AI soccer: covering an opponent not in possession of the ball

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Abstract

Virtual robot soccer competitions have been rising in popularity in recent years, due to their easier accessibility than physical robot soccer. This is also the reason these virtual competitions were created. The goal is to compete in the AI world cup, one of the virtual soccer competitions. A coach-based framework has already been built, and the aim is to create strong defensive capabilities for the robot team. This paper in particular focuses on covering opponents without the ball.

The marking strategy and specific opponent covering that have been devised for this are explained. Both are completely rule-based, and opponent covering has been thoroughly tested with an in-house developed batch-runner. In short, opponent covering consists of standing at the optimal position between the passer and receiver, and when the ball is passed going to the closest intercept point. This optimal position is learned with the batch-runner.

Opponent covering performs well in the generated test cases. Some specific algorithms counter attacking strategies which have not been implemented yet, therefore it was not possible to evaluate those algorithms. They are theoretically optimal however.

1 Introduction

Ever since AI was first created, people have been trying to make AI do what humans can do. One example of that is soccer. For two decades, robots controlled by AI have been attempting to play soccer in a tournament called RoboCup. The performance of the robots is still far inferior to humans, however. This is due to many physical inabilities of the robots, like communicating with others, seeing the surroundings, walking and turning quickly, and kicking the ball accurately.
Recently, many new competitions have started focusing solely on the AI aspect of the robots, by simulating the game in a digital environment and thus discarding all physical aspects. As the game are completely virtual, many strategies can be tried out, and the development of the AI can proceed much faster than it does for RoboCup.

One of these virtual competitions is called the AI world cup, and this paper is about an AI driven robot team participating in it. Currently, the defensive aspects of the AI are being built. There are many aspects of defending in a game. There is the keeper, a defender close to the goal, a player trying to dispossess the ball from the opponent, and other players covering attackers not in possession of the ball. This paper in particular focuses on covering opponents who are not in possession of the ball. For an extensive description of this problem, see Section 2.

In this paper the terms 'marking' and 'covering' are used. Marking is the strategy of the defenders used to decide which defender covers which attacking opponent. Covering is the physical act of trying to stop the covered opponent from taking possession of the ball.
The term 'carrying' the ball is also used. In the AI world cup environment, a player can 'carry' the ball, which means that the ball is locked to its position, and it is the only way the environment registers possession. Touching the ball or being close to it does not count as possession.

1.1 Related Work

In order to acquire knowledge of the AI soccer topic, literature research was performed. A summary of the findings now follows.
Kutsenok (2004) describes a good rule-based algorithm which is used in this paper, as well as explores swarm-AI. Habibi et al. (2002) talk about a coach for the players, but it is a coach for RoboCup, not a virtual competition. Reis et al. (2001) go into homogeneous agent positioning, but this is a distributed solution and this research's intention is a more centralized approach. Kuhlmann et al. (2006) describe a coach with an omniscient view of the field, but that coach is only allowed to give general advice. In the AI world cup the coach can give direct orders. Dashti et al. (2006) use Voroni Cells to position the agents on the field, but this is more useful for an attacking strategy. MacAlpine et al. (2013), like Reis et al. (2001), talk about decentralized agent positioning. Ismael and Mohajer (2010) describe all of the skills their agents have, but is quite brief and the field positioning is designed for 10 players in the field instead of 4. Voorter (2014) analyses different strategies, but these strategies are not very advanced and use hard-coded positioning.

Contribution of Related Work

In conclusion, there are many papers available about defensive soccer AI, but almost none are relevant and cover the exact required topics. Only the rule-based algorithm from Kutsenok (2004) is useful for answering the research questions.
Therefore not many references are made in this paper, and almost all knowledge in this paper has been self-gathered during the research.

1.2 Research Questions

The main research question of this paper is: 'What are the most effective methods for a defender to cover the attacking opponents who are not carrying the ball?'.
Covering attackers consists of two aspects: deciding which opponent to cover (marking), and getting in the best covering position for that opponent. Subsequently, the following questions have been chosen for solving these problems:

1. Which marking strategy gives the opponent a lower pass success rate: zonal marking or man-to-man marking?
2. What is the best position for a player to be in, in respect to the ball carrier and another opponent when assigned to cover that opponent?
3. Can Q-learning be used to learn the optimal covering positioning, and does it outperform a rule-based solution?

