Mobile Robot Navigation Amidst Humans with Intents and Uncertainties: A Time Scaled Collision cone Approach

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Outline

Motivation

Human Intention prediction

Proactive collision avoidance in intent space

Motivation

- Robots and humans are beginning to occupy the same work spaces.
- Account for human intent in robot's navigation and avoidance Maneuver.
- ▶ Uncertain and Haphazard local movements of human.

Outline

Motivation

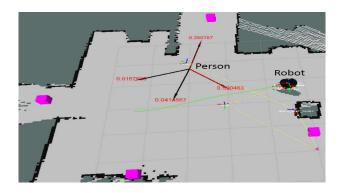
Human Intention prediction

Proactive collision avoidance in intent space

Human Intention prediction

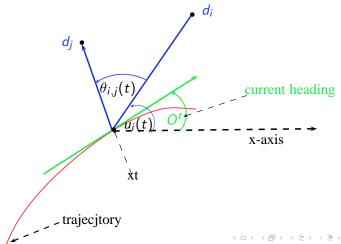
- Characterize intents as the final destinations a person might reach.
- ▶ Let $D = \{d^1, d^2, ..., d^m\}$ be the set of final destinations a person can go to in a given environment.
- Compute the probability of each of these intents Using Hidden Markov Model.
- ► Characterize local Haphazard movements as a gaussian $\mathcal{N}(\mu_i(\mathbf{x}^t), \sigma_t)$.

Human Intention prediction

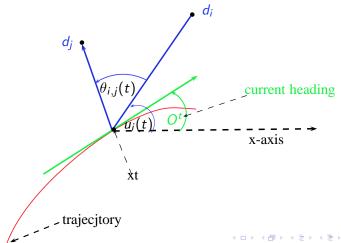


- Let $S^t \in D$ represent the intent of a person to reach destination S^t at time t.
- D represents set of states in HMM.
- ▶ Human trajectories are represented as $X(T) = \{x^1, x^2, ..., x^T\}$.

- $ightharpoonup O^t$ is the angle defined by the first derivative of the trajectory at point x^t.
- ▶ Given the current position and orientation we compute the probability of reaching each of the destination $d^i \in D$.



- $\blacktriangleright \mu_i(t)$ is the measure relative to the destination \mathbf{d}^i .
- $ightharpoonup O^t$ is the global measure of the target orientation.
- $ightharpoonup heta_{ij}(t)$ is the measure between final destinations $\mathbf{d^i}$ and $\mathbf{d^j}$ relative to the current position x^{t} .



▶ $b_i(O^t)$ is the probability of observing heading O^t given that the person is following the intent \mathbf{d}^i at time t.

$$b_i(O^t) = p(O^t|S^t = \mathbf{d^i}) = \mathcal{N}(O^t|\mu_i(t), \sigma_o)$$

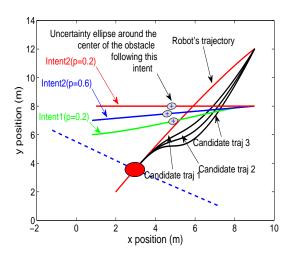
▶ $a_{ij}(t)$ is the probability that the human changes his intent from $\mathbf{d^i}$ to $\mathbf{d^j}$ at any discrete instant t

$$a_{ij}(t) = p(S^{t+1} = \mathbf{d}^{\mathbf{j}}|S^t = \mathbf{d}^{\mathbf{i}}) = \eta \mathcal{N}(\theta_{ij}(t)|0, \sigma_a)$$



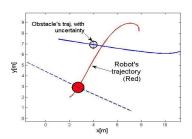
- Let $O^{1:T} = \{O^1, O^1, ..., O^T\}$ is the set of measurements obtained till time T.
- Our task is to calculate $p(S^t = \mathbf{d}^{\mathbf{i}} | O^{1:T}, \lambda)$.
- ▶ In HMM this term is usually referred to as $\gamma_t(i)$ To find this we use standard forward and backward algorithms.

- ► To propose an optimization framework, That achieves an elegant balance between minimizing risk and ease of collision avoidance maneuver.
- ► Ease of Collision avoidance maneuver directly relates to factors like deviation from current path and acceleration and deceleration capabilities of robot.
- Minimizing risk boils down to biasing the maneuver towards avoiding the most likely intent with higher confidence.



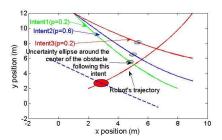
Formulation steps

Formulation for finding a relation between a particular collision avoidance maneuver and its confidence of safety, for a particular obstacle/intent.



