# Robofoot ÉPM Team Description – RoboCup2006 MiddleSize League

Julien Beaudry, Julian Choquette, Pierre-Marc Fournier, Louis-Alain Larouche, François Savard

Mechatronics Laboratory, École Polytechnique de Montréal, Montréal, Québec, Canada
{julien.beaudry, julian.choquette, pierre-marc.fournier, louis-alain.larouche, francois.savard}@polymtl.ca
http://www.polymtl.ca/robofoot

**Abstract.** This paper presents the research aspects and developments on which Robofoot ÉPM mainly concentrates for the current RoboCup season. The team will be at its second RoboCup participation and after having the bases established last season, it can now concentrate on more advanced subjects. First, a whole new omnidirectional robot platform is presented and novel trajectory generation algorithm is developed in conjunction. The sensing and localization techniques used are currently being revisited to insure of robust auto-localization and robots identification. For this last topic a combination of two techniques is proposed, using vision and communication respectively. Concerning multi-robot cooperation, the hierarchical decision mechanisms used since last year have proven to be efficient and supervision capabilities open the way to interesting developments.

## Introduction

After a year of competitions, Robofoot ÉPM has gained valuable experience and it has proven that it masters most of the scientific and technical elements needed for a MiddleSize League RoboCup to play autonomously against other competitive teams. The team can now develop new ideas and focus on more detailed aspects of the multi-robot system involved. Most of the ongoing developments concentrate on a new omnidirectional platform which is expected to encompass existing platforms of its kind in terms of dynamic control and ball handling. There are also major works done on computer vision to complete auto-localization and player identification. Artificial intelligence has not been a serious subject yet but the architecture recently developed is offering powerful capabilities. The next paragraphs present relevant aspects of the Robofoot ÉPM project.

## The team of robots: heterogeneous multi-robot system

The Robofoot robot team for the 2006 RoboCup is composed of four differential drive robots and two omnidirectional drive robots. The differential drive system has not dramatically changed since last year, but development is being done to improve the system. The battery system is being revised to supersede the lead-acid batteries and to replace them with high-discharge Ni-MH cells or high-discharge Li-Ion cells. In comparison, the omnidirectional robot is already equipped with a Ni-MH battery pack. Additionally, to improve ball detection and handling, theses robots will be equipped with a passive (mechanical switch) or active (IR or CMUCam) ball detection system. The differential drive system is still capable of achieving longitudinal speeds of 2.5 m/s, rotational speeds of 17.5 rad/s and accelerations of 3.5 m/s$^2$. But the omnidirectional drive system boasts impressive speeds.

### Omnidirectional drive system

The omnidirectional platform was chosen as a successor for the differential drive platform. Compared to the differential drive platform, the ball handling is much more precise because of its holonomous drive system. Observed from previous competitions, a robot's ability to control the ball often determines the winner at RoboCup. This new platform is now part of the heterogeneous team. This robot has four 90W Maxon DC motors coupled with 80 mm polyurethane omnidirectional wheels. The omnidirectional robot weights approximately 15 kg, can attain speeds of at least 5 m/s, can accelerate to at least 5 m/s$^2$ and has a rotational acceleration of 10-15 rad/s$^2$. Compared to the differential drive robots, this omnidirectional platform requires far more energy. As a result, this platform uses Ni-MH cells. The battery pack is rated at 8500 mAh and 30 V. Furthermore, this battery pack can handle currents up to 110 A. The maximum power consumption of this omnidirectional robot is 360 W.

To maximize acceleration and stability, the heaviest components have been placed at the bottom of the robot. This way, the center of gravity is as low as possible. When designing this platform, two main objectives were set: a top speed of 5 m/s and an acceleration of 5 m/s$^2$. The latest test has shown that the robot has attainted theses objectives. In the future, it is improbable that the omnidirectional robot will surpass theses figures because the friction between the playing surface and polyurethane is not high enough to handle accelerations superior than 5 m/s$^2$.

