AI World Cup: Robot-Soccer-Based Competitions

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***Abstract*—Games have been used as excellent testbeds for research on artificial intelligence (AI) and computational intelligence for their diversity and complexity. In this article, we present AI World Cup, a set of AI competitions based on the game of soccer. We provide an introduction to the three challenges that concern a robot soccer match using both value-based and image-based state representations. AI Soccer runs the robot soccer match by participants managing each team of five two-wheeled robots. AI Commentator and AI Reporter observe the AI Soccer match and output real-time commentary and a summary article, respectively. Also, we introduce the AI World Cup platform along with rationale behind notable design choices. The official international AI World Cups held in 2018 and 2019 and the AI Masters competition held in 2019 as a part of the World Cyber Games are briefly discussed. Technical aspects of the strategies developed by participants are also discussed.**

***Index Terms*—Artificial intelligence (AI) Commentator, AI Competition, AI Reporter, AI Soccer, robot soccer.**

I. Introduction

For decades, games have been accepted as extensive testbeds for research on artificial intelligence (AI) and computational intelligence for their diversity and complexity that span from relatively simple classic board games such as checkers [1] to real-time video games [2]–[4]. For example, Deep Q-Learning [5] was tested using various Atari 2600 game environments in the Arcade Learning Environment [6] to show the suggested method's capability to learn human-level play skills. AlphaGo [7] presented a breakthrough result by defeating a top-level human player through the famous board game of Go.

Because of their competitive nature and easy appeal to the public, many games such as *StarCraft* and *League of Legends* were easily adopted into worldwide competitions. Similarly, the emergence of game AI competitions is thus a natural direction for promoting research with game environments as testbeds. Indeed, game AI competitions using different types of games have been introduced for supporting different research subjects. The Dota 2 bot competition [8] focuses on the real-time control of a single agent in a one-versus-one environment. On the other hand, the Visual Doom AI Competitions [9] attempt to tackle single-agent control in a one-versus-many environment. The StarCraft AI Competitions [10] approach the domain of resource management and planning under an adversarial environment through the famous real-time strategy game. The Text-Based Adventure AI Competition [11] provides a text-based environment where natural language processing (NLP) skills can be tested.

Some other competitions utilize game environments with additional modifications in settings for enriching the task domains. The *Ms. Pac-Man* versus ghost team competition [12] adopts the classic arcade game *Ms. Pac-Man*, but the system is modified to allow the participants to develop a multiagent system that can control the ghost enemies in the game. The StarCraft Multi-Agent Challenge [13], instead of using the regular full game of StarCraft II, focuses specifically on the micromanagement of individual units in combats to provide a testbed for decentralized control in a multiagent system.

A multiagent environment is bound to be a highly dynamic and challenging task domain because decisions made by each agent simultaneously affects the environment in a different way. The aforementioned challenges targeted for multiagent research have shortcomings. The games used in these challenges were originally not designed as multiagent environments so that a large number of rules had to be overhauled in order to be used as multiagent task domains. The participants, as a result, faced the additional difficulty of understanding rules that they are unfamiliar with. A way to relieve the unnecessary complexity is to choose a game that already includes the multiagent nature where the researchers can be already familiar with. We find the game of soccer, traditionally used for control, computer vision, and AI research as in FIRA RoboworldCup [14] or RoboCup [15], an adequate domain for multiagent research. Both organizations provide a variety of robot-soccer-based competitions that are held with physical robots and simulated robots. While physical robots provide lively offline matches, the participants are required to purchase or build robots and repair the robots at their own expense when problems occur. Also, the use of physical robots hinders the development of control algorithms based on machine learning techniques as learning algorithms are prone to

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make mistakes that end up increasing the maintenance costs. Using a simulated environment would be the solution to cope with the limitations and the aforementioned organizations have also accommodated the simulated version of robot soccer like FIRA Simurosot [16] and RoboCup Simulation 2D/3D Leagues [17], [18].

Over 20 years of events, robot soccer simulations have provided a great opportunity for participants to investigate multiagent systems. The participants have tried various approaches to design a program for playing the robot soccer game. The champion team of RoboCup 2000 Simulation League FC Portugal [19] used an expert system approach based on situation-based strategic positioning with dynamic exchange of player roles. Celiberto *et al.* [20] used a type of reinforcement learning technique, heuristically accelerated Q-learning, to speed up the learning process in RoboCup 2D Simulator. With the FIRA Simurosot platform, Rabelo *et al.* [21] tried automatic code generation of game strategies using finite-state machines. Tavafi and Banzhaf [22] accommodated genetic programming into a decision-making system for the optimization of the robot soccer strategy. In more recent years, Team HELIOS [23] has attempted tree-search-based action sequence generation while pruning unintended actions using support vector machines, resulting in winning the Robocup 2D Simulation League twice in a row. Fukushima *et al.* [24] also used the tree-search-based approach with the addition of an evaluation function modeled by a neural network. In the most recent year, Team Fractals [25] used guided self-organization via dynamic constraint annealing to boost their previous algorithm Gliders2d, and won over the former champion Team HELIOS.

As exemplified by previous works presented, simulations worked as a cradle for effective algorithms in multiagent coordination fields. However, the existing simulations have drawbacks that hinder catering to newly joining researchers. In the case of FIRA Simurosot, the simulator lacks support for automated game management so that deep learning approaches cannot easily be used as human needs to keep manage the simulation program for data collection. In the case of RoboCup 2D Simulation, the challenge complexity is too high for new researchers to the multiagent systems as the challenges provide a full-sized 11 versus 11 soccer game. In the case of RoboCup 3D Simulation, when compared to the 2-D scenario, the complexity is even higher because humanoid robots are used. Humanoid robots need complex control of joints to form primitive behaviors.

To further enrich the task domains examined by the game-based AI research, we introduce the AI World Cup, a set of competitions derived from the robot soccer simulation game. AI World Cup currently comprises of three challenges: AI Soccer, AI Commentator, and AI Reporter. AI Soccer is targeted for introducing a multiagent environment friendly to researchers who are relatively new to the field. The other two events are rather experimental and aim for creating an AI agent that is capable of providing expert analysis on the match played by AI Soccer agents. Depending on the event, the expert analyst is asked to provide real-time commentaries or summary of the match at the end.

