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

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Abstract

Robotic soccer is an adversarial multi-agent research domain, in which issues of perception, multi-agent coordination and team strategy are explored. One area of interest investigates heterogeneous teams of humans and robots, where the teammates must coordinate not as master and slave, but as equal participants. We research this peer-to-peer question within the domain of Segway soccer, where teams of humans riding Segway HTs and robotic Segway RMPs coordinate together in competition against other human-robot teams. Beyond the task of physically enabling these robots to play soccer, a key issue in the development of such a heterogeneous team is determining the balance between human and robot player. The first ever Segway soccer competition occurred at the 2005 RoboCup US Open, where demonstrations where held between Carnegie Mellon University (CMU) and the Neurosciences Institute (NSI). Through the execution of these soccer demonstrations, many of the challenges associated with maintaining equality within a peer-to-peer game were revealed. This paper chronicles our experience within the Segway soccer demonstrations at the 2005 US Open, and imparts our interpretation and analysis regarding what is needed to better attain this goal of teammate equality within the peer-to-peer research domain. We begin with an explanation of the motivations behind the Segway soccer and peer-to-peer research, providing details of the game rules and flow. We then describe our approach to the building of a heterogeneous Segway soccer team, in which we developed a robot-dominated soccer strategy. Robot decision making was autonomous, and the human player reacted to the robot's chosen actions. Our analysis of the experience at the US Open is presented, giving regard to both research challenges as well as difficulties in the physical execution of a Segway soccer game. We evaluate the strengths and weaknesses of our robot-driven approach within the context of game performance, as well as in contrast to the human-driven approach of our opponent team from NSI. While each team displayed either a strong bias towards the human or the robot, the intent of these peer-to-peer games is in fact teammate equality. Based upon our observations from the actual demonstrations, and interpretation of the research goals of the league, we offer a revised set of game rules. We conclude with thoughts on the direction of future research within the Segway soccer domain.

Keywords: Segway soccer, human-robot teams

1 Introduction

There has been considerable research into both human-robot interaction [11], and multi-agent teams [8]. Additionally, since the inception of RoboCup robot soccer [2], there has been considerable research into robot teams operating in adversarial environments. To our knowledge, however, there has been no work yet that combines these attributes; namely, to examine human-robot interaction within an adversarial, multi-robot setting where humans and robots are team members with similar capabilities and no clear role hierarchy [4, 13, 3]. Segway soccer is such a domain, where human and robot are teammates, both running on the Segway platform and thus uniform in physical capabilities. In such a human-robot team, how should we define the relationship between the human and the robot in a teamwork framework? Apparently, we can imagine two extremes in terms of the robot autonomy. One is a fully autonomous robot without any interaction with the human player. The other is a tele-operated robot without any autonomy at all. Of course, neither of the extreme condition is what we want to see. Since as a human player, we are now more intelligent than the robot, and we want to give general advice but not specific command of what to do to our robot teammate. Therefore, the human and the robot should be equally important teammates on the field. There are no master/slave relationship between them.

The first ever Segway soccer competition recently occurred at the 2005 RoboCup US Open, hosted by the Georgia Institute of Technology in Atlanta. During 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 of 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.

Motivated by the observations from US Open games, we propose a peer-to-peer human robot team as our goal. Peer-to-peer means each player in the team are equally autonomous to accomplish tasks. Though in some specific condition, some player may take a leading role, e.g in Segway soccer, the one that has the ball. A peer-to-peer human-robot team has no central commander. Equal peer players simultaneously function as both “commander” and ”listener” to the other players in the team.

The format of the paper is as follows. In section 2, we describe the specifics of Segway Soccer; its goals, challenges, game flow and rules. Section 3 describes our development of a soccer playing Segway RMP. Following this, we describe our experience at the 2005 US Open and analyze the difference between our approach and NSI approach. We then focus on our thoughts on future human-robot games and propose a revised set of Segway soccer game rules, leading to our conclusions.

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 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 - the Segway platform developed by Segway LLC [10]. 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 need to 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.

