Construction of Football Agents by Inverse Reinforcement Learning Using Relative Positional Information Among Players

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Abstract: Recent advancements in reinforcement learning have made it possible to develop football agents that autonomously emulate the behavior of human players. However, it is still challenging for existing methods to successfully replicate realistic player behaviors. In fact, agents exhibit behaviors like clustering around the ball or shooting prematurely. One cause of this problem lies in reward functions that always assign large rewards to certain actions, such as scoring a goal, regardless of the situation, which bias agents towards high-reward actions. In this study, we incorporate the relative positional reward and the positional weight for shooting into the reward function used for reinforcement learning. The relative positional reward, derived from the positions of players, the ball, and the goal, is estimated using inverse reinforcement learning on a dataset of real football games. The positional weight for shooting is similarly based on actual shooting positions observed in these games. Through experiments on a dataset derived from real football games, we demonstrate that the relative positional reward helps align the agents' behaviors more closely with those of human players.

1 INTRODUCTION

With advancements in reinforcement learning techniques, the development of sophisticated autonomous agents for tasks such as self-driving and robotic control is rapidly progressing (Prudencio et al., 2024). These autonomous agents are being applied across a wide range of domains. In the field of sports, particularly football, numerous studies have focused on developing football agents within simulation environments (Kitano et al., 1997; Kurach et al., 2020) using reinforcement learning to explore and analyze the behavior of football players (Scott et al., 2021; Lin et al., 2023; Fujii et al., 2023; Song et al., 2023a). Developing football agents that closely mimic real players can offer systematic, simulation-based methods for addressing various tasks in this domain, including exploring diverse strategies and assessing the performance of actual football players (Scott et al., 2021; Song et al., 2023b).

Zhu et al. (Zhu et al., 2020) addressed the task of controlling a single player in an 11 vs. 11 scenario. In their study, they employed Long Short-Term Memory (LSTM) (Hochreiter and Schmidhuber, 1997) and Proximal Policy Optimization (PPO) (Schulman et al., 2017) to develop a football agent named WeKick. Lin et al. (Lin et al., 2023) proposed a distributed multi-agent reinforcement learning system leveraging Multi-Agent Proximal Policy Optimization (MAPPO) (Yu et al., 2022) to control 10 players, excluding the goalkeeper, in an 11 vs. 11 scenario. They adopted a learning framework designed to train agents in environments with sparse rewards. This framework includes curriculum self-play learning, where the scenario's difficulty is gradually increased for bots with low difficulty, and challenge self-play learning, where the agent competes against a past version of itself that has been previously trained. However, the football agents developed using existing methods often struggle to replicate the movements of real players, exhibiting behaviors such as excessively crowding around the ball or shooting prematurely. To address the domain gap between the actions of reinforcement learning-based football agents and those of real football players, Fujii et al. (Fujii et al., 2023) proposed a method that combines supervised learning and reinforcement learning using a football dataset derived from actual games. However, the resulting agents learned only to pass the ball and shoot, with-

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out moving toward the goal. One possible reason for this unnatural behavior is the reward function used in existing methods, which consistently assigns large rewards to certain actions, such as scoring a goal, regardless of the context. This approach encourages agents to favor specific actions with high reward values. However, it overlooks situational factors on the pitch, such as the relative positions of players or the number of nearby defenders, which are critical considerations for decision-making in football.

In this study, we introduce a novel reward, termed the relative positional reward, into the reward function used in reinforcement learning. The relative positional reward is derived from state features, such as the relative distances between players, with weights estimated from actual football games using inverse reinforcement learning. This approach aims to enable the resulting agents to exhibit behaviors that more closely resemble those of human players. Furthermore, we introduce a positional weight into the reward for shooting. This weight is based on the distribution of shooting positions observed in actual matches, assigning larger values to areas where real players are more likely to take shots. This weight helps suppress unnatural shooting from unrealistic positions. In the experimental evaluation, we demonstrate the effectiveness of the proposed method in training agents to exhibit behaviors that closely resemble those of real players. Specifically, we analyze the distance between the positional distributions of football agents trained on actual football datasets and those of real players, as well as the distance between their action distributions.