**Figure 1: Omnidirectional robot platform**

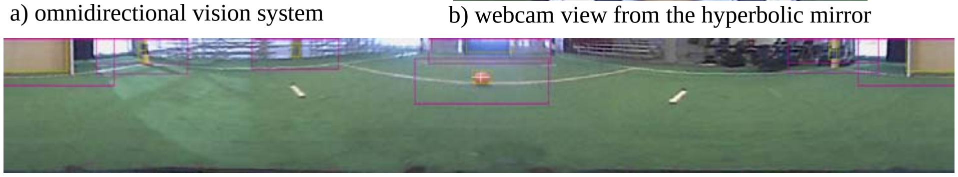
## Sensing and localization

### Distributed omnidirectional vision with local and global Kalman filtering

The robots perception and localization are based on two measurement systems: odometry (measurement of wheels rotation) and an omnidirectional vision system. The measures returned by the vision system are respectively the horizontal angle between the object and the front of the robot, and the vertical angle between horizon and the object. As the main vision device, the robots use a high-quality webcam with a hyperbolic mirror to achieve low-cost and efficient omnidirectional vision. The camera's image is converted into a panoramic image to simplify further treatments and to facilitate the human interpretation. The conversion is very fast since it uses a predefined look-up table translating pixels from omnidirectional image to pixels in panoramic image. Since the objects of the RoboCup's soccer field use predefined colors, HSI color space is used to achieve precise and robust color or black and white segmentations. Object recognition is based on the estimation of the object's size and position in the image compared to the segmentation results. The next figure shows the physical aspects of the vision system and its image representations.

a) omnidirectional vision system

b) webcam view from the hyperbolic mirror



c) panoramic image used for object detection

**Figure 2: Basic elements of the omnidirectional vision system.**

## Data Sharing using Global Kalman Filtering

The robots use an innovative and efficient algorithm to share the ball's position and theirs (Marleau, 2005). Data are always shared with an absolute time reference corresponding to the time of their last update and an estimation of their precision (Bierman, 1977). The absolute time reference allows robots to predict how data changed since they were sent and to reevaluate the data's precision. The data are combined proportionally to their estimated precisions. For example, this algorithm allows robots to consider more a recent ball's position sent by a robot close of it then an older ball's position sent by a robot far of it. Prediction and correction are done by two other Kalman filters, one on the data sharing server and the other on each robot.

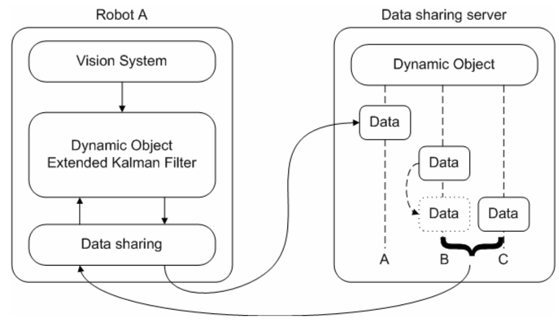



**Figure 3: Data sharing mechanism within the robots distributed perception.**

## Obstacle Detection Algorithm

The solution proposed for obstacle detection is a distinct algorithm from localization vision algorithms. It is crude but highly efficient in terms of CPU time. The only information retrieved on the nature of the obstacles are their size and location. A specific zone is considered to be an obstacle when it has a color that should not normally be found on the field. Because of this, the algorithm also detects other obstacles such as humans, tools or the obstacles of technical challenge 1. The following is a summary of how it works.

First, the region of the field where the robot will pass within a certain time frame is determined. Then, this region is mapped to a rectangle on the panoramic image, which is divided into a number of smaller rectangles. By testing the color ranges of selected rectangles, in HSI color space, each one is marked as containing an obstacle or not. Such ranges are predefined with "safe" color, most notably colors found in the environment, the soccer field in this case, while other colors are considered "unsafe". Finally, contiguous regions are assembled into a list of angular and distance ranges, and regions smaller than a certain threshold are ignored. Short computing times are essential for this algorithm. In order to diminish the computing time, at the cost of some precision, the size of the rectangles within the analysis region can be increased, which effectively lessens the resolution of the analysis. In order to assign a single HSI value to each rectangle (which is composed of many pixels), we use the color value of a pixel near the center of the rectangle. While this method may introduce more errors than methods involving average calculations, we have found that it gives satisfying results, while demanding low computing times.