AI Commentator is the first of two experimental events and is targeted for short-term situation recognition and natural language description through generating real-time commentaries on an AI Soccer match. Despite of the fact that an AI Commentator competition does not exist in RoboCup, previous researchers addressed the problem of generating real-time commentary. The main purpose of these research works was to increase the enjoyment of the audience watching the games and to create expert analysis in multiagent environments. André *et al.* [26] summarized three commentary systems introduced in RoboCup of 1998. The Rocco system [27] generates TV-style commentaries by using an event recognition system that provides information to fill predefined commentary templates. Binsted and Luke [28] proposed an animated talking head named Byrne to generate an affective speech and entertain the audience. The Mike system [29] generates commentaries with a multiagent system, in which six agents are used to detect events and generate high-level commentaries. Using prerecorded human speech, Nijholt *et al.* [30] developed a live soccer commentary system for the 3-D simulation system in the 2006 Robocup. Chen *et al.* [31] proposed a commentary system that could learn in an end-to-end framework only with sample language commentaries paired with the respective environment state. Note that most of the mentioned works also include a text-to-speech module as the final step of their systems, while in the AI Commentator, the output is a text commentary displayed on the simulator screen in real time.

AI Reporter is targeted for recognizing and summarizing a long-term situation through article generation regarding one full AI Soccer match. Video summarization has already been addressed in the computer vision research field in the form of generating a set of key frames in the target video clip [32]–[35]. In addition to key-frame extraction, Sah *et al.* [36] have provided an integrated video summarization system that uses a video captioning algorithm and text summarization to provide a summary paragraph describing the input video clip. In the meantime, Zhang *et al.* [37] investigated the possibility of generating a report from live commentaries in real soccer games. As the research in text summarization of temporal sequence data is still in the early stages, it is a great opportunity to use robot soccer games to promote the field and introduce the AI Reporter competition.

In all three challenges, we provide both the value-based information and the pixel-based information, which the participants can freely choose which type of input data to use regarding their research interest. The rest of this article is organized as follows. Section II introduces the concept of the AI World Cup and its current three challenges. Section III describes the AI World Cup platform on which all three challenges can simultaneously be held. Section IV provides a brief summary of the previous AI World Cup events held and algorithms participants have used. Finally, Section V concludes this article.

II. AI World Cup Competitions

In opening a competition, selecting an attractive game is beneficial for the long-term prosperity of the competition, and

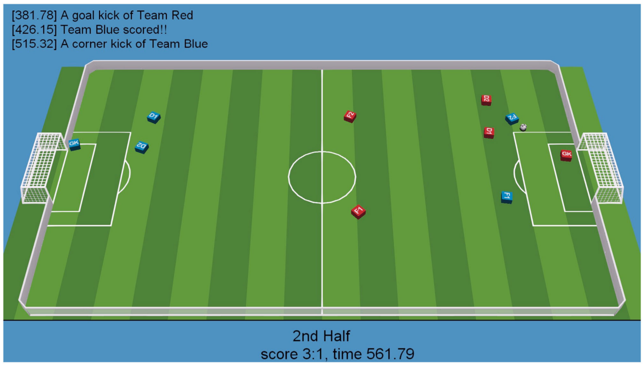


Fig. 1. Screenshot of AI World Cup platform used in the AI World Cup 2019. Unlike a regular soccer game, the soccer field is surrounded by walls preventing agents and the ball from leaving the field easily.

thus, promoting research on the challenge we provide [38]. AI World Cup is a set of competitions inspired by soccer, one of the most famous team sports gaining worldwide attention through competitions such as FIFA World Cup, UEFA European Championship, and AFC Asian Cup. We saw a great opportunity in public attractiveness of soccer in promoting research from all around the world and in a wide range of age groups.

Because of the well-known nature of soccer, the participants and spectators of the competition can easily understand the game rules, and thus, have opportunity to focus on the competition in depth. Thus, we built a simulation game system, AI Soccer, based on soccer, which uses two-wheeled agents. The rules are modified to cope with two-wheeled agents and in order to mitigate the difficulty of the game while retaining the core challenge that a game of soccer can provide. Also, we added two more challenges, AI Commentator and AI Reporter, based on the simulated game match itself to promote different fields of research other than agent controls and team managements.

Fig. 1 displays the game screen of the AI World Cup, where an AI Soccer match is run by two AI Soccer programs, while an AI Commentator program is making real-time commentaries on the game. An AI Reporter's output cannot be seen on the screen as the result article is stored as a text file when a match ends. The following subsections briefly introduce the three challenges we provide in the AI World Cup.

A. AI Soccer

In order to excel in a soccer game, great teamwork is required along with individual players' skills and the players need to be adaptive to the quickly changing circumstances. Also, to be a top soccer team, the team needs to be capable of winning over many opponent teams with different types of strategies. As a result, a soccer game is highly dynamic, cooperative, and competitive, making the soccer game a very challenging environment for AI algorithms.

The main goal in the AI Soccer challenge development is to simplify the robot soccer game so that participants can easily understand and join the competition, focusing on the core challenge we would like to provide via the game of soccer: multiagent cooperative/competitive behavior among robotic agents. The soccer game is simplified in three main aspects. The first aspect is the game environment. The AI Soccer challenge is performed in a simulated environment, while other competitions, such as the RoboCup Middle Size League [39] and Small Size League [40], involve robot hardware implementation.

Another aspect is regarding the robot complexity. The soccer game is simplified into the game played by two-wheeled agents to remove the complexity in the humanoid robot control such as locomotion controls and posture controls that participants had to deal with in competitions such as RoboCup Simulated 3D League [18]. However, soccer's multiagent dynamic nature, which we regard as the core aspect of the soccer game, is still retained.

Also, AI Soccer rules are modified and simplified version of the regular soccer game rules so that the challenge's difficulty is manageable to newly joining AI developers. For example, AI Soccer did not directly adopt the concept of offside since we regarded the rule as having complexity beyond our scope of challenge as the rule is exerted based on relations between positions of both teams' agents and an action of an agent. Further descriptions on the rule designs will be provided in Section III.

