 8b)).

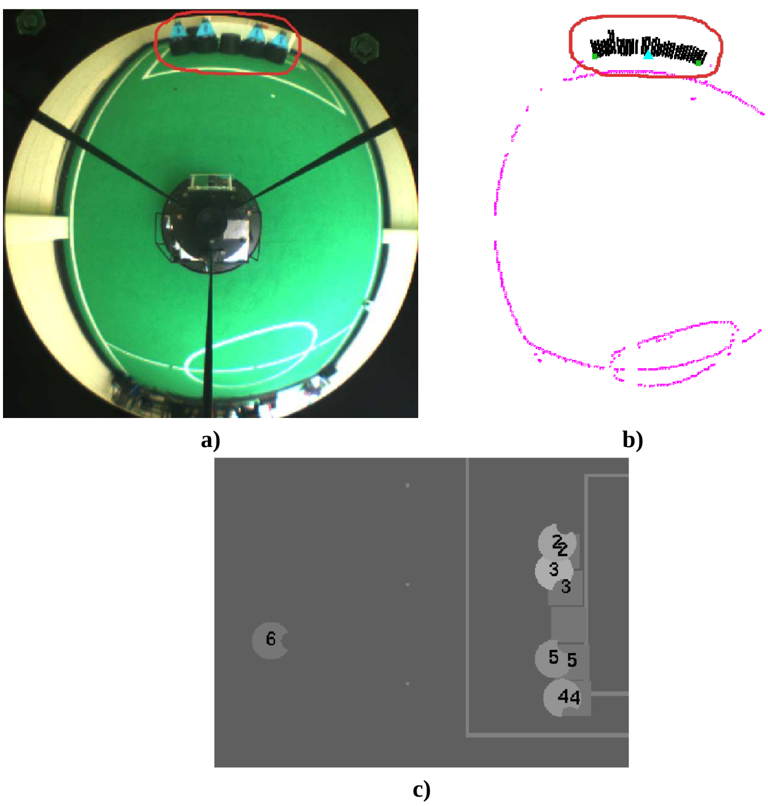

Fig. 8. Illustration of multiple obstacles identification. Top Left **a)**: image acquired from the robot camera, denoting the obstacles aligned (with a line surrounding it); Top Right **b)**: the same image after processing. Visually, the aligned robots are only one large obstacle (marked with its centre with a triangle and side limits with squares); Bottom **c)**: image of the control station, where each robot represents itself and robot 6 (the darker grey) draws all the 5 obstacles (represented by squares with the same grey scale as itself). The visual obstacle was successfully separated into the several composing obstacles, and all of them were correctly identified as the correspondent team mate (marked by its corresponding number over the obstacle square) and the opponent is also represented with no number.

4 Obstacle sharing

With the purpose of improving the global perception of the team robots, the sharing of locally known information is an important feature. Obstacle sharing allows the team robots to have a more global perception of the field occupancy, allowing them to estimate, for instance, passing and dribbling corridors more effectively.

However, one have to keep in mind that, mainly due to illumination conditions and eventual reflexive materials, some of the detected obstacles may not be exactly robots, but dark shadowy areas. If that is the case, the simple sharing of obstacles would propagate an eventually false obstacle among the team. Thus the algorithm for sharing the obstacles makes a fusion of the several team mates information.

The fusion of the information is done mate by mate. After building the worldstate by its own means, the agent checks all the team mates available, one by one. Their obstacles are matched with the own ones. If the agent does not know an obstacle shared by the team mate, it keeps that obstacle in a temporary list of unconfirmed obstacles. This is done to all the team mates obstacles. When another team mate shares a common obstacle, that same obstacle is confirmed and it is transferred to the local list of obstacles. In the current cycle, the temporary obstacles that were not confirmed are not considered. An outline of the algorithm is presented next.

```
for c := 1 to total_number_of_team_mates
  for o := 1 to total_obstacles_of_team_mate
    for m := 1 to total_own_obstacles
      if m matches o
        I already know this obstacle, do nothing
      else
        if previously known by another team mate
          obstacle confirmed and added
        else
          obstacle considered temporarily
          waits for confirmation by another team mate
        end
      end
    end
  end
end
```

The matching of the team mate obstacles with the own obstacles is done in a way similar to the matching of the obstacle identification with the team mate position described in Section 3. The cambada pivot in Fig. 6 is replaced by the current team mate obstacle for the matching test.

