Plan Recognition for Behavior Estimation in a Robotic Soccer Player

Douglas Antunes Tesch
Pontifical Catholic University of Rio Grande do Sul

Abstract

The main goal of this work is to identify the behavior of a robot during an action, using the state of the art in motion planning. In addiction, we propose a self formulation for the problem. This proposal is a partial work of the *Planejamento em Inteligência Artificial* graduation course at PUCRS.

Introduction

The advantage of plan recognition is the ability of anticipate the agent behavior. This is important in many of applications, such as traffic monitoring (Pynadath and Wellman 2013), dialog system (Carberry 1990), crime detection and prevention, and prevent an enemy strategy plan in the military area (Azarewicz, Fala, and Heithecker 1989; Agmon et al. 2008; Pearce, Heinze, and Goss 2000).

In the first works, most of the plan recognition approaches employed plan library to represent the full behavior of an agent; thereby, the library hold all plans of achieving a set of goals (Geib and Goldman 2005). Most recent works are using planning domain to represent the potential agent behavior. This formulation enable the use of off-the-shelf (OTS) planner algorithm (Ramírez and Geffner 2010), and was named as Plan Recognition as Planning (PRP).

In many applications, the problem formulation is defined in the discrete world. However, when deal with robotic angles, translations, positions, and motions they are in continuous world. The robot interactions with the environments and behaviors must be discretized to use in PRP algorithms. Unfortunately, without any information about the dynamic, a fixed discretization lead us to a lost of information (Nash and Koenig 2013).

The present work uses the planning formulation named mirroring (Kaminka, Vered, and Agmon 2018). The main contribution of mirroring is that the planning could considered the discretization as a change variable. Thus, for any recognition problem in continuous world the planning could always find a discretization that represents the observations.

Domain Formulation

A domain theory W is a tuple $\langle F, V, A, cost \rangle$, where F is a finite set of fluents, V is a set of sets where $\{V_f | \in F\}$, A is a discrete and possible infinite set of actions, $cost$ is the metric to evaluate the transformations between states. The fluent F are basic used to described states, for example, a fluent of a 2D soccer robot described by position and orientation in a Cartesian plane is given by

$$F = \{x(r), y(r), \theta(r)\}, \tag{1}$$

where r is a constant to represent the robot. A set of fluents literal $s = \{x(r) = 10.14, y(r) = 7.13, \theta(r) = 45°\}$ is a state with following properties: it is consistent, and assigns a value to all fluents in F. A set of fluents is considered inconsistent if there is a $f = v_1$, $f = v_2$, where $v_1 = v_2$.

The actions $a \in A$ transforms the fluent literals, changing their values. Plans π is a finite sequence of actions $\pi = (a_1, \ldots, a_k)$ from initial state s_0 to goal state s_g, such that a_1 is applicable in s_0 and so on.

Plan Recognition Problem

A recognition problem is a tuple $R := \langle W, O, I, G \rangle$, where W is domain theory defined above, O is a sequence of observations, I ∈ W is a initial state, and G ∈ W a set of goals. The sequence $O = [o_0, \ldots, o_n]$, where $n \in N$ and $o_0 = I$, is a sequence of observations from robot states. Every o_i is a one time observation. R is call a offline problem when the n is known, otherwise R is an online problem. Due the nature of the soccer robot problem, we will consider a online problem in our experiments.

The observed sequence O that is already known by the problem, can be considered in a offline problem given by

$$\pi_R = \underset{\pi \in W}{\operatorname{argmax}} P(\pi|O) \tag{2}$$

where π_R is the plan hypothesis. The plan recognition defines the problem of find a hypotheses π that maximizes the joint probability $P(\pi|O)$.

The Bayes rules can be used to determine the π whose match with the observations and therefore maximizes $P(\pi|O)$. Considering that the observed robot is pursuing a single goal, we can compute the joint probability as

$$\begin{aligned} P(\pi|O) =& \beta P(O|\pi)P(\pi) \\ =& \beta P(O|\pi)P(\pi|g)P(g), \end{aligned} \tag{3}$$

where $P(g)$ is a uniform distribution probability that robot is pursuing the goal g. β is a normalizer depending on $P(O)$.