2 Problem Description of Covering Opponents

As stated in Section 1.2, the problem of covering opponents without the ball consists of marking opponents and covering a specific opponent.
The problem of marking is to decide which of the two existing strategies is optimal in the AI world cup environment. The main problem of opponent covering is where to stand between the two players executing a pass. Side problems of opponent covering are intercepting aerial passes and predictive passes (attacker shoots to the side instead of directly at the receiver).

2.1 Marking

There are two marking strategies in real-life soccer: man-to-man marking and zonal marking. In man-to-man, each player is assigned an opponent, and it will cover that opponent for the whole game. In zonal marking, a player covers an opponent based on both of their positions. If a zonal marking algorithm is executed, there exist zones which indicate the correlation of an attacker's position and by which defender he is covered. These zones are decided by the specific rules of the algorithm, and shift based on player positions. Hence it is called zonal marking. The advantage of this strategy over man-to-man is that after an attack, players can potentially get to their covering positions quicker.
Players in the AI soccer environment differ substantially from real players, especially in the movement aspect, so it was not evident whether one of the aforementioned strategies is the optimal strategy for the AI soccer environment.
It was beyond the scope of this research to try and combine the two marking strategies, conceive a new marking strategy, or to investigate whether marking is useful at all in this environment. Instead, the research question was attempted to be answered, in order to find the optimal of the two strategies.

2.2 Opponent Covering

A player which covers an opponent without the ball, wants to stop the ball being passed from the ball carrier to the opponent it is covering. In real-life soccer, the covered opponent can quickly change direction to come out of cover or try to catch the covering player by surprise with a sudden dash. In the AI soccer environment however, player movement is a lot more cumbersome and the game state is analysed every frame, leaving no opportunity for anything quick or unexpected. Further more, receiving a ball in the AI soccer environment is a very precise process, if the player is not lined up correctly the ball will bounce off of the player's feet.
There are also different types of players in the environment: Forwards and Defenders. Forwards are quicker than Defenders, but also turn slower. Therefore the type of the player can have an effect on their optimal covering position.
Besides shooting directly at the receiver, the attacker can decide to shoot over the defender (aerial pass) or to the side (predictive pass). To intercept these types of shots, the defender has to move to a better intercepting position, as they are specifically made to by-pass the defender. Frame analysis and exact movement is required in order to stop these type of passes.

Based on the abilities of the players, a straightforward solution for covering an opponent without the ball is: position the player on the line between the two attackers. To find out where on the line that is, the research question was answered.

3 Algorithms for Covering Opponents

3.1 Algorithm Evaluation

In this paper, most of the presented algorithms have been evaluated with a batch-runner. This runner was developed from scratch for this research. A reason that a batch-runner was needed is that the best and quickest way to reset the simulation is to restart the environment, discarding any results in memory. A 'loop' code construct would therefore not work, and something more robust was required. The batch-runner writes temporary results to disk, and uses a configuration file to set up the parameters each test.

Another reason that a batch-runner was needed is that there are many parameters for a test, and in order to find the best values for these parameters many batches with different parameters have to be run. Doing this by hand is extremely time consuming, and the computer is also not usable during these tests, as the simulation is restarted by emulating keyboard presses to the active window. A batch-runner which can run all the tests during the night is the perfect solution for this.

More specifically for this research, a test consists of a passer and a receiver, and potentially an intercepting defender. The ball is then passed, and the defender tries to stop this pass from succeeding. The performance of the defender is measured as: the amount of successful passes over the total amount of passes, i.e. pass success rate.
The receiver is given enough time to get tot the desired position. This is done to greatly improve the pass success rate without a defender, as when he is not given enough time the success rate drops by as much as 0.30.

3.2 Marking

The process of marking is performed by the team coach. The clear advantage of the coach performing the marking as opposed to each player doing it individually, is that there is no agent coordination necessary. This eliminates the need for some complex communication protocols.
Man-to-man marking is very simple to implement: each player is assigned an opponent to cover by the coach at the start of the game. Usually Defenders cover Forwards and vice-versa.
Zonal marking is bit more complex than man-to-man (see Section 2.1). Kutsenok (2004) describes an efficient and elegant rule-based algorithm for zonal marking, which has been implemented with a small change. This change consists of making players close to the ball carrier also eligible to cover him, as a player closely behind the ball carrier can get to him quicker than a player at the other side of the field, but which is between the goal and the ball carrier.