2.1 Goals and Challenges

The rules of Segway Soccer are a combination of soccer and Ultimate Frisbee [1]. The objective of the game is to score the most goals by kicked soccer ball. Adjustments to soccer rules were necessary, however, given the consideration of teams being a mixture of robots and humans. So that robots and humans will not contest each other for ball possession, for safety reasons a player in possession of the ball has a 1m radius in which to reposition and pass to a teammate. Furthermore, to ensure robots and humans will collectively be involved, a mixed team cannot officially score unless both a robot and a human interact with the ball on the way to the goal. Placing humans, robots, and robot competitors on an equal physical level using the Segway platform allows their different perception and cognitive abilities to be tested. The dynamic balancing, speed, and size of the Segway allows this human-robot interaction at a human scale.

2.2 Communications

There is no restriction on audible (speakers and microphones) communications between team members (humans or robots). Wireless communication is allowed only between team members (and not to any off-field computers), using the IEEE 802.11b/g standard. In the spirit of RoboCup, the robots must be autonomous and should communicate with players only to receive updates as to where things are in the field. 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 joysticking 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 [5]. Kick offs 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 - may not be 'dribbled' - for the team to maintain possession. A time limit requires the ball be passed else possession be overturned.

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 meters of the player currently in possession of the ball. In the spirit of the game, and until the robots become more proficient, humans are not allowed to mark the opponent robot.

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

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

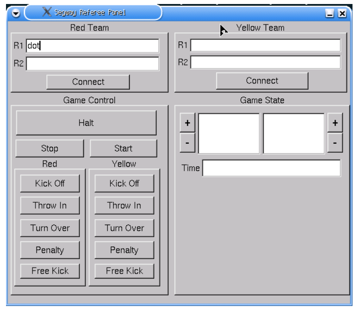

Figure 1: GUI of the Referee box.

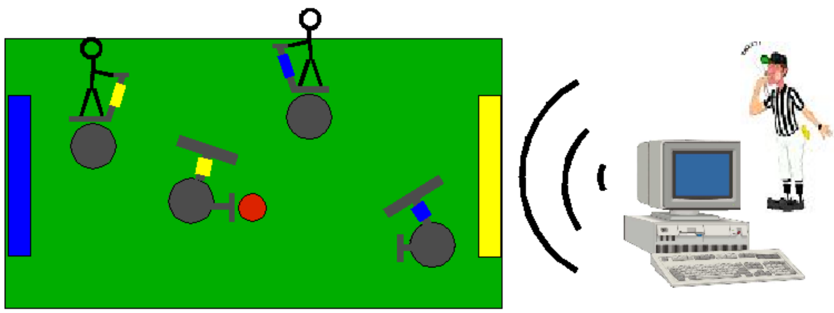

Figure 2: The Referee box communicates wirelessly with the robotic soccer players.

participate in a given play by either shooting the goal or passing to their teammate. No restrictions are placed on which teammate is allowed to score a goal.

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 eventually standardize and have all teams run the same program, 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.

In the current setup, before a game begins, we click one of the "Connect" buttons (depends on our team color) to connect with our robot player on the field. Whenever a whistle is heard, we first "Stop" the robot, then click one of the game control buttons, "Kick Off", "Throw In", "Turn Over" or "Free Kick", followed by "Start" to inform the robot that it is time to run again.

3 Our Development of a Soccer Playing Segway RMP

Soccer is an adversarial multi-agent coordination task, currently being researched within a robotic domain on multiple different platforms. The intent of Segway soccer specifically is, within this domain, to research the concept of peer-to-peer games; that is, games in which humans and robots coordinate in soccer play as equal teammates. Physically, this requires normalization across the human and robotic platforms, as well as the outfitting of each for soccer play. Conceptually, this additionally requires team coordination between human and robot. Finally, development of the robotic player specifically 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 augmented with additional sensors for the acquisition of this world belief state, and processes their output to form an internal world model.