The goal of an AI Soccer participant is to develop a program that controls the five two-wheeled robots in a team to win over the opponent participant's program. The program can directly manage the velocities of wheels to develop movement patterns or more complex actions. For simplicity in communication, our competition simulation system only communicates with one program per team, assuming a centralized control. As will be further explained in Section III, the game state data use a global coordinates/vision system. In this way, sending the global state to multiple programs would be redundant. However, the control of robot agents is not restricted to be centralized. Participants can freely approach this challenge as decentralized control of multiple agents by spawning separate threads for each agent and have a decentralized way of decision making. The main goal of the AI Soccer challenge is to provide a simple and enjoyable testbed friendly to new researchers and the general public interested in multiagent systems. We expect AI Soccer competition would promote developments in research fields such as multiagent reinforcement learning, cooperative-competitive training, and agent controls.

B. AI Commentator

In professional team sports games, a match usually accompanies with live broadcasting where a sports commentator provides real-time analysis on the game progress and sometimes includes entertaining commentaries. The commentaries help the spectators understand the game progress more clearly and enjoy the game further. The presence of real-time commentaries is also included as a feature in soccer video games, such as FIFA video game series by EA Games and Football Manager by Sports Interactive. Although the actual algorithm that generates the commentaries in soccer video games is not known since the games are not open sourced, the methodology behind the commentaries seems to be preparing numerous recorded sentences and using appropriate sentences when triggered by events. While the method would work well in an environment where most events are foreseeable, it would show difficulties in handling unexpected situations.

The goal of AI Commentator participant is to develop a program that generates real-time commentary on an AI Soccer match of two AI Soccer participant programs. AI Commentator participant programs have access to the same global coordinates/vision data available to AI Soccer participant programs. From the provided data, occurrences of game events can be inferred. For example, when the distance between a robot and the ball is decreasing and the robot is heading toward the ball, it can be inferred that the robot is chasing the ball. Afterwards, if the distance between the ball's moving direction changes toward another robot with high velocity after the robot touched the ball, it can be assumed that the robot passed the ball to its ally.

The AI Commentator challenge's main difficulty lies in the concept of an AI generating commentaries describing what another AI is doing. When the AI Soccer participants' programs' strategy levels may vary far more than regular soccer games, using traditional approaches of preparing a set of predetermined sentences may not be practical. To develop a commentary system capable of generating real-time commentary on AI Soccer matches, more adaptive approaches using recent language models would be needed. For example, an AI commentary system may consist of a key event detection algorithm such as dense-captioning events model [41] that extracts event occurrences from a stream of AI Soccer state images and a state-of-the-art language model GPT-2 [42] to generate commentaries from the detected events. End-to-end approaches such as the one proposed by Chen *et al.* [31] combined with deep learning architectures can gain more attention from the research community since the same architecture can be generalized for other sports with minimal adaptations.

The evaluation criterion for the AI Commentator challenge is subject unlike the AI Soccer challenge, where the evaluation can simply done with the scores. As will be described in detail in Section IV, human referees evaluated the AI Commentator results to decide the winner of the challenge in previously held events. The subjective grading system consisted of the following five criteria: predictability (how accurately the AI predicts future events), readability (how easy and enjoyable the commentaries generated are), veracity (how accurate generated commentaries are), turing testability (to what extend the AI-generated commentaries are distinguishable from human generated ones), and informativeness (how useful and rich the generated commentaries are to the audience). The aforementioned criteria evaluate important characteristics of the AI Commentator, such as the capacity to predict future events and provide useful information to the audience beyond game descriptions.

For AI World Cup being a fledgling event, we see AI Commentator as an experimental challenge where we would like to see how well AI-generated commentaries can be formed compared to the commentaries generated by traditional approaches such as expert systems. As we allow both learning-based approaches and expert systems to be submitted as entries for the AI Commentator, the two approaches can be compared directly in the challenge. However, we do not expect learning-based approaches to excel in the commentary generations from early stages. As recent breakthrough deep learning approaches to NLP use large datasets for training, we expect the AI-generated commentaries would not be much sophisticated until enough data would be available as AI Soccer challenge starts to see various entries from participants. Although we expect most entries would be based on traditional approaches at first, we hope to see learning-based approaches emerging as competitive entries over time. We hope the AI Commentator challenge can eventually become a worthy natural language description challenge as our competition makes progresses.

C. AI Reporter

After a sports match ends, reporters summarize the game to inform those who have not watched the game. The summary typically includes context information regarding the game such as the team and players, the result of the match, player statistics, and selected highlight moments in the match. Match summary generation is also important in soccer management simulation video games such as Football Manager to boost the user experience. However, as Juknevičienė and Viluckas [43] claimed, currently there exist major differences between AI-generated and human-generated reports. The AI-generated reports tend to reuse the same sentences multiple times and repeat the same sentence structure that the paragraphs generated look rigid and do not flow naturally. Writing an informative article requires the capability to distinguish important and unimportant events in the match and the language modeling ability.

The AI report generator should be able to analyze the game context and consider the entire The system developed to create the game report should analyze the game context and the entirety of the game states to generate text. Recent research investigated on generating text based on input videos [44], [45]. As the global state coordinates is also given, recurrent-neural-network-based architectures such as [46] and [47] can also be used to tackle this problem. The ability to create an informative organized report is a great challenge in the area of AI, and thus, is the motivation for the AI Reporter challenge.

