RoboCupSimData: A RoboCup soccer research dataset

Olivia Michael[1], Oliver Obst[*1],
Falk Schmidsberger[2], Frieder Stolzenburg[2]

[1]: Western Sydney University, Centre for Research in Mathematics
[2]: Harz University of Applied Sciences, Automation and Computer Sciences Department
[*]: Corresponding author: `o.obst@westernsydney.edu.au`

Abstract

RoboCup is an international scientific robot competition in which teams of multiple robots compete against each other. Its different leagues provide many sources of robotics data, that can be used for further analysis and application of machine learning. This paper describes a large dataset from games of some of the top teams (from 2016 and 2017) in RoboCup Soccer Simulation League (2D), where teams of 11 robots (agents) compete against each other. Overall, we used 10 different teams to play each other, resulting in 45 unique pairings. For each pairing, we ran 25 matches (of 10 mins), leading to 1125 matches or more than 180 hours of game play. The generated CSV files are 17 GB of data (zipped), or 229 GB (unzipped). The dataset is unique in the sense that it contains both the ground truth data (global, complete, noise-free information of all objects on the field), as well as the noisy, local and incomplete percepts of each robot. These data are made available as CSV files, as well as in the original soccer simulator formats.

1 Introduction

RoboCup is an international scientific robot competition in which teams of multiple robots compete against each other. The RoboCup soccer leagues provide platforms for a number of challenges in robotics research, including locomotion, vision, real-time decision making, dealing with partial information, multi-robot coordination and teamwork. In RoboCup, several different leagues exist to emphasize specific research problems by using different kinds of robots and rules. There are different soccer leagues in the RoboCup with different types and sizes of hardware and software: small size, middle size, standard platform league, humanoid, 2D and 3D simulation (Kitano et al., 1997). In the soccer simulation leagues (Akiyama et al., 2015), the emphasis is on multi-robot team work with partial and noisy information, in real-time. Each of the robots is controlled by a separate program that receives sensor information from the simulator as an input, and, asynchronously to sensor input, also decides on a next action that is sent back to the simulator, several times a second. This complexity of the environment, with continuous state and action spaces, together with the opportunity to compete against each other, makes RoboCup soccer an interesting testbed for multi-robot learning among many other applications.

To assist automated learning of team behavior, we provide a large dataset generated using 10 of the top participants in RoboCup 2016 or 2017. While it is possible to use the simulator for robot learning, we also generate additional data that is not normally available from playing other teams directly: We modified the simulator to record data from each robots local perspective, that is, with the restricted views that depend on each robots situation and actions, and also include the sensor noise. In addition, for every step of the game (100 ms), we recorded ground truth information (such as positions and velocities) of

all objects on the soccer field, as well as basic actions of each robot. This ground truth information is usually recorded in a logfile, but not available to teams during a match.

To create our dataset, we ran all pairings of the selected teams with 25 repetitions of each game, that is, 1125 games in total. With 11 robots in each team, a single game dataset consists of 22 local views plus a global (ground-truth) view. These views are made available as CSV files (comma-separated values). We also provide the original logfiles that include additional sensors, actions of each robot recorded as text files, and the software we created to patch the simulator and to convert recordings into CSV.

The provided data are useful for various different tasks including imitation learning (e.g., Ben Amor et al., 2013), learning or testing of self-localization (e.g., Olson, 2000), predictive modeling of behavior, transfer learning and reinforcement learning (e.g., Taylor and Stone, 2009), and representation learning for time series data (Michael et al., 2018). The next sections describe the environment, robots, and data in more detail.

2 Description of the environment

The RoboCup Soccer Simulation Server `rcssserver` (Noda et al., 1998) is the software used for the annual RoboCup competitions that have been held since 1997. It is hosted at `github.com/rcsoccersim/`. We used the rcssserver version 15.3.0 to create the data for this paper. The simulator implements the (2D) physics and rules of the game, and also handles the interface to the programs controlling each player. By default, players use a 90 degree field of view, and receive visual information every 150 ms. Throughout the game, this frequency can actively be changed by each player individually to 75 ms, 150 ms, or 300 ms, by changing the field of view to 45 degrees, 90 degrees, or 180 degrees, respectively. Visual information is transmitted in the form of (Lisp-like) lists of identified objects, with the level of detail of information depending on object distances. Potential objects include all other players on the field, the ball, and landmarks like goal posts, flags, and side lines. Each player also

receives additional status information, including energy levels, referee decisions, and the state of the game, every 100 ms. Each robot can issue parameterized actions every 100 ms, to control its locomotion, the direction of its view, and its field of view. A more detailed description of the information transmitted can be found in the simulator manual (Chen et al., 2003).