A big picture breakdown of the states in a soccer world is which team is in possession of the ball, and below that to which player the ball belongs specifically. As a soccer player, the robot's action choices are necessarily heavily dependent upon this world state. Should the other team have possession of the ball, the robot should not, for example, wait to receive a pass; the logical opponent would never pass the ball to a player besides their own teammate. Likewise, should its own teammate have the ball, the robot should not choose to position itself defensively to block a ball entering their own goal; the logical teammate would never shoot on its own goal. Observation of the world and interpretation of its state is the motivating force behind the development of soccer play on our robots.

In this section we begin by describing the implementation of the control architecture for soccer play on our robots, which was accomplished via hierarchical state machines which we call skills. Within the context an example skill, we explain the structure of, and actions taken by, these state machines. Our offensive and defensive strategies, as they were first implemented for the 2005 RoboCup US Open, are described. For the realization of such actions, our robots were augmented with additional manipulators and sensors, about which details are provided. Lastly explained is 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 subskill. It is from this calling of subskills that a hierarchy is formed.

The state of the world (for example, the ball location being unknown) is interpreted by the robot from external and internal sensors. Both interpretation 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.

In this section we will outline, within the context of an example skill, the cycling through of one of these state machines. Included in the skill outline will be descriptions of the particulars of any executed action, including that action's use of our added manipulators and sensors.

3.1.1 An Example Skill: Its States and Actions

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 subskill.

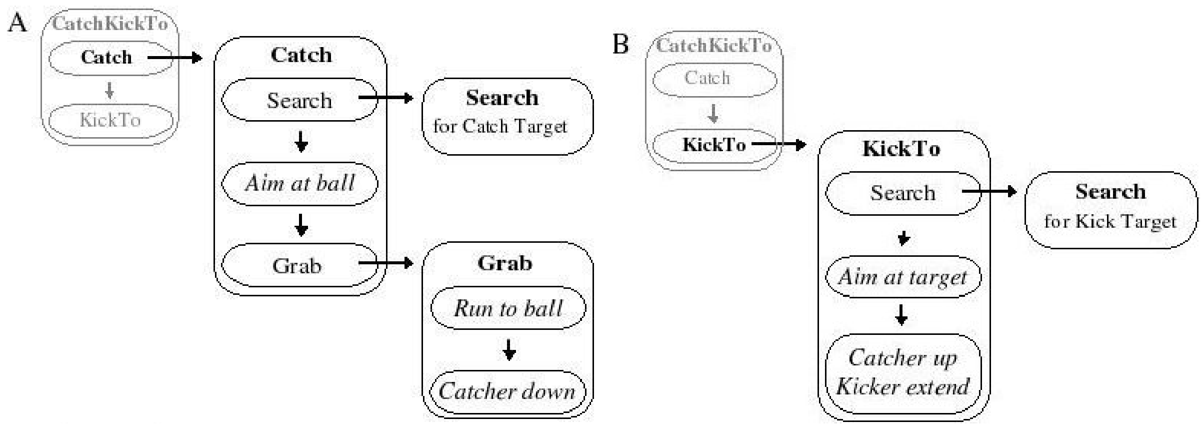

Figure 3: A. The first state of the skill CatchKickTo calls the subskill Catch. Catch calls a search subskill, performs the action of aiming at the ball and finally calls the subskill grab, which performs the actions of going near the ball and putting down the catcher. B. The second state of the skill CatchKickTo calls the subskill KickTo. KickTo calls a search subskill and performs the actions of aiming at the kick target and kicking.

The subskill called by the first state of CatchKickTo is Catch. The Catch skill begins with a search state, looking for either a ball or teammate. Most basic to our skill building are the vision searches: every skill is dependent upon the detection of a vision object, and thus also a vision search. Vision is the primary source of world information on our robots. For the acquisition of visual data, two cameras were added to the robot (Fig. 4,the stock Segway RMP has no visual sensing capabilities).

The subskill Catch then aims at the ball (in preparation to receive the pass), and runs up to the ball once it is near (from within the subskill Grab). Both running up to the ball, and turning to aim towards the pass, require the ability to command robot motion. Actions were developed to control the motion of the SegwayRMP, to which we are able to command velocity and turn angle. Our developed actions include the ability to send the robot to a given location by the specification of x,y coordinates (in global or relative space), as well as to have the robot turn in place. Once the ball is within range of the robot, its detection and capture is handled by our added infrared (IR) sensors and catcher. The two IR sensors are located near the base of the robot and are intended for ball detection, while the catcher is intended to trap the ball near the robot. Upon IR sensor firing, the catcher is commanded down and the ball is now within the robot's possession.