1. Select the players between the goal and the ball carrier, and those near the ball carrier.
2. Out of these players able to best cover the ball carrier, the closest to the ball carrier is assigned to cover him. If no players are eligible, then the player closest is assigned to him.
3. The rest of the attackers, ordered by closest to the goal first, are assigned the defender closest to them.

A check for defending decides if the team is on the defense. Marking is the team strategy for defending, and therefore executed when the defensive check succeeds. The defending

check and potentially the marking algorithm are executed every frame. This is no problem time-wise, as they take less than a millisecond to perform.
The defending check is as follows: check how long ago the most recent opponent possession of the ball was. If this is less than a certain amount (there is an opponent pass in progress), and if the own team also does not have the ball, then the team is defending and marking should be performed.
If a pass takes too long (failed pass), or the ball is intercepted and taken into possession by one of the friendly players, the check fails and the team is on the attack.

As mentioned in Section 2.1, zonal marking is theoretically more efficient than man-to-man, as the walking distance is minimized since the closest player to an opponent is assigned to that opponent. Other advantages of the zonal marking algorithm are that there is always a player assigned to the ball carrier which can cover the goal, and that opponents closer to the goal are prioritised for covering.

Marking is applied during a game, to defend from attackers. Unfortunately, there is no capable attacking AI available, so it is impossible to validate that the algorithms works and to check if zonal marking outperforms man-to-man marking. No statistics about the efficiency of the algorithms can be gathered either.

3.3 Opponent Covering

The algorithm for opponent covering and its performance is now described, as well as the impact of some key features on the overall effectiveness. This was measured with the batch-runner as described in Section 3.1.

In order to block passes between the two attackers, the defenders objective is to stand on the line between them. In this environment, just a move order is not a quick and reliable method of getting to a certain point. The player tries to get to the exact position, but it usually overshoots its target, and it then has to turn around and walk back.
To counteract this, a margin is added to the move order, and the player now gets to the desired position much quicker. The player is not in the exact required position, but still in the path of the ball.
This margin has a clear effect on the pass success rate, as it goes down from 0.03 without the margin to 0.01 with the margin. In the tests, the receiver and interceptor are given plenty of time to get into position, in order to achieve an as high as possible pass success rate without a defender. The margin's effect is therefore limited in these tests. The quicker an opponent shoots, the more effect the margin will have.

To still stop the pass if the defender cannot get into position on time, the ball path is determined once the ball has been shot. Then the closest point on that line to the defender is calculated and set as destination for the defender, with the aforementioned margin. This is especially useful during a game when the defender will likely not be able to always be on time to its position. This shot interception mechanism is also used for other types of passes, as described later in this section.

The best and easiest way to prepare for an opponent action, is to mimic the turned angle of the opponent. Now whatever the receiver will do, the interceptor is optimally situated to counter it. For a direct pass to succeed, the receiver must be turned towards the passer. As the interceptor mimics the receiver's turn, the ball rolls into its feet and the interceptor can take possession of the ball. This works well, as the possession rate is 0.60 (0.55 for a Forward, 0.65 for a Defender), and the pass success rate is not affected.
Turn mimicking allows the defender to anticipate anything the receiver will do, besides

preparing for a direct pass, it also helps counter other types of passes, this is discussed in the Predictive Pass Interception section.

Aerial Passes

Besides shooting a pass over the ground, the attacker can also pass a ball through the air. The ball then goes over the defender's head, into the feet of the receiver. To intercept this pass, the defender jumps at the right moment. In the algorithm, the ball position is predicted, and the interceptor jumps so that the ball is just behind him at the apex of his jump.

Figure 1: Different jumping positions

Besides jumping at the right moment, the defender should also jump at the right position. As the trajectory of the aerial pass is parabolic, the more the interceptor goes towards the receiver the lower the ball will be at interception.

This is illustrated by the fact that the defender by default stands some way apart from the receiver, and the aerial pass success rate is 0.18 as a result. In Figure 1 the different jumping locations are shown, where the red arrow is the default location and the green arrow is a more optimal location. It is clear in the figure that jumping at the green location would stop the ball.