3 Overview on the provided data

In robotics, data collections often comprise lidar data recorded by laser scans. This is very useful in many applications, e.g., field robotics, simultaneous localization and mapping (SLAM) (Tong et al., 2013), or specific purposes such as agriculture (Chebrolu et al., 2017). However, in many contexts, there is not only one but several robots which may be observed. The data from RoboCup that we consider here includes information about other robots in the environment and hence about the whole multi-robot system.

Data from multi-agent systems like the RoboCup or the multi-player real-time strategy video game StarCraft (Lin et al., 2017) provide information on (simulated) environments as in robotics. However, in addition, they contain data on other agents and thus lay the basis for machine learning research to analyze and predict agent behavior and strategies, which is important in applications such as service robotics and multi-robot systems in general. To provide a diverse dataset, we include several teams from the last two RoboCup competitions, allowing for different behaviors and strategies.

Perception and behavior of each robot during a game depends on the behavior of all other robots on the field. Game logfiles, that is, files containing ground truth information obtained from recording games, can be produced from the simulator, and are recorded in a binary format. Access to individual player percepts, however, is only possible from within the player code. To learn from behavior of other teams, it is useful to use the exact information that individual players receive, rather than the global (and noise-free) information in recorded logfiles. We therefore modified the simulator to additionally also record all local and noisy information as received by the robots on the field, in individual files for

2016	2017
CSU_Yunlu	CYRUS
Gliders	Fra-UNIted
HELIOS	HELIOS
Ri-one	HfutEngine
	MT
	Oxsy

Figure 1: Teams from the RoboCup 2D soccer simulation world championships 2016 in Leipzig (Germany) and 2017 in Nagoya (Japan) selected for the dataset.

each player. This information is stored in the same format as it is sent to players. We also provide code to translate these individual logs into CSV files that contain relative positions and velocities.

We chose the top-ten teams from the RoboCup 2D soccer simulation world championships 2016 in Leipzig (Germany) and 2017 in Nagoya (Japan) (see Figure 1). Team binaries including further descriptions can be downloaded from: `archive.robocup.info/Soccer/Simulation/2D`. We played each team against each other team for 25 times, resulting in about 17 GB of data (zipped CSV files). For each game, we record the original logfiles including message logs. We also generate files with ground truth data as well as local player data in human-readable format. Finally, we made our generating scripts available, so that they can be used to reproduce our results or to produce additional datasets using other robotic soccer teams. There is also a smaller subset of 10 games where the top-five teams play against each other once (163 MB CSV files plus 217 MB original logfiles). Our data is available at `bitbucket.org/oliverobst/robocupsimdata/`.

4 Description of the ground truth data

According to rules of the world soccer association FIFA, a soccer pitch has the size of $105\,\mathrm{m} \times 68\,\mathrm{m}$. This is adopted for the RoboCup soccer simulation league. Nevertheless, the physical boundary of the area that may be sensed by the robots has an overall size of $120\,\mathrm{m} \times 80\,\mathrm{m}$. For the localiza-

tion of the robot players, the pitch is filled with several landmark objects as depicted in Fig. 2: flags (f), which are punctual objects, lines (l), the goal (g), and the penalty area (p). The origin of the coordinate system is the center point (c). The pitch is divided horizontally (x-direction) into a left (l) and right (r) half and vertically (y-direction) into a top (t) and a bottom (b) half. Additional numbers (10, 20, 30, 40, or 50) indicate the distance to the origin in meters. Since every soccer game takes place on the same pitch, there is only one file with infomation about the landmarks for all games that lists all these coordinates, given as a table in CSV format, with name `landmarks.csv`. For example, the row `f r t,52.5,34` says that the right top flag of the pitch has the (x, y)-coordinates $(52.5, 34)$.

Further table files provide information about the respective game. The names of all these files – all naming conventions are summarized in Fig. 3 – contain the names of the competing teams, the final scores for each team, possibly extended by the result of a penalty shootout, a time stamp (when the game was recorded), and some further identifier.

The central SoccerServer (Chen et al., 2003) controls every virtual game with built-in physics rules. When a game starts, the server may be configured by several parameters which are collected in one file with the identifier `parameters`. For example, the row `ball_decay,0.94` denotes that the ball speed decreases by the specified factor (cf. Stolzenburg et al., 2002). However, from a robotics point of view, most of the information in this file is not very relevant, like the stamina of the robots, the noise model, or the format of the coach instructions. We thus skip further details here.

