AI Soccer: the Most Effective Methods to Dispossess the Opponent Player

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Abstract

In this paper, one of the challenges that comes with defending in AI soccer is highlighted and an attempt is made in finding a solution for the problem. In soccer, defense is an important part of the game and the research question in this research is formulated as follows: what are the most effective methods to take by surprise and dispossess the attacking opponent player who carries the ball? To find the most optimal solutions for this problem, the Webots AI Soccer environment is used, which simulates a game of five versus five soccer. To be able to answer the research question, several approaches and strategies are implemented in the environment and their success is compared. This has led to the conclusion that, in this particular environment, defensive actions like slide tackling cannot be performed and thus cannot be used to defend. Therefore, other solutions are necessary, as a result, a combination of approaches is the most important way of making the dispossession strategy as successful as possible. This combination consists of predicting where the opponent is moving to with the ball and determining the optimal side to approach the opponent from.

1 Introduction

Artificial Intelligence (AI) is a very widespread concept and is used in many technologies, this has led to many people knowing about it. AI "works by combining large amounts of data with fast, iterative processing and intelligent algorithms, allowing the software to learn automatically from patterns or features in the data" [10]. AI is used in many different research areas as it can be used for a lot of purposes, one being robot soccer, for which AI is very suitable as it helps creating teams and players that can learn from previous experiences. Artificial Intelligence (AI) soccer competitions have been popular for some time and are under constant development. One of the reasons for this popularity is the fact that soccer is one of the most watched and practiced sports in the world. Although this largely contributes to the popularity, it certainly is not the only reason, another important factor is that these competitions provide researchers with a great opportunity to experiment with different AI techniques by using them for AI benchmarking [7]. The RoboCup [5] was one of the first robot soccer competitions to be organised, aimed at physical robots competing with each other on a pitch, which has already been taking place for more than 20 years. More recently, other competitions like the AI World Cup were introduced [4]. In the AI World Cup, physical robots are no longer used, instead of physical robots, two teams of five virtual robots play each other in simulated matches. The tactics and techniques used for those simulations are implemented by algorithms, which can be improved and optimized using machine learning. Machine learning is a part of AI which tries to learn from the data provided by finding patterns, the aim is to be able to recognize such patterns in the future such that subsequent events can be predicted more accurately.

1.1 Research Question

What are the most effective methods to take by surprise and dispossess the attacking opponent player who carries the ball in AI soccer? This is the main research question to answer during the research. This specific problem is of importance for a team's defense in general, not only in real life soccer, but also in AI soccer, since this resembles real life soccer in many ways. The defense of a team in soccer is crucial, as the goal is to score goals to win a game and the defense tries to prevent the opponent from scoring. The proposed research question has been divided into two main sub-questions:

- What possible approaches should be considered to try to dispossess the opponent player carrying the ball?
- How can the dispossession methods be combined in a single dispossession strategy in the best way?

The first sub-question is aimed at determining which approaches are successful and should be considered to be used as dispossession attempts in a defensive strategy in general. As soon as these successful approaches have been determined, they can help answer the second sub-question, which follows up on the first. The goal of the second sub-question is to combine different approaches to dispossess a player into a single dispossession strategy that can be used by the defense of an AI soccer team. This strategy should then be able to determine which actions should be taken within specific situations to maximize the probability of dispossessing the opponent.

1.2 Current Situation

The current TU Delft AI Soccer team is still relatively new and thus not very experienced, which means this team can be improved in many areas. To be able to compete with opponents, a team should be complete, meaning that it should at least include a working defense and attack, where it is self-evident that the defense tries to prevent the opponent from scoring, while the attack tries to score goals in the opponent's goal. Currently, the team is not able to perform all aforementioned tasks, it does for instance not contain a defense that is able to perform all tasks it should to prevent an opponent from scoring. In addition, the literature currently present does not provide a sufficient solution for this specific topic, their aim is mainly to improve the ball-manipulation skills [1], ball trajectory prediction [6] or pass interception [11], [13]. Although the functionalities that come with the mentioned literature can be crucial in developing a competitive team, they do not sufficiently contribute to dispossessing an opponent. This leaves a gap in a relevant research area, namely the AI soccer defense in general and dispossession of the opponent more specifically.

