From Global Localization to Contextual Perception – A Novel Approach to Stable Decisions in Robot Soccer

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Abstract. Decision-making in humanoid robot soccer is usually approached from the perspective of a team-level strategy. Existing approaches typically rely heavily on accurate global positional information derived through self-localization. However, maintaining a complete, consistent, and accurate global model can be challenging in situations with a high degree of uncertainty that often occur in robot soccer due to limitations in perceptual capabilities, limited computational resources, and the dynamic nature of the game. Humans and other animals are able to navigate such situations by relying on accurate local cues and approximate global perception for individual decisions, while coordination on the team level emerges implicitly, resulting from the anticipation of other players' decisions. In this work, we study the role of global and local information in decision-making and the interplay between them. In an isolated example scenario, we demonstrate that an accurate decision can be made based on the local perceptual information while the global model is only needed to resolve ambiguities in the local view. With this, the task of the global model is reframed from localization to a classification task that helps identify the relevant local context, significantly reducing the demand for accuracy. We show how this approach can be integrated with the anticipatory approach for decision-making based on internal simulation. Preliminary experiments indicate that with this, accurate and stable decision-making can be achieved without complete and accurate global knowledge.

Keywords: decision-making · anticipation · self-localization · local perception

1 Introduction

In humanoid robot soccer, robots must make rapid decisions to coordinate both their individual actions and team behavior. Unlike other experimental setups,

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robot soccer allows for dynamic situations with a high degree of uncertainty, making it well-suited for studying decision-making in complex situations.

In robot soccer scenarios, the decision making is mostly considered from the perspective of team coordination in a global context, where the decisions of the individual players are derived from general strategic decisions made for the entire team. These decisions require a global representation, which usually includes the positions of the robots involved in a situation and explicit communication between the players to synchronize the decisions within the team. Studies focusing on individual decisions are sparse and typically rely on a global representation of the situation. In addition, a large portion of studies into decision-making are limited to experiments in simulated environments. A recent survey [2] provides an overview of decision approaches within the robot soccer domain. The survey approaches the decision-making from the perspective of "game strategies" – "team strategies and joint decision-making processes", and also includes approaches for decision-making on the individual level.

Coordinated team play in human soccer seems to emerge synergetically from individual player decisions, rather than from a global strategic plan, as supported by recent studies such as [3] and [27]. Essentially, individual players do not "plan for the entire team" during a game to derive their actions from the common strategy. On the contrary, they focus on their local situation to make decisions using the common strategy as a guideline and rely on others to act in accordance with it as well. This separation is crucial for dealing with the high uncertainty that the players are experiencing during a game. This approach alleviates the need for a complete and accurate global representation of the entire game and the need for extensive explicit negotiation between the players during a game.

In this work, we focus on individual decisions under limited perceptual information. We argue that coordination on the team level, like passing a ball, will emerge from individual decisions. To achieve that, individual agents need to be able to anticipate the outcome of their actions, which can also be used to predict the behavior and decisions of other players.

We will use an example of selecting a kick action to study the role of local and global information in decision making. This work expands on the preliminary discussion published in [18] and draws from the [17]. We propose an approach based on anticipation and internal simulations that combines global information about the robot's location with local perception to enable accurate decisions despite inaccuracies in self-localization. For this, we introduce an extension to the predictive decision approach presented in [21,20].

2 Decision-Making in Robot Soccer Scenarios

In the following, we briefly review a selection of relevant approaches for decision mechanisms that focus specifically on the setting of robot soccer and discuss them from the perspective of the perceptual information that is required to make decisions.

The most robust and widely used approaches in scenarios with real robots remain based on probabilistic and heuristic approaches with a hierarchical structure. This structure divides the decision problem into manageable components, like the task of positioning and path planning to approach the ball. It allows for each of those components to be made stable. An example of such an approach can be found in a recent study [24], where a probabilistic decision system for team coordination for wheeled soccer robots in the RoboCup Midsize-League is discussed. Due to their construction, the robots in the Midsize-League allow for stable perception with a large global overview of the situation, which is not the case for humanoid robots.