2 RELATED WORK

Reinforcement learning is a framework of machine learning where an agent learns to perform specific tasks through interactions with its environment. In this process, the agent observes the current state of the environment and determines its actions accordingly. The actions the agent takes cause a transition in the state, and based on the new state, the agent receives a reward from the environment. By repeating this process, the agent learns a policy, i.e., a strategy for action, that maximizes the cumulative reward. Q-learning (Watkins and Dayan, 1992) is a fundamental reinforcement learning method that learns a policy based on the Q-value, which represents the value of taking action a in state s. It repeatedly updates the action-value function $Q(s,a)$, which predicts the Q-value. In contrast, Deep Q Network (DQN) (Watkins and Dayan, 1992) is a deep reinforcement learning algorithm that uses a neural network to approximate the action-value function in Q-learning. The neural network that approximates this action-value function is referred to as the Q Network. In DQN, the same action-value function is used for both selecting actions and evaluating them, which introduces noise into the estimation process and often results in overestimated action-values. To address this, Hasselt et al. (Van Hasselt et al., 2016) proposed Double Deep Q-Network (DDQN), which separates the action-value function used for action selection from the one used for evaluation, effectively reducing noise and mitigating overestimation.

In the domain of building football agents, Zhu et al. (Zhu et al., 2020) tackle the task of controlling a single player at all times in an 11 vs. 11 scenario within the Google Research Football (GRF) environment, which is a 3D football simulation environment designed for reinforcement learning. In the GRF environment, agents learn to dribble, shoot, and pass through interactions, ultimately mastering the skills necessary to score goals. They developed a football agent called WeKick, using Long Short-Term Memory (LSTM) and Proximal Policy Optimization (PPO), which is one of actor-critic reinforcement learning methods. Wang et al. (Wang et al., 2022) addressed the challenge of sparse rewards in a 5 vs. 5 multi-agent scenario by proposing a method where agents learn two distinct policies: one driven by individual rewards for actions such as shooting and passing, and another based on team rewards for achieving goals. Their approach incorporates the similarity of action selection probabilities between the two policies into the loss function. Li et al. (Li et al., 2021) proposed a loss function that maximizes the mutual information between the trajectories of agents in a 3 vs. 1 scenario to promote diversity in agent behavior. This approach encourages agents to explore extensively and select diverse actions. As a result, during offensive plays, off-ball agents began choosing actions that effectively draw defenders away.

On the other hand, in a multi-agent environment scenario controlling 10 players (excluding the goalkeeper) in an 11 vs. 11 game, Lin et al. (Lin et al., 2023) proposed a distributed multi-agent reinforcement learning system using Multi-Agent Proximal Policy Optimization (MAPPO) (Yu et al., 2022). To train agents in environments with sparse rewards, they introduced a learning framework incorporating two strategies: curriculum self-play and challenge self-play. Curriculum self-play gradually increases the scenario difficulty against lower-skilled bots, whereas challenge self-play involves agents competing against earlier trained versions of themselves. In evaluation experiments, their football agents demonstrated superior performance compared to existing agents in both win rate and goal differential. Similarly, Song et al. (Song et al., 2023a) developed a highly capable football agent through self-play learning. While these football agents are designed to achieve a high win rate against rule-based bots or reinforcement learning agents, they still face challenges in closely replicating the movements of real players.

Unlike these studies, some research focuses on building agents with more realistic movements by utilizing trajectory data derived from real players. Huang et al. (Huang et al., 2021) proposed an offline reinforcement learning approach, leveraging pre-training demonstration data from the behavioral data of the WeKick football agent, which includes states, actions, and rewards. In this framework, actions with higher rewards in the demonstration data are assigned greater weight to ensure they are prioritized during training. As a result, their method achieved the highest win rate compared to existing football agents in an 11 vs. 11 scenario. Additionally, they demonstrated that their approach improves the learning speed of multi-agent reinforcement learning.

Fujii et al. (Fujii et al., 2023) proposed a learning method combining a pre-trained action classifier and reinforcement learning to bridge the domain gap between football agents and real players. The classifier, trained on a football dataset derived from real matches, predicts player actions for given states. Using DDQN, they trained the agent by sampling actions in the reinforcement learning environment with the pre-trained model and integrating these samples with demonstration data stored in a buffer. As a result, their football agents achieved higher accuracy compared to existing ones in terms of reward acquisition and trajectory similarity to demonstration data, measured using the DTW distance (Vintsyuk, 1968). However, the agents failed to exhibit realistic behavior, as they learned only to pass and shoot the ball without moving toward the goal. This unnatural behavior can be attributed to the fixed nature of the reward function, where rewards for events like goals and shots are always the same regardless of the situation. Such a rigid reward structure tends to bias the agent toward specific high-reward actions, while neglecting contextual factors essential for decision-making in football, such as player positioning and the number of surrounding defenders.

