Prediction of Rapidly Changing Environmental Dynamics for Real Time Behavior Adaptation using Visual Information

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Abstract This paper features a method for acting in a real world environment with rapid dynamics, based on behaviors with different complexity, that emerge from: (1) direct sensing (2) on-line prediction about the future development of the environmental dynamics, and (3) internal restrictions derived by the robots strategy. The method is built upon the understanding of perception as dynamic integration of sensing, expectations, and behavioral goals, which is necessary when the environmental dynamics depends also on other intelligent agents. Two central aspects are considered: prediction of the development of environmental dynamics and the subsequent integration. The integration captures the dynamics of processes that happen in different temporal intervals but relate to the same perception. A real time object tracking method that is used is briefly described. Experiments made in a RoboCup environment with physical robots illustrate the plausibility of the method.

1 Introduction

In real-time dynamic environments reactive control has proven to be advantageous to the usage of symbolic representations and world modeling alone [1]. Reactive control relates direct sensing to robot actions, reflecting the understanding of perception as sensing. In this work is argued, that perception has to be considered as dynamic integration of factors related to the surrounding environment as sensing and predictions about the expected changes in the environmental dynamics, and the internal constraints of the robot as derived mainly by its behavioral goals. The internal constraints are also shaped by the robots physical body and the predefined constraints of the environment. Such an assumption is by far more realistic when the underlying environmental dynamics can deliberately be changed by other intelligent agents.

The integration is worked out within the application framework of the RoboCup scenario: competing robot teams in a soccer game. Since the goals of the two teams are obviously incompatible, the opposite team can be seen as a dynamic and obstructive environment [5]. The context of the environment narrows the possible specter of plausible actions. Since sensor readings are available and behavioral goals are definable during the robots operation, the prediction of the opponent players behavior (which in a general context is a prediction of the dynamics of the environment) will further determine the best action.

Gross et al.[4] and the preceding works of Kosslyn [6], Moeller [8], and Pfeifer & Scheier [9] emphasize on the interrelated nature of action and perception, and lead towards an anticipatory model of perception, i.e. perception defined by the anticipatory action. Gross et al.[4] realize an internal anticipation and evaluation of several alternative sensory-motor sequences as a basis for an action-oriented perception. In addition, search methods are proposed, that will help selection of anticipative action. The performance of this neuro-biologically plausible model showed good results in navigation tasks in a static environment.

In dynamic environments however, the behavioral goals, which determine rather strategy-defined than logically straightforward actions, is a substantial part of the perception-action cycle. For instance, often in a real world the prediction of what is going to happen will determine one type of behavior, but goals, which have to be achieved can lead to completely different behavior.

To enable prediction, visual input data needs to be processed. The most widely used approach for object recognition in RoboCup is assigning pixels to color classes by thresholding, segmenting images by color, and assigning objects to so-called blobs in the segmented data [2]. It is clear that thresholding needs adjustment in different environments and that blob assignment to objects works only under highly restricted conditions. A newly developed approach that is robust under lighting conditions and that makes use of knowledge from the environment is proposed.

This paper is organized as follows: Section 2 outlines our hypothesis and approach. In Section 3 the vision method that is developing towards the state-of the art requirements of the sensing system is described. Section 4, features the prediction method. Some results with data from real games are shown. Section 5 outlines the integration process and finalizes the paper.

2 Perception-action model

The suggested perception-action scheme (Figure 1) accentuates on three elements of the action-oriented dynamic perception: direct Sensing, Predictions (expectations) and Behavioral goals and constraints. Sensing denotes the information, that is directly recorded by the sensors. It refers to the instant moment. Predictions are made on the basis of the on-line learned information about the environmental dynamics during the recent history and describe the expectations about its future development, i.e. it describes a future time event. The Behavioral goals (and constraints) reflect the available knowledge to the robot about the short-term goals it has to fulfill by taking the restrictions of the environment and its physical body into account.