Two notable examples of decision making on a team level for humanoid robot soccer are [8] and [26]. In [8], the authors present an approach where the selection of a kick action is made based on stochastic simulation as part of a probabilistic framework for team coordination. The decision relies on global knowledge of the positions of other players. The study was conducted in an abstract simulation. In [26], Röfer et. al. discuss a multi-layered approach to decision-making that is deployed in real soccer games with humanoid robots. To decide on team behavior, such as the direction of a pass, the robots rely on accurate representations of the global positions of players from both their own and their opponent's teams.

In robot soccer, adaptation in the form of learning is often done in simulated environments and, in some cases, transferred to real robots. The learning architectures studied in simulated environments often do not consider the limitations and significant uncertainty in perception that arise in real robot soccer. This severely widens the *reality gap* and limits the possibility of transfer to real-world scenarios.

In the study [15], humanoid agents learn to play soccer in a simulated environment, whereby all aspects are learned in a multi-stage process, beginning with skills to strategic decisions. The analysis results show, in particular, that the agents acquire an ability to predict the behavior of opponents and teammates. The analysis also shows a positive correlation between the higher performance of an agent and its ability to predict future game states. This approach was extended to real robots in [11], where small humanoid robots learn to play soccer "one versus one" in an isolated environment. The robots develop and demonstrate impressive skills such as running, getting up, and scoring goals against each other. The uncertainty in this setup is reduced by using soft walls and the floor to limit the chance of damage and by an external tracking system providing robots with accurate, detailed information regarding the state of the environment.

The study [14] introduces layered learning, a machine learning framework designed to address complex, multi-agent tasks like robot soccer by breaking them into a hierarchy of subtasks. For example, basic skills like moving to the ball are first learned, followed by more advanced skills like passing and shooting. Finally, these individual skills are combined into team strategies that require coordination and adaptation to dynamic game situations. The approach was applied in the physical, simulated scenario in RoboCup, where their team won the championship over several years. In a reduced setting, the authors demonstrate that certain specific skills, like ball interception and shooting behaviors, learned in simulation could be transferred to real robots. This, however, required manual fine-tuning to account for such aspects as actuator limitations and sensor inaccuracies.

A number of works focus on the task of selecting an optimal kick-action. In [6], a probabilistic approach is used to describe the kick selection problem, which is then solved using the Monte Carlo simulation. In [8], the kick is chosen to maximize a proposed heuristic *game situation score*, which reflects the goodness of the situation. In [1], the authors use an instance-based representation for the kick actions and employ a Markov decision process as an inference method.

3 Self-Localization in RoboCup

Self-localization is an integral component in mobile robots in general and has been studied in RoboCup soccer since the very beginning [5,7]. It seems natural that a robot needs to know its location in the environment to navigate and perform tasks, and an explicit representation of the robot's position is convenient and universal.

Because of its universality and convenience, self-localization is often used as a central point of the robot's behavior and as a basis for *global and local decisions*. This demands the self-localization to be both - *stable* regarding integrating percepts from different modalities over extended periods of time, and *accurate* to enable fine-grained local decisions. Trying to accommodate both demands is challenging and might lead to either inconsistency in self-localization or low fidelity in local navigation due to inaccurate estimation of the robot's global position.

This issue has been extensively studied from different perspectives: alternative state space representation and explicit detection of inconsistencies [10,9], questioning of the Markov Assumption [12], analyzing and finding more stable sensor models [19], and studying geometric stability of landmarks [16,12] and more recently [22].

Typically, the self-localization in RoboCup SPL is based on particle filters (Monte Carlo approximations) [5,7,25,4] or Multi-Hypothesis approaches[23] and [28]. Because of the limitation in computational resources, they are usually implemented with a high degree of discretization, e.g., with a low number of particles or hypotheses.

Of course, higher precision and robustness can be achieved with more sophisticated approaches that would require a significant expansion of the state, e.g., memorizing past locations and considering correlations between individual observations, similar to approaches like Graph-Based SLAM or approaches based on Deep Neural Networks. While such methods are available, they come with a significantly increased complexity in implementation and computational effort, and a fundamental question remains unanswered: *do we need (an accurate) localization to make accurate decisions?*

The classical view on predictive reasoning in space is planning. In the well-known book "Planning Algorithms"[13], LaValle remarks that many tasks can be achieved without knowing the exact state. On the other hand, humans are able to realize accurate behavior by combining rough *cognitive maps* for global decisions [29] and accurate *perceptual maps* for local decisions.