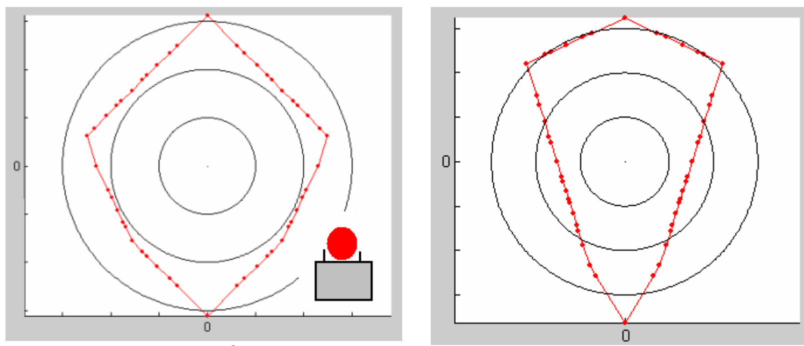
**Figure 4: Panoramic image from vision system with obstacle detection activated. Boxes within magenta region are detected obstacles.**

## Players Identification using Obstacle Maps

A piece of information that is quite useful for the team is the location of its opponents. However, the obstacle detection algorithm gives, as its name implies, the location of *obstacles*, which are, in general, team members of either sides. There is therefore a need to differentiate between those types of obstacles. In a given region of the image identified as an obstacle, there might be more than one robot present. Here, the choice is made to focus on only one of them, the nearest. To comply with RoboCup rules, robots must have a colored band at a certain height indicating their team. It is therefore possible to locate, in the image, the position of band of this nearest robot. By comparing the count of pixels located in each team color's HSI spectrum, an attempt is made to identify whether a robot is an opponent or teammate. Position of obstacles identified as such are added to a current list of opponents maintained by the robot. This list is shared with others on a central server. Several approaches can then be used to merge the positions found by the different robots. The problem here is that a single opponent might be seen in slightly different locations. The solution selected here is to create a master list and then iterate among robots' lists to add to this master list the positions that are not close enough to any one already in it. This algorithm presents the advantage of not requiring too much processing on robots The tradeoff is one of autonomy: a robot cannot determine, on its own, the position of all players. Also, if opponents are very close to each other, they could be recognized as a single entity.

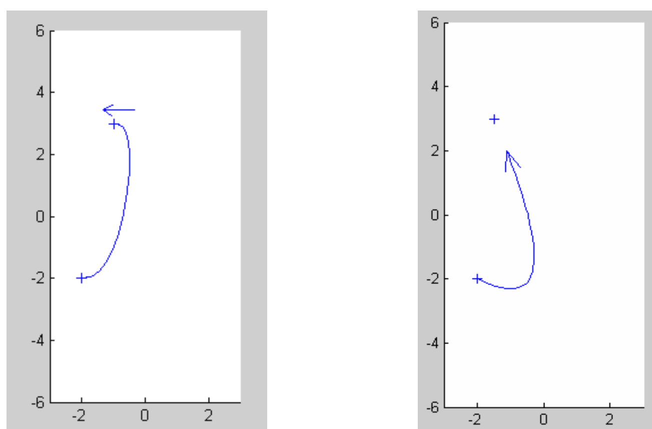
## Improved Wheels Configuration for Omnidirectional Vehicle

Most omnidirectional robots have their wheels tangent on a circle centered on the robot and equally distanced angularly (standard configuration). Our recent design uses innovative wheels configuration. It has been deducted that it would be preferable to have better accelerations in the area in the front of the robot to improve ball handling. The new configuration also allows a more compact design where the center of mass can be kept very low, and shifted towards the front of the robot to share more equally the efforts on all the motors. To quantify the maximal accelerations, the forces on the wheels have been precisely evaluated (Kalmar-Nagy, 2003). In result, accelerations in the front of the robot are somewhat constant in the area +- 0.6 rad and are improved by up to 20% in the area +- 1 rad. Following images illustrate the maximal acceleration in function of the acceleration's direction.




a)standard configuration b)proposed configuration

**Figure 5: Omnidirectional robot acceleration distribution**




a)desired final direction b)desired final speed

**Figure 6: Trajectory generation on the soccer field**

To get more efficient movements on the playing field and better ball handling, trajectory generation algorithms have been developed. To get theoretical optimized trajectories, a norm is fixed for the acceleration, and the equations in function of the destination point. The final speed or the final direction are numerically solved to get the required direction of acceleration. The optimized trajectories can only be closely followed under some orientation conditions since acceleration in function of the direction is not constant (Figure 5b). All predefined trajectories will be revised to respect obstacles avoidance target revision.