Moreover, since perception is an intrinsically active process, it guides the actions of the robot and, conversely, the actions can take place in order to capture sensory information. The integration of the instant perceptions in the context

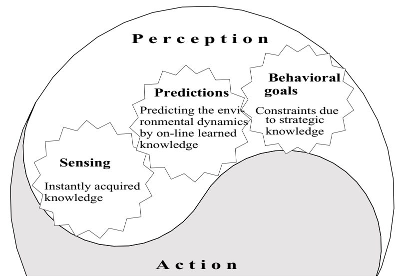

Figure 1. Proposed scheme of the perception-action interplay. The dynamic nature of this cycle is not explicit in this scheme, but has the following meaning: A history of sensing triggers predictions, the predictions shape the short-time behavioral goal which determine the action. Conversely, the action can be chosen to gather specific sensory information.

of the current situation (e.g. learned experiences and prediction about future development of the environmental dynamics) is the ultimate aim to be achieved.

The plausibility of this model has few aspects. First, it is closer to the actual nature of the perceptual process. Second, the multi-agent dynamic environment adds another degree of complexity to the behavior-oriented robotics: the robots action depends on various moving objects, some of which can commit deliberate changes into environmental dynamics due to opposite behavioral goals.

3 Object recognition

The proposed system for object recognition is build on a novel solution of real time object recognition. A combination of color and spatial reduction of image data insures a strong reduction of the visual information stream, and eases real time processing. Due to the fast dynamics of the environment this reduction is advantageous to all existing object recognition and tracking methods in RoboCup. The method insures real time perception and therefore makes prediction possible.

Detection of objects for a soccer playing robot comprises the following stages: color space reduction, spatial data reduction, color grouping, and object recognition.

Color space reduction transforms a full color image to an image of 7 different colors, white, black, green, blue, yellow, orange, and magenta. This reduction method is similar to the evaluation of colors by humans and therefore robust to lighting conditions, contrast differences, and moderate noise. Spatial reduction is performed to guarantee real time processing and is obtained by constructing a two dimensional perspective grid. The gridlines are obtained by calibration of both lens and camera angle with respect to the playground. The gridlines are separated by steps of 10 cm in the real world, which suffices, since all objects are at least 20 cm in size. The constructed grid is used to perform color segmentation. Objects, in turn, are evaluated as a set of segments and evaluated by their physical properties.

a) b)

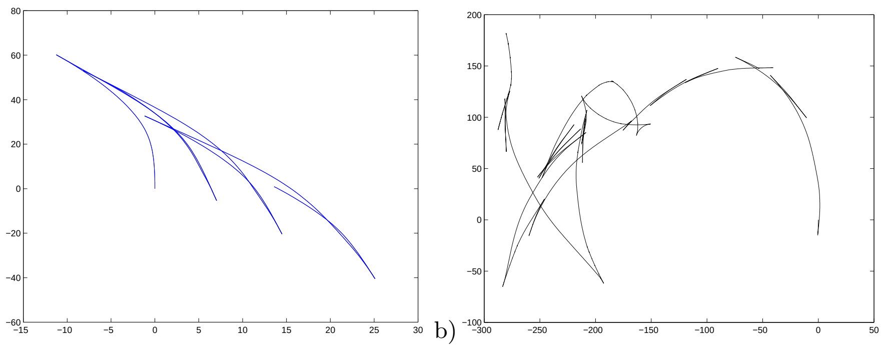

Figure 2. Robot path by no-attack a) and attacks from the left b).

4 Forecasting the environmental dynamics

Forecasting is build upon learning of the opponent robots behavior, or (initially) on the assumption of what the opponents behavior might be in the current scenario. Real-time prediction of the upcoming event based on on-line coming sensory cues is a very ambitious task. Instead, the forecast of a "type" or a "model" of the opponent behavior, is made during the ongoing game.

The on-line learned information of how the environmental dynamics tends to change, is a basis for predicting the complete upcoming event. The on-line coming sensory readings alone can be a base of a prediction of upcoming temporal history of the considered variables, if a drastic change does not take place. In environments with rapid dynamics unexpected changes are very possible. To cope with that fact, a representation on event level of abstraction is needed, together with incorporating the knowledge for the behavioral goals, the robot has to achieve.

More concretely, forecasting is build upon learning of the opponent robots behavior and the ball trajectory, or (initially) on the assumption of what the opponents behavior might be in the current scenario. For experimental testing an attacker-robot is used, that has to predict the goalie behavior. Within the RoboCup scenario, there are several possibilities for the behavior of a goalie: it opposes the movement of the ball; it opposes the movement of the ball and the attacker, it makes intermediate strategic movements (for instance in randomly chosen direction) in order to increase the complexity of the attackers decisions, the robot has unpredictable behavior (due to inaccuracy or malfunctioning).