We will demonstrate that an accurate representation of the robot's location is not necessary to make stable decisions, and we will show that stable and accurate behavior can be realized with *simple methods* like Monte Carlo sampling and only rough approximations of motion and sensor models. We will split the task of representing the environment into local and global contexts. With this, self-localization can focus on a stable estimation of the robot's location with low requirements for accuracy. We will reformulate the task of the global model from the *estimating robot's global position* to *identification (classification) of the local context*. Our preliminary experiments indicate that this division can significantly improve the stability of the robot's decisions.

4 Localization of Decisions

Making decisions on the soccer field, like choosing a direction for a kick, requires the robot to have a representation of the objects in its surroundings. Dynamic objects involved in the immediate interaction, such as a ball or obstacles, are typically represented by local models. Static objects like lines or goals are represented implicitly as part of a map, paired with the estimated position of the robot within the map. When choosing a direction for a kick, the robot essentially aims to control the relationship between the ball and other objects, such as the goal (the ball needs to be inside), the outer line (the ball should not cross and leave the field), or between the ball and an obstacle (the ball should not collide).

The interactions between the objects in the local frame can usually be estimated with a high level of accuracy because the objects are observed close to each other in time and might even be directly visible in the same image of the robot's camera. The interactions between the ball and the static objects, like goals, are typically done in the global frame (global field coordinates) and involve computations based on local (ball model) and global models (self-localization). Effectively, this corresponds to considering the relationship **BF**. The mismatch implies that the robot attempts to control the relationship **BG** between the ball and the goal indirectly by controlling the relationship between the ball and the field **BF**. Making accurate decisions would require high accuracy in the estimation of the robot's location on the field, at least in the proximity of important objects like goals or outer lines. On the one hand, this can be challenging to achieve on a robot with limited resources in a dynamic game with a limited number of observations. On the other hand, humans are able to combine only a rough global representation with local perceptual information to make and execute accurate decisions. In the future, we can expect robots to play on fields with varying sizes and incomplete or unconventional features, like two backpacks marking a goal, as in the "Any Place Challenge" in RoboCup SPL in 2014.

Fig. 1. The left figure shows an example scenario where the robot observes a ball in front of a line. The figure on the right shows the situation from the perspective of the robot's camera.

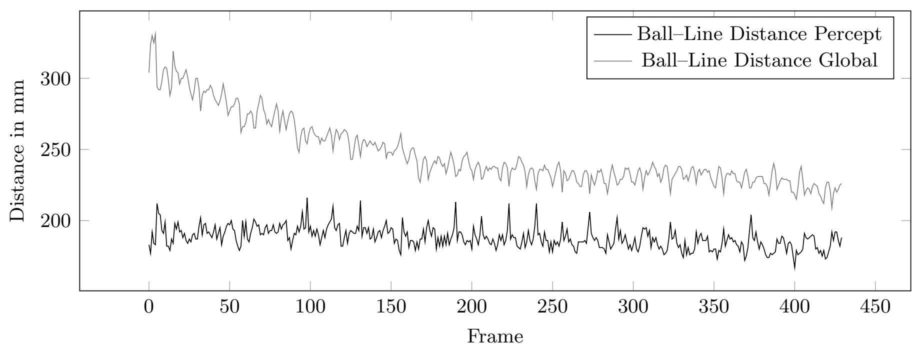

Fig. 2. Distance between the line and the ball estimated based on the local perception (black) and based on the global self-localization (gray) while approaching the ball.

Consider an example scenario where a robot must decide whether a ball is inside or outside the soccer field, as illustrated in Figure 1 left. Figure 1 right illustrates the view from the perspective of the robot's camera. A ball is located close to an outer line of the field, and the robot can observe both the ball and the line.

This type of decision can play a crucial role in a real setting of robot soccer. The ball leaving the field triggers a protocol (*set-piece*) that drastically changes the situation, where a human referee manually relocates the ball to a specific location, and a special set of rules is activated. This drastic change might introduce additional uncertainty in the robot's behavior. For instance, from the robot's perspective, the ball might seem to disappear and reappear at another location, resulting in a discontinuity in the ball's behavior. The robot can use this decision to react adequately to the situation.