2 Dispossessing the opponent

Dispossession of a player in possession of the ball has always been an interesting topic for analysts as there is no single straight forward method that can be used for every situation. In real life soccer, players always have to decide on the way they will attempt the dispossession, for example by awaiting an opponent error, trying to take the ball or performing a slide tackle. In open play, only a few methods are successful, namely slide tackling or intercepting an attempted shot or pass [9]. To a lesser extent, this problem also applies to AI soccer, where similar decisions have to be made, based on the situation the defender is located in. Implementing a solution to solve this problem comes with some challenges as the degree of difficulty is strongly dependent on the opponent. Therefore it is important to be careful when working on a strategy to dispossess players, since the developed strategy might be over-specialized on certain opponents, but very ineffective against others, in addition, losing a duel where a dispossession is attempted can result in the opponent being given a free passage to the goal, since the defender is out of position [3]. Often, goal scoring chances originate from such situations, as the defender is no longer able to intervene, which could possibly lead to a goal being scored. The proposed methodology and experiments, supported by figures, all represent situations in which the own goal, which should be defended, is located on the right side of the pitch. To not give the opponent a chance at scoring, this is the location the defender should prevent the attacker from moving to.

2.1 Determining the best dispossession methods

To determine how a dispossession can be performed in AI soccer, experiments have to be ran. Initially, the aim of the experiments is to determine the most successful dispossession methods in general, which corresponds to the first subquestion. The way these methods are determined is by ensuring that the defender is able to get close to the opponent, to then perform an attempt at dispossessing this opponent. The most suitable way of experimenting with several dispossession methods and assessing their success is by creating situations in which only one attacker, in possession of the ball, and one defender, trying to perform a dispossession, are involved. This can be achieved by instructing all other players within the simulation to move to the side of the pitch, such that they will not interfere with the experiment. The defender is then given rule-based instructions, such that it moves to the opponent and performs the specified action, aimed at dispossessing the attacker. To determine the success of such actions, which gives an indication of actions that can be used for the team's defensive strategy, it is observed whether a dispossession occurs after the action is performed.

2.2 Approaching the opponent

Another important aspect of the dispossession strategy is the ability to get close to the opponent, which, in most situations, is more complicated than assuming the opponent will move in a straight line at a constant speed. This is caused by the fact that the behavior of the opponent is in many situations more complicated and can therefore not be predicted with a simple prediction. Therefore, it is important to be able to predict the movement of the opponent more precise, using data regarding the opponent during the simulation in Webots. A possible way of predicting the trajectory that has been proposed is abstracting the robot of its numerical values relative to the ball and ball velocity using qualitative descriptions of the environment [11], another possible way is teaching the robot to intercept the ball using Reinforcement Learning [2]. Although these methods can be helpful, they will not be used for this specific case, since their main focus is the prediction of the ball trajectory, which cannot be regarded in the same way as the trajectory of an opponent. The data that can be used for the prediction, as provided by Webots, consists of the opponent's current and previous rotations, speeds and coordinates. To determine the effectiveness of the trajectory prediction, the opponent is given instructions to move to varying coordinates, often changing direction, after which the defender is instructed to move to the predicted coordinates. The purpose for the defender is that it should be able to perform a dispossession attempt after having arrived at the coordinates, which gives an indication of the accuracy and success of the prediction.