3 PROPOSED METHOD

3.1 Overview

This study aims to develop football agents that exhibit behaviors closer to those of real football players. To this end, we introduce a novel reward, referred to as the Relative Positional Reward, into the reward function of a reinforcement learning framework. This reward is calculated based on the values of state features and adjusts the basic reward for an agent's actions by either enhancing or discounting it, depending on the positional relationships between the target agent and other entities, such as other agents, the ball, and the goal. In the proposed method, inverse reinforcement learning is applied to demonstration data obtained from real football matches to estimate the weights for the state features used in calculating the Relative Positional Reward. In ordinary reinforcement learning, the goal is to learn a policy that selects appropriate actions in each state based on rewards provided by the environment. In contrast, inverse reinforcement learning optimizes a reward function to enable learning the correct policy by using the actions of experts as a reference. The overview of the proposed method is illustrated in Figure 1.

As illustrated in Figure 1, the proposed method comprises three steps: preprocessing, inverse reinforcement learning, and reinforcement learning. In the preprocessing step, the demonstration data is constructed using tracking data from real football matches. Specifically, we derive sequences of consecutive actions from the real tracking data. The state at each time-step in a sequence is described with state features. We adopt two types of state features: global state features and relative state features. The global state features represent the overall environment, such as the positional coordinates of all players. In contrast, the relative state features, which are based on each player, describe the relative relationships from the perspective of that player, such as the distances between the target player and other players. For the relative state features, we further calculate their expectations for player k, $\boldsymbol{\mu}_{E,k}$. In the inverse reinforcement learning step, the weights of the relative state features, $\boldsymbol{w}_k$, used to compute the Relative Positional Reward R_k^* are optimized to minimize the difference between the expected values of the relative state features for a real player (expert) k, $\boldsymbol{\mu}_{E,k}$, and those of its corresponding agent under policy π_k, $\bar{\boldsymbol{\mu}}_{E,k}(\pi_k)$. In the final reinforcement learning step, each football agent k is trained to behave similarly to a real football player by learning the policy π'_k. This training uses a total reward function composed of the sum of the Relative

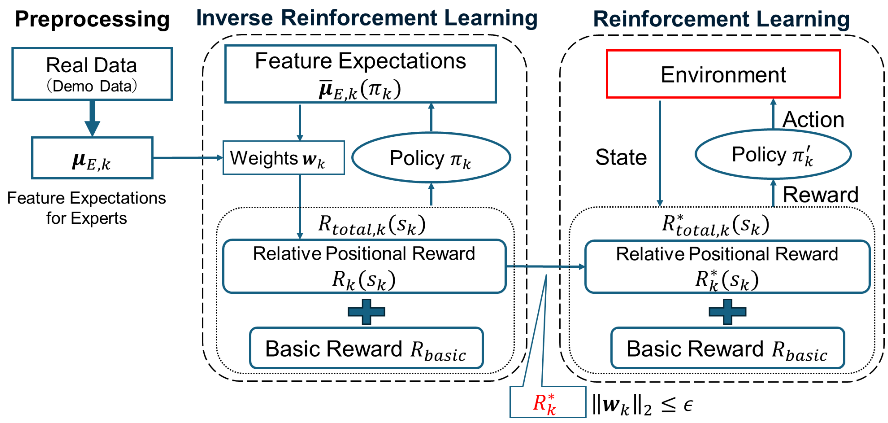


Figure 1: Overview of the proposed method for developing an agent that corresponds to expert player k, wherer s_k represents a state associated with player k.

Table 1: Relative state features with respect to agent a.

Type	State Features (notation)
Distance	distance to the n-th closest offensive player ($D_n^{\text{off}}(a)$), distance to the n-th closest defensive player ($D_n^{\text{def}}(a)$), distance to a keeper ($D_{\text{keeper}}(a)$), distance to the ball, distance to the goal ($D_{\text{goal}}(a)$)
Proportion of players in a specific area	proportion of offensive players within a radius r ($P_r^{\text{off}}(a)$), proportion of defensive players within a radius r ($P_r^{\text{def}}(a)$). proportion of offensive players up to the goal line ($P_{\text{goal\_line}}^{\text{off}}(a)$), proportion of defensive players up to the goal line ($P_{\text{goal\_line}}^{\text{def}}(a)$), proportion of offensive players up to the goal ($P_{\text{goal}}^{\text{off}}(a)$), proportion of defensive players up to the goal ($P_{\text{goal}}^{\text{def}}(a)$), proportion of offensive players unobstructed by defenders on a direct line from the agent a ($P^{\text{off}}(a)$), proportion of defenders on the direct line to the ball ($P_{\text{ball}}^{\text{def}}(a)$)
Angle	angle to the goal ($A(a)$)

Positional Reward R_k^* and a basic reward R_{basic}, which is a discrete reward for specific events commonly employed in existing research.

