

The First Segway Soccer Experience: Towards Peer-to-Peer Human-Robot Teams *

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ABSTRACT

In this paper, we focus on human-robot interaction in a team task where we identify the need for peer-to-peer (P2P) teamwork among robots and humans. We define a P2P team as one where there is no fixed hierarchy for decision making. Instead, all team members are equal participants and decision making is truly distributed. We have fully developed a P2P team within Segway Soccer, a research domain that we have introduced to explore the challenge of P2P coordination in human-robot teams in dynamic, adversarial tasks. Segway soccer builds upon RoboCup robot soccer, a research domain with standardized tasks for comparing multi-robot team strategies. We recently participated in the first Segway Soccer games between two competing teams at the 2005 RoboCup US Open. We believe these games are the first ever between two human-robot P2P teams. Based on the competition, we realized two different approaches to P2P teams. We present our robot-centric approach to P2P team coordination and contrast it to the human-centric approach of the opponent team. Based on our analysis, we recommend a set of further refinements to the Segway Soccer domain to foster more effective P2P teams.

Keywords

Segway soccer, human-robot teams

1. INTRODUCTION

Within the field of robotics, there has been considerable research into multi-robot coordination for a variety of domains and tasks (e.g., [20, 3, 33, 10, 12, 25]). In particular, there has been an ongoing effort to explore multi-robot

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teamwork in dynamic, adversarial tasks within a standardized domain: RoboCup robot soccer [17, 32, 2, 26] (see also <http://www.robocup.org>), which offered a pioneering multi-robot challenge. Throughout, a variety of techniques have emerged to effectively coordinate teams robots. Inevitably we need distributed approaches in which each team member is able to make decisions and communicate [31, 24, 11, 27]. An ongoing challenge in multi-robot research is how to effectively coordinate heterogeneous teams [5, 29, 16, 18]. In this paper, we focus on such teams composed of humans and robots, as opposed to only robots, specifically in dynamic tasks that require robust real-time action.

Much of the recent work on human-robot interaction [15, 22, 13, 23] focuses on the challenging problem of how to effectively communicate commands (both low and high-level) and information between a human and a robot. Indeed, there is often a well defined decision making hierarchy whereby the human is the leader. We call such an approach a human-centric team strategy. We conjecture, that in many team scenarios the real world factors of dynamics, partial observability, and communication limits, mean that such coordination may produce sub-optimal team performance. That is, the inflexibility of such a master-slave relationship may degrade the team's ability to respond to dynamic opportunities or problems as would a centralized approach to multi-robot coordination.

Our insights come from our work on developing a scenario where teams of humans and robots would face adversarial environments as peers. We have developed Segway Soccer to explore balanced, flexible, and distributed approaches to human-robot coordination, as we introduce *Peer-to-Peer* (P2P) teams. P2P teamwork is encouraged by requiring both humans and robots to have identical motion capabilities by deriving from the Segway mobility platform. Specifically, humans ride Segway Human Transports (HT) while robots are built from Segway Robot Mobility Platforms (RMP).

In this paper, we concretely define a P2P team as one where team members are equal, in the sense that each team member has equal power to make decisions and the responsibility to do so. Thus, there is no fixed decision making hierarchy, no fixed leader, and coordination is distributed. Key decisions will flow back and forth across the team as the

situation dictates.

Segway soccer aims at providing a standardized research domain to explore and evaluate P2P teams. Building upon our extensive experience with different RoboCup robot soccer leagues and teams, we designed the new Segway soccer league consisting of two human-robot teams that play against each other with a precise set of soccer and ultimate-frisbee based rules [6]. As with RoboCup, the robots must be fully autonomous [7, 30, 4].

Recently, the first ever Segway soccer games were held as part of the 2005 RoboCup US Open, hosted by the Georgia Institute of Technology. We believe these were the first human-robot P2P competition with two participants, namely CMBalance'05, our team from Carnegie Mellon University (CMU) and BrainWorks, from the Neurosciences Institute (NSI) [19]. The games truly enriched our understanding of P2P teams, which we report in this paper. We realized two different approaches to P2P teams. We present our robot-centric approach to P2P team coordination and contrast it to the human-centric approach of the opponent team. Based on our analysis, we recommend a set of further refinements to the Segway Soccer domain to foster more effective P2P teams.