2.2.1 Opponent trajectory prediction

To improve opponent trajectory prediction from initially assuming a linear movement, a prediction function is proposed that should produce a more accurate prediction of the movement of the opponent in possession of the ball. This function predicts the future rotation, velocity and coordinates using data provided by the simulation. The maximal velocity of the opponent depends on the role of that specific player, whenever the player is an attacker, it moves at a maximal speed of 2.55 m/s, which is decreased with 20% whenever the player has possession of the ball, corresponding to $v_{max} = 2.55 \cdot 0.8 = 2.04$ m/s. For the case of a defender, where the maximal speed is 2.1 m/s, which is also decreased by 20% if that player is in possession of the ball, the following speed is obtained: $v_{max} = 2.1 \cdot 0.8 = 1.68$ m/s. In addition, the predicted rotation r_4 of the opponent during the next frame is calculated, which is done using the opponent's three most recent rotations, chronologically listed r_1, r_2, r_3. This calculation is presented in Equation 1, listed below. Afterwards, the predicted velocity, v_3, can be calculated, using the opponent's two most recent velocities, also in chronological order, v_1 and v_2, as can be seen in Equation 2. Equation 3 shows how, using the predicted velocity, the expected size of the step that the opponent will take during the successive frame is calculated. There are two important points worth mentioning, first of all, the predicted velocity is divided by 20, which originates from the fact that each frame lasts 50ms, meaning one second in the game consists of 20 frames. Secondly, a distance of 0.16m is added to the predicted step, due to the fact that a player carries the ball at approximately 0.16m in front of itself and after all, the goal is to take the ball of the attacker. All previously calculated values are then used to predict the expected location of the opponent in the next frame, Equation 4 contains the x-value calculation and equivalently, Equation 5 is used to calculate the y-value. The predicted values that result from these calculations can be used to repeat the described trajectory prediction for the desired amount of frames in the future. However, it is important to note that the prediction becomes less accurate the higher the amount of frames that should be predicted in the future becomes since they are predictions instead of actual data, increasing the uncertainty of the values.

$$r_4 = r_3 + ((r_3 - r_2) + ((r_3 - r_2) - (r_2 - r_1))) \tag{1}$$

$$v_3 = max(min(v_2 + (v_2 - v_1), v_{max}), 0) \tag{2}$$

$$step = (v_3/20) + 0.16 \tag{3}$$

$$predicted\ x = x - step \cdot cos(r_4) \tag{4}$$

$$predicted\ y = y - step \cdot sin(r_4) \tag{5}$$

2.2.2 Avoiding the opponent

Whenever the defender is moving towards the location where the opponent is predicted to move to, it might occur that the opponent is located between the defender and the ball, which could cause difficulties for the defender. To overcome this problem, a method is proposed in which the defender is instructed to move to the predicted coordinates of the opponent, where these coordinates are then modified with a small offset in order to decrease the probability of the attacker blocking the defender. To calculate these offsets, the area around the attacker is divided into 10 equally large zones, thus each zone having an angle of 36°, this can be seen in Figure 1.

For each zone, a different pair of offsets is calculated, where a pair consists of both an x- and y-value. For each zone, this pair is applied to the predicted x- and y-coordinates of the opponent, whenever the rotation of the opponent falls within that specific zone. Initially, only one offset is used per zone, in Figure 2, a visual representation is given for the case that the attacker's rotation falls in zone 5.