The second subskill called by CatchKickTo, after Catch, is KickTo. After finding its kick target of either the teammate or the goal, KickTo calls the subskill AimKick. In AimKick, the robot first rotates to align itself with the identified kick target. Once aligned, the catcher is lifted and the actual kick performed. The kick is executed either via playback of a prerecorded bucking motion, or by the extension of our added pneumatic kicking plate. (For details on our added sensors and manipulators, please refer to the hardware section.)

3.2 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 required

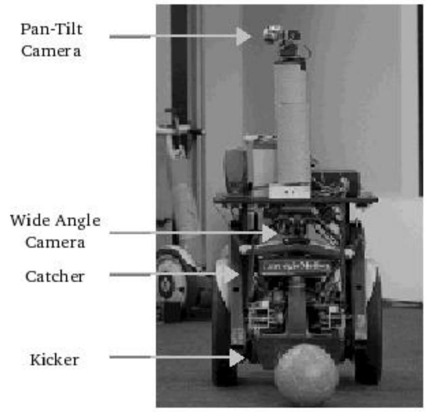

Figure 4: Our Segway RMP soccer robot equipped with a kicker, a catcher, infrared sensors, a wide-angle camera, and a camera mounted on a custom pan-tilt unit.

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; being interested 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 visually identifying the human and then passing the ball to them). As a direct result of this, all robot decision making during the demonstrations was autonomous.

3.2.1 Offense

While in preparation for the 2005 RoboCup US Open, our initial offensive human participation was dependent upon teammate vision almost exclusively. That is, the robot did not presume their teammate to be in any given position, or 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 teammate was not searched for explicitly, but the ball was (and the teammate was often also found during this ball search). The human teammate responded to the actions of the robot; that is, the teammate would wait and see if the robot was running up to or aiming at the ball, and then react accordingly.

After kickoff, our robot's offensive strategy presumed only to receive a pass, and therefore never ran up and grabbed the ball (since an open ball, able to be grabbed, would imply our side having lost the ball, and therefore also imply a possession turn over). Once having received the pass and being in possession of the ball, the robot then decided whether to pass to its teammate or shoot on the goal. Again, this behavior was dependent upon teammate detection, and additionally on goal detection. If the teammate was not seen, the robot would shoot on the goal; likewise, if the goal was not seen, the robot would pass to the teammate. If both were seen, the robot would base its decision on its distance from the goal, choosing to shoot if within a satisfactory kicking distance. If neither were seen, the robot would continue searching up to the possession timeout, at which point it would just kick the ball away from itself. This last case, however, never happened during the actual US Open demonstrations, as the field was small enough for the goals to be detected from any point on the field. After passing to the teammate, the robot would then position itself a set distance down field, towards the opponent's goal.

This dependence upon teammate detection as a gateway into the execution of the majority of our offensive soccer play proved to be a crutch during our actual US Open demonstrations. Our offensive strategy, therefore, was modified to presume more about our teammate's actions and thus rely less heavily on their actual detection (for further details, please refer to section 4.2.2).

3.2.2 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 attempting 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 our 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.

3.3 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.

3.3.1 Vision

In our work with the Segway RMP platform [10], we have been exploring techniques to enable a vision-centric robot to be able to play soccer in outdoor environments where illuminate is variable [3, 6]. 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. For more details of this approach, see our paper [6].

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.

3.3.2 Tracking

Tracking in essence consists of using sensory information combined with a motion model to estimate the position of a moving object. Tracking efficiency completely depends on the accuracy of the motion model and of the sensory information [14]. When tracking is performed by a robot executing specific tasks acting over the object being tracked, such as a Segway RMP soccer robot grabbing and kicking a ball, the motion model of the object becomes complex, and dependent on the robot's actions [7]. 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. 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

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

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

Finally, we use particle filtering to track the motion model m and the ball state b [12]. Particle filter maintains the belief state at time k as a set of particles $p_k^{(1)}, p_k^{(2)}, \cdots, p_k^{(N_s)}$, 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:

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

for $i = 1 : N_s$

    draw $m_k^{(i)} \sim p(m_k | m_{k-1}^{(i)}, b_{k-1}^{(i)}, s_k, t_{k-1})$.