Concretely, the format of the paper is as follows. Section 2 describes the specifics of Segway soccer, namely its goals, challenges, game flow and rules. Section 3 briefly summarizes our development of a soccer playing Segway RMP. Section 4 focuses on our approach to the development of a Segway soccer team, including an overview of our offensive and defensive strategies, the analysis of their respective game performances, and the modifications which were made for their improvement. In Section 5, we analyze our experiences at the 2005 RoboCup US Open, and follow with thoughts on future human-robot games discussed in Section 6.

2. SEGWAY SOCCER

Segway soccer is a game that requires mixed teams of humans and robots to cooperate to achieve the maximum reward in an adversarial task. To investigate balanced P2P interactions, and thus ensure interesting cooperation, both humans and robots are equipped with similar capabilities. We achieve this difficult task by requiring that both humans and robots use the same drive platform, specifically the Segway platform developed by Segway LLC [21]. Our goal is to create a task that requires advanced robot intelligence, combined with robust human-robot interaction skills. We hope to extend the powerful aspects of RoboCup-competition, an adversarial domain requiring fast decisions, and a well understood task - to incorporate human-robot interaction. The need for this new domain lies in the lack of study for human-robot interaction where decisions must be made quickly. As robots become more integrated into society, they will inevitably have to interact with humans and/or legacy robots in complex tasks. For some of these tasks, decisions may need to be made quickly and roles of both humans and robots may not be clearly defined a priori.

In the following paragraphs, we outline the game of Segway soccer, particularly focusing on the modifications to standard soccer rules necessary to accommodate the presence of

both humans and robots on the field.

2.1 Goals and Challenges

The rules of Segway soccer are a combination of soccer and Ultimate Frisbee¹. The objective of the game is to score the most goals by kicked soccer ball. Adjustments to soccer rules were necessary, however, to take into account the mixture of humans and robots on the field. Most importantly, consideration was given to the size and weight of the robot, as the Segway RMP carries considerable power as a robotic platform. For safety, so that robots and humans will not contest each other for ball possession, a player in possession of the ball has a 1.0m radius in which to reposition and pass to a teammate.

To encourage equal teammate participation, a team cannot officially score unless both robot and human teammates interact with the ball on the way to the goal. A passing sequence is therefore required prior to a goal shot, thus ensuring the collective involvement of both the robot and human teammate in a goal score. Humans are only allowed to kick the ball with the Segway HT platform and not with any part of their bodies. To prevent double teaming, only one defender is allowed to be within 2.0m of the player currently in possession of the ball. Until the robots become more proficient, humans are not allowed to mark the opponent robot.

2.2 Communications

There is no restriction on audible (speakers and microphones) communications between teammates (humans or robots). Wireless communication is allowed only between team members, and not to any off-field computers. In the spirit of RoboCup, the robots must be autonomous and make their own decisions, and thus communicate with human players only for reasons of team coordination. Some level of commands may be given to the RMP (such as waypoints, or general directions on the field as to where to play or go), but direct teleoperation of the robot is not allowed.

2.3 Game Flow

A game consists of three parts, a first half, a break, and a second half [6]. Kickoffs occur at the start of the game or after a goal, at which time the ball is placed at the goal spot on the defensive side of the team with possession. Afterwards, players gain possession based on proximity to the ball when it is "free" or whenever the other team scores a goal. Once a player obtains possession opponents are not allowed to contest the ball, and the ball must be passed - it may not be 'dribbled' - for the team to maintain possession. A time limit requires the ball be passed else possession be overturned.

Upon the scoring of a goal, the game is immediately halted and then restarted from the kickoff position with a turnover in possession. Goals are only awarded when both the robot and human participate in a given play by either shooting on the goal or passing to their teammate. In the original rules, no restrictions were placed on which teammate is allowed to score a goal.

¹Rules for Ultimate Frisbee can be found at <http://www.upa.org>

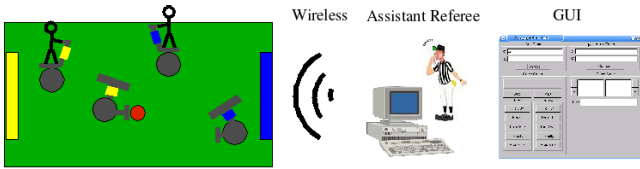


Figure 1: The Referee box communicates wirelessly with the robotic soccer players. It is controlled by an off-field human, via the Referee box GUI.