Going more towards the receiver seems straightforward at first, but it is not. Only after the ball is shot does the interceptor know what type of pass it is. The defender is turned towards the ball as it is mimicking the receiver. This setup can be seen in Figure 2. The optimal walking pattern is straight back, indicated by the green line. The built-in environment action however, makes the player walk the red line, turning around at the middle and the end. This is far from optimal.

Figure 2: Two ways of walking back

Despite not being optimal, performing the red walking pattern still decreases the pass success rate to 0.11. This is due to the fact that the line is not completely followed, as the main objective is still to be on the line between the two attackers. The defender therefore does not get to the receiver completely, but still close enough. If the defender is further away from the receiver when the pass is performed, the red walking pattern will perform much worse.

To perform the green walking pattern, a self made action is used, which first makes the player line up to the target (the ball in this case) and then walks in a straight line. This action was not easy to implement, as a player slightly deviates from the desired angle when it starts walking, and there are very precise angle requirements before the walk can be started. With this action, the pass success rate is 0.08. This action is also less bothered by the starting distance from the receiver, as the player can walk a large distance in one straight line.

Predictive Pass Interception

The ball carrier can decide to shoot not directly to the receiver but slightly to the side, this is called 'predictive passing', as the ball is shot to the predicted location of the receiver. The ball is shot when the receiver is not there yet, but it will get to the ball at the perfect frame. This makes the ball roll into the receiver's feet from the side, and he does not have to stop and turn towards the ball.
Just as with any pass, the defender goes towards the nearest point on the path of the ball to intercept it (as described earlier). Except now, the defender is never already on the path of the ball when it is shot.
In order to not allow the receiver to get a head start at the run to the ball, turn mimicking is applied, as described earlier in this section. The ball receiver has to line up in the direction of where he must go in order to catch the pass. Since the defender is also turned in that direction, the defender will get to the ball first if he starts moving at the same time as the receiver does, as he is closer to the ball.

Predictive passing is not currently available in the environment. This means the interception cannot be evaluated like the other methods in this section, as when no pass can succeed, the pass success rate will always be zero. It could be evaluated so that a pass is successful when the receiver touches it, but there is still the issue of where to pass. If you do not know that, you are not testing the interception of actual predictive passes, but just shots not directly at the receiver.

However, a theoretical evaluation can be performed, which still gives a good indication of the interception performance. The only way the receiver can gain an advantage, is to start running before the defender does. This actually works, despite the defender analysing every frame. This is due to the fact that when a movement order is given to the environment, actual movement only starts two frames later. Only then does the defender see movement and starts the movement process itself.
If the ball is passed and the movement is started on the same frame, the defender can start moving immediately, as it analyses the pass and knows where to go. A predictive pass method is therefore more effective if the pass is not immediately made.
Concluding, the predictive pass interception is not frame perfect, but it will suffice for predictive passes with a couple frames of margin.

3.3.1 Distance Ratio

To cover an opponent, the player stands on the line between the two attackers. It is not immediately clear however where on that line to stand, which can also be expressed as the ratio of the distance between the two attackers, away from the receiver. This distance ratio is represented by a parameter in the algorithm and testing different ratios is therefore simple.

Logically, covering will work best when the defender has to change positions as least as possible, as when it is moving between positions the receiver is not fully covered. In the environment, passing can be done quickly, but receiving is a precise process and the receiver needs quite a bit of time to get to the exact receiving location. So just as in real soccer and in other ball sports, it makes sense for the defender to be close to the receiver.

The results of testing distance ratios for direct passes for both a Forward and a Defender can be found in Figure 3.

pass% - possession%		interceptor			interceptor	
		f	d		f	d
distance ratio	0.1	0.013 - 0.693	0.000 - 0.653			
	0.15	0.013 - 0.666	0.000 - 0.853		0.006 - 0.686	0.003 - 0.770
	0.2	0.000 - 0.733	0.066 - 0.706		0.003 - 0.706	0.026 - 0.693
	0.25	0.000 - 0.706	0.026 - 0.760		0.030 - 0.680	0.026 - 0.66
	0.3	0.026 - 0.640	0.026 - 0.680			
	0.35	0.053 - 0.573	0.053 - 0.613			
Runs		75			300	

Figure 3: Results of different distance ratios for direct passes

First, several distance ratios across a large range were tried with a smaller amount of runs. The best ratios were then tried again, but with more runs to get a more accurate result. As can be seen in the figure, the best ratio for a Forward is 0.2 and for a Defender 0.15, for both blocking the pass and taking possession of the ball.