The goal of the AI Reporter participant is to develop a program that generates an article summarizing the AI Soccer match ran by two AI Soccer participant programs. Same with the AI Commentator, AI Reporter program has access to the same global coordinates/vision available to the AI Soccer program. The core difference between the AI Reporter and AI Commentator is that there is no real-time requirement for an AI Reporter to generate the summary output. The AI Reporter program can aggregate long-term information to extract important events without hard time limitations. In previously held events, the AI Reporter was evaluated by human referees based on a subject system consisting of the following five criteria: organization (how useful and rich the generated commentaries are to the audience), readability, veracity, turing testability, and informativeness. Compared to the AI Commentator criteria, four criteria are identical with AI Commentator and the predictability factor is substituted by the organization factor. The criteria evaluate important characteristics of the AI Reporter, such as the capacity of creating an

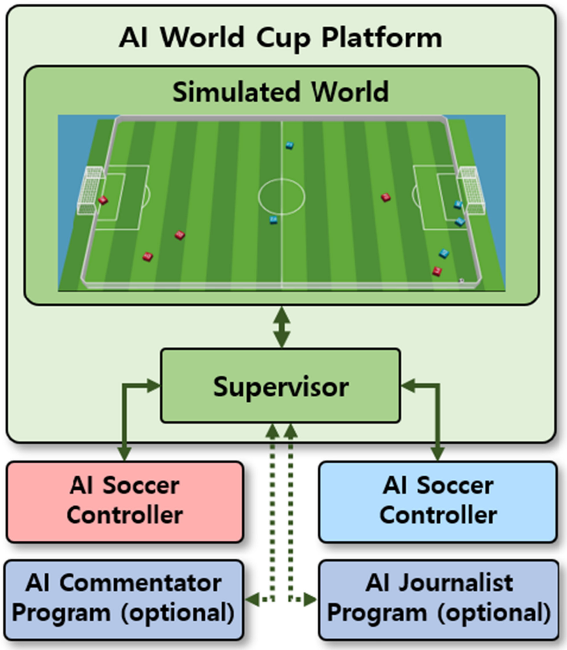


Fig. 2. AI World Cup platform system layout.

organized informative text that explains the events that occurred in the game precisely. Similarly to the AI Commentator, we regard the AI Reporter challenge as rather experimental and hope to see how well the learning-based approaches can summarize the match events.

III. AI World Cup Platform

AI World Cup platform (available in [48]) is a robot soccer simulation system built using Webots Robot Simulator [49]. Webots Robot Simulator is a robot simulation software designed for simulating realistic robot experiments using Open Dynamics Engine [50] as the physics engine. The platform's structure is shown in Fig. 2. The simulated world consists of two teams, red and blue, of five two-wheeled robots on a soccer field. In the simulation, a supervisor process running inside the AI World Cup platform governs the soccer rules in the simulation and collects information of the simulated world. Also, the supervisor communicates with the participant programs using AI World Cup application programming interfaces (AIWC APIs) to distribute the game information and accept the requests to control the robots, display the comments, and save the report. Two AI Soccer controllers are mandatory for running the simulation system, while AI Commentator and AI Reporter programs can optionally be attached to the game.

In the following subsections, the core features of the AI World Cup platform and notable AI Soccer rules are delineated.

A. AI World Cup Game Information

As stated in the previous section, the goal in designing the AI Soccer challenge is to make the game and system simple that the participants feel less overwhelmed by the challenge's complexity. This design choice is also reflected in how the game information is provided to the participant programs. As we wish the participants to not struggle in data acquisition and object recognition and rather focus on developing the multiagent coordination algorithm, we provide a global data structure that includes positions and orientation of robots and the ball, game states such as whether a goal happened or robots were relocated due to fouls or stalemate situations, robot state such as whether the robot was sent out due to fouls or whether the robot is currently in contact with the ball or not. Also, to encourage various types of algorithms to be developed, the AI World Cup platform accommodates image-based state representations too in addition to value-based representations. The participants may utilize either or both of the data types according to their algorithm.

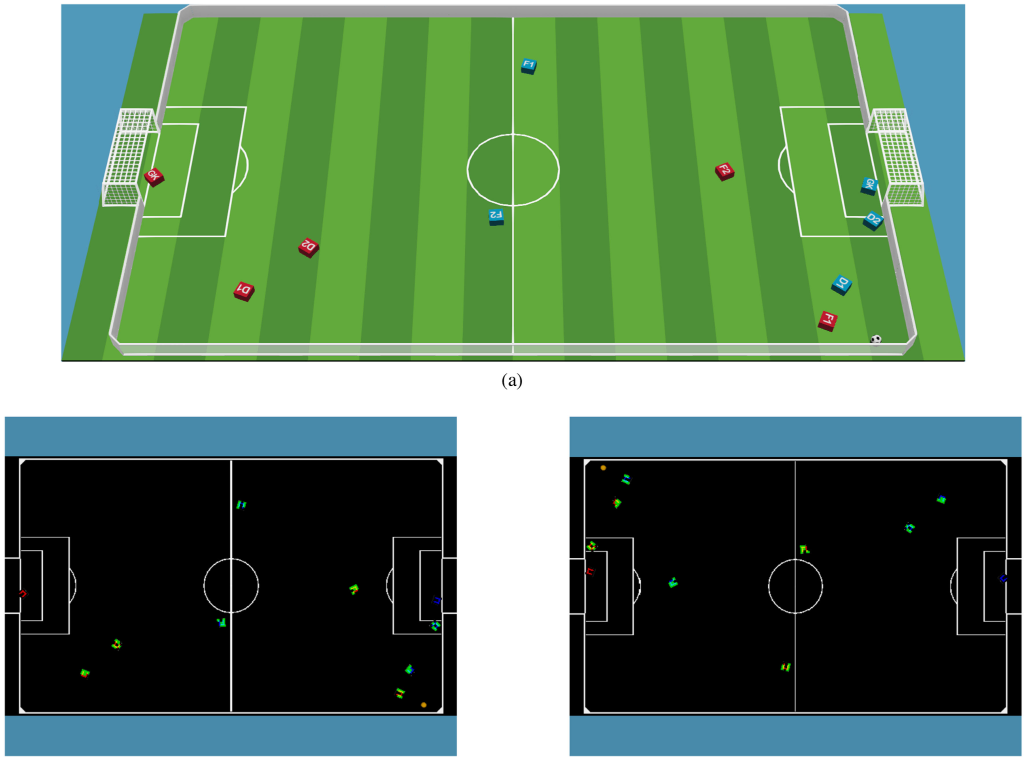
1) Coordinate Representation: AI World Cup platform provides a coordinate-system based representation of the game state where the positions of robots and ball are represented as coordinates in a Cartesian coordinate system where the origin is set at the center of the soccer field and the orientations of robots in a polar coordinate system where the origin is set at the center of the robot of concern. For convenience in information handling, the coordinate systems are adjusted in the way that participants of AI Soccer need not to know whether they are Team Red or Team Blue or whether the game is in the first half or the second half. The coordinate systems are automatically rotated by 180° when needed that the participant's side is always located on the left of the origin in the coordinate system. The AI Commentator and AI Reporter receive the same data sent to Team Red.