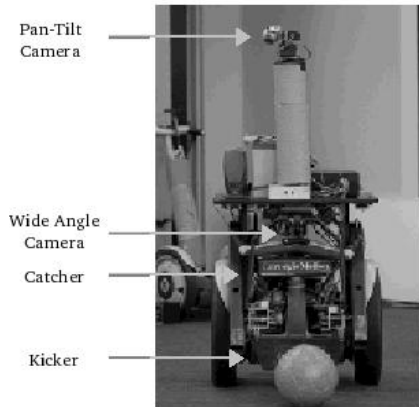


Figure 2: Our Segway RMP soccer robot equipped with a kicker, a catcher, infrared sensors, a wide-angle camera, and a camera mounted on a custom pan-tilt unit.

2.4 The Referee Box

The referee box is a program tasked to link the referee whistle and robot understandable messages (Fig. 1). While the intent is to standardize and have all teams run the same program, as in other RoboCup leagues, for the 2005 US Open the referee boxes were developed by each team individually. Our implementation specifically requires human interaction with a GUI, where the button corresponding to the referee whistle is selected. In this way, the robot is updated with the current game state.

3. OUR DEVELOPMENT OF A SOCCER PLAYING SEGWAY RMP

Development of a robotic soccer player requires a control architecture for the execution of soccer actions. This control architecture is dependent upon the robot's current actions, as well as its perceived state of the world. Our robot has been enhanced with additional sensors for the acquisition of this world belief state, and processes its output to form an internal world model. Observation of the world and interpretation of its state is the motivating force behind the development of soccer play on our robots. For the gathering of visual data, two cameras were added to the robot (Fig. 2, the stock Segway RMP has no visual sensing capabilities). To enable ball handling, the robot was augmented with a catcher, to trap the ball near the robot, and a pneumatic kicker, for passing and goal shooting.

In this section we begin by describing the implementation of the control architecture for soccer play on our robots, which

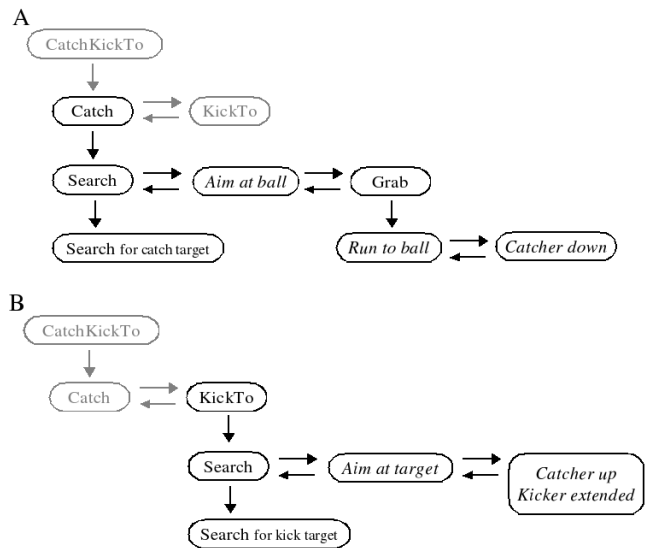


Figure 3: (A) The first state of the skill CatchKickTo calls the sub-skill Catch. (B) The second state of the skill CatchKickTo calls the sub-skill KickTo. *Actions* are distinguished from subskills by italicization.

was accomplished via hierarchical state machines which we call skills. We then explain the use of sensor input to update our belief of the world state, specifically with respect to vision processing and vision object tracking.

3.1 Soccer Play: Control by Skills

At the highest level, a soccer playing robot must choose to act, given the state of the world and the team goal for that state. Our robot is entirely autonomous in this process, and thus makes all on-field decisions independently of its human teammate. For the actual decision process, a control structure was implemented in which finite state machines organize into a hierarchy. We call these state machines skills. Skills process information from the believed world state and then generate action commands, either by execution of the action within the state or by calling another skill as a sub-skill. It is from this calling of sub-skills that a hierarchy is formed.

An example high level skill is CatchKickTo (Fig. 3). The overall goal of CatchKickTo is to receive a pass from the teammate, and then kick the ball to a specified target (teammate or goal). The skill consists of two states, each of which calls a sub-skill.

