Abstract. This paper outlines the organization and architecture of our robotic soccer team, Team Edinferno, and serves as the qualification document for the 2012 RoboCup Standard Platform League competition. We competed for the first time in the RoboCup 2011 competition held in Istanbul, Turkey. Our primary research interests are centered on issues of robot learning, especially for effective autonomous decision making and strategic behaviour in continually changing worlds. With this in mind, our entry this year will leverage the B-Human framework to provide a software base and modules for walking and low-level vision. Based on this, we are developing our own behaviour module, multi-robot localization and coordinated motion as well as specialized behaviours such as for the goal keeper, kicking and ball handling.

1 Introduction and Team Composition

Team Edinferno is a relatively new team, consisting of graduate and undergraduate students, as well as experienced researchers from the School of Informatics at Edinburgh. We come from a strong research group studying robot learning, situated within a diverse community of AI and computer science researchers - the largest and best in the UK. The team leader is Dr. S. Ramamoorthy, who has extensive background in robotics and machine learning, in academia and industry. Research within our group is organized around the theme of developing autonomous decision making mechanisms in continually changing and strategically rich environments.

2 Software Modules and Architecture

Our earliest attempt at robot soccer was based on a completely home-grown software implementation building directly on Aldebaran’s NaoQi. By the time we competed in RoboCup 2011, we had moved to an implementation based on the rUNSWift framework \(^1\), partly to benefit from the speed of the rUNSWift walk, but also because our limited resources were better served by focussing our own attention on specific modules where we had the expertise and manpower to innovate, leveraging existing technology elsewhere. So, we exploited rUNSWift’s pre-existing low-level functionalities for walking, 

sensor management and memory access. After a season of trials and after careful consideration of our long term needs, we decided to switch to the B-Human framework which, among other things, gives us a faster and more energy-efficient walk. We do find the overall structure of the B-Human framework is more intricate than with rUNSWift, but it also features several flexible components, such as the Extensible Agent Behaviour Specification Language (XABSL). Thus, it is possible to re-use low-level components, while focusing our own attention on the development of high-level algorithms for behaviour, etc. - our primary research focus where we expect to bring something new to the league. The core architecture of our agent is summarized in figure 1.

![Diagram of software architecture](image)

**Fig. 1.** Software architecture - major modules.

**On-board Vision** While our low-level vision is based on the B-Human code, we are introducing a few key modifications and improvements. Firstly, using the new heads, we are changing the vision processing to exploit the increased field of view obtained from the simultaneous use of both cameras. We use the two-camera information to verify or refute assumptions made in each image separately. This yields a more accurate world model. Secondly, we are taking advantage of the increased processing power in order to create a better robot recognition algorithm aiming to extract orientations as well as positions.

**Probabilistic Localisation** Our 2011 entry implemented a particle filter algorithm with heuristics for resampling. A drawback of this system was the limited number of features we could visually obtain (central circle, goalposts, penalty spots), which forced the algorithm to often make 'blind' updates, leading to unreliability. This year we have the ability to identify field lines which improves things. The core algorithm is changed from a simple particle filter to a probabilistic multi-hypothesis tracker. We use a number of hypotheses to estimate a probability distribution over robot pose. To track each hypothesis we implement an Extended Kalman Filter (EKF). By maintaining a number of hypotheses, it is possible to exploit the advantages of EKF without having to worry about cases where the EKF breaks down, e.g., in the kidnapped robot scenario. Such an implementation requires some ‘bookkeeping’ of hypotheses, and since in each step all hypotheses should be updated it is preferable to have a few number of hypotheses active at each time step. This in turn means we need mechanisms for hypothesis generation, track splitting and hypothesis pruning.

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The significant change in the SPL rules this year is that both goals will be yellow and disambiguating the attacking side from the defending side will be a major issue. We solve the problem through team information sharing. As an example of our approach, the location of the ball is a suitable landmark on the field, with a global ball hypothesis being generated from the observations of all playing robots. Given several such landmarks that are observed by subsets of the team, we are in a position to fuse the information necessary for disambiguation. As this particular rule has only been introduced recently, our specific ideas are continually being developed, as of this writing. However, the notion of sharing information as a team and exploiting common knowledge has been a part of our longer term agenda, independent of this rule change.

**Locomotion and Behaviour** In the earlier version of our framework, the behaviour module was tightly coupled with other perception-related modules (vision, localisation), with information flowing directly between these components. We have revised this structure, so that our previously developed strategies are now written in the XABSL scripting language. XABSL is fully decoupled from the core functionalities of the system, and as such there is no need to recompile the entire code every time a change is made. So, this facilitates the development and comparison of new behaviours that were previously harder to test. As before, behaviours are structured around the relevant strategic roles, such as attacker (Figure 2), defender, and goalkeeper (see Section 3).