Figure 5: In both figures, the red and pinky 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

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***.

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. 5) for an example of particle filter representation of the ball position. For more details of the tracking, see our paper [9].

4 Opponent Approach to Team Coordination: Human Driven

The opponent Segway team was developed by the Neurosciences Institute in San Diego, CA. The sensing capabilities on the NSI robot included a pan-tilt camera, a forward facing SICK laser, and both forward and backward facing IR sensors. Additional manipulators were a ?? catcher, a solenoid powered kicker and a ball capture mechanism, which consisted of a skirt of tubing intended to trap an out of sight ball which the robot would then sense and turn towards until the ball rested within the catcher. Their human Segway was likewise outfitted with a similar catcher and kicker, and additionally a headset through which the human player could communicate with its robot teammate. In contrast to our robot-dominated approach to peer-to-peer 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 play. The plays spoken by the human player to the robot were shoot, pass, position, ???.

5 The 2005 US Open Experience

Five Segway soccer demonstrations were played between Carnegie Mellon University (CMU) and the Neurosciences Institute (NSI) at the 2005 US Open.

5.1 Logistics Difficulties

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 cause.

5.1.1 Robot Movement

In an ideal peer-to-peer game, equal amounts of teammate mobility would be shown. Such equality is necessary not only in 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 our robot practically immobile. Additionally, this rule was interpreted differently by each team; the 1.0m as a radius was defined by CMU as extending from a point particle centered on the robot, and by NSI as extending from the outer perimeter of the robot.

The reduction in field size, compounded with the distance restriction between players, so congested the field that robots frequently 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. Such behavior was additionally encouraged by the small size of the field, since positioning would have been difficult even without the safety distance and the goal was within reasonable shooting distance from most points on the field.

5.1.2 Robot Participation in Passing

Equality in how each teammate participates in a pass is likewise required of a true peer-to-peer game. The human and Segway teammates are not completely normalized across their wheeled platforms, but rather are still divided by the very basic reality of one being an organic form, and the other a mass of steel. Such a difference 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 the back of an unsuspecting teammate. Perhaps founded

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

in courtesy to their fellow human, it is also likely that this does not occur because the aiming accuracy of the deflected ball would be unpredictable without the direct involvement of the deflecting teammate. This is not, however, true of a robotic teammate. Deflection off of an inflexible hunk of metal is much more controllable than deflection off of a bendable, unpredictable human; and so it might be possible for a robotic teammate to be used as an unknowing springboard. The problem here, within the context of a peer-to-peer game, is the unknowing part. Wanting our teammates to be actually equal, we accordingly want them to be equally aware of a coordinated action. Additionally, should the teammates choose to use each other as springboards, equal teammates would at least both exercise the technique. However, as we observed the springboard approach being used by the NSI team, the robot never chose to use the human as a springboard. It was also unclear, though by appearances seemed as though it did not, as to whether their robot was aware that any of these deflections were taking place.

The safety distance required between players additionally introduced the question of what is classified as an acceptable pass. Within human soccer games ball possession is not guaranteed for a set radius around a player, and so the ball is much more aggressively contested. Thus a pass being considered successful is simply determined by whether the team which passed also caught the ball. Within Ultimate Frisbee, a pass is considered successful only if the receiving player actually catches the frisbee, and is enforced by requiring it never touch the ground. Segway soccer is a bit of a mix of these two. That a player is considered to be in possession of the ball if it is within 1.0m means that the ball may not be as aggressively fought for as in human soccer. Therefore a possession turnover is defined by whether or not the pass was received by the teammate. Unlike Ultimate Frisbee, however, the ball never leaves the ground, and so what defines a received pass is not as easy to determine. During the US Open, the NSI human player would deflect a ball off of their robot and then catch it again himself (seemingly to reset the possession clock and thus allow the robot more positioning time). Intuition considers such a pass as uncaught and therefore bad, but how to explicitly classify it as such is much more difficult.