It is important to say that the robot soccer programming and development environment provides processed sensory information in real time. For instance, instead of raw images, time series of distances and angles to the ball, goal, and recently other robots are available. In addition, the dynamics of behaviors like "following the ball" or "avoiding obstacles" can be recorded. A snapshot of sensor recordings and behavioral dynamics during a RoboCup game are shown in Figure 3a.

By combining the data from sensory and behavioral tracking the trajectory of the goalie is restored. The robot trajectories from many games and from simu-

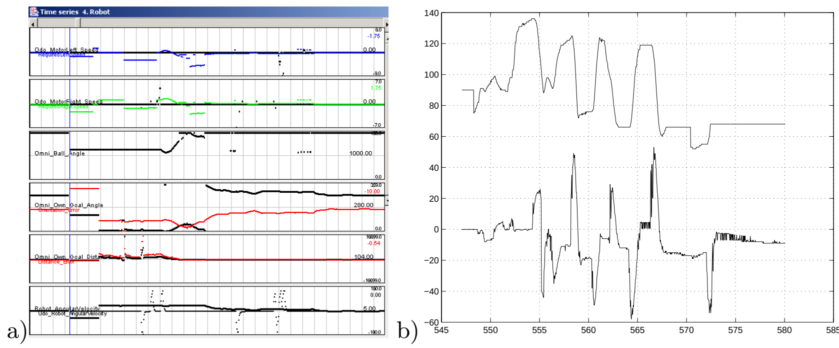

Figure 3. a) Recordings of sensor and behavior time series from a soccer game. b) Correlation between ball angle (top) and angular velocity of the robot (bottom).

lations are clustered by a neural gas algorithm [7] to represent various attacks or non-attack situations. In Figure 2 two typical trajectories of a goalie are shown: no attack (Figure 2a), and two subsequent attacks from left (Figure 2b). The trajectories, as clustered by the neural gas algorithm are used to derive the time the attacker has and the itinerary it has to take.

Once the dataset of trajectories are clustered, on-line classification of data takes place. The type of the attack situation is distinguished and the corresponding trajectory can be added to the attackers ”normal” movement.

In the second experimental stage the relational trajectories are clustered, instead of trajectories that describe the movement of the robot. The relational trajectories describe the behavior of the goalie with respect to other moving objects: the ball and the attacking robot. Figure 3b illustrates that there is a strong correlation between the direction of movement of the ball and the response, i.e. the movement, of the goalie. Strong correlations can be found as well between the movement of the goalie with respect to the combined trajectories of ball and attacker.

5 Integrated perceptions in perspective

The dynamic interplay between the three elements (sensing, perception and behavioral goals) reveals the following stages: Initially, sensing and the straightforward behavioral goals are naturally integrated into the programmed behaviors. Acting in dynamic environments requires forecasting the tendency of environmental changes for adapting the behavioral outcome. Drastic changes in the robots surrounding indicate dynamics, caused by the actions of other intelligent agents or moving objects. They accentuate the need of incorporating the strategic knowledge, expressed as emerged short-term behavioral goals into the behavioral system. The three elements finally are expressed as trajectories or deviation from the trajectory, that will be taken by direct sensing only. Hence, the integration task transforms to combining the corresponding trajectories.

Previously, integration based upon temporal coherence principle has been proposed [3]. Due to its dependence of temporal cooccurrence of the information, the approach is not directly applicable for events that have happened in different temporal segments: sensing (current time), predictions (reflecting a future event, estimated on recent history), and (predefined) strategic knowledge. In this work the temporality is defined as relatedness to an event. After defining which part of every trajectory is related to the same event, the method proposed in [3] can be applied. In addition, the combination of the three trajectories has to cope with the problem of competing aims and is a self-contained problem to be solved in the future.

The suggested prediction method remains the central problem in this work. It has been put forward, that the prediction has to be made only within the interdependence of sensing and behavioral goals. The prediction captures the strategy of the goalie trough on-line analysis of the motion trajectories of the robot and its surrounding objects. To accomplish the on-line analysis, classification to previously learned types of behavioral models is made. The neural gas algorithm allows inclusion of a new class, if an unknown situation is encountered. As discussed before, this makes it suitable for on-line processing. An on-line version of the algorithm, that does not subdivide between clustering and classification will be considered. Additional experiments will be made that adapt to the extensions of the newly developed vision system.

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