3.3.2 Player Composition

Since different players have different abilities, the defender might perform badly in a certain player composition. In order to find out if this is the case, all possible compositions were tested. The results are in Figure 4.

pass% - possession%		passer			
		f		d	
75 runs		receiver		receiver	
		f	d	f	d
interceptor	f	0.000 - 0.613	0.000 - 0.760	0.026 - 0.493	0.120 - 0.360
	d	0.000 - 0.693	0.026 - 0.706	0.000 - 0.693	0.000 - 0.653

Figure 4: Results of different player compositions for direct passes

From the figure it can be seen that when the interceptor is a Forward and the passer a Defender, the possession rate is far below average. This makes sense, as a Defender can turn more quickly than a Forward, which means a Defender is turned towards the ball sooner and can take possession more often.
When the receiver changes from a Forward to a Defender, the pass success rate goes up.

This also makes sense, as the interceptor always misses some passes, but the receiver is now better at receiving them. This does not happen when the passer is a Forward, as the passer turns slower and therefore also shoots slower. This gives the interceptor more time to get into position.

4 Responsible Research

All relevant data acquired during this research was aggregated into the statistics presented in this paper, so no data has been dropped or made up.
No humans or other parties have been involved in this research, and it is unlikely that any will be involved in the future of this research about AI soccer. Therefore ethical issues like violating the GDPR and data biases are not applicable to this research.
All of the research in this paper was conducted in a closed environment, so reproducing the results of the algorithms that have been presented in this paper should be very doable, once the environment, developed code and configuration files are all freely available. There are some random factors in the tests, so there might be some slight deviation in any reproduced results.

5 Discussion

5.1 Marking

It is unfortunate that the marking strategies cannot be evaluated in practice. Zonal marking is optimal in respect to walking distance whilst also satisfying two other criteria (see Section 3.2). Man-to-man marking is neither optimal nor satisfies the criteria, so it is reasonable to assume that zonal marking will outperform man-to-man marking in a real match.

5.2 Opponent covering

As explained in Section 2.2, due to the cumbersome movement of the players and precise requirements for receiving a pass, performing a successful pass is not a quick process. In Section 3.1 it is described how the tests accommodate for this fact. As described, the receiver is given enough time to get into position, and so the interceptor also has enough time. One can argue that the low pass success rate for direct passes is not representative of the success rate in a real game, as there will be situations where the interceptor does not have enough time to get into position.
This is true, but it still has been shown in Section 3.3 that direct passes are blocked very well provided the defender has enough time. If there is not enough time, then the interceptor is still far away from the receiver. Then it is the fault of one of the many factors in the game, and not of the covering algorithm that the pass is successful. It therefore does not make sense to test these situations, as they are not the responsibility of the covering algorithm.

Testing with the setup as described in Section 3.1 might seem too simple, as there are many more possible situations. This paper is about just one player covering one other player, however, and as said before the receiver needs enough time in order to have enough successful passes without a defender. The player positions are randomized, and other setups would either not be relevant to this research or boil down to the setup already in place.

Aerial passes are blocked less effectively than direct passes. This is due to the fact that there are more steps to take, and they are also quite precise, as explained in Section 3.3

Aerial Passes. For the attackers the setup is the same however, and this gives them an advantage. The pass success rate for aerial passes is still quite low, and it is likely neither a direct pass or an aerial pass would be performed if the receiver is covered. Instead, a predictive pass would be performed.

Predictive passes are more likely to be performed by the attacker, as shooting directly at the interceptor is not very appealing. These types of passes can be countered almost frame perfect with turn mimicking, as described in Section 3.3 Predictive Pass Interception. Only when the opponent has a frame perfect solution will they succeed.

Potential Improvements

As stated in Section 2.2, the opponent covering algorithm is currently straightforward, and mostly consists of standing on the line between the two attackers, and mimicking the receiver's turn. When one sees this algorithm, they might think it is too simple and restricted, as there are many more aspects to a real game. Standing more in the direction of the goal to better block predictive passes is incentivizing and seems logical, as shown in Figure 5.