A soccer simulation game in the RoboCup 2D simulation league lasts 10 mins in total, divided into 6000 cycles where the length of each cycle is 100 ms. Logfiles comprise information about the game, in particular about the current positions of all players and the ball including their velocity and orientation for each cycle. This information is collected for the whole game in a table with the identifier `groundtruth`. For each time point, the play mode (e.g. kickoff), the current ball position coordinates and its velocity is listed. Furthermore, the positions and velocities

Figure 2 — Flags and lines in the robotic soccer simulation (labels):

(flag t l 50) (flag t l 30) (flag t l 10) (flag t 0) (flag t r 10) (flag t r 30) (flag t r 50)
(flag t l 40) (flag t l 20) (flag t r 20) (flag t r 40)
(flag l t) (line t) (flag c t) (flag r t)
(flag l t 30) (flag r t 30)
(line l) (line r)
(flag l t 20) (flag p l t) (flag p r t) (flag r t 20)
(flag l t 10) (flag r t 10)
(flag g l t) (flag g r t)
(flag l 0) (goal l) (flag p l c) (flag c) (flag p r c) (goal r) (flag r 0)
(flag g l b) (flag g r b)
(flag l b 10) (flag r b 10)
(flag l b 20) (flag p l b) (flag p r b) (flag r b 20)
(flag l b 30) (line b) (flag c b) (flag r b) (flag r b 30)
(flag l b) (flag r b)
(flag b l 40) (flag b l 20) (flag b r 20) (flag b r 40)
(flag b l 50) (flag b l 30) (flag b l 10) (flag b 0) (flag b r 10) (flag b r 30) (flag b r 50)
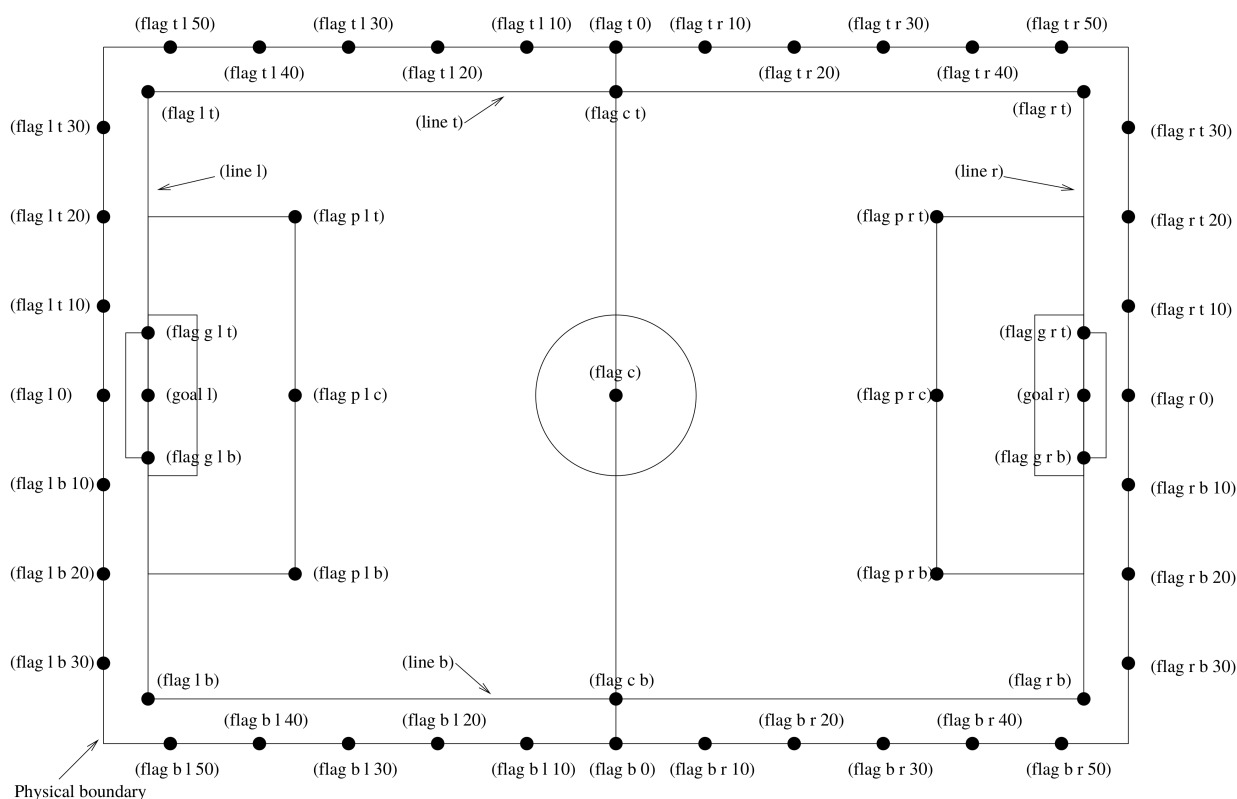Physical boundary

Figure 2: Flags and lines in the robotic soccer simulation (cf. Chen et al., 2003).