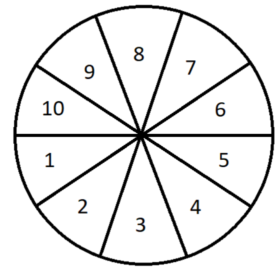

Figure 1: Division into 10 zones

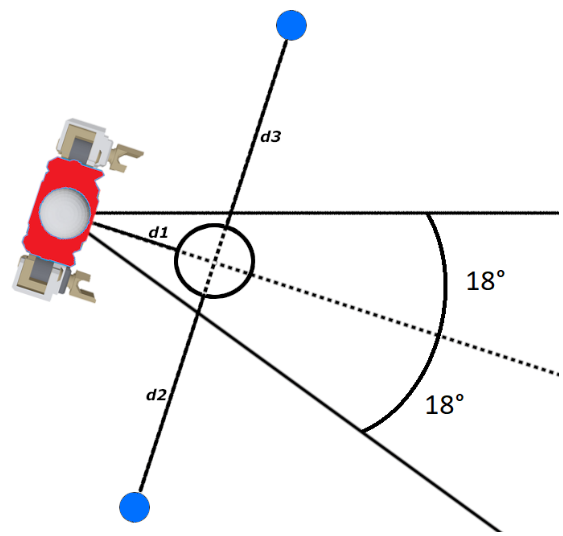

Figure 2: Applying offset for zone 5

The calculation of the offsets is done by assuming the opponent carries the ball in a straight line in front of itself at a distance of 0.16m whenever in possession, this is represented by line $d1$ in Figure 2. For each zone, the rotation of the opponent is taken to be in the middle of that specific zone, one of the two points perpendicular to the line through the ball is calculated at a distance of 0.25m, represented by $d3$ in Figure 2. By subtracting the predicted location of the opponent from this calculated point, the offset is found. Initially, only one offset per zone is calculated, the success of this method is then compared to the method which makes use of offsets for both sides, visualized by both blue points in Figure 2. The offsets that are applied using the above reasoning are listed per zone in Table 1.

Subsequently, to have a higher expected success, two offsets are defined per zone instead of one, which should increase the probability that a defender is able to dispossess the attacker, since the defender can perform the action from either side, as displayed in Figure 2.

$d2$ and $d3$ represent the distance of 0.25m between the ball and the coordinates the defender is supposed to move to. Depending on the location of the defender, either the

Zone	x	y
1	0.08	-0.24
2	0.20	-0.15
3	0.25	0
4	0.20	0.15
5	0.08	0.24
6	0.08	-0.24
7	0.20	-0.15
8	0.25	0
9	0.20	0.15
10	0.08	0.24

Table 1: Initial offsets per zone

offset sending the defender to the higher or to the lower point is chosen. Two examples are presented in Figure 3 and 4, the path that is followed without applying an offset is indicated by the red arrow, while the green arrows represent the sequence of movements taken by the defender whenever the offset is applied. In Figure 3, the defender is closer to the point above the ball and therefore moves to that location, before being instructed to dispossess the attacker. In Figure 4, the opposite is the case, as the defender is located closer to the point below the ball and therefore is instructed to move there.

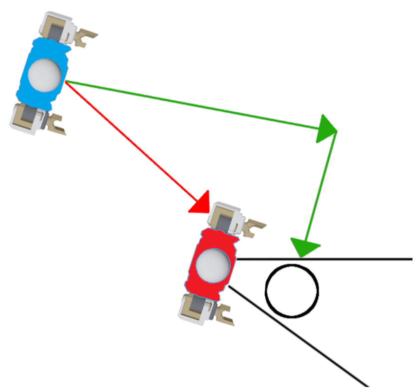

Figure 3: Approaching the ball from above

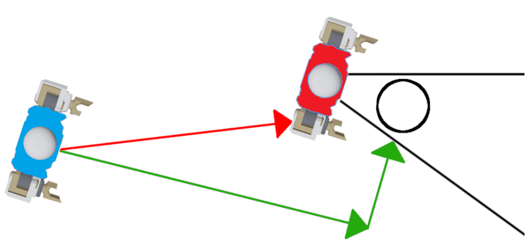

Figure 4: Approaching the ball from below

2.3 Dispossession in team strategy

The ultimate goal of the research is to find the most effective methods to dispossess an opponent, to then also have these methods be combined into a single dispossession strategy that is able to determine how the dispossession attempt can best be performed for each specific situation. Therefore, a single dispossession strategy is proposed, which contains a combination of the methods that turn out to be most effective. In this combined strategy, the defender is instructed to move to the coordinates predicted by the opponent trajectory function whenever the distance to the attacker is greater than 0.125m. In addition, one of both offsets is applied, depending on the location of the defender with respect to the attacker, whenever the distance is between 0.5m and 1m. Whenever the defender is within 0.125m of the attacker, no prediction or offset is used anymore, in this situations, the defender should already be positioned well enough to be able to dispossess the opponent and is therefore being sent straight to the location of the ball.

By combining all components, the part of the defense responsible for dispossessing the opponent can be integrated with other parts more easily, of which the defensive positioning [14] and marking of opponents not in possession of the ball [12] are most important, although the goalkeeper [8] also plays a role in this combined defense.

3 Experimental Setup and Results

Within the research, experiments are conducted to obtain data that should help answer the research question and its subquestions. For the experiments, it is important to have a clear idea of the environment and framework being used, as well as the experimental setup, as these circumstances lead to the results that are obtained and presented.