2) Image Representation: Along with the coordinate-system-based game state representation, the AI World Cup platform also provides the information-rich 640×480 top-view image representation of the game state as shown in Fig. 3. The field image is a simplified version of the raw soccer field where the robots can be identified and located with markers. Instead of using a local view from each robot's perspective as in a regular soccer game, our competition uses a global vision system to simplify the state recognition task.

Similar to the coordinate system's case, the image is automatically adjusted in the way that the participants of the AI Soccer can assume they are Team Red and their side is located on the left of the field. AI Commentator and AI Reporter share the same vision system with Team Red.

3) Robot Markers: The robot shapes in Fig. 3 are relatively small compared to the field size that the roles inscribed on the robot are hardly distinguishable when seen from top view in which the entire field can be seen. Thus, we have designed robot markers to be used in the image states that are more information-rich compared to the small size of robots shown in the images. The design criteria behind the robot markers were to provide a set of markers that can uniquely identify each robot in the game, easily detectable in the image state representation both by image processing and deep learning techniques.

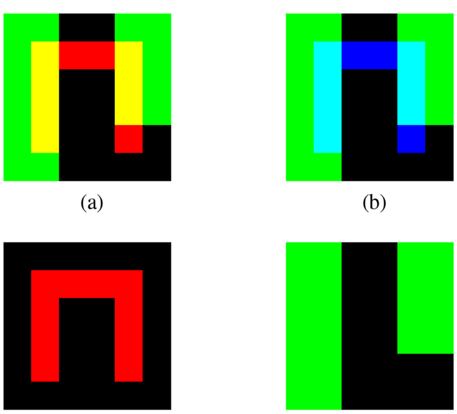
A sample of a robot marker used in the image state representation in the AI World Cup platform is shown in Fig. 4. A robot marker is an RGB square image that is a combination of two different markers: a team marker and an ID marker. Since the team marker only uses R and B channels and the ID marker only



(a)

(b) (c)

Fig. 3. Image representation of a game state. (a) AI Soccer game frame displayed in the simulation screen. (b) Image representation of game state shown in (a) sent to AI Soccer Team Red, AI Commentator, and AI Reporter. (c) Image representation of the same state sent to AI Soccer Team Blue. The field state is rotated by 180° and the team marker colors are swapped so that Team Blue participant program can still regards its own team as Team Red.



(a) (b)

(c) (d)

Fig. 4. Sample of a robot marker used in the AI World Cup platform. A robot marker shown as (a) in one team's image frame will be seen as (b) in the opponent team's image frame. A robot marker can be decomposed into (c) team marker and (d) ID marker.

uses G channel, the robot marker can easily be decomposed into the two markers by setting filters on each color channel and be processed to extract information from each marker. Unlike other robot-soccer-based competitions that provide image representations like the RoboCup Middle Size League [39] and Small Size League [40], AI soccer challenge does not allow participants to customize the robot markers. This is to reduce the variation in the image state so that the participants or the learning program would have less difficulty in the recognition process.

A team marker is an indicator for the robot's position, orientation, and affiliation. All robots use the same ⊓ shape that can be used to infer the robot's position, which would be the center of the shape, and orientation, where the robot would be oriented to head upward in case of the marker orientation shown in Fig. 4(c). The color of the shape indicates the robot's affiliation where red means the robot belongs to the participant's team, while blue means the robot belongs to the opponent participant's team. Since the image state representation received by each participant will guarantee that the receiver's team is red on the image, a robot shown as Fig. 4(a) in one team's image will be shown as Fig. 4(b) in the other team's image. This simplifies the image recognition process on participants' side that the participants can always treat themselves as Team Red in using image data.

An ID marker is an indicator for the robot's ID to identify it among five robots in a team. The ID marker embeds a 9-bit binary string by dividing the marker into 3×3 square grid regions and assigning each region either on (green) or off (black) from left to right, and then, from up to down according to the associated binary string. In case of Fig. 4(d), the associated binary string would be "101101100." The five binary strings used for identification of robots are codewords designed to have the minimum Hamming distance of 5 that up to 2-bit errors can be corrected. The error-correctable codewords are useful in AI World Cup's image state representation system because the images are prone to distortions when the robots are not oriented in multiple of 90°.

Throughout all matches, the simulation system uses a fixed set of ID markers where each ID is designated to each position of the robot (as in goalkeeper, defender 1, etc.) that the recognition process is further simplified for the participants.

B. AI World Cup APIs

AI World Cup uses the Web Application Messaging Protocol (WAMP) for communication between the simulation platform and the participant programs. The WAMP is a simple open-standard protocol that provides publish/subscribe messaging routines and remote procedure calls (RPCs). When the simulation starts, the supervisor process initiates an instance of the WAMP router and generates access information such as IP, port, and access keys to the router. The access key is a uniquely generated string that works as a temporary password to joining the simulation game that only the designated participant can have access to the simulation and participants or outsiders cannot masquerade as other participants running in the simulation.

After the access information is generated, the simulator passes the information to child processes (two to four processes based on whether a commentator and/or an article exist in the game). Each child process corresponds to each of the simulation's participants: two AI Soccer, one commentator (optional), and one reporter (optional) participants.

With the access information, the participant programs can use AI World Cup APIs described later in this subsection to communicate with the simulation platform. Along with the simulation platform, we provide sample participant programs that already implemented the WAMP protocol and AI World Cup API usages for C++ and Python that the participants may start developing the AI Soccer/Commentator/Reporter programs without the direct knowledge of the protocol and APIs. The participants may develop the participant programs in other languages as long as the programs follow the WAMP protocol and our APIs. For other languages, the WAMP provides client-side library implementations on several different languages on the WAMP official webpage [51].

