# Plan Recognition for Behavior Estimation in a Robotic Soccer Player

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## Plan Recognition

The final objective in [Kaminka et al., 2018] is to recognize the path of a robot in one ambient of free collision.

The problem can be formulated as:

$$\pi_R = \operatorname*{argmax}_{\pi \in W} P(\pi|O) \tag{1}$$

With Bayes Rules we can compute the  $P(\pi|O)$ 

$$P(\pi|O) = \beta P(O|\pi)P(\pi)$$

$$= \beta P(O|\pi)P(\pi|g)P(g),$$
(2)

where P(g) is an uniform distribution probability that robot is pursuing the goal g

## Plan Recognition

The common approach in literature:

- Search a linear path between two points, in other words, a straight line. (shortest distance)
- Any consideration about time.
- Any restriction about robot velocity

#### Problem of this approach

Linear trajectories are problematic because they imply constant velocity and consequently discontinuous accelerations in the initial and final instants [Niku, 2020].

#### The proposal

Use cubic trajectories because they have a smoother velocity profile.

The cubic function can generate any trajectory for this problem.

$$T_{x}(t) = A_{3}^{x}t^{3} + A_{2}^{x}t^{2} + A_{1}^{x}t + A_{0}^{x}$$
(3)

$$T_{y}(t) = A_{3}^{y}t^{3} + A_{2}^{y}t^{2} + A_{1}^{y}t + A_{0}^{y}$$
 (4)

$$T_{\theta}(t) = A_3^{\theta} t^3 + A_2^{\theta} t^2 + A_1^{\theta} t + A_0^{\theta}$$
 (5)

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

How the initial and final positions are known, the equations (3-5) can be calculated from analytic way as:

$$A_0^{\eta} = T_{\eta}(t_0) \tag{6}$$

$$A_1^{\eta} = \dot{\mathcal{T}}_{\eta}(t_0) \tag{7}$$

$$A_2^{\eta} = \frac{3}{t_f^3} (T_{\eta}(t_f) - T_{\eta}(t_0)) - \frac{2}{t_f} \dot{T}_{\eta}(t_0) - \frac{1}{t_f} \dot{T}_{\eta}(t_f)$$
 (8)

$$A_3^{\eta} = -\frac{2}{t_f^3} (T_{\eta}(t_f) - T_{\eta}(t_0)) + \frac{1}{t_f^2} (\dot{T}_{\eta}(t_f) + \dot{T}_{\eta}(t_0)), \quad (9)$$

$$\eta \in \{x, y, \theta\}$$

where  $t_0$  and  $t_f$  are respectively the initial and final time.

► The Final time is the last variable that can be uncovered to calculated the coefficients  $A_i^{\eta}$ .

To finding the final time, we can use the planning domain formulations as

$$W_t := \langle T, A_t, \cos t, I, G \rangle, \tag{10}$$

- T is an infinite set of fluents composed:  $T = \{ T_x(t), T_v(t), T_\theta(t) \}$
- ▶  $A_t \in \{t_0, \dots, t_f\}$  is an infinite set of actions.
- ightharpoonup cost is the metric to guide the search (min  $t_f$ ).
- ▶  $I \in T$  is an initial state at time  $t_0$ .
- ▶  $G \in T$  a set of goals at final time  $t_f$ .

The optimal cubic trajectory for each goal can be calculated as

$$T_{\eta}^{g}(t)^{*} = A_{3}^{\eta}t^{3} + A_{2}^{\eta}t^{2} + A_{1}^{\eta}t + A_{0}^{\eta}$$

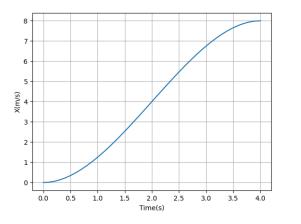
$$t \in \{t_{0}, \dots, t_{f}^{*}\}$$

$$\forall g \in G$$

$$\forall \eta \in \{x, y, \theta\}$$

$$(11)$$

#### Example of optimal cubic trajectory

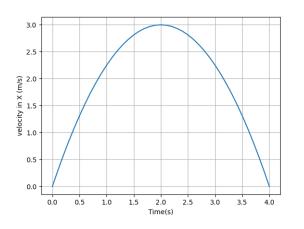


$$I = \{0\}$$

$$t_f = 4.02$$

Figure:  $T_x(t)^*$ .

#### Example of optimal cubic velocity



• 
$$g = \{8\}$$

$$t_f = 4.02$$

Figure:  $\dot{T}_{x}(t)^{*}$ .

#### Algorithm Outline

At each observations arrived, the recognition algorithm find the trajectory that best fits the sequence of observations and predict the trajectory to each goal.

The online recognition problem is a tuple

$$R_t := \langle W_t, O_t, I, G \rangle \tag{12}$$

- $ightharpoonup W_t$  is the domain theory defined in previously slides.
- $ightharpoonup O_t$  is a sequence of observations.
- ▶ / the initial states.
- ► *G* the set of hypothesis goals.