## Multi-robot system architecture: distributed decision mechanisms with central supervisor

The architecture used by Robofoot for handling its multi-robot system is called Hierarchical Decision Machine (Beaudry, 2005). It uses a hierarchical structure really simply represented and it works as a succession of sequential decision taking mechanisms. A decision line is terminated with a behaviour willing to activate various actions offered by the robotic system. The HDM is designed with the objective of being distributed on every robot of a multi-robot system. Decision taking mechanisms are then implemented in a distributed fashion. In order to introduce cooperative behaviours between robots of a system, for example resources sharing or dynamic role allocation, pre-established agreements can be used on each decision machine, similar to locker-room agreement concept (Stone, 2000). The graphical representation of the HDM and its decision mechanism are illustrated in Figure 7. *XABSL* (Lötzsch and al., 2003) is a good example of similar architecture taking profit of this simple representation.

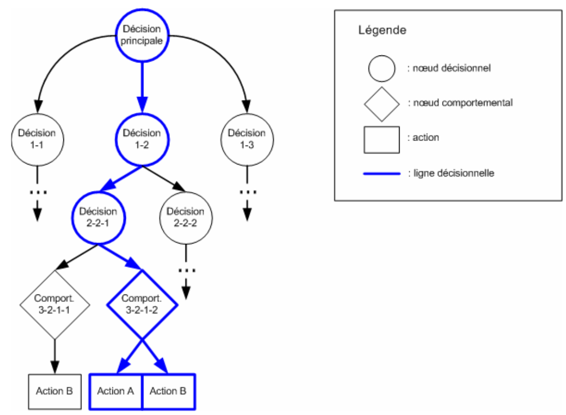



**Figure 7: Hierarchical Decision Machine (HDM).**

It is however possible that a certain system be a source of decision conflicts between robots, in particular if perception capabilities are also distributed. This is true for robotic soccer as played in the MSL. In this case, instead of using negotiation between robots, a technique frequently used for this type of problem (Emery and al., 2002), the concept of Decision Supervision is introduced. When it is judged necessary, a centralized process using a client/server approach can handle the supervision of distributed decision taking and detect situations where intervention is appropriate. Decision supervision is possible on the complete hierarchy of a given decision machine and on every robot of the system. Decision line of each robot of the system can be represented as a Decision Vector $V_{D_i}$. These vectors can be used by the supervisor to form the Decision Matrix $M_D$. Once this matrix is obtained and continuously updated, the supervisor can detect situations where supervision is necessary. The supervisor will in this case define a Supervision Matrix $M_S$ composed of Supervision Vectors $V_{S_i}$ for each robot of the system. Once a robot receives its Supervision Vector it can deliberately respond to supervision order.

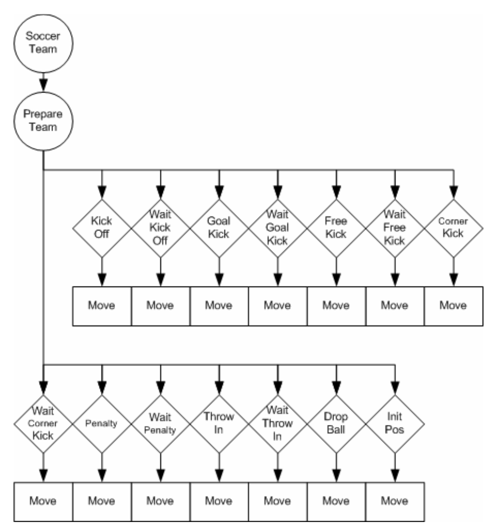



**Figure 8: Soccer Team HDM for game stop situations.**

**HDM test bench: Team of soccer-playing robots**

In order to test and validate the HDM, the team of soccer-playing robots developed by Robofoot has been used. With the competitions and numerous experimentations achieved, it has been possible to take many performance measures concerning the HDM concept. The decision machine for the soccer team consists of a 5 levels hierarchy: *Mode*, *Pattern*, *Role*, *Behaviour* and *Action*. Two important *Modes* are used in order to play soccer when game is on and respond to various game stop situations called by the *Referee box*. The HDM segment for game stop situations is shown in Figure 8. Every situation corresponds to a different pattern but is defined using the same basic behaviour where only the position pattern is changed. For the soccer playing decision mechanisms, it was chosen that predefined and dynamically allocated formations were a good approach for defensive and offensive team play. An example of formation used for offensive play is shown on Figure 9. The *Leader* and the *Followers* are dynamically allocated by distributed HDMs. The HDM segment corresponding to this offensive pattern is showed in Figure 10. This dynamic role allocation scenario is a good example where Decision Supervision can yield to impressive gain in performance. It has been measured that decision conflicts occurring using the predefined collaboration rules can be reduced from a near 45% to a level of approximately 2.5% of the total working time (Beaudry, 2005).