5.1.3 Robot Goal Scoring

Equal teammates additionally would be expected to equally attempt shots on the goal. By the completion of the third demonstration, however, a goal had yet to be scored a robot. Beyond positioning difficulties allotting robots fewer opportunities to score in the first place, any attempted robot shots on the goal were inevitably blocked by the human opponent. Considering the demonstration to be too human-dominated, the teams agreed to the addition of two rules to restrict the

Figure 7: 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. The NSI Segway robot was trying to mark.

human players. A human was no longer allowed to score a goal, and the human player was prevented from defending their goal should a robot opponent be attempting a shot within 1.0m of the goal. While the instantiation of these restrictions resulted in many fewer attempted and successful goals, that all were scored by robots increased their participation in the game dramatically.

5.2 The CMU Experience

In the following section we describe the experience of our team particularly at the US Open, both with respect to the afore mentioned logistical difficulties and our opponent team, and our resultant adaptation in offensive and defensive strategies.

5.2.1 Initial Analysis

The most obvious failing the robot displayed when executing our initial strategies (as described in section 2.2) was appearing to be in a constant state of search.

While the goals were large and nearly always detected, the ball and teammate were often occluded and therefore not. 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. The folly in this was that often the remainder of a play might have still been successful even without teammate detection; for example, if instead of continuing to search for the teammate the robot had just quickly kicked the ball forward, the human teammate, able to easily detect the robot and therefore likely already positioned appropriately, would have often been able to receive the pass anyhow. The robot's defensive goal blocking required ball detection, but the reality of a full ball search often had the robot looking away from a partially occluded ball when a shot was attempted. Even when the ball was detected, the robot's interception capabilities were generally slower than an attempted shot on the goal.

Additional confounds to the use of the robot as a goal keep was the observed difficulty in robot positioning, due to the reduced field size. In the frequent case of the robot being unable to position properly, an eventual timeout would cause the robot to begin defending the goal even if it was not within the goal. That is, the robot would search for the ball and in the event of ball detection would attempt interception, but only allowing itself to cover minimal distance in this interception (presuming itself to be in the goal and therefore the ball to be its concern only if very near).

5.2.2 Evolved Offense

As our offensive strategy developed, coordination with the teammate, and therefore presumptions about their actions, became stronger. At a kickoff for our side, the robot assumed their teammate to begin with the ball, and therefore was positioned advantageously to attempt a shot on the opponents' goal. However, should the robot always shoot on the goal at a kickoff, this behavior would be easily predicted, and therefore blocked, by the human opponent player. An element of randomness, therefore, was added. With a predefined (but configurable demonstration to demonstration) probability, the robot chose to either kick on the goal or at a set angle from the goal. The human player would position themselves 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 was used throughout the offensive play. An additional element of randomness was introduced to the actual goal shot by having the robot aim towards the left, center or right sides within the goal, with equal probability.

5.2.3 Evolved Defense

Changes to our defensive strategy brought the robot out of the goal. The robot's defensive target was now to intercept the ball. While respecting the distance minimums required between players, the robot at all times attempted to grab the ball; that is, the ball was marked, and should the ball no longer be within the distance minimum of another player, it would be grabbed. This strategy proved far more effective than the robot as goal keep. Not only did the robot often effectively position itself between the opponent players, thus obstructing an intended pass, but on occasion an opponent pass was not just blocked but actually intercepted.

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 of 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.

With the aim of more balanced human-robot team coordination, we propose the following rule changes [5].

6.1 Proposed Change of Rules

6.1.1 Field Size

The reduced field size at US Open 05 restricted robot movement, and thus restricted both positioning and passing. Alternative solutions:

- A bigger indoor space.
- To take the game to an outside field.

We propose a bigger indoor field for 2006, and to go outside later.