The main issue of joint probability (3) is compute the terms $P(O|\pi)$ and $P(\pi|g)$. The first term can be computed synthesizing a plan hypothesis π_g^O that passes through the observations and continues for each $g \in G$. Note that for each g in $P(O|\pi_g^O)$ the probability is maximal. The second term can be computed when pursuing a specific goal, the robot prefer the optimal plan $\hat{\pi}_g$. Thus a closer a plan π_g to an optimal plan $\hat{\pi}_g$ for a given g, more should we see a increase in $P(\pi|g)$ (Ramírez and Geffner 2009). Therefore, we could use the following function to approximate the joint probability of $P(\pi|g)$

$$\forall g \in G, P(\pi|g) := \frac{cost(\hat{\pi}_g)}{cost(\pi)} \tag{4}$$

Proposed Formulation

Generating a path trajectory is not a trivial problem in robotics. (McKerrow and McKerrow 1991) demonstrates that there are a lot of problems in choose and compute a algorithm for path generation. The choose depends on the desirable shape of the path, the control limitations, and landmarks. In a robotics competition, is easy to consider that any team has your own path generation with your own desirable dynamic. Instead of use a fixed cost function that measures only the path length, we proposed a formulation that focus on finding the path generation equation.

The robot soccer problem is well defined in 2D axis, exemplified in equation (1). For this configuration a cubicle equation can describe any trajectory as

$$T_x = A_3^x t^3 + A_2^x t^2 + A_1^x t + A_0^x \tag{5}$$

$$T_y = A_3^y t^3 + A_2^y t^2 + A_1^y t + A_0^y \tag{6}$$

$$T_\theta = A_3^\theta t^3 + A_2^\theta t^2 + A_1^\theta t + A_0^\theta \tag{7}$$

where t is the real time and A_i^η, $i \in \{0,1,2,3\}$, $\eta \in \{x, y, \theta\}$ are the unknown coefficients. T_η are the trajectories in each axis conform subscript.

To use the formulation described in (Kaminka, Vered, and Agmon 2018) with this proposed plan recognition, a few adaptations are required. We redefine the fluent literals (1) as

$$T = \{T_x(r), T_y(r), T_\theta(r)\}, \tag{8}$$

The main objective (2) is now redefined as

$$\alpha_R = \underset{\alpha \in W}{\operatorname{argmax}} P(\alpha|O) \tag{9}$$

where A is a vector as

$$\alpha = \otimes[A_0^\eta, \dots, A_n^\eta]^T \;\; \eta \in \{x, y, \theta\} \tag{10}$$

where the objective of this formulation is finding the coefficients A that maximize the joint probability $P(\alpha|O)$ given the observation.

The joint probability (3) is redefined as

$$\begin{aligned} P(\alpha|O) =& \beta P(O|\alpha)P(\alpha) \\ =& \beta P(O|\alpha)P(\alpha|g)P(g), \end{aligned} \tag{11}$$

where the probability $P(O|\alpha)$ and $P(\alpha|g)$ are obtained following the same methodology of (Kaminka, Vered, and Agmon 2018) and described above. The first one can be computed synthesizing the trajectory hypothesis T_g^O that passes through the observations and continues for each $g \in G$. Thus, extracting the coefficients A from trajectory T. Therefore, we could use the following function to approximate the joint probability of $P(\alpha|g)$

$$\forall g \in G, P(\alpha|g) := \frac{cost_i(\hat{\alpha}_g)}{cost_i(\alpha)}. \tag{12}$$

Note that the cost function in Equation (12) have a subscript. The recognition problem at this stage should generate some cost function hypothesis. At this moment, the proposed work is describe a small library with some cost function. In fact, this is not a huge problem because there is not a huge number of possibilities of cost. For example, shortest path, small time, small control actuator or a linear combination of the three methods.

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