The state of the world (for example, the ball location being unknown) is perceived by the robot from external and internal sensors. Both interpreted perception of the world and the action being taken by the robot within that world (for example, the ball location being unknown and the robot performing a search for it) define a state within a skill. State transitions are controlled by a change in either of these defining factors (for example, the ball location is now known and the robot terminates its search), or by a timeout on the state.

3.2 Perception

Perception is where the robot autonomy comes from. In this section, we briefly introduce the two key components, vision and tracking in our large system. Based on vision, we construct our world model to further implement robot autonomy. Since the objects we have interest in are not always visible, we need tracking to estimate their position and velocity consistently.

3.2.1 Vision

In the work with the Segway RMP platform [21], we have been exploring techniques to enable a vision-centric robot to be able to play soccer in outdoor environments where illumination is variable [7, 8]. Furthermore, as the task is adversarial and highly dynamic, the combination of robot speed and ball speed means that it is essential that the vision algorithms be both robust, and extremely efficient. Indeed, only a fraction of the CPU resources can be devoted to vision processing as the remainder of the CPU resources must be used for cognition in order to get low-latency robot behaviors.

We have developed a new technique for fast color-object recognition that is suitable for use in robot platforms like the Segway. Its key feature is that it is able to adapt its segmentation process to different lighting conditions. The segmentation technique is motivated by the observation that for most of the domains of interest here changes in illumination lead to small changes in color value and that these changes are relatively uniform across all colors. In other words, with modern cameras with automatic shutters and gain control, red pixels may vary in color but will stay in the same region of color space. Therefore, we propose that if pixel classification thresholds are able to adapt by small amounts, it should become possible to robustly classify pixel colors across moderate changes in illumination. Our goal is to achieve such a robust, adaptive system but without significantly increasing computational requirements [8].

The approach includes the following four main components:

- Image segmentation
- Histograms building
- Thresholds adaptation
- Object recognition

The key idea is to use a soft labeling of pixel class, followed by a hard decision using an adaptive threshold. The combination of soft-labeling and adaptive thresholding provides the plasticity for lighting variation. Following this, connected pixels can be conglomerated using a connected component analysis. Objects are detected and recognized by searching for nearby regions that match priori models, with soft-comparisons to account for variations in shape, size, and missing features. This new technique requires only moderate additional computational resources beyond existing fast color vision algorithms.

3.2.2 Tracking

Tracking in essence consists of using sensory information combined with a motion model to estimate the state of a moving object. Tracking efficiency completely depends on the accuracy of the motion model and of the sensory information [34] as well. When tracking is performed by a robot executing specific tasks acting over the targets being tracked, such as a Segway RMP soccer robot grabbing and kicking a ball, the motion model of the target becomes complex, and tightly dependent on the robot's actions [9]. A single motion model is not exact enough to describe the complexity of the motion due to the interactions between the robot and the ball. We therefore use a tactic-based multiple model approach to model the ball motion [14]. Explicitly, we use the following three single models.

- *Free-Ball*. The ball is not moving at all or moving straight with a constant speed decay d which depends on the environment surface.
- *Grabbed-Ball*. The ball is grabbed by the robot's catcher.
- *Kicked-Ball*. The ball is kicked therefore its velocity is equal to a predefined initial speed plus the noise.

Next, a model index m determines the present single model being used ($m = 1, 2, 3$ for the above three single models respectively). We need to decide how to transit between each models, which is done by a tactic-based approach. We assume that the model index, m_k , conditioned on the previous tactic executed t_{k-1} , and other useful information v_k (such as ball state \mathbf{x}_{k-1} , infrared measurement s_k , or the combination of two or more variables), is governed by an underlying Markov process, such that the conditioning parameter can branch at the next time-step with probability

$$p(m_k = i | m_{k-1} = j, t_{k-1}, v_k) = h_{i,j} \quad (1)$$

where $i, j = 1, \dots, N_m$.

Finally, we use particle filtering to track the motion model m and the ball state b [28]. A particle filter maintains the belief state at time k as a set of particles $p_k^{(1)}, p_k^{(2)}, \dots, p_k^{(N_s)}$, where each $p_k^{(i)}$ is a full instantiation of the tracked variables $\mathbf{P}_k = \{p_k^{(i)}, w_k^{(i)}\}$, $w_k^{(i)}$ is the weight of particle $p_k^{(i)}$ and N_s is the number of particles. In our case, $p_k^{(i)} = \langle b_k^{(i)}, m_k^{(i)} \rangle$.