The following APIs are used throughout the simulation routine for participant programs to communicate with the simulation supervisor.

1) Topic Subscription: In each game time step, the AI World Cup simulation system distributes the frame information such as the object coordinates or the top-view image of the soccer field through WAMP protocol's publish/subscribe messaging routines. To fetch the data, the participant program must subscribe to a topic the simulation system provides where the supervisor will publish frame information. The topic name is identical to the access key string that each participant can only have access to the one topic specifically provided for the participant. The participant program should subscribe to the topic before the game begins for the data to be available throughout the game.

2) Remote Procedure Calls (RPCs): The AI World Cup simulation system utilizes five RPC APIs. Unlike the publish/subscribe routines where the supervisor actively generates frame data, RPCs are used from the participant's side to notify, and request information, or provide instructions to interact with the game. For all RPCs, the access key must be provided as the first element of the argument tuple in order to verify the participant's identity. The AI World Cup RPC APIs are summarized in Table I.

C. AI Soccer Rules

As stated in Section II, the goal for the AI Soccer rule design was to modify the regular soccer rules to keep the difficulty level manageable for new AI researchers. While some rules such as offside were removed for simplicity, several new rules were introduced to prevent exploitations and account for the difference between humans and two-wheeled robots. On the other hand, other rules such as goal kick, penalty kick, kickoff, and corner free kick are implemented similar to a regular soccer game to resume the game after pauses caused by goals or fouls. Also, the rules are fully automated by the simulation program so that participants can easily automate the learning process when using machine learning techniques. While detailed descriptions on all AI Soccer rules are provided in the AI World Cup repository [48], we provide explanations on the design behind notable AI Soccer rules in this subsection.

1) Field Boundary: A key difference between a human player and a two-wheeled robot is in how a player can manage the soccer ball. While a human player can dribble, kick, do a heading, and even throw and catch the ball with hands in special cases, the two-wheeled robot can basically only push the ball with its body. Because of the difference, the robot player cannot abruptly change the direction it is pushing the ball toward unlike the human player who can simply step on the ball and turn around the ball to change direction. The main problem arising from this problem is that the ball can easily leave the soccer field when robots are pushing the ball around to avoid opponent robots' defensive actions. To cope with this issue, a wall is set around the boundary of the soccer field so that the ball can bounce off from the wall instead of leaving the field.

2) Stalemate Prevention: In AI Soccer, the game sometimes can meet a stalemate situation. One frequent case is when the ball approaches one of the corners since the soccer field is surrounded by walls in AI Soccer, the ball can be stuck in a corner with robots unable to push the ball away from the corner. Also, several robots of two teams can sometimes track the ball together that they may end up in a clogged situation where the algorithms do not yield to make spaces for any robots to move. The AI Soccer management system detects the stalemate situations by checking the ball's movement and makes the game proceed to a corner free kick, penalty kick, or goal kick, or simply relocates the ball's position to resolve the stalemate situation. A corner free kick is a hybrid of the soccer's corner kick and free kick since the soccer field in the AI Soccer is surrounded by walls that the robots cannot kick the ball outside the field into the field.

3) Recovery From Falling Down: Two-wheeled robots cannot recover from tripping easily only by the wheel controls, unlike human players who can easily stand up after falling. The AI Soccer management system detects such events and relocates the nullified robot if the robot cannot recover by itself within a short period.

TABLE I
LIST OF REMOTE PROCEDURE CALLS USED IN THE AI WORLD CUP SIMULATION SYSTEM

RPC Name	Argument (Tuple)	Description
aiwc.get_info	(access_key)	Requests for the basic game information such as game duration, field dimensions, and robot dimensions. All information available through this RPC are static variables throughout the game that the participant program only needs to request the data once at the beginning of the game.
aiwc.ready	(access_key)	Notifies the supervisor that the participant program is ready to begin a game. The participant program should initialize parameters that take some time such as loading trained neural network parameters before calling aiwc.ready. This RPC should be called within 30 seconds after the simulation program launched the child processes. Otherwise, the participant not responding will be dropped from the game. In case of when any of AI Soccer participant programs failed to respond, the game will terminate immediately.
aiwc.set_speed	(access_key, wheel_speed)	(AI Soccer only) Requests the supervisor to update the velocities of robot wheels in the participant's team. A vector of ten velocity values must be sent in the argument tuple along with the access key. If the participant program does not call this RPC in each game time step, the supervisor keeps the wheel velocities same as the previous time step's values.
aiwc.commentate	(access_key, comment)	(AI Commentator only) Submits a new comment to the supervisor. A comment string must be sent in the argument tuple along with the access key. When the supervisor receives the request, a timestamp is attached to the comment and pushed into a commentary buffer whose contents are displayed on the simulation screen in real-time. The commentary buffer is designed as a circular buffer that keeps recent three comments.
aiwc.report	(access_key, report)	(AI Reporter only) Submits a new article to the supervisor. An article is a vector of strings that must be sent in the argument tuple along with the access key. When the supervisor receives the request, the article internally kept in the simulation system is updated to the newest article submitted. Since the supervisor only keeps the most recent article, AI Reporter program only needs to call this RPC once at the end of the game. After the game, the article is written into an output file by the supervisor.

4) Fouls: While the majority of fouls in regular soccer deals with the handling of the ball and dangerous reckless plays, AI Soccer game does not need such rules as the simulated agents are arm-less and cannot be damaged. For that, we first have removed the majority of the foul rules. However, through AI World Cup events held so far, we have observed several teams using the same and repetitive strategies that easily trivialized the challenge. To cope with the trivialization, we introduced fouls rules in an attempt to prevent the exploitations. As of AI Soccer in the AI World Cup 2019, three foul rules are set and deal with the agent behaviors near the goal.