1. landmarks: `landmarks.csv` (static information for all games, 1 file)

2. game data: `<time>-<team left>_<score left>-vs-<team right>_<score right>-<id>.csv`
   where `<id>` =
     - `parameters` (server configuration parameters, 1 file)
     - `groundtruth` (logfile information for each game, 1 file)
     - `<team name>_<player number>-<suffix>`
       where `<suffix>` =
         - `landmarks` (relative distances and angles to landmarks, 22 files)
         - `moving` (relative distances and angles to ball and other players, 22 files)

Figure 3: Name conventions for the data files.

of each player of the left (L) and the right (R) team including the goalkeeper (G) is stated. For example, the column with head `LG1 vx` contains the velocity of the left goalkeeper in x-direction. Finally, information about the robots body and head orientation and their view angle and quality is included. The absolute direction a player is facing (with respect to the pitch coordinate system) is the sum of the body and head direction of that player.

5 Description of local player data

The visual sensor of the players reports the objects currently seen. The information is automatically sent to players every sense step with a frequency depending on the player view width and quality; by default it is set to 150 ms. Thus, in addition to the three files mentioned above, 44 more files are available for each game. For each of the altogether 22 robots (ten field players and one goalkeeper per team), two files with local player data is provided, hosting information about where the respective player sees the landmarks and moving objects, respectively.

The file with final identifier `landmarks` provides the distances (in meters) and angles (in degrees) to the respective landmarks relative to the robot head orientation for each step. Analogously, the file with final identifier `moving` provides the actual relative distances and angles to the ball and all other players. Sometimes the player number or even the team name is not visible and hence unknown (u) to the robot. In this case, the respective piece of information is left out. If data is not available at all, then this is marked by `NAN` in the respective table element. The server also provides information about the velocity, stamina, (yellow and red) cards, and the commands (e.g. dash, turn, or kick) of the robots. In some cases there is also information about the observed state of other robots available, in particular, whether they are kicking (k), tackling (t), or are a goalkeeper (g).

6 Code

The soccer simulator communicates with players using text messages in form of lists, via UDP.

As described above, the frequency of these messages is dependent on the width of view that the player selects, one message every 150 ms by default. Every 100 ms, players also receive status information, so-called body messages. These individual messages are not recorded in the simulator logfiles. Developers of teams can implement recording of messages that their own agents receive, but in order to record messages sent to any team, the simulator software had to be modified instead. Our code contains patches to the simulator that allow recording of visual and body messages in individual files for each player. The messages are stored in their original format to keep the amount of additional processing during the game minimal. Playing a game with the modified simulator will result in a number of recorded files:

- the visual and body messages (two files for each player). The file names follow the same naming convention as the game data CSV files (cf. Fig. 3), but use the `.rcv` suffix for visual messages and `.rcb` for body messages.

- a recording of the game (the ground truth in a binary format), using the suffix `.rcg`

- the commands from players as received by the simulator (in plain text), using `.rcl` as a suffix

To convert visual messages into CSV files, we provide a `see2csv.py` Python program that translates player visual messages into two files: a CSV file for moving objects (other players and the ball), and a CSV file with perceived landmarks.

To convert the simulator logfile (ground truth) into a CSV file, we provide `rcg2csv`, a C++ program that is built using the open source `librcsc` library (see `osdn.net/projects/rctools/releases/p3777`). Logfiles are recorded at regular intervals of 100 ms. `rcg2csv` can optionally also store all simulation parameters in an additional CSV file.

7 Conclusions

We released a large and unique dataset (RoboCupSimData), creating using a tourna-

ment of top RoboCup simulation league teams. Creating this dataset required modification of the simulation software. We ran 25 repetitions of 45 matches that last 10 mins, each. The dataset will allow a number of problems to be investigated, from learning and testing approaches to self-localization, predictive world-models, reinforcement learning. In this respect, the dataset shall be useful for the whole robotics community.

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