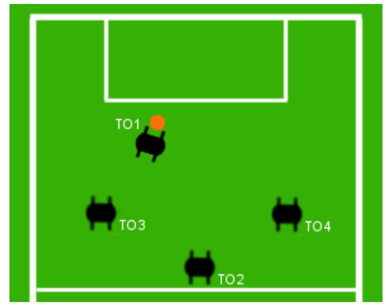



**Figure 9 : Soccer Team offensive formation.**

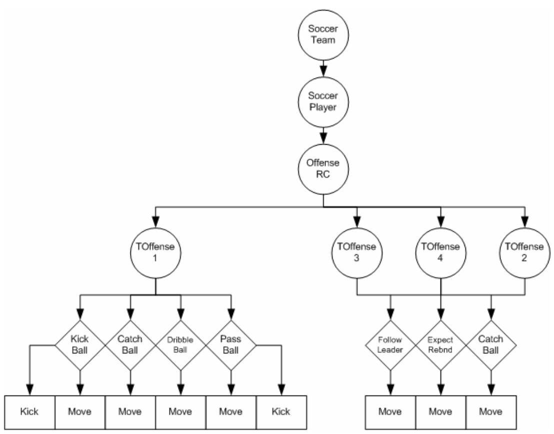



**Figure 10 : HDM for offensive soccer player.**

## References

Arkin, R.C.. **Behavior-Based Robotics**. The MIT Press, Cambridge. 1998.

Beaudry J.. **Machine décisionnelle pour systèmes multi-robots coopératifs**. M.Sc.A. thesis, Département de génie électrique, École Polytechnique de Montréal. 2005.

Beaudry J., Mailhot P.-Y.. **Navigation d'un robot mobile dans un environnement dynamique**. ELE6207 report, Département de génie électrique, École Polytechnique de Montréal. 2003.

Bierman, G. J. **Factorization Methods for Discrete Sequential Estimation**. Academic Press. 1977.

Chainowicz L., M.F.M. Campos M.F.M., Kumar V.. **Dynamic Role Assignment for Cooperative Robots**. Proceedings of the 2002 IEEE International Conference on Robotics & Automation. 2002.

Emery R., Sikorsky K., Balch T.. **Protocols for Collaboration, Coordination and Dynamic Role Assignment in a Robot Team**. Proceedings of the 2002 IEEE International Conference on Robotics & Automation, 2002, pp.3008-3015.

Kalmar-Nagy T., D'Andrea R., Pritam G.. **Near-Optimal Dynamic Trajectory Generation and Control of an Omnidirectional Vehicle.** Robotics and Autonomous Systems, vol. 46. Elsevier B.V.. 2003.

Lenser S., Veloso M.. **Visual Sonar: Fast Obstacle Avoidance Using Monocular Vision**. In Proceedings of IROS'03, Las Vegas, 2003.

Lötzsch M., J. Bach J., Burkhard H.-D., Jüngel M.. **Designing Agent Behavior with the Extensible Agent Behavior Specification Language XABSL**. In 7th International Workshop on RoboCup 2003 (Robot World Cup Soccer Games and Conferences), Lecture Notes in Artificial Intelligence, Padova, Italy. 2003.

Marleau S.. **Système de perception et localisation pour une équipe de robots mobiles**. M.Sc.A. thesis, Département de génie électrique, École Polytechnique de Montréal. 2005.

Parker L. E.. **ALLIANCE: An Architecture for Fault Tolerant Multi-Robot Cooperation**. IEEE Transactions on Robotics and Automation. 1998.

Pirjanian P., Huntsberger T.L., Trebi-Ollennu A., Aghazarian H., Das H., Joshi S., Schenker P.S.. **CAMPOUT: A control architecture for multi-robot planetary outposts.** In Proceedings of the SPIE Symposium on Sensor Fusion and Decentralized Control in Robotic Systems III, Vol. 4196, Boston, MA, Nov. 2000.

Richer-Commisso M.-A., Béliveau M.. **Conception et contrôle d'un robot omnidirectionnel**. PFE report, Département de génie électrique, École Polytechnique de Montréal. 2005.

Stone P.. **Layered Learning in Multiagent Systems**. The MIT Press, Cambridge. 2000.

Welch G., Bishop G. **An Introduction to the Kalman Filter**. Department of Computer Science, University of North Carolina at Chapel Hill. 2004.