Anticipatory Approach to Combining Local and Global Perception for Stable Decision-Making

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***Abstract*—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 accuracy because the objects are observed close to each other in time and might even be in the same image. 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). For accurate decisions, this 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 features, e.g., two backpacks marking a goal, as in the "Any Place Challenge" in RoboCup SPL in 2014. 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.**

***Index Terms*—decision-making, anticipation, self-localization, local perception**

I. Self-Localization in RoboCup

Self-localization has been an integral part of RoboCup Soccer and mobile robots in general since the beginning of robotics research. It has been studied in RoboCup soccer since the very beginning [1], [2].

It seems natural that a robot needs to know its location in the environment to navigate and perform tasks. An explicit representation of the robot's position seems 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 the integration of percepts from different modalities over longer 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 [3], [4], questioning of the Marcov Assumption [5], analyzing and finding more stable sensor models [6], and studying geometric stability of landmarks [5], [7] and more recently [8].

Typically, the self-localization in RoboCup SPL is based on particle filters (Monte Carlo approximations) [1], [2], [9], [10] or Multi-Hypothesis approaches [11] and [12].

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 the 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 [14] 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 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 representation of the environment into local and global contexts. With this self-localization, we can focus on a stable estimation of the robot's location with low accuracy requirements. We will reformulate the task of the global model from the *estimating robot's global position* to *identification*

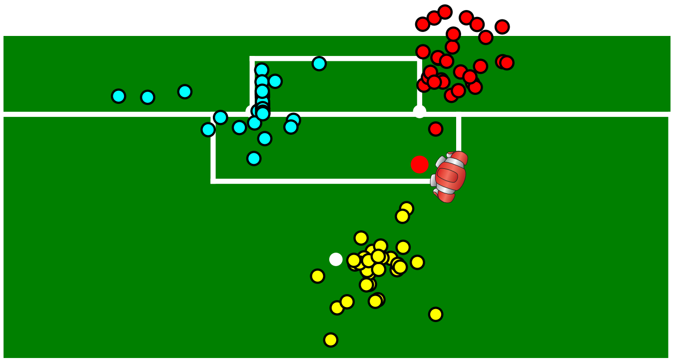

Fig. 1. Simulation of three different kicks: sampled distributions of the possible ball positions after a left (yellow) and right (red) sidekick, and the forward kick (cyan).

(classification) of the local context. Our preliminary experiments indicate that this division can significantly improve the stability of the robot's decisions.

II. Predictive Decision-Making based on Internal Simulation

This section briefly summarizes a decision approach based on anticipation and internal simulation discussed in [15], [16]. 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 1 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*.

a) 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.

b) 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.

c) Select: The selection uses the 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.

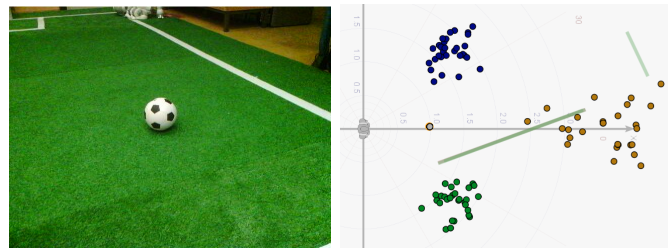

Fig. 2. Left: outer field line, seen by the robot's camera; Right: local view of the robot with the projections of detected lines and predicted results of the kicks (left - blue, right - green, forward brown)

III. Local and Global Evaluation

In this section, we propose an extension to the predictive decision approach

In the decision approach introduced in the previous section, 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 a goal and lines, which can be challenging and would introduce an additional level of complexity. Instead, we propose to classify the individual simulated particles based directly on visual perception.

Figure 2 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 precise for the correct classification of the local perception,

IV. 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. Both tasks do not require precise self-localization. Resulting in a stable and precise decision scheme. Experiments with different situations on the field are being carried out.

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