Typically, this decision could be solved by transforming the perceived location of the ball into a global coordinate system and comparing this global position

Fig. 3. Situation perceived by the robot. Left: Local representations of an observed line (green bar) and the ball (orange circle); the line is identified as "0" (red number) - meaning "right outer field line". Right: Global situation model derived from partial models: particle cloud models the robot's position on the field; the lines detected in the image are classified by the voting of the particles (blue lines with the corresponding number of votes).

of the ball with the map of the field to determine whether the ball is inside or outside the field area. The accuracy of this decision depends directly on the accuracy of the estimated position of the robot. Figure 2 shows the distance between the ball and the line computed based on the robot's global position and direct local perception while approaching the ball. We can see that the global estimation is significantly less accurate than the local one.

Let's take a closer look at the example setup Figure 1 (left) with the question: What minimal information is needed to decide whether the ball is inside or outside the field? If we look at the picture taken by the robot's camera in Figure 1 (right), we see that the ball is located on the same side of the line as the robot. One image alone is enough to extract this information (local context). Depending on the robot's location on the field, the ball might be inside or outside of the field, or inside or outside of the goal (global context). To resolve this, we need to know which line exactly the robot is seeing in the picture. This can be decided based on the robot's location on the field (global context).

The Figure 3 illustrates this inference process. On the left side in Figure 3, we can see the relation between the ball and the line in the local coordinates of the robot. The identifier 0 assigned to the line identifies the line as the *right outer line*. On the right side in the Figure 3, we see the global context - the cloud of particles representing possible locations of the robot is used to determine the local context by classifying the relevant lines.

This conceptualization allows us to structure our inference based on the context. In our example, metric information, like the distance between the ball and the line, can be derived in the local context. The identity of the line is the only

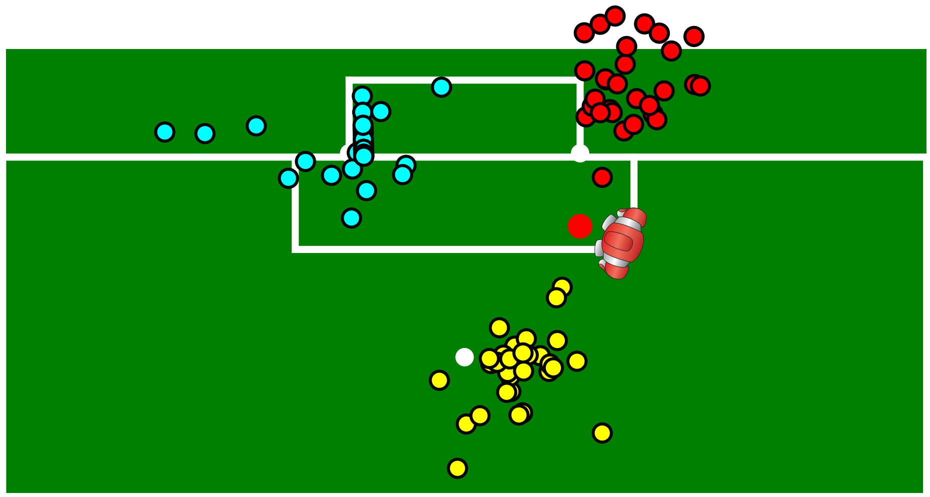

Fig. 4. Simulation of three different kicks: sampled distributions of the possible ball positions after a left (yellow) and right (red) sidekicks, and the forward kick (cyan).

additional information that is needed from the global context. The robot's location on the field does not need to be known accurately to correctly identify the line. We can allow a high level of ambiguity in the robot's location on the field. On the other hand, the relationship between the line and the ball can be estimated with high fidelity based on local information. This significantly reduces the precision required to estimate the robot's location and simplifies the modeling procedure. At the same time, it significantly reduces the uncertainty in decisions.

This approach effectively shifts the role of the global model from estimating the robot's position in the global context to identifying the objects and perceptions in the local context.

5 Predictive Decision-Making based on Internal Simulation

In this section, we briefly summarize and extend the decision approach based on anticipation and internal simulation introduced in [21,20]. The algorithm was tested in simulation and real games and is being used in games by the team *Berlin United* in the SPL league.