The first two fouls are the penalty area fouls by the defense and offense team, respectively. In the first AI World Cup event, the most common strategy for the participants was to use all five agents to push the ball together into the opponent's goal. As a single goalkeeper does not have enough power to block five agents' pushing force, the defending team also had to use all five agents to push the ball into the other direction, resulting in frequent stalemate situations where all ten agents in the game are pushing each other in opposing directions. Thus, these two fouls were added to prevent the agents from forcing through the opponent's defense or offense by multiple agents pushing the opponent agents together. The defense team shall not put more than three of their agents including the goalkeeper in their penalty area. When the defense team has four or more agents in their penalty area, the game proceeds to a penalty kick of the offense team. The offense team shall not put more than two of their agents in the opponent's penalty area. When the offense team has three or more agents in the opponent's penalty area, the game proceeds to a goal kick of the defense team.

The third foul is the goal area foul by the offense team. After the first two fouls have been introduced, the frequent stalemate situations due to agents gathering in one place and pushing each other have been reduced. However, a new exploitation strategy of blocking the goalkeeper has emerged. An agent could be assigned to continuously push the opponent goalkeeper away from the goalpost to effectively nullify the goalkeeper. As this exploitation greatly harms the role of a goalkeeper, a time limit for an agent to stay in the opponent's goal area has been set. When an agent stays in the opponent's goal area for more than 1 s, the agent is sent back to a designated position. Also, the offense team's goalkeeper is sent out from the game for 5 s as a penalty.

5) Goalkeeper Relocation: Even if the goalkeeper cannot be blocked for more than 1 s in the goal area, the agents may block the goalkeeper from returning to the goal after the goalkeeper has left the goal area. To prevent this, the goalkeeper is automatically returned to its default position when it stays outside the penalty area for more than 3 s.

IV. PREVIOUSLY HELD AI WORLD CUP EVENTS

In this section, summaries for the previously held major AI World Cup events and algorithms used by teams are presented.

A. AI World Cup 2018

The first international AI World Cup [52] was held on August 20–22, 2018 at Korea Advanced Institute of Science and Technology (KAIST) in Daejeon, Korea. A total of 29 teams from 12 countries participated in the three challenges. Fig. 5 shows the final match of the AI Soccer challenge won by 6-4 by the KAIST team AFC_WISRL against the also KAIST team Team_SIIT. The AI World Cup 2018 AI Soccer final match video is available in [53]. The AI Commentator challenge was won by

Fig. 5. AI World Cup 2018 Final Match [52].

Fig. 6. WCG AI Masters 2019 Podium [57].

the Arizona State University team ASUAIC. The KAIST team SIIT_REPORTER won the AI Reporter challenge.

The champion AFC_WISRL team focused on a deep reinforcement learning-based strategy trained to choose between 16 discrete actions for each robot based on the robot and ball information during four consecutive frames. Proximal policy optimization (PPO) [54] with multibatch experience replay [55] was used to train their model that tried to maximize rewards based on a distance factor, between their own team robots and the ball, and a game score factor. The trained policy was shared among players. A rule-based approach for effective role switch to keep numerical superiority in defensive and offensive phases was used by the ASUS team [56].

The ASUAIC team submitted a commentator using a learning-based model that interprets the current situation of a robot soccer game in a similar manner to a human commentator by observing past states regarding the players and the ball coordinates, orientation, and speed. SIIT_REPORTER team submitted a reporter using a set of knowledge-based rules to store and analyze meaningful events that happened during the game, such as goals scored and ball possession by each player. General statistics on the recognized events were featured in the generated report.

B. WCG AI Masters 2019

The AI Soccer challenge, named as AI Masters, was a part of World Cyber Games held in Xi'an, China on July 18–21, 2019. World Cyber Games [57] is an international e-sports competition that attracts hundreds of players from various countries to compete in worldwide popular games such as *Dota 2, Crossfire, StarCraft 2*, and *Warcraft 3*. In 2019, the competition had the New Horizon section to introduce future sports platforms that included robot soccer, robot fight, and virtual reality games. For this event, the game rules were changed to include four additional situations: kickoff, goal kick, corner free kick, and penalty kick. A total of 103 teams from 38 countries applied for the competition, with the main round consisting of 16 teams from five countries. The champion was decided by the best of three matches and the KAIST team KGSGT won the competition by 2-0 against the Masaryk University team Pavol Zatko in the final. The podium of the competition is shown in Fig. 6. The WCG AI Masters 2019 final match video is available in [58].

With the additional changes, the AI Soccer match has become more dynamic. Fully offensive strategies were not as effective as in previous competitions. The champion KGSGT team combined Deep Q-Learning [5] with a set of knowledge-based rules to decide the best set of parameters throughout the game. They also developed a prediction system to detect situations where kick attempts would result in a higher chance of scoring while keeping the positioning stable against counterattacks by the opponent team. Pavol Zatko team focused on exploiting the dynamics of the game by blocking the opponent's team players and using a simple set of strategical rules. Their strategy changed the game dynamics into a four against four game, in which their defensive stability was an advantage. The FGL Team used proportional–integral–differential (PID) control focusing on achieving maximum speed combined with a set of complex positional rules. The team also used a special path planning to kick with the desired angle and velocity when given enough time to execute the estimated route.

C. AI World Cup 2019

In the second AI World Cup held on November 1–3, 2019, AI Soccer rules were improved further based on the results of WCG AI Masters 2019. One major issue pointed out was that a single agent could push the opponent goalkeeper away from the goalpost. Two rules were added to prevent the "goalkeeper blocking" strategy and keep the goalkeeper capable of defending the goal. In 2019, a poster session was opened along with the AI World Cup competitions to promote information sharing on the developed algorithms. The final match was held between KVILAB team from KAIST and FGL Team who was in third place in the WCG AI Masters 2019. KVILAB team won the final match by 7-4 against the FGL Team.

KVILAB team approached the AI Soccer challenge with a machine learning technique based on the multiagent deep deterministic policy gradient (MADDPG) algorithm [59] where actor networks work in a decentralized way, while critic networks take the centralized approach. As the input states, the provided global game state data were decomposed into local 120 data points around each agent to be fed into corresponding decentralized actor networks. Four frames of data were stacked to be used in a single timestep. They prepared several knowledge-based strategies including circular defense, shoot, kick, and penalty avoidance where all strategies took the ball's expected position in the future into account. The actor networks selected appropriate action among them to be executed. The reward system consisted of team cooperation reward, where overall team's efforts such as keeping the ball away from their goalpost were taken into account, and individual reward, where each agent's efforts such as shooting attempt were taken into account.