We use the Sample Importance Resampling (SIR) algorithm to update the state estimates [1]. The sampling algorithm is as follows:

$$\{b_k^{(i)}, m_k^{(i)}, w_k^{(i)}\}_{i=1}^{N_s} = \mathbf{SIR}[\{b_{k-1}^{(i)}, m_{k-1}^{(i)}, w_{k-1}^{(i)}\}_{i=1}^{N_s}, z_k, s_k, t_{k-1}]$$

```

01 for  $i = 1 : N_s$ 
02   draw  $m_k^{(i)} \sim p(m_k | m_{k-1}^{(i)}, b_{k-1}^{(i)}, s_k, t_{k-1})$ .
03   draw  $b_k^{(i)} \sim p(b_k | m_k^{(i)}, b_{k-1}^{(i)})$ .
04   set  $w_k^{(i)} = p(z_k | b_k^{(i)})$ 
05 end for
06 Calculate total weight:  $w = \sum \{w_k^{(i)}\}_{i=1}^{N_s}$ 
07 for  $i = 1 : N_s$ 
08   Normalize:  $w_k^i = w_k^i / w$ 
09 end for
10 Resample.
```



Figure 4: In both figures, the red and pink cross represent the two goals, and each blue dot represents the one of the particle estimation of the ball position. In the left figure, the ball is visible to the robot. In the right figure, the ball is out of sight and the particles are scattered

The inputs of the algorithm are samples drawn from the previous posterior $\langle b_{k-1}^{(i)}, m_{k-1}^{(i)}, w_{k-1}^{(i)} \rangle$, the present vision and infrared sensory measurement z_k, s_k , and the tactic t_{k-1} . The outputs are the updated weighted samples $\langle b_k^{(i)}, m_k^{(i)}, w_k^{(i)} \rangle$. In the sampling algorithm, first, a new ball motion model index, $m_k^{(i)}$, is sampled at line 02. Then given the model index, and previous ball state, a new ball state is sampled at line 03. The importance weight of each sample is given by the likelihood of the vision measurement given the predicted new ball state at line 04. Finally, each weight is normalized and the samples are resampled. Then we can estimate the ball state based on the mean of all the $b_k^{(i)}$. See (Fig. 4) for an example of particle filter representation of the ball position.

4. OUR APPROACH TO TEAM COORDINATION: ROBOT DRIVEN

The combination of skills, both simple and complex, into a large state machine constitutes our soccer game play. Soccer is a team sport, and therefore the building of our game strategy requires not only execution of this large state machine, but also coordination with our teammate, the human player. Our approach was both robot and research driven; that is, given our interest in the autonomy of the robot, our team strategy was a robot controlled one. There was no communication occurring from the human to the robot, and communication from robot to human was minimal. The robot would at times speak to cue the human as to its current state in the skill; for example when aiming at the ball during Catch, it would say “pass to me”. Thus all robot-to-human coordination, and the majority of human-to-robot coordination, was based upon observation alone. For example, the robot would choose to pass the ball to its teammate only after visually identifying them. As a direct result of this, all robot decision making during the demonstrations was autonomous.

In this section we will begin with a description of our initial offensive strategy, an analysis of its effectiveness and the subsequent modifications enacted to improve both team performance and coordination. We will follow with a similar treatment for our defensive strategy. Finally, we will overview the approach to team coordination taken by our opponent team, the Neurosciences Institute.

4.1 Offense

While in preparation for the 2005 RoboCup US Open, the initial human participation in our offensive strategy was de-



Figure 5: The left figure shows our Segway robot holding the ball and turning to search for its teammate. The right figure shows our Segway robot positioning to receive a pass, and being marked by the NSI robot.

pendent upon teammate vision almost exclusively. Thus the robot relied entirely upon teammate identification, and did not presume their teammate to be in any given position, nor to be taking any sort of action, besides waiting to receive the robot’s pass.

At a kickoff for our side, the robot first decided whether to run up and grab the ball, or to wait and receive a pass. This decision was dependent upon the teammate being seen, and if they were seen, whether the teammate or robot were closer to the ball. The human player responded to the actions of the robot; that is, they waited to see if the robot was running up to or aiming at the ball, and then react accordingly. Offensive strategy after kickoff consisted of the robot repositioning itself towards the opponent goal, detecting either the teammate or the ball to receive a pass, and then deciding whether to shoot on the goal or pass to the teammate (Fig. 5). To make this kicking decision, the robot first visually identified either (or both) of the targets, and then reasoned based upon its distance to each.