![Decision making architecture - attacker module.](image)

**3 Key Novel Technical Advances in Our 2012 Team**

**Probabilistic Localization with Team-level Communication** An important technical issue in our 2012 team is the solution to the problem of visually similar goal posts, which make colour cues insufficient. Our current approach involves a combination of multi-hypothesis estimation at the level of a single robot and team-level communication between robots to maintain a persistent state that enables the required disambiguation. We are also investigating the use of visual features in the background visual field, as potential landmarks to aid localization.
Behaviours for Goalkeeping  Our current work on behaviour is divided into three threads: robust single-agent behaviours, team-level cooperation and, to a limited extent, strategic reasoning about adversaries. With single agent behaviours, a primary focus this year is on developing good action sequences for the goalkeeper. From our experience in 2011, we believe that weaknesses in this area owing to the difficulty of explicitly scripting this behaviour cost us heavily. There are several aspects to this problem that we are currently working on - deciding if and when the goalkeeper should dive to save the ball, how he should move along the goal line depending on the ball position, how frequently he should attempt to localise and re-position inside the box, and how should the motion of the field players affect his own.

Behaviours for Coordinated Motion  For team behaviours, we are primarily interested in disambiguation and role assignment between field players, especially between team-mates who are interacting closely (e.g. when two robots are close to the ball, determine who should be the one to kick). Furthermore, we are developing coordination strategies, for example, where should a supporting player go when another robot is about to kick. Finally, with the medium and longer term in mind, we are interested in moving towards reactive strategies that reason about the behaviour of the adversaries. We have some research experience [2, 4] in strategic adversarial modelling under physical limitations and uncertainty, which we use as a basis for considering what could be implemented in real competition robots.

Kicking Engine  In 2011, we used a small collection of key-framed kicking motions. This proved somewhat inflexible, with our robots often narrowly missing the goal because of limited range of motion. Furthermore, these static motions produced slower kicks than others. We are now working on improving the quality and speed of these key-framed motions, as well as developing simple parameterised actions that can control the angle of a kick. Moreover, we are investigating the possibility of developing novel kicking motions, such as the dynamic side kick introduced by B-Human 3, which can be fully integrated with our strategic behaviour. In addition to improving our repertoire of key-framed kicks, we are also investigating the use of reinforcement learning for optimization of parametrized kicks.

4 Future Developments and Connections to Research

Our team is composed primarily of researchers interested in intelligent autonomous robotics. So, in addition to the thrill of adventurous competition, we participate in RoboCup to advance our scientific agenda. Here, we outline a few key areas where this has already begun to happen and how we envision a two-way exchange between our RoboCup team and broader research.

– Strategic Interaction: We are exploring ways to make strategic decisions in response to opponent strategies that may not be known ahead of time. With this in mind, we have been investigating ways to infer the behaviour of other players in terms of pre-computed models [5], estimated finite-state models [3], distributions over template plans [2, 4], etc. The goal of all of these experiments is to achieve a degree of flexibility in interactions within open environments assuming limited prior knowledge.

Multi-agent Learning in Ad Hoc Teams: We are investigating algorithms for multi-agent learning in ad hoc team settings, i.e., coordination between learning agents without explicit prior knowledge or agreements [1], which is a realistic model for many interactions in football. While our work in this direction is still preliminary, we anticipate being able to incorporate some of these insights into our RoboCup work in the longer term.

Full-body Humanoid Robot Behaviours: A long standing strength within our research group is in the area of machine learning for humanoid locomotion [8] and full-body humanoid behaviours [7]. We are now working to implement such ideas on the Nao. Similarly to the kicking case, we define a low-complexity parametrization in the form of a pendulum-based model which is then optimized through a reinforcement learning procedure. At this time, we expect our 2012 team to just use the existing B-Human walking engine. However, depending on the progress of our own approach, we hope to deploy and test the results of this approach soon.

5 Conclusions

Team Edinferno is a relatively new SPL team from the United Kingdom. Our research work builds on strong background in robot learning and seeks to advance the state of the art in autonomous decision making. Although still in early stages as a team, we have successfully implemented and deployed a fully functional set of robots that competed capably against established teams in the Istanbul 2011 competition. Our qualification video includes footage from actual competition play against a team that went on play in the 2011 finals. Building on such experience, we look forward to better performance and to winning matches.

References


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4 This work [7] was considered as a finalist for the RoboCup Best Paper Award at IROS 2010.