6.1.2 Communication

In the spirit of RoboCup, coordination between teammates on the field should be equal, with neither teammate dominating the other. Similarly then should communication between teammates be equal, with neither human nor robot consistently verbally commanding the other. Alternative solutions:

- Limit what the human is able to tell the robot, either by predefining a list of commands, or by placing a limit on the size and rate of messages.
- Require equal amounts of communication between robot and human; that is, the number of human-to-robot commands must be matched by the number of robot-to-human commands.
- Limit the human to reporting only his own information, for example "I am open" instead of "Pass to this location (me), at this time (now)".

While requiring equal amounts of communication seems the right solution, we are uncertain as to how such a rule might be reasonably enforced.

6.1.3 Human Shooting

The issue of human domination in goal scoring was observed, and to a certain extent addressed, during the US Open. Human scoring was at that time banned, but other possible solutions exist with varying degrees of human restriction.

Alternative solutions:

- Only robots are allowed to shoot on the goal.
- Only robots are allowed to defend the goal.
- For a human goal to count, a robot must have touched the ball within the last 2 seconds (thereby retaining option for a human deflection into the goal).

Since simple enforcement of a 2s rule seems difficult, for 2006 we propose that only robots are allowed to shoot on or defend the goal.

6.1.4 Human Marking

Restrictions on the amount of defense directed towards a robot are required if any sort of reasonable offense is expected from the current robot players. Already in existence was the rule of no double teaming (where no two players may block the same robot) and no human being allowed to mark a robot. However, a more interesting display of robot capabilities might be possible should further restrictions be implemented.

Alternative solutions:

- No interspecies marking. That is, humans mark humans, robots mark robots.
- Require the maintenance of a predefined distance between the marker and marked players.
- Enforce a timeout on marking a robot.

We support the instantiation of no interspecies marking.

6.1.5 Avoidance Distance

In the current rules, the origin of the distance minimum between players is not clearly defined. Humans were by far the worst offenders of this rule, while the robots tended to both calculate and respect the avoidance distance. By the same calculation reasoning, as the referee is human, the maintenance of such a distance is difficult to enforce.

Solution with two aspects:

- The distance is defined as a radius extending from a point particle centered on the robot, since the robots as augmented for soccer vary in size from team to team.
- For safety, this distance should be increased from 1.0m, but also needs to be flexible.

6.1.6 Timeouts

The number and length of timeouts were not predefined, and were abused throughout the games.

Solution:

- A maximum of 3 timeouts, with a maximum total time 10 minutes.

6.1.7 Passing

No rule currently exists which restricts the use of a robot teammate as a springboard. Consequently, robots can "catch" the ball as humans cannot; that is, with their backs turned and the ball merely deflecting off of them. While we would like to retain the ability for deflection goals, we also want the robot to be aware of and actively involved in the action.

Solution:

- Contact with the ball must happen at the kicker for a catch to be considered valid. For example, a pass bounced off the back of the robot is no longer considered good, but a pass bounced off the kicker of either player is considered good.

6.1.8 Possession Clock

The current possession clock is too long and unclear.

Solution with two aspects::

- The possession clock is reduced from 30 to 10 seconds.
- The clock begins to countdown when the ball touches the kicker.

6.1.9 Goal Space

We want to improve player interaction with the goals.

Alternative solutions:

- Instantiate a goal box, inside of which either no human player is allowed or human players have a timeout.
- Instantiate a try line instead of goal; that is, a teammate beyond the field line must catch the goal shot. (This requires at the least a larger field space, and at best an outside field.)

Either one is okay for 2006.

6.1.10 Self Referee

As a suggestion, to borrow another rule from Ultimate Frisbee, we might do away with the field referee and have all players call their own fouls.

7 Conclusions

Motivated by the experience in RoboCup US Open 05, we propose the peer-to-peer human-robot teams as the goal of future human-robot games. We give the definition of peer-to-peer, and the reason why we need such peer-to-peer human-robot teams. We create a soccer game to explore this new domain. We evaluate the strengths and weaknesses of our robot-driven approach, as well as in contrast to the human-driven approach of our opponent team. We then propose the direction of future human-robot games and a revised set of game rules.

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