3.2 Status Features

As mentioned above, each state comprising an action sequence is described using relative state features, alongside the global state features commonly employed in the literature. The positional coordinates of players and the ball are typical examples of global state features. In contrast, relative state features are based on a specific player or agent. For example, these features include the distances between the player/agent and other players/agents. Table 1 provides the complete list of relative state features used in this study.

Among these features, the distance between players is modeled by considering the distribution of relative distances observed in real game play. Specifically, instead of the actual distance between players x_n^α, the value of the following Gaussian function $f(x_n^\alpha)$ is used as one of the relative state features:

$$f(x_n^\alpha) = e^{-(3x_n^\alpha - d_n^\alpha)^2}, \tag{1}$$

where α is an index that indicates whether the distance refers to that to an offensive player, a defensive player, or the goalkeeper. Accordingly, the value x_n^α represents the distance from the observed player or agent to the n-th closest agent of type α. Meanwhile, d_n^α denotes the average distance to the n-th closest player, derived from real data. The value of $f(x_n^\alpha)$ increases as x_n^α gets closer to d_n^α.

3.3 Preprocessing Real Tracking Data

In the preprocessing step, action sequences are extracted from real tracking data (demonstration data), and the state at each time step is represented using the previously described state features. The global state features are defined for each state, while the relative state features are specified for each player within a state. We further calculate the expected values of relative status features for a player k, $\boldsymbol{\mu}_{E,k}$, which are used as the expert's values in inverse reinforcement learning. $\boldsymbol{\mu}_{E,k}$ is a vector defined as follows:

$$\boldsymbol{\mu}_{E,k} = \frac{1}{m}\sum_{i=1}^{m}\sum_{t=0}^{\infty}\gamma^t \phi(s_{t,k}^{(i)}), \quad (2)$$

where $s_{t,k}^{(i)}$ is the i-th state transition sequence of length m for player k in the demonstration data, and $\phi(\cdot)$ is a function that transforms the state s_t into a vector representing the values of the relative state features. Namely, $\phi(s_{t,k}^{(i)})$ represents the relative state features for the state $s_{t,k}^{(i)}$.

3.4 Reward Function

The reward function in the proposed method consists of the basic reward function, which is commonly used in existing research, and the Relative Positional Reward newly introduced in this study. The basic reward R_{basic} is defined as follows:

$$\begin{aligned} R_{basic} = w_{shot} * R_{shot} + R_{goal} + R_{conceded} + R_{gain} \\ + R_{lost} + R_{receive} + R_{block} + R_{offside} \end{aligned} \quad (3)$$

where R_{shot}, R_{goal}, $R_{conceded}$, R_{gain}, R_{lost}, $R_{receive}$, R_{block}, and $R_{offside}$ are the reward values given for shooting, scoring a goal, conceding a goal, winning the ball, losing the ball, receiving a pass, blocking, and being offside, respectively. The shot reward R_{shot} is a reward directly assigned to a shooting action. This encourages the agent to recognize shooting as the most effective action for scoring a goal, which carries a high reward value. To mitigate this bias toward shooting, we divided the football half-court into a grid and applied the position-specific shot rate w_{shot}, derived from actual data, as a weight for the shot reward. This method is expected to discourage the agent from learning behaviors that involve taking forced shots from positions far from the goal. The basic reward is assigned exclusively to the relevant player, whereas the offside reward is distributed to the entire team. Additionally, the basic reward is utilized in both the inverse reinforcement learning and reinforcement learning processes. On the other hand, the relative positional reward $R_k(s_k)$ of the agent k is defined as follows:

$$R_k(s_k) = \boldsymbol{w}_k \cdot \phi(s_k), \quad (4)$$

where $\boldsymbol{w}_k$ is a weight vector associated with the state s_k, which is represented by the relative state features.

3.5 Learning Relative Positional Reward with Inverse Reinforcement Learning

In inverse reinforcement learning, the weight vector $\boldsymbol{w}_k$ is optimized. Specifically, the relative positional reward $R_k(s_k)$ is estimated together with the basic reward R_{basic}, considering the total reward function $R_{total,k}(s_k)$ in the reinforcement learning performed within the inverse reinforcement learning step. $R_{total,k}(s_k)$ is defined as follows:

$$R_{total,k}(s_k) = R_{basic} + R_k(s_k) \quad (5)$$

When the expert's feature expectation value $\boldsymbol{\mu}_{E,k}$ is given, the weights $\boldsymbol{w}_k$ are determined in such a way as to minimize the error between the expert's feature expectation value $\bar{\boldsymbol{\mu}}_{E,k}(\pi_k)$ and the expert's feature expectation value $\boldsymbol{\mu}_{E,k}$ under the policy π_k, which obeys the reward function $R_{total,k}(s_k)$. Here, the observed feature expectation value, $\bar{\boldsymbol{\mu}}_{E,k}(\pi_k)$, is defined as in Equation (6).

$$\bar{\boldsymbol{\mu}}_{E,k}(\pi_k) = \mathbb{E}[\sum_{t=0}^{\infty}\gamma^t \phi(s_k)|\pi_k], \quad (6)$$

where γ is the discount factor in reinforcement learning. In this study, we use the Projection-based Method (PM), an inverse reinforcement learning method proposed by Abbeel and Ng (Abbeel and Ng, 2004), to estimate the weight $\boldsymbol{w}_k$.