The recognition objective is now defined as

$$T_{\eta}^{R} = \operatorname{argmax} P(T_{\eta}|O_{t})$$
 (13)  
 $T_{\eta} \in W_{t}$ 

With Bayes Rules we can compute the joint probability defined as

$$P(T_{\eta}|O_{t}) = \beta P(O_{t}|T_{\eta})P(T_{\eta})$$

$$= \beta P(O_{t}|T_{\eta}^{g})P(T_{\eta}^{g}|g)P(g),$$
(14)

The  $T_{\eta}^{g}(t)$  is the trajectory that passes through the observations and continues for each  $g \in G$ .

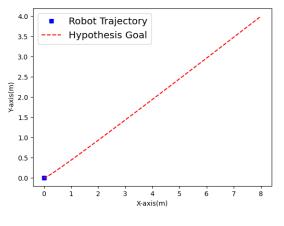
From 
$$t_0$$
 to  $t$ :

 $T_{\eta}^{g}(t) = o(t)$ 

From  $t$  to  $t_f^*$ :

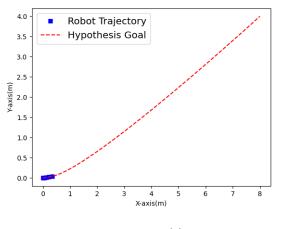
 $A_0^{\eta} = T_{\eta}(t)$ 
 $A_1^{\eta} = \dot{T}_{\eta}(t)$ 
 $A_2^{\eta} = \frac{3}{t_f^{*2}}(T_{\eta}(t_f^*) - T_{\eta}(t)) - \frac{2}{t_f^*}\dot{T}_{\eta}(t) - \frac{1}{t_f^*}\dot{T}_{\eta}(t_f^*)$ 
 $A_3^{\eta} = -\frac{2}{t_f^{*3}}(T_{\eta}(t_f^*) - T_{\eta}(t)) + \frac{1}{t_f^{*2}}(\dot{T}_{\eta}(t_f^*) + \dot{T}_{\eta}(t))$ 
 $T_{\eta}^{g}(t) = A_3^{\eta}t^3 + A_2^{\eta}t^2 + A_1^{\eta}t + A_0^{\eta}$ 
 $\eta \in \{x, y, \theta\}$ 
 $\forall g \in G$ .

Example of  $T_{\eta}^{g}(t)$  generation The robot is pursuing a fake goal in  $\{8,1,0\}$ 



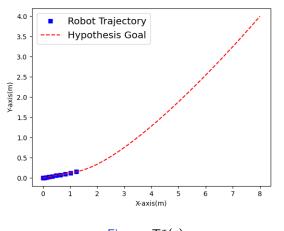
- $I = \{0, 0, 0\}$
- $t_f^* = 4.02$
- $ightharpoonup U_{max} = 3$
- $ightharpoonup g_1 = \{8, 4, 0\}$

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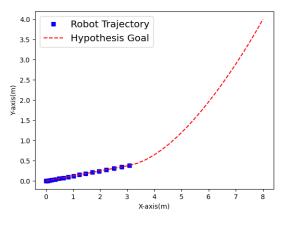
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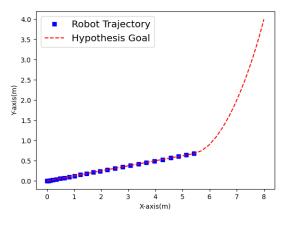
Figure:  $T_{\eta}^{g}(t)$ .

Example of  $T_{\eta}^{g}(t)$  generation The robot is pursuing a fake goal in  $\{8,1,0\}$ 



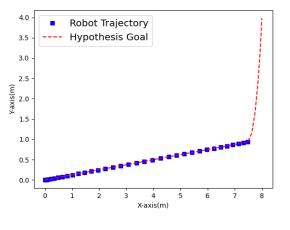
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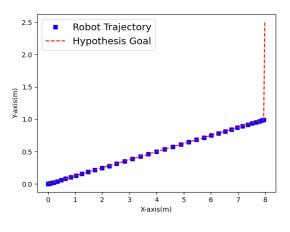
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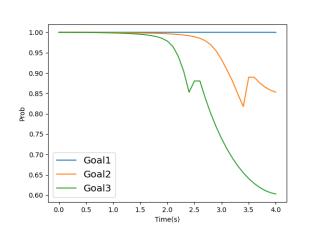
Finally, we could use the following function to approximate the joint probability of  $P(T_{\eta}^{g}|g)$ 

$$\forall g \in G, P(T_{\eta}^{g}|g) := \frac{cost(T_{\eta}^{g*})}{cost(T_{\eta}^{g})}.$$
 (16)

where  $cost(\cdot)$  is a cost function that measure the trajectory length from  $t_0$  to  $t_f^*$ .

### Simulated Experiment

Simulated experiment of navigation The robot is pursuing the goal 1



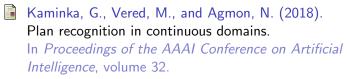
- $I = \{0, 0, 0\}$
- $ightharpoonup g = \{8, 4, 0\}$
- $t_f = 4.02$
- $V_{max} = 3$
- $g_1 = \{8, 4, 0\}$  $g_2 = \{7, 3, 0\}$ 
  - $g_3 = \{5, 2, 0\}$

Figure:  $P(T_{\eta}^{g}|g)$  by the time.

#### **Future Works**

- ▶ To insert collisions in the formulation.
- To add multi robots iterations.

#### References



Niku, S. B. (2020).

Introduction to robotics: analysis, control, applications.

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