Formulation steps

▶ Formulation extending it to multiple intent space



Explanation of Formulation one

- Finding a relation between a particular collision avoidance maneuver and its confidence of safety, for a particular obstacle/intent [1].
- [1]: Bharath Gopalakrishnan*, Arun Kumar Singh*, K.Madhava Krishna, Closed form characterization of Collison free velocities and confidence boinds for Non- holonomic robots in uncertain dynamic environments- To appear in IEEE Proc of IROS 2015.

Recap of time scaled collision cone:

► Time scaled collision cone constraint takes the following from.

$$f_i^s \geq 0$$

• where f_i^s is given by

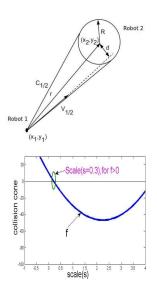
$$f_{i} = (x^{t_{c}} - x_{i}^{t_{c}})^{2} + (y^{t_{c}} - y_{i}^{t_{c}})^{2} - R^{2}$$

$$- \frac{(s\dot{x}^{t_{c}} - \dot{x}_{i}^{t_{c}})(x^{t_{c}} - x_{i}^{t_{c}}) + (s\dot{y}^{t_{c}} - \dot{y}_{i}^{t_{c}})(y^{t_{c}} - y_{i}^{t_{c}})^{2}}{(s\dot{x}^{t_{c}} - \dot{x}_{i}^{t_{c}})^{2} + (s\dot{y}^{t_{c}} - \dot{y}_{i}^{t_{c}})^{2}}$$

$$, \forall i = 1, 2...n$$

• f_i^s denotes the collision cone constraint for the i^{th} obstacle as a function of scale s. which depends on the state of the robot and obstacle at time $t = t^c$ which gets reduced to

$$a_i s^2 + b_i s + c_i \ge 0$$



Probabilistic version of time scaled collision cone

▶ If at time $t = t_c$ the obstacles state are given by

$$\mathbf{x}_i^{t_c} = \mathcal{N}(\mu_i^{\mathsf{x}}, \sigma_i^{\mathsf{x}}), \dot{\mathbf{x}}_i^{t_c} = \mathcal{N}(\mu_i^{\dot{\mathsf{x}}}, \sigma_i^{\dot{\mathsf{x}}})$$

$$y_i^{t_c} = \mathcal{N}(\mu_i^y, \sigma_i^y), \dot{y}_i^{t_c} = \mathcal{N}(\mu_i^{\dot{y}}, \sigma_i^{\dot{y}})$$

▶ Then the objective would be to find the scale that maximizes

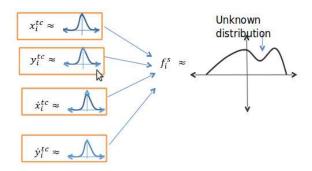
$$P(f_i^s \geq 0)$$

Objective

$$\underset{s}{\operatorname{argmax}} \{ P(f_i^s \geq 0) \}$$

Challenge

f_i^s is a random variable with unknown analytical expression for its probability distribution.



Solution

- ▶ Though the pdf of f_i^s is does not have an analytical expression we can get its mean and standard deviation in closed form as a function of s.
- By the law of unconscious statistician.

$$E[f_i^s] = \mu_{f_i^s} = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f_i^s(.) P_i(.) dx_i^{t_c} dy_i t_c d\dot{x}_i^{t_c} d\dot{y}_i^{t_c}$$

Which evaluates as.

$$\mu_{f_i^2} = A_i s^2 + B_i s + C_i$$

Where A_i, B_i and C_i are the function of robot states and obstacle distribution parameters , $\mu_i^1, \mu_i^2, \sigma_i^1, \sigma_i^2$

Solution

Similarly

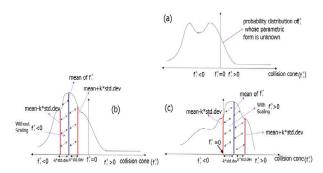
$$\sigma_{f_i^s} = \sqrt{E[(f_i^s - E[f_i^s])^2} = \sqrt{D_i s^4 + E_i^3 + F_i^2 + G_i s + H}$$

Where D_i, E_i, F_i, G_i , and H_i are the function of robot states and obstacle distribution parameters , $\mu_i^1, \mu_i^2, \sigma_i^1, \sigma_i^2$