Such an offensive strategy was biased heavily towards dependence on the robot, both in team decision making and execution. True team coordination would ideally have greater equality between its members. This is not only advantageous from the standpoint of the research within, and the spirit of, P2P games, but also holds the potential to produce a better, more competitive team. For example, during the actual US Open demonstrations, the ball and teammate were often occluded and therefore not always detected. By making no offensive assumptions about its teammate’s behavior, the robot was dependent upon teammate detection as a gateway into transitioning to execute the remainder of a play. A strategy modified to presume more about teammate actions, and thus rely less heavily on actual identification, would in this case likely enhance team performance.

As our offensive strategy developed, coordination with the teammate, and therefore assumptions about their actions, became stronger. At a kickoff for our side, the robot considered its teammate to begin with the ball, and therefore was positioned advantageously to attempt a shot on the opponents’ goal. With a predefined but configurable probability, the robot then chose to either kick on the goal or at a set angle from the goal. The human player would position them-

selves to receive this off-goal kick, and the robot presumed the human to be in that position. That is, the off-goal kick was not dependent upon the robot visually detecting its human teammate. This randomness in goal on- or off-shooting improved interactions between the teammates, and was used throughout the offensive play.

4.2 Defense

Our initial defensive strategy relied more heavily on the human player. The robot positioned itself inside of our goal with the intent of catching attempted shots on the goal. Any defensive actions besides goal keeping - such as to intercept or block opponent passes - were performed by the human player.

Constraints on field size at the US Open seriously restricted the motion of all robots, and thus made consistent positioning inside the goal infeasible. Our defensive strategy was therefore likewise modified, to take the robot out of the goal and mark the ball in attempts to gain possession of it. The result was a swap in teammate roles, for the responsibility of goal keeping now lay with the human player.

As one would hope in a heterogeneous P2P team, this identification of individual player strengths, and the appropriate allocation of roles based upon them, strengthened the team performance. While the robot had been unable to intercept even one attempted shot on the goal, the human player was able to intercept nearly all. In its new role, the robot not only effectively positioned itself often between opponent players, thus obstructing intended passes, but on occasion an opponent pass was not just blocked but actually intercepted.

4.3 Opponent Approach to Team Coordination: Human Driven

The opposing Segway soccer team was developed by the Neurosciences Institute in San Diego, CA (<http://vesicle.nsi.edu/news/segway>). Their players were additionally normalized across platform, with the outfitting of the human Segway with a catcher and kicker similar to those augmenting their robot. Their Segway HT was also equipped with a headset, through which the human player could communicate with its robot teammate. In contrast to our robot-dominated approach to P2P team coordination, NSI developed a human-dominated game strategy. Their human player performed the majority of the decision making on the field, and then informed their robot, by voice, of the chosen action.

5. THE 2005 US OPEN EXPERIENCE

Five Segway soccer demonstrations were played between Carnegie Mellon University and the Neurosciences Institute at the 2005 US Open. The actual execution of multiple Segway soccer demonstrations made evident several issues with the game implementation, both as a result of the stated game rules as well as the setup of the physical space. In this section we describe our observations regarding what these issues were, as well as our interpretation of their causes.

5.1 Robot Movement

In an ideal P2P game, equal amounts of teammate mobility would be shown. Such equality is necessary not only in



Figure 6: The field at US Open 05 was too tight to pass and position easily.

the interest of normalizing capabilities, but also because a bias in mobility will undoubtedly lead to a bias in field performance and participation. The US Open demonstrations, however, overall displayed a marked lack of robot positioning. We believe the cause of this reduced mobility to be twofold.

The first culprit which constrained robot movement was field dimension. Due to size constraints at the US Open venue, the field occupied approximately a quarter of the area as was originally stated in the rules, being halved in each dimension. The second culprit confounding robot movement was the safety distance (of 1.0m) required between players, which by and large was respected by the robots. That the human players were able to maneuver more easily was due largely to their disregard for, and the difficulty of referee enforcement of, this distance rule. In the early demonstrations, CMU navigation was particularly conservative, and therefore the robot practically immobile.

The reduction in field size, compounded with the distance restriction between players, so congested the field that robots were unable to position themselves (Fig. 6). This lack of positioning had the immediate effect of a reduction also in passing between teammates, where often the more mobile human player would execute only the minimum requirement of one pass to its robot teammate before shooting on the goal. The small size of the field additionally encouraged such behavior by placing the goals within reasonable shooting distance from most points on the field.