3.6 Learning Behaviors with Reinforcement Learning

During reinforcement learning, the policy π_k' is learned using the estimated relative positional reward $R_k^*(s_k)$ and the basic reward R_{basic} defined by Equation (3) as the reward function for the football agent. The reward function $R_{total,k}^*(s_k)$ used in reinforcement learning is expressed by Equation (7).

$$R_{total,k}^*(s_k) = R_{basic} + R_k^*(s_k) \quad (7)$$

4 EXPERIMENTAL EVALUATION

4.1 Experimental Setup

4.1.1 Learning Environment

In this study, we used Google Research Football (GRF) (Kurach et al., 2020) as the football simulation environment. GRF is a reinforcement learning environment for learning football movements, and the agent learns how to score goals such as passing and shooting through interaction with the environment. The size of the pitch is in the range -1 to $+1$ on the x axis and -0.42 to $+0.42$ on the y axis, and the size of the goal is in the range -0.044 to $+0.044$ on the y axis. In this study, we only experimented with the offense in order to simplify the experiment, and conducted experiments with a scenario of four offensive players and eight defensive players. For the defense, we used a bot that follows the ball and moves to its own team using a rule-based approach provided by GRF. The initial positions of the agents in each episode were set to the positions of all the players when they received an assist pass in the shooting sequence of the real data. The actions taken by the agents were limited to 12 types: moving in 8 directions in 45-degree increments, doing nothing, high pass, short pass, and shoot. The states observed by the agents were 44-dimensional (the x and y coordinates for each player, the position coordinates of the ball, a one-hot vector of 3 dimensions for the team holding the ball (left team, right team, and non-ball-holding state), and a one-hot vector of 11 dimensions for the player IDs (11 players per team), for a total of 61-dimensional vectors. The episode ended when the conditions for switching between offense and defense were met, such as when a goal was scored, a goal was conceded, or the ball was lost, or when 100 steps had elapsed. For the weight of the shoot reward, we divided the half court of football into five parts on the x axis and eight parts on the y axis, and used the percentage of shots by position in the goal sequence of the actual data calculated for each grid.

4.1.2 Dataset

In this study, we used event data and tracking data from 95 J1 League games in 2021 and 2022 provided by the 2023 Sports Data Science Competition. From this dataset, we extracted 1,520 sequences from the time an assist pass was made to the time a shot was taken, and divided them into 141 goal sequences and 1,379 shot sequences. As a preprocessing step, we extracted only sequences in which there were 22 players and a ball on the court, and downsampled them from 25 Hz to 8.33 Hz. We used these sequences for inverse reinforcement learning (proposed method), pre-training (comparison method (Fujii et al., 2023)), and reinforcement learning. For inverse reinforcement learning (proposed method) and pre-training (comparison method), the data was divided into 102 training sequences and 39 validation sequences for the goal sequence. For reinforcement learning, the initial position data for the shoot sequence was divided into 1,179 training initial positions and 100 test initial positions for the positions of all players when they receive an assist pass. In addition, 100 shooting sequences were used as the teacher data to be stored in the buffer during reinforcement learning in the comparative method. The four offensive players selected as the experimental subjects were the players who made the assist pass, the player who took the shot, and two other players who were close to the goal but not the two players mentioned above. The eight defensive players were seven players close to the goal and the goalkeeper.