Solution

$$\underset{s}{\operatorname{argmax}} \{ P(f_i^s \geq 0) \} \Longrightarrow \mu_{f_i^s} \pm k * \sigma_{f_i^s}$$

This can be suitably achieved by changing the value of k



Lower bound on $P(f_i^s) \ge 0$

- In the previous section we found out on how to obtain scale s for various values of k that would end up maximizing $P(f_i^s) \ge 0$.
- ▶ Since the pdf of $P(f_i^s) \ge 0$ does not have an analytical form ,it is not possible to get the probability of f_i^s for a particular value of s.
- ▶ Hence we can only bound $P(f_i^s) \ge 0$ by a lower bound and this can be done by Cantelli's inequality.

Lower bound on $P(f_i^s) \ge 0$

▶ The lower bound are thus obtained through

$$P(f_i^s \ge 0 | \mu_{f_i^s} - k * \sigma_{f_i^s} > 0) \ge \frac{k^2}{k^2 + 1}$$

► Thus solving for larger *k* increases the lower bounds and thus improves the confidence measures.

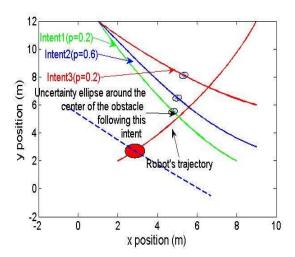
Collision Avoidance in Multiple Intent space

- ► As stated earlier, the objective is to Find maneuvers that maximize the confidence of safety for more probable intents.
- ► As seen in formulation one, the expression on the Lower bound of confidence is.

$$P(f_i^s \ge 0 | \mu_{f_i^s} - k * \sigma_{f_i^s} > 0) \ge \frac{k^2}{k^2 + 1}$$

▶ Hence confidence of safety is directly related to variable *k*

Collision Avoidance in Multiple Intent space



Cost function for Collision Avoidance in Multiple Intent space

Optimization Formulation

minimize
$$w_t \Delta t + w_r \Delta r$$

subject to $\mu_{f_i^s} \pm k_i * \sigma_{f_i^s} \geq 0, \ i = 1, \dots, n, \ .$

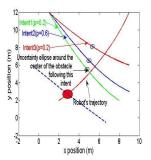
- ▶ Where $\Delta t = (s-1)^2$ and $\Delta r = -\sum_{i=1}^{n} \gamma_i * k_i$
- ▶ Here $\mu_{f_i^s}$ and $\sigma_{f_i^s}$ are the mean and the standard deviation of the collision cone respectively.
- ▶ *k* is the variable directly relating to the confidence of safety as described in Cantelli's inequality.
- $\triangleright \gamma_i$ is the probability of intent i

Cost function for Collision Avoidance in Multiple Intent space

- Δt ensures a collision free velocity very close to the current velocity.
- $ightharpoonup \Delta r$ relates the risk associated with the avoidance maneuver.
- ► This biases the solution space towards avoiding the most likely intent with higher confidence.

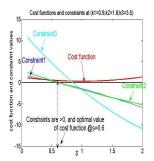
Illustration, Scale along the current robot path

► Consider the Scenario shown in the following figure



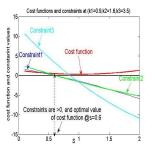
Illustration, Scale along the current robot path

► The cost function and the constraint for the above scenario is shown in the following figure.



Illustration, Scale along the current robot path

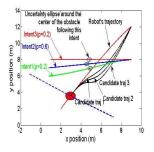
▶ It can be noticed from the above figure, that the values of scale s, k_1 , k_2 , k_3 , at which the cost function has an optimal value are s = 0.6, $k_1 = 0.9$, $k_2 = 1.6$, $k_3 = 2$.



From the values of k_1 , k_2 , k_3 , we can say that the scale s=0.6 corresponds to 75% of safety/confidence for intent two (most probable) and 30% confidence / safety for intent one.

Illustration, for multiple candidate trajectories

▶ In some cases, it may become imperative to deviate from the current path to avoid collisions.



► For example in the figure, and in the table below, it is concluded that there is no solution (scale:s) possible along the robots current path(red).

Illustration, for multiple candidate trajectories

Candidate Trajectory	k_1	k ₂	k ₃	scale
Robot Original	NULL	NULL	NULL	NULL
Candidate 1	0.2	2	2	0.6
Candidate 2	0.67	2	2	0.916
Candidate 3	1.73	2	2	1

► From the above table it is clear that Candidate Trajectory 2 can be preferred .