Pass in Human Style: Learning Soccer Game Patterns from Spatiotemporal Data

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***Abstract*—Passing patterns in soccer are one of the key characteristics of tactical team behavior. Thus, in the course of development of believable AI soccer teams, it is necessary to ensure that human-like passes are properly simulated. We propose learning passing behavior from real-life soccer teams and share experimental results, indicating that our approach indeed allows to obtain passing patterns similar to the ones present in human tracking data. We also show that a typical rule-based soccer AI team exhibits notable differences in passing behavior in comparison with real teams.**

Keywords—soccer, player tracking, passing, human-like AI.

I. Introduction

Efficient game AI systems, able to beat human players, are already developed for many genres of computer games, including multi-agent team environments [1]. However, skill is not the only essential requirement for a game AI: its primary purpose is to facilitate immersion and contribute to user engagement. Studies show that people generally prefer playing with other people rather than with bots [2], and perceive human-like NPCs as more enjoyable; thus, the goal of creating believable, human-like AI agents is important for practical game development [3, 4].

The importance of AI believability is especially high in computer simulations of real-life games, such as sports video games. People playing computer soccer or basketball expect to see a faithful rendition of their favorite sports, including realistic representation of athletes' behavior. This task can be approached by learning behavior patterns from actual human tracking data, as demonstrated in several recent works [5, 6].

Our ultimate goal is to create human-like teams for the video game of soccer by learning from tracking data obtained from real-life soccer teams. Since this is a complex task involving numerous different objectives, we are trying to address some of them independently. Our experimental setup is based on a SimpleSoccer simulator with a built-in AI engine, developed by Mat Buckland [7]. The present paper reports our preliminary results on modeling human-like ball passing behavior.

Passes is one of the key elements of a team strategy in soccer. Distinctive passing patterns can be observed even on the level of individual teams [8, 9], so, presumably, they are connected to certain human-like behavioral traits, recognizable by the players. Furthermore, passes are abundant in any soccer match (unlike shots on goal, for example), and are easy to classify and compare.

II. Previous Work and Methods

One of the principal presumptions in our project is the availability of limited datasets of player tracking data. With the growing adoption of tracking systems, we can expect a higher availability of such data in general. However, a typical professional soccer team plays only several dozens of matches per season, so if we plan to learn team-specific behavior patterns, we will have to rely on small data samples, especially for processing relatively rare game events (such as shots on goal or throw-ins). For learning passing behavior, we can expect a professional team to make 365-370 passes per game on average [10].

Taking into account these considerations, we decided to conduct preliminary experiments with the methods used in our previous projects [11, 12]. They rely on a combination of case-based reasoning decision making with Markov chain-like database of human actions. In brief, agent knowledge is represented as a graph, having individual game situations as vertices, and actions as weighted edges. This way, it represents the fact that the situation A turns into the situation B as a result of a certain action during the learning phase. Decision making algorithm tries to find the best match for the current game situation and acts accordingly.

For learning passing behavior, each game situation is represented as a set of the following attributes:

- The coordinates of the player with the ball (the passer) in the 18×10 grid.
- The "danger to move forward" heuristic estimation on the scale of 0 to 5 (depends on the distance to the nearest opponent in the forward direction).
- The current movement direction of the passer (8 directions are supported).
- The direction (0-7) of the closest opponent (from the passer's perspective).
- The distance to the closest opponent (from the passer's perspective), on the scale from 0 to 2.
- The "safest pass danger" heuristic estimation on the scale of 0 to 5 (depends on locations of both teammates and opponents).
- The "safest forward pass danger" heuristic estimation on the scale of 0 to 5.
- The Boolean attribute indicating that at least one safe pass (with danger estimation of 0-2) is found.

Each action we learn is a pass action, characterized by the coordinates of both sending and receiving players.

During decision making, the system tries to find a perfect match for these attributes, and if it is found, makes a pass. If no actions are found or they are not applicable in the given context (the actual onscreen coordinates of senders and receivers are significantly different from the values in the data structure), the system fallbacks to the built-in AI agent, responsible for player movements and shots on goal.

We use STATS.com “Soccer Dataset” [13] as the training set for the learning algorithm. It consists of 7500 game sequences, represented as series of game situation snapshots, taken at the rate of 10 snapshots per second. Each snapshot (frame) contains the coordinates of all 22 players and the ball. The sequences are taken from actual European league matches, and represent around 36 hours of playing time. Since there is no event markup in this data, we use a simple rule-based algorithm to detect passes using closeness of the ball to individual players as a criterion of ball possession.

III. Experiments and Results

To evaluate the performance of a new passing algorithm, we compared the characteristics of passes made by the new algorithm, the old (default) algorithm, and by the real-life teams. We simulated a number of AI vs. AI matches using old and new algorithms until 500 passes are made in each case, and extracted 500 random passes from the STATS.com dataset. The passes were classified according to their length and direction (see Table 1 and Table 2).

TABLE I. Pass Length Distribution

Team	Pass length, m (%)				
	0-10	**10-20**	**20-30**	**30-40**	**40+**
Default AI	0.00	11.74	52.84	27.84	7.58
New AI	17.44	47.29	20.74	7.36	7.17
Real Teams	28.40	49.63	16.89	3.71	1.37

TABLE II. Pass Direction Distribution

Team	Pass direction (%)							
	FW	**FR**	**R**	**BR**	**B**	**BL**	**L**	**FL**
Default AI	8	11	21	11	8	9	17	14
New AI	16	14	17	10	4	7	16	16
Real Teams	10	14	16	12	9	12	15	12

To compare passing patterns, we represented pass length and pass direction values for different teams as vectors and calculated their cosine similarity ratios (see Table 3).

TABLE III. Similarity of Passing Patterns

	Distance Similarity / Direction Similarity (%)		
	Default AI	**New AI**	**Real Teams**
Default AI		95.64	97.89
New AI	56.15		95.87
Real Teams	43.35	97.45	

The obtained results show that the original AI system does not exhibit human-like passing patterns in terms of distance. However, the distribution of pass directions is close to the distribution found in real data. Our system, based on learning by observation, shows human-like passing behavior according to these criteria.

IV. Discussion and Conclusion

Soccer is a complex multi-agent game, challenging for AI technologies. The diversity and sophistication of technologies used in modern RoboCup AI teams shows how difficult it is to design a skillful AI system for soccer [14]. However, with the advancements in practical AI development, the importance of other factors such as believability of AI-controlled teammates and opponents will grow. These factors contribute to the overall enjoyability of the computer game, and the main purpose of a game is to entertain the players.

We analyzed the passing behavior of human teams and compared it with a rule-based AI system according to two features: pass length and pass duration. Our tests show that real teams significantly differ in their passing patterns from the AI. We also created a learning by observation-based system, able to acquire passing behavior from actual human tracking data, and demonstrated that it exhibits more human-like passing patterns.

It is interesting to note that according to the passing direction criterion, both AI systems are reasonably human-like. It is possible that the distribution of passing directions in real matches indeed reflects certain general logic of the game of soccer, and depends on individual team tactics to a lesser degree. It is also possible that our direction/distance classification does not adequately reflect the complexity of passes in real soccer, and passes have to be categorized according to other criteria as well, such as danger estimation or pass quality evaluation, as proposed in [15].

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