4.1.3 Learning Parameters

We implemented the proposed method using DDQN for the reinforcement learning component and DQN for the inverse reinforcement learning component. This method, referred to as DDQ_IRL, was then compared with both DDQN and DQAAS (Fujii et al., 2023). Table 2 shows the basic learning parameters for DQN and DDQN, such as batch size and discount rate. We set common values for these parameters in both methods. Additionally, the number of update steps for the Q-Network, a parameter specific to DDQN, was set to $10,000$. Moreover, we used Prioritized Experience Replay as a sampling method for experience data from the buffer, as in Fujii et al. (Fujii et al., 2023). In the loss function of DQAAS, λ_1, the weight for the supervised learning term, was set to 0.04, while λ_2, the weight for the regularization term, was set to 1.00. The convergence threshold for inverse reinforcement learning in DDQN_IRL, ε, was set to 0.1. In addition, for the parameters of the state feature, we used four different values for r, the radius used to calculate the proportion of people: 0.1, 0.2, 0.3, and 0.4. For d_n^α in Equation (1), which represents the distance to the n-th closest offense or defense player, or the distance to the keeper, we adopted the following values: in ascending order of relative distance, 0.16, 0.25, and 0.36 for offense; 0.08, 0.13, 0.16, 0.21, 0.24, 0.28, 0.33, and 0.44 for defense; and 0.35 for the keeper. Note that α denotes either “offense,” “defense,” or “keeper.”

4.1.4 Evaluation Metrics

In this study, we used the Kullback-Leibler (KL) divergence (Yeh et al., 2019) shown in Equation (8) as an evaluation metric to evaluate the distance between the position distribution and the action distribution of the learned football agent and the real player.

$$KL(P \parallel Q) = \sum_x P(x) \log \frac{P(x)}{Q(x)} \tag{8}$$

Here, $P(x)$ represents the distribution of players in the real data, and $Q(x)$ represents the distribution of

Table 2: Settings for the basic parameters of DQN and DDQN.

Parameter	Value
Batch size	500
Intermediate layer size	256
Discount rate	0.99
Learning Rate	0.00025
Optimizer	Adam
n step	16
Warm-up samples	2,000
Initial terminate condition ε	1.00
Last terminate condition ε	0.02
ε decay step	10,000

Table 3: The distance between the position distributions of the agents in each model and real players.

	offensive agents		
Model	all	on-ball	off-ball
DQAAS	0.095	0.273	0.174
DDQN	0.158	0.444	0.167
DDQN_IRL	**0.060**	**0.205**	**0.081**

the learned agent. In addition, in the evaluation of the position distribution distance, x represents each grid when the football half-court is divided into grids, and in the evaluation of the action distribution distance, x represents the action. Using these metrics, we compared our proposed method, DDQN_IRL with the method proposed by Fujii et al. (Fujii et al., 2023), DQAAS, and DDQN.

4.2 Results and Discussion

The position distribution distances and action distribution distances of the agents of each model and the real players are shown in Tables 3 and 4 respectively. From Table 3, we can see that the football agents using the proposed method have the position distributions closest to those of the real players in all items for the entire offense, on-ball agents, and off-ball agents, compared to DQAAS and DDQN. From Table 4, we can see that the proposed method's agents have the action distribution closest to that of real players. This shows that the relative positional reward introduced in the proposed method contributes to making the position distribution and action distribution of the football agents after learning closer to that of real players.

In this section, we analyzed the agents in each model by dividing them into on-ball agents and off-ball agents. Here, to check whether the on-ball agents shoot near the goal like real players, we examined the distance between the on-ball agent's shooting position and the goal. The results are shown in Table 5. In order to maintain fairness in the comparison, only sequences in which the agents of each model shoot the ball were extracted. In this case, the average distance from the initial position of the agent to the goal is 0.270. From this result, it can be seen that the agents in the proposed method tend to shoot the ball from the position closest to the goal. In addition, it can be seen that DQAAS tends to shoot from a position further away than the initial position, and that DDQN tends to shoot from a position slightly further away than the real player. Next, we show some trajectories of the real players and the on-ball agents of each model until they shoot the ball in Figures 2a and 2d . In these diagrams, the initial position of the agent is represented by a red dot, the movement trajectory by a blue line, the shooting position by a yellow star mark, and the passing position by a yellow square. From Figure 2b, we can see that the comparative method DQAAS has a strong tendency to choose a path. On the other hand, from Figures 2c and Figure 2d, it can be seen that the proposed method, compared to DDQN, moves closer to the goal before shooting, as in the case of a real player (Figure 2a), even when the initial position is far from the goal. From this, we can see that relative positional reward can contribute to the learning of shooting actions in positions close to the on-ball agent's goal.