Figure 9 shows a situation where robot 2, in the goal area, was too far to see the obstacle on the middle of the field. Thus, it considered the obstacle in question, only because it is identified by both robots 5 and 6, as visible in the figure.

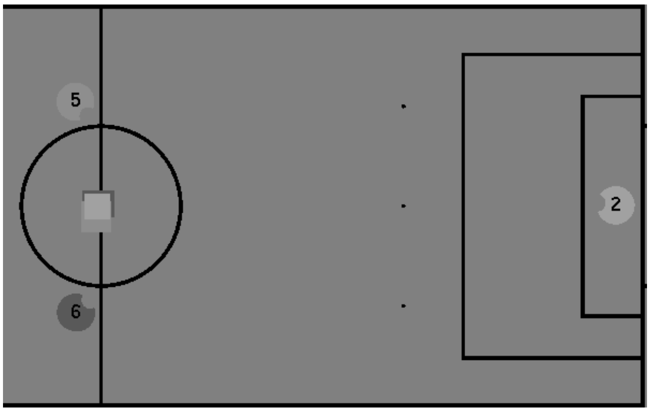

Fig. 9. Image of the control station showing an obstacle of robot 2 that was not seen by itself (on the centre of the field). In this case it assumes the obstacle by confirmation of both robots 5 and 6.

5 Conclusion

The integration of obstacles in the robot representation of the world is an important issue for it to be able to play the game. Even though the performance of the described work is yet to be tested in competition, the intensive tests of the detection and identification have shown a good effectiveness of the process so far.

The improvement on obstacle treatment allows modifications on the overall team strategy, particularly regarding passing possibilities. It also allows the improvement of the robots movement, since team mate obstacles can have a different treatment than the opponents, because team mates have velocities and other information available.

Having achieved the 1st place in the Portuguese robotics open Robótica2008 and in the Robocup2008 world championship, one of the ways to try to improve the CAMBADA team performance was to increase the world model accuracy. This new obstacle treatment, although not yet tested in competition environment, is expected to open new opportunities for the game effectiveness in the next competitions.

Acknowledgements

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References

1. Kitano, H., Asada, M., Kuniyoshi, Y., Noda, I., Osawa, E.: RoboCup: The Robot World Cup Initiative. Proceedings of the first international conference on Autonomous agents (1997) 340–347

2. MSL Technical Committee 1997-2008: Middle Size Robot League Rules and Regulations for 2008 (2007)
3. Neves, A., Corrente, G., Pinho, A.: An omnidirectional vision system for soccer robots. In Neves, J., Santos, M.F., Machado, J.M., eds.: Progress in Artificial Intelligence. Volume 4874 of LNAI., Springer (2007) 499–507
4. Cunha, B., Azevedo, J., Lau, N., Almeida, L.: Obtaining the inverse distance map from a non-svp hyperbolic catadioptric robotic vision system. In Visser, U., Ribeiro, F., Ohashi, T., Dellaert, F., eds.: RoboCup 2007: Robot Soccer World Cup XI. Volume 5001 of LNAI., Springer (2008) 417–424
5. Neves, A., Martins, D., Pinho, A.: A hybrid vision system for soccer robots using radial search lines. In: Proc. of the 8th Conference on Autonomous Robot Systems and Competitions, Portuguese Robotics Open - ROBOTICA'2008, Aveiro, Portugal (2008) 51–55
6. Lenser, S., Veloso, M.: Visual sonar: Fast obstacle avoidance using monocular vision. Proceedings of the 2003 IEEE/RSJ International Conference on Intelligent Robots and Systems (2003) 886–891
7. Das, A.K., Fierro, R., Kumar, V., Southall, B., Spletzer, J., Taylor, C.J.: Real-time vision-based control of a nonholonomic mobile robot. Proceedings of the 2001 IEEE International Conference on Robotics and Automation (2001) 1714–1719
8. Koyasu, H., Miura, J., Shirai, Y.: Realtime omnidirectional stereo for obstacle detection and tracking in dynamic environments. Proceedings of the 2001 IEEE/RSJ International Conference on Intelligent Robots and Systems (2001) 31–36
9. Manduchi, R., Castano, A., Talukder, A., Matthies, L.: Obstacle detection and terrain classification for autonomous off-road navigation. Autonomous Robots (2005) 81–102
10. Michels, J., Saxena, A., Ng, A.Y.: High speed obstacle avoidance using monocular vision and reinforcement learning. Proceedings of the 22nd International Conference on Machine Learning (2005)