On the other hand, the FGL Team approached the AI Soccer challenge with a pure rule-based algorithm. The FGL Team introduced a "coach" algorithm that observes the game state, plans actions, and provides high-level commands to each agent in their team. They roughly divided the field into four zones, the penalty areas, and the remaining parts of half fields for each team, and assigned different action sets for the agents. For example, when the ball is located in FGL Team's penalty area, the two defender agents try to push the ball out of the area, while the two attacker agents position themselves ahead of the ball at different distances and seek for a chance to counterattack when the defenders manage to push the ball forward. In low-level control of agents, the FGL Team used PID controllers to move an agent from one point to another point in a straight line, pure pursuit controllers to make turns, and bang–bang controllers when speed was of utmost importance such as goalkeeper defending against a penalty kick.

In the AI Commentator and the AI Reporter challenges, all participants approached the challenges with the traditional way of preparing a collection of predefined sentences and selecting the most adequate sentences to generate commentaries and the match summary. We have invited two professional journalists from newspaper and magazine companies and one academic researcher to evaluate the commentaries and reports. The most noticeable result was that all entries received near-zero scores on turing testability. The evaluators easily noticed the programs using identical sentences when facing similar events and not being able to generalize to the different set of possible events in the AI Soccer.

V. Discussion and Conclusion

This article presented the AI World Cup, a set of AI competitions based on the game of soccer, designed to provide challenges targeted for multiagent environments and natural language processing research fields. Three soccer-inspired challenges are presented, AI Soccer, AI Commentator, and AI Reporter. AI Soccer is a 5:5 robot soccer game targeted for the development of multiagent algorithms in dynamic and adversarial environments. AI Commentator and AI Reporter competitions focus on natural language processing regarding short-term real-time events and a long-term stream of events, respectively. We also introduced the AI World Cup platform, where both coordinate and image representations of the game states are provided at the same time so that the participants can investigate different approaches toward the competitions.

Through previously held events held in 2018 and 2019, we have investigated the feasibility of holding a robot soccer-based competition. As of 2019, we still have observed problems that may hinder the challenges in perspective from both the competition holder and the participants. From the competition holder's perspective, the main reoccurring issue was the exploitation strategies. Although we have already found various exploitation methods and prevented them by adding foul rules as described in Section III, new exploitation strategies emerged to trivialize the challenge beyond our expectations. The exploitation strategy that emerged in the most recent AI Soccer competition was using the kickoff time to directly shoot toward the opponent's goal by rerouting the forward to circumvent around the ball to attack instead of passing to an ally. We can prevent this exploitation strategy by limiting the goal's direction toward the ally's side in kickoff, but we expect that more exploitation strategies will emerge over time. As exploitation strategies are mostly unforeseen, we can only fix them in an *ad hoc* manner one after another.

The *ad hoc* management of the exploitation strategies results in the rule of the AI Soccer challenge changing over each year. With the rules changing constantly, outdated algorithms, especially learning-based ones, cannot be reused and must be adjusted. While outdating last year's algorithms work in a beneficial way from the competition holder's perspective as it prevents the same algorithm to rule over multiple years, this introduces another difficulty for researchers to participate in AI Soccer over sequential years. To cope with this, participants may be able to address transfer and continual learning methods such as the surgery method Berner *et al.* [60] has suggested for Dota 2 training.

In the case of AI Commentator and AI Reporter challenges, the main difficulty lies in the lack of an adequate dataset. As we could not provide a dataset, the participants had to build their algorithms with match data collected using only sample AI Soccer programs. As the provided sample AI Soccer program is a heuristic knowledge-based baseline, the dataset that the participants could make only consisted of relatively static matches without much variations. To promote research for the AI Commentator and the AI Reporter challenges, we, as the competition holder, need to either provide a rich dataset or providing more sample programs for the participants to collect data and test their algorithms. As of now, we encourage AI Soccer participants to open-source their projects, and we hope to use past open-source strategies to build a dataset for the AI Commentator and AI Reporter challenges. Although the AI Soccer programs submitted to past events would not work well in the new environment due to changes made in rules over time, AI Commentator and AI Reporter challenges may benefit from this as frequent rule violation events would enrich the dataset.

Previously held AI World Cup events provided valuable feedback on the impact the proposed challenges can have on the research community. In the AI Soccer challenge, we regard the developed platform as a comprehensive testbed for state-of-the-art control, prediction, path planning, and deep learning algorithms. As of now, the strong teams such as the winner of the 2019 AI Soccer challenge approached the challenge using a hybrid of a knowledge-based method and a learning-based method. To accelerate the development in overall quality of the submitted entries and help new researchers learn the promoted research fields faster, we, as the competition holder, held a poster session along with the competitions to share the knowledge among participants to work as a stimulus to each other.

Because the AI World Cup is a recently established event and targeted for researchers relatively new to the promoted fields, the strategies developed so far are rather primitive compared to existing competitions such as Simurosot and RoboCup simulation leagues. However, as the AI World Cup progresses and participants develop complex strategies, we expect the overall strategy levels in the AI Soccer challenge to become higher. This may introduce wide level gaps between participants in the future, which can discourage new researchers to participate in the competitions. As discouraging new researchers is against our motivations for holding competitions, we need to mitigate the issue in the future. For this, we plan to provide another environment with higher difficulties, such as using more agents or adding more actions available to agents. We would encourage more skilled participants to challenge themselves in the more complex version of the AI Soccer by providing a bigger prize to the challenging environment. Then, the current AI Soccer challenge can still work as a friendly environment for new researchers. For AI Commentator and AI Reporters, the varying participants level in AI Soccer would provide more variety of situation to deal with to keep the challenges not stagnant. We hope the AI World Cup platform and the upcoming AI World Cup competitions can continuously promote an influx of new researchers into the research fields of AI such as NLP and multiagent systems, eventually contributing to the improvements in the state-of-the-art algorithms.

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