3.1 Experimental Setup

In order to determine the most effective methods to take, the Webots robot simulator [15] is used in combination with the AI Soccer framework created by the TU Delft. In this environment, the robots that are simulated, from both the own and the opponent team, can be given specific instructions in order to create a strategy to play a match. A soccer match within the framework resembles a real life soccer match in many aspects. One being that the players all have different initial starting positions on the pitch, all on their own half, where one team gets to kick the game off. On the other hand, there are also differences with respect to a real life soccer match, such as the fact that both teams only consist of five players each and the absence of fouls and a referee on the pitch. The players of each team have several roles, one goalkeeper, two defenders and two attackers. During a match, each frame lasts 50ms, meaning one second in the game consists of 20 frames, during each frame, the information about the game is updated. This information primarily consists of the x-, y- and z-coordinates of players and the ball and the state of the game, such as the score and the player and team in possession of the ball. This information can be used to give new instructions to each player, which can be done for every frame. Not all specifications are mentioned, but the exact and complete specifications of the environment that has been used can be found in [4].

For the own team that should try to dispossess the opponent player carrying the ball, the instructions given are rule-based, which means the instructions are given based on the current state of the game, such as the location on the pitch of both the own defender and the opponent player, a player's velocity and the distance between players. The opponent team uses fixed instructions which do not depend on the state of the game. Throughout the project, simulations are ran both manually and by using an automated simulation runner, which provides the ability to store data for later use. In this case, per simulation it is stored whether a simulation results in a dispossession or not, thus decreasing the time needed to collect data.

3.2 Results

To test the performance of the solutions that have been proposed, two different variants of experiments are used, the first being one versus one in which the single defender tries to dispossess the single opponent who is in possession of the ball. The other experiment consists of complete teams on both sides, meaning each team consists of 5 players. Both variants produce results for different aspects of the dispossessing strategy.

3.2.1 Subdividing the area around the opponent

First of all, when running experiments in a one versus one situation, it becomes clear that, in contrast to real life soccer, the Webots AI Soccer environment does not support certain defensive actions, the most important being slide tackling. In addition, a defender is not able to kick the ball away whenever the opponent is in possession, even if the defender is located next to the ball. Instead of kicking the ball away, the defender should try to hit the ball by walking into it. One versus one simulations in which the defender attempts to dispossess the attacker, who moves to varying coordinates, show that the success of a dispossession attempt strongly depends on the side the opponent is approached from. Roughly four different sides, with respect to the opponent's orientation to the ball, can be identified: front, back, left and right, which is displayed in Figure 5. In this figure, the left and right side are marked green and the other sides are red. In addition, the angles are specified for each of the red and green areas, from which it becomes clear that the green areas combined are approximately equally large as the red areas combined.

For each of the four areas, an explanation regarding the success of the area arose from the simulations. Approaching the opponent from the small red area in front of the attacker is not successful in general. The simulations lead to this observation since this situation most often does not result in a dispossession due to the fact that, when the defender tries to hit the ball, it often bounces back to the opponent who is standing on the other side of the ball. The approach from the red area at the back of the attacker is the least successful, since the opponent is standing between the defender and the ball, therefore blocking the defender's path to the ball and not giving the opponent the possibility to get to the ball. In contrast to the front and back, the approaches from left and right, indicated in green in Figure 5 are significantly more successful. Approaching the attacker from either side does not cause the issues present in both previously described areas, as the opponent does not stop the defender from getting to the ball or hitting the ball such that it rolls away.

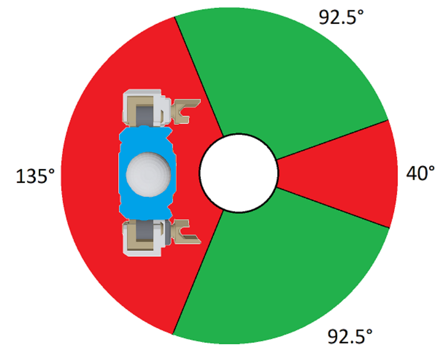

Figure 5: Top view of a player carrying the ball

After having performed multiple simulations using the offsets listed in Table 1 in Section 2, some values have been slightly modified to increase their effect on the success of a dispossession. In addition, an extra pair of offset values is used, $(x2, y2)$, to be able to send the defender to both sides of the attacker, depending on the location of the defender with respect to the attacker. The new offsets can be found in Table 2 below.