The approach was implemented to decide on a kick direction. Figure 4 illustrates an example situation where the ball is located in front of the robot, and the robot needs to select between the three possible kick actions - kick forward, left, or right. The decision scheme consists of three different phases: *predict*, *evaluate*, and *select*.

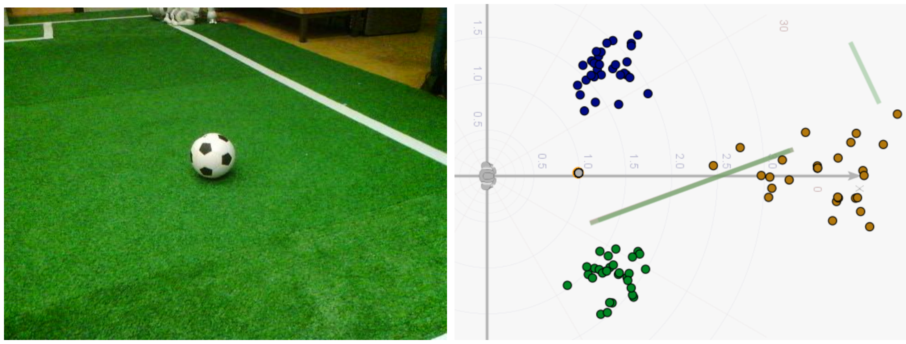

Fig. 5. Left: outer field line, seen by the robot's camera; Right: local view of the robot with the projections of detected lines and predicted results of the kicks (left - blue, right - green, forward brown)

Predict For each kick, the robot simulates possible final locations of the ball after the kick is executed. The simulation approximates a kick model with a Monte Carlo sampling and a rudimentary physical simulation of the ball. It captures only the essential aspects: the final location of the ball and collisions, which are assumed to be non-elastic. The task of the simulation is to capture the essence of the uncertainty in the kick action in a local situation.

Evaluate The results of the simulation of each action are evaluated according to two separate models: (1) a value function that captures the global static aspects of the game, e.g., closer to the goal is better, and (2) the likelihood of discrete events *own goal*, *opponent goal*, *out*, *field*, explicitly capturing the local situation. The value function is computed as an expected value over all samples of the action. The likelihood of the events is computed as a relative frequency; for this, each sample is classified and counted.

Select The selection uses the estimated likelihoods of discrete events to reject actions with a high likelihood of scoring an own goal or the ball leaving the field and to select an action that is likely to score a goal. If the decision cannot be made based on the local decision model, then the expected value is used to decide on an action.

In the experiments presented in [21,20], both steps of the evaluation – the value function and the event likelihoods – are estimated using a global model (the robot's location on the field and the map). The estimation of event likelihoods captures the local situation and needs to be as accurate as possible, while the value function captures the global aspects, like the geometry of the field and the general strategy, and can be approximate. Thus, it makes sense to compute the value function based on the global model (robot's position on the field) and estimate the likelihood of the events based on a more accurate model of the local situation. This would require a specific model for such objects as goals and lines, which can be challenging and would introduce an additional level of complexity. Instead of estimating explicit local models of objects, we propose to classify the individual simulated particles based directly on visual perception as discussed in Section 4.

Figure 5 illustrates the first experiments demonstrating the approach. The decision of whether a ball (particle) crossed a line can be made on the visual perception of a line. The line can be classified based on the global model (self-localization) to decide which line it is. The self-localization does not need to be accurate for the correct classification of the local perception.

6 Discussion

In the proposed approach, we decouple the decision-making from the global model. Local decisions such as "ball over a line" or "ball inside goal" can be made based on local perception alone. A global model is necessary to classify the local perception and to evaluate the predictions when no clear event can be predicted, i.e., the ball stays within the field. Neither of the two tasks requires accurate self-localization, resulting in a stable and accurate decision scheme. Our current work focuses on the formalization of the proposed approach and experiments with different situations that might arise during a game.

In the presented framework, the decisions of others can be represented implicitly through their effect on the environment and the possible outcomes of the robot's own decisions. From this perspective, we do not require an explicit representation of other players; we only need to predict the effect of their possible actions on the environment. This way, the decisions and coordination on a team level emerge directly from the framework for individual decisions.

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