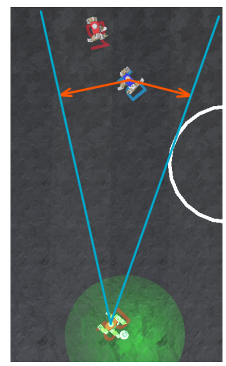

Figure 5: Covered area for predictive passes

Despite seeming logical at first, the only advantage of this strategy is that passes cannot be in a certain direction. There are several drawbacks to standing in the direction the goal, however.

The biggest drawback of standing more towards the goal is that the player has to be turned in the direction of the direct pass in order to catch that pass, and the defender is on the side of its own goal. Catching a pass within the covered area now has a high rate of success, but the opponent will most likely not attempt it. Shooting outside of the covered area is logically much better, and since the defender is now turned away from the goal, the receiver will get to a predictive pass in the direction of the goal first as it has to do less turning.

Another disadvantage of this strategy is that taking possession of shots no longer works, as there is no time to go the path of the ball and turn towards it.

Turn mimicking, which was shown to be very useful also cannot be used anymore with the strategy of standing in the direction of the goal.

5.3 Machine learning

The original intent for opponent covering was to first make a crude rule-based covering algorithm, and then apply Q-learning to learn the optimal positioning. The hard-coded algorithm already performed great however, and when the environment got more familiar, doubts about applying Q-learning arose.

After some tweaks to the rule-based algorithm (Section 3.3), it performed so well that it seemed unlikely that machine learning could improve the result, and the rule-based solution was further developed to counter different kinds of passes. These are the reasons Q-learning was not applied:

- The reward of an action has to be propagated back through 200 frames and a changing environment. It is not feasible for this to be done, as there is not enough Q-learning experience available.

- The only objective is to stop the ball, so there is no reward for almost stopping the ball. Good attempts are therefore not rewarded.
- Training has to be performed with the built-in environment actions, these actions are cumbersome and a good position might not be rewarded due to player movement.
- If the Q-learning is to compete with the rule-based algorithm, more than just positioning has to be learned. This means more freedom and possibilities have to be given to the learning process, slowing down the process exponentially. As the environment is already almost too slow for batch-testing (slower than real-time), advanced Q-learning and therefore competing with the rule-based algorithm is definitely not feasible.
- Q-learning can only respond to states it has trained upon, as for each state every action has a reward mapped to it. If a new state is encountered, no rewards for the actions are learnt yet, and the player does not know what to do.

6 Conclusions and Future Work

1. Which marking strategy gives the opponent a lower pass success rate: zonal marking or man-to-man marking?

   Although the strategies cannot be compared or evaluated in practice, zonal marking is more optimal in theory, and will logically perform better in practice.

2. What is the best position for a player to be in, in respect to the ball carrier and another opponent when assigned to cover that opponent?

   The best position before a pass is made is on the line between the attackers performing the pass, at a certain distance ratio (ratio of the distance between the two attackers, away from the receiver). For a Forward a distance ratio of 0.2 is optimal, for a Defender 0.15 is optimal. This means a Defender stands a little closer to the receiver than a Forward.

3. Can Q-learning be used to learn the optimal covering positioning, and does it outperform a rule-based solution?

   It is unlikely the optimal positioning can be learnt. The rule-based solution is already practically optimal, and uses strategies other than just positioning for opponent covering, which are very hard to learn with machine learning. It is therefore very unlikely Q-learning will out-perform or even match the rule-based solution.

This research focused mainly on developing a marking strategy and covering a single opponent without the ball. Most aspects of opponent covering were evaluated by performing many pass tests automatically with an in-house developed test runner.
Marking and predictive pass interception could not be verified in practice, which is due to the strategies they are countering not being available. They are theoretically optimal, however.

There proved to be too many difficulties for Q-learning to be applied, the main reason for these difficulties was the environment being slow and imprecise. It also turned out that the problem of covering opponents was much more complex than just standing at a position, which made applying Q-learning even less feasible.
The rule-based solution to opponent covering does perform very well however, so there still is a good solution to the problem.

Future Work

The most pressing thing to do is to verify the effectiveness of the algorithms which have not been verified yet. This will be possible once an attacking AI and a predictive pass system are in place.
Besides that, a prioritization system could be set up for covering attackers. An attacker at the back of the field might not be worth covering, and the defender assigned to him might be more useful near his own goal. Finally, the state of the passer could be analysed to predict future actions, in the same way it is already being done with the receiver.

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