5.2 Robot Participation in Passing

The human and Segway teammates are not, in reality, entirely normalized across their wheeled platforms, but rather are still divided by the very basic reality that the bodies above the platforms are physically different. Such a distinction logically might result in a difference in action execution on the playing field. At the US Open, we observed this within the context of teammate passing.

While ball deflection is common within human soccer games, it is also unlikely that a human player would attempt to deflect the ball off of an unsuspecting teammate. Such consideration is no longer necessary, however, when that teammate is no longer human. These deflections, as observed in use by NSI, were at times again caught by the human player. It is possible that the robot knew of these passes and inten-

tionally missed them to allow for more time, or attempted to catch the ball but failed, but it is also possible that the robot was not aware such passes occurred at all. In the spirit of P2P games, the robot should be an active and aware participant in any coordinated actions, and, properly constructed, the game rules should enforce this spirit. However, to determine robot awareness explicitly, and not just intuitively, is a difficult and situation dependent task.

Another question presented by the experience was what classifies an acceptable pass. Within human soccer games ball possession is not guaranteed for a set radius around a player, and so the ball may be more aggressively contested than in Segway soccer. By contrast, in Segway soccer a pass might possibly be considered valid though it actually remains untouched by the receiving player, since they gain possession should the ball come within the 1.0m safety distance. Judging the validity of such a pass is unable to be helped by the rules of Ultimate Frisbee, where an unsuccessful pass is defined by the frisbee touching the ground, and is thus clearly uncaught by the receiving player. In Segway soccer, often the ball has never left the ground in the first place. As such, what fairly defines a received pass requires further investigation.

5.3 Robot Goal Scoring

True P2P teammates would be expected to attempt shots on the goal equally across platform; that is, delegation to a specific soccer role might influence a player's shooting frequency, but whether they are human or robot should not. By the completion of the third demonstration, however, a goal had yet to be scored by a robot. Beyond positioning difficulties allotting robots fewer opportunities to score in the first place, any attempted robot shots on the goal were blocked by the human opponent. Considering the game to be too human-dominated, the teams agreed to a rule addition to restrict the human players: a human was no longer allowed to score a goal. While the instantiation of this restriction resulted in many fewer attempted and successful goals, that all were scored by robots increased their participation in the game dramatically.

6. FUTURE HUMAN-ROBOT GAMES

Each team was unaware, until the first game, of the development angle chosen by the other team; that our strategies were opposite in player dominance was not intentional, but their contrast did exemplify many of the difficulties with the development of human-robot balance within the game. CMU's initial strategy, so focused in thrust on robot autonomy, placed too little importance on the human player. The result was a lack in team performance, as our robot was in reality not a strong enough player to carry that much team dependence. In contrast, NSI was able to coordinate well and accomplish tasks as a team, but at the expense of minimal robot decision making during the game. As the intent of this research domain is true human-robot coordination, where the players are equally autonomous yet also able to accomplish tasks, it seems a balance somewhere between the two approaches must be found. Such a balance will by necessity restrict the human players initially, but as the robots become more capable, so also will interspecies equality between teammates become less artificial.

7. CONCLUSIONS

In summary, we have introduced the concept of peer-to-peer (P2P) teamwork for human-robot teams, where a P2P team is one where all teammates are equal and decisions are made in a distributed manner. We believe P2P human-robot coordination to be a powerful concept that is of great import to effective human-robot team coordination in dynamic environments. We have presented the development of Segway soccer as a standardized research domain for exploring and validating P2P coordination techniques. After participating in the first Segway soccer games at the RoboCup US Open, which we believe to be the first of its kind, we identified a number of key changes to the structure of the Segway soccer domain to further promote balanced human-robot interaction. Concretely, we have proposed rule modifications that encourage greater robot autonomy and participation in the key offensive portions of the game, and more complex human-robot interaction during general game play. We will further explore these proposed changes in our future work.

8. ACKNOWLEDGMENTS

This work was supported by United States Department of the Interior under Grant No. NBCH-1040007. The content of the information in this publication does not necessarily reflect the position or policy of the Defense Advanced Research Projects Agency (DARPA), US Department of Interior, US Government, and no official endorsement should be inferred.

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