Zone	$x1$	$y1$	$x2$	$y2$
1	0.18	-0.24	-0.18	0.24
2	0.30	-0.15	-0.30	0.15
3	0.35	0	-0.35	0
4	0.30	0.15	-0.30	-0.15
5	0	0.24	0.08	-0.24
6	0	-0.24	0.08	0.24
7	0.30	-0.15	-0.30	0.15
8	0.35	0	-0.35	0
9	0.30	0.15	-0.30	-0.15
10	0.18	0.24	-0.18	-0.24

Table 2: Final offsets per zone

3.2.2 Developing a complete dispossession strategy

To determine the most effective strategy to dispossess the opponent in simulations, five different strategies are used in a one versus one situation to determine the success of each of them. Each of these strategies is applied to the situation where one opponent player moves to the other goal through random coordinates. If the player manages to reach the box without losing the ball, the dispossession attempt of the own defending player is marked as failed. If however the opponent loses the ball before this moment and does not regain possession within 10 frames, the dispossession attempt is marked as successful. All proposed strategies are tested under the same conditions. Per solution, 25 simulations are ran. For each simulation, the attacker moves through different coordinates before moving to the box such that the defender would have to successfully perform a dispossession in changing circumstances regarding the movement of the opponent. Six different strategies are proposed and compared, for each of the proposed strategies that uses some kind of prediction, the amount of steps it has to predict in the future, also referred to as the prediction step is calculated in the same manner. This calculation is done using the following equation: $prediction\ step = distance/stepsize$, where the maximal stepsize of a player per frame can be calculated, since its maximal speed is known and $distance$ represents the distance between the defender and the ball. The six different strategies that are applied and compared are the following:

1. Moving to the coordinates where the ball is currently located, without using any additional functionalities
2. Moving to the predicted coordinates of the ball, which assumes the ball has a linear movement
3. Moving to the predicted coordinates of the opponent using the opponent trajectory prediction
4. Moving to the predicted coordinates of the ball, which assumes the ball has a linear movement, corrected with the initial offset from Table 1 in Section 2
5. Moving to the predicted coordinates of the opponent using the opponent trajectory prediction, corrected with the initial offset from Table 1 in Section 2
6. Moving to the predicted coordinates of the opponent using the opponent trajectory prediction, corrected with one of both offsets from Table 2

By running the experiment for each of the strategies under the previously described circumstances, the following success rates are obtained:

Method number	1	2	3	4	5	6
Success	32%	72%	68%	72%	88%	92%

Table 3: Success rates per method

From the percentages in Table 3, it becomes clear that the first approach, as expected, is very ineffective. The same holds, to a lesser extent, for the third method, which assumes a linear movement. The second and fourth turn out to be slightly more successful, both using the predicted coordinates of the ball instead of the opponent. However, both the fifth and sixth method result in a significantly higher amount of dispossessions.

4 Responsible Research

This research does not involve any ethical aspects as no humans or sensitive data are involved. In addition, this research is conducted independently, thus without any external persons influencing any experiment or outcome. Therefore, there is nothing else to report on responsible research.

To be able to reproduce the conducted research, in most cases, the steps mentioned in Section 2 and 3 should be followed. By following these steps, the situations in the Webots environment can be reproduced in the same way they have been used in the conducted experiments. Exact specifications and the full implementation of the team, as well as the different experiments carried out will not be made public at the moment of publication. The main reason for this is to not give any unnecessary advantage to other AI Soccer teams. The solutions to the problem have been described in this paper and are of importance with respect to AI Soccer defending, but will thus not be made available to not favor other AI Soccer teams.