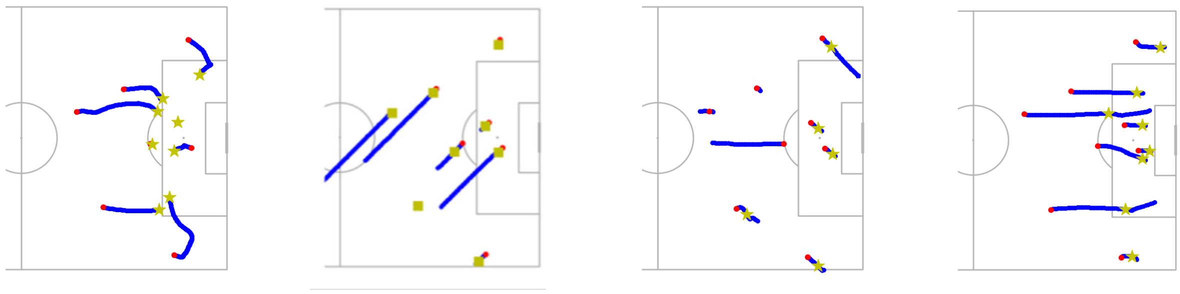
Table 4: The distance between the action distributions of the agents in each model and real players.

	offensive agents		
Model	all	on-ball	off-ball
DQAAS	9.950	10.20	10.800
DDQN	0.406	5.10	0.440
DDQN_IRL	**0.262**	**2.64**	**0.344**

Table 5: The average distance from the shooting position to the goal.

Model	Average distance
Real players	0.245
DQAAS	0.289
DDQN	0.255
DDQN_IRL	0.221

Here, the weights of the reward function estimated by inverse reinforcement learning are shown in Table 6. Agent 1 represents the on-ball agent, and agents 0, 2, and 3 represent the off-ball agents. By observing the individual weights, we can see that the weights for the distance features of the on-ball agent with the keeper are positive. In addition, the weights for the distance to the goal and the percentage of defenders within the goal line have negative weights, and the absolute values of these weights are larger than the weights for similar state features of the off-ball agents. These weights may contribute to the learning



(a) Real players. (b) DQAAS. (c) DDQN. (d) DDQN_IRL.

Figure 2: The trajectory leading to the shot for agents trained with each method.

Table 6: The weights of the reward function of on-ball agents.

	$agent_0^{\text{off}}$	$agent_1^{\text{on}}$	$agent_2^{\text{off}}$	$agent_3^{\text{off}}$
D_{keeper}	0.041	0.061	0.020	0.039
D_{goal}	−0.010	−0.058	−0.022	−0.043
P_r^{def} $(r = 0.1)$	0.024	−0.019	0.016	0.007
$(r = 0.2)$	0.022	−0.015	−0.002	−0.010
$(r = 0.3)$	−0.008	−0.005	−0.000	−0.062
$(r = 0.4)$	−0.009	−0.066	−0.007	−0.056
$P_{\text{goal\_line}}^{\text{def}}$	−0.009	−0.066	−0.007	−0.056
$P_{\text{goal\_line}}^{\text{def}}$	−0.017	−0.023	−0.023	−0.002

of shooting behavior in positions close to the goal for on-ball agents. In addition, negative weights are also given to the weights for the percentage of defenders within a radius r and the percentage of defenders up to the goal, and in particular, the weight for the percentage of defenders up to the goal is -0.066, and the absolute value of the weight is large compared to the weight of the off-ball agent. This weight is thought to represent the characteristics of the on-ball player who is aiming to shoot.

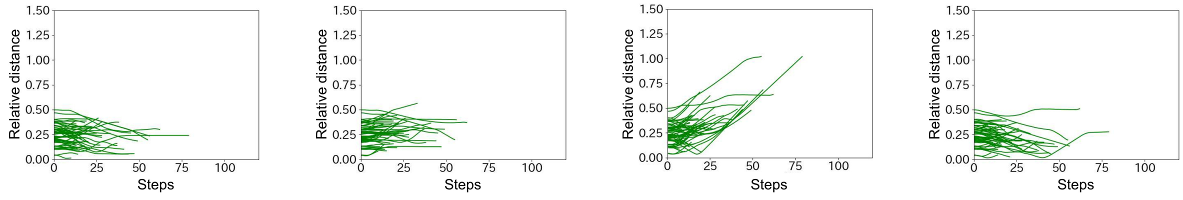
Next, we checked whether the relative distances taken by the off-ball and on-ball agents were close to the distribution of the relative distances taken by real players. The relative distances between the off-ball and on-ball agents of Agent 2 in the test sequences (100 cases) are shown in Figures 3a and 3d . In order to unify the verification environment, the on-ball agent and the defense agent were made to move in the same way as real players. As a result, from Figure 3d, we can see that the relative distance taken by the off-ball and on-ball agents of the proposed method is close to the distribution of the relative distance taken by the off-ball and on-ball players in real players (Figure 3a). Similarly, from Figure 3b, we can see that DQAAS also has a distribution of relative distances that is close to that of real players. On the other hand, from Figure 3c, we can see that the relative distance of DDQN tends to increase with each step. From this, we can see that relative positional reward may contribute to the off-ball agent learning movements that

Table 7: The weights of the reward function for off-ball agents.