5 Discussion

The obtained results show that effective ways of dispossessing a player in AI soccer cannot be compared to those for real life soccer. The environment being used limits the possibilities largely, therefore demanding different approaches. Where dispossessing in real life soccer often consists of defenders performing slide tackles or dueling with the attacker, these actions cannot be performed in AI soccer. Dispossessing becomes more effective when the defender tries to approach the attacker from its left or right side, by moving to the location the attacker is predicted to move to. Afterwards, in contrast to real life soccer, the defender can optimally attempt to take the ball from the attacker by moving in front of the attacker. While this is not proven to be the case, there is a high probability that, in terms of the way real life soccer does not resemble AI soccer, the same holds for other aspects of an AI soccer strategy, such as the attack. This should be taken into account, as it might be difficult to approach such situations from a different perspective, thus having to come up with other methods to build a strategy upon.

Another important observation is the fact that many of the cases in which the optimized dispossession strategy was not able to successfully perform a dispossession, this was caused by the fact that the attacker changed direction at the moment that the defender came close to the attacker. Although the opponent trajectory prediction is meant to tackle this issue and is able to do so in many cases, it cannot prevent such situations from occurring at all. The main explanation for this being that sudden changes in direction or speed are unpredictable and, especially whenever defender and attacker are close to each other, will result in the defender moving in the wrong direction.

A benefit of the environment being used is the fact that the data belonging to the state of the game, such as coordinates of the players and the ball, can easily be used to base the implementation of strategies on. On the other hand, the environment also has an important limitation, which is the fact that running multiple simulations, in order to collect data, is a time consuming and computationally intensive process. The Webots environment is not created for this purpose, which complicates the testing of different methods in order to determine their success. Both factors should be taken into account when using the Webots environment in combination with AI soccer.

6 Conclusions

In this paper, the most effective methods to dispossess an opponent player in possession of the ball are studied and a solution is proposed. Two sub-questions are formulated to help answering the main research question, which is aimed at finding the most effective methods to dispossess the opponent player in possession of the ball. The first sub-question focuses on finding possible approaches that can be used to dispossess a player. From the experiments that were conducted, it became clear that not many different actions can be taken within the Webots environment using the AI Soccer framework. Through the experiments it also became clear that the opponent can best be approached from the left or right side in order to increase the success of a dispossession attempt. Although this observation limits the possibilities to dispossess, it contributes to the defense, since other approaches are required, resulting in a prediction function to determine the next steps of the opponent more accurately. Predicting the opponent trajectory more accurately gives the defender the opportunity to get closer to the attacker before attempting to dispossess this attacker. To ensure this dispossession attempt can be performed from either the left or the right side of the attacker, a small offset is used, which is applied to the coordinates the defender has to move to whenever it is close to the opponent. This offset is based on the conclusion that the success of a dispossession attempt depends on the side the attacker is approached from.

The second sub-question aims at creating a strategy that is able to dispossess the opponent player in general, combining all approaches proposed. This dispossession strategy makes use of the opponent trajectory prediction and combines this with the small offset in the coordinates which the defender should move to before attempting to take the ball. All components are combined into a single dispossession strategy, which gives instructions to the defender that should perform the dispossession based on factors such as coordinates. The simulations that were ran confirm that the combination of components of the strategy significantly improves the success of the dispossession strategy compared to low-level strategies which do not make use of the same methods. This can be explained by the fact that these methods use both a more accurate prediction of the movement of the opponent as well as a way of getting close to the opponent in such a way that the dispossession attempt has a bigger probability of being successful.

In the future, the AI Soccer team can be improved in multiple areas. This research has only aimed at a specific part of the defense of a team, the dispossession, although other parts of the defense, specifically positioning [14], covering [12] and goalkeeping [8], have also been worked on. Integration between these areas has been performed such that a fluent cooperation is obtained, this could however be improved to optimize their effect on the team's defense, for example by refining the decision making on which the instructions given to the defense are based. In addition, these specific defensive contributions combined only partially contribute to a complete team. A particle of the team that is at least as important as the defense remains almost fully untouched to this moment, which is the attack, meaning there is plenty of possible work that can be performed on this part of the team. Alternatively, from an AI perspective, Reinforcement Learning could be used to learn how dispossession could best be implemented. By comparing the results generated by Reinforcement Learning to those presented in this paper, one could get a notion of the usefulness of this technique within AI soccer.

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