	$agent_0^{\text{off}}$	$agent_1^{\text{on}}$	$agent_2^{\text{off}}$	$agent_3^{\text{off}}$
D_1^{off}	−0.004	−0.025	−0.007	−0.005
D_2^{off}	0.004	0.015	0.002	0.002
D_3^{off}	0.019	0.005	0.002	0.001
D_{ball}	−0.004	0.011	−0.029	−0.013
D_{goal}	−0.010	−0.058	−0.022	−0.043
$P_{\text{ball}}^{\text{def}}$	0.007	0.020	−0.022	0.010

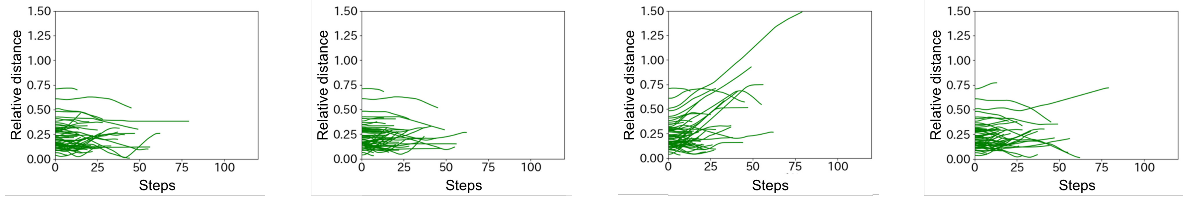
approach the distribution of the relative distance in reality. As shown in Figures 4 and 5, a similar trend can be seen for other agents.

Here, the weights of the reward function estimated by inverse reinforcement learning are shown in Table 7. From Table 7, we can see that the weights for the distance features of the off-ball agent's closest offense are all negative, but the absolute value is smaller than the weight of -0.025 given to the similar state features of the on-ball agent. Therefore, it is possible to say that the weights attached to the distance features contribute to the off-ball agent learning movements that make the relative distance between the on-ball agent and the off-ball agent closer to the distribution of the relative distance in reality. In addition, the weights for the distance to the ball and the distance to the goal for the off-ball agents are all negative, meaning that the weights are such that the off-ball agents learn to behave in a way that brings them closer to the on-ball agents and the goal. On the other hand, the weights for the percentage of defenders on a straight line to the ball are positive for Agents 0 and 3, at 0.007 and 0.010 respectively. As one of the roles of an off-ball player is to receive passes from on-ball players, it is desirable that the weight here is negative rather than positive.



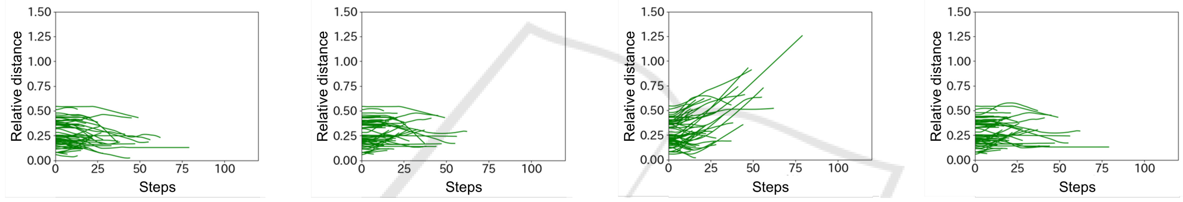
(a) Real players. (b) DQAAS. (c) DDQN. (d) DDQN_IRL.

Figure 3: The relative distance between the on-ball player/agent and the off-ball player/agent 2.



(a) Real players. (b) DQAAS. (c) DDQN. (d) DDQN_IRL.

Figure 4: The relative distance between the on-ball player/agent and the off-ball player/agent 0.



(a) Real players. (b) DQAAS. (c) DDQN. (d) DDQN_IRL.

Figure 5: The relative distance between the on-ball player/agent and the off-ball player/agent 3.

5 CONCLUSION

This study proposes a method to develop a football agent mimicking real players by estimating player-centric relative rewards from actual football data using inverse reinforcement learning and applying them as reward functions in reinforcement learning. We also demonstrated the effectiveness of the proposed method quantitatively and qualitatively through the experiments using real football data. For future work, we plan to establish a correlation between the basic reward function and the state reward function. In the proposed method, the state reward function is independently learned from the basic reward function using inverse reinforcement learning. However, as actions like shooting or passing depend on the current state, it is essential to design the reward function so that the state influences the rewards for these actions and to learn the extent of this influence. Additionally, the adversarial learning strategy used in this study needs refinement to ensure the resulting agents' behaviors are more stable.

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