

# 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

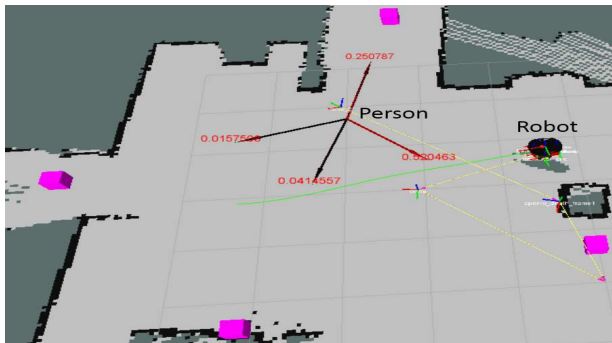
Human Intention prediction

Proactive collision avoidance in intent space

# Human Intention prediction

- ▶ Characterize intents as the final destinations a person might reach
- ▶ Let  $D = \{\mathbf{d}^1, \mathbf{d}^2, \dots, \mathbf{d}^m\}$  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

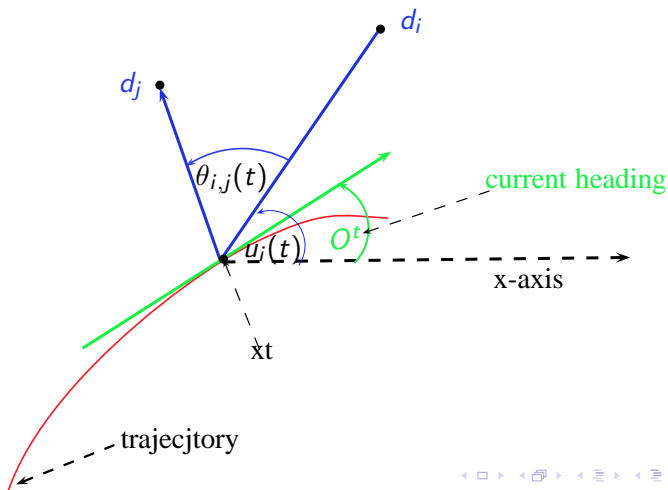


# HMM for Intention prediction

- ▶ 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  $X(T) = \{\mathbf{x}^1, \mathbf{x}^2, \dots, \mathbf{x}^T\}$

# HMM for Intention prediction

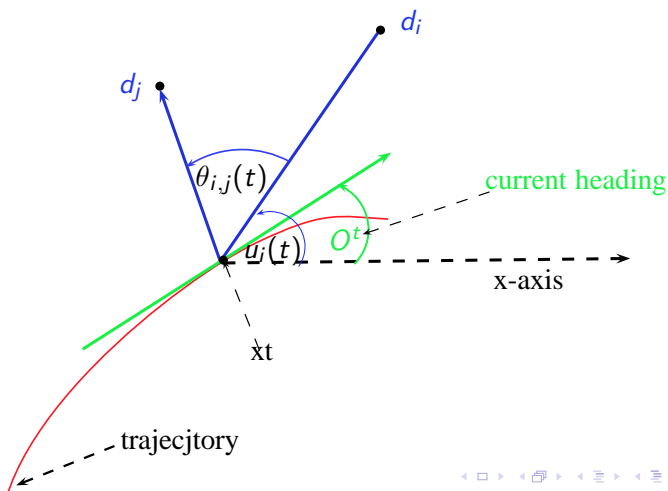
- ▶  $O^t$  is the angle defined by the first derivative of the trajectory at point  $\mathbf{x}^t$
- ▶ Given the current position and orientation we compute the probability of reaching each of the destination  $d^i \in D$





# HMM for Intention prediction

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



# HMM for Intention prediction

- ▶  $b_i(O^t)$  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  $t$

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

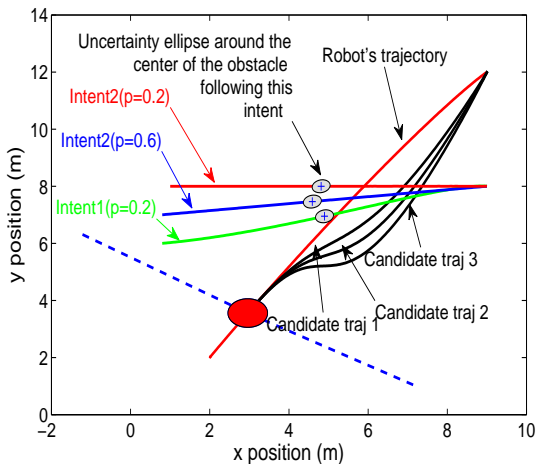
# HMM for Intention prediction

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

# Proactive collision avoidance in intent space

- ▶ 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.

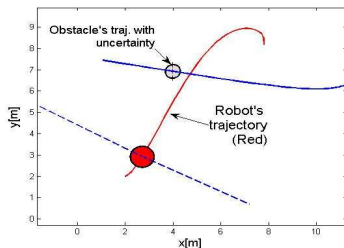
# Proactive collision avoidance in intent space



# Proactive collision avoidance in intent space

## Formulation steps

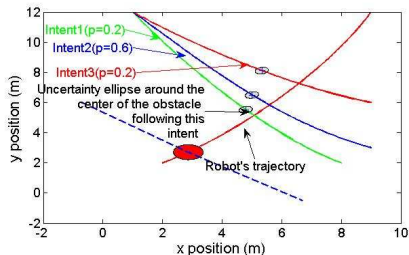
- Formulation for finding a relation between a particular collision avoidance maneuver and its confidence of safety, for a particular obstacle/intent.



# Proactive collision avoidance in intent space

## Formulation steps

- Formulation extending it to multiple intent space



# Proactive collision avoidance in 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 Collision free velocities and confidence bounds for Non- holonomic robots in uncertain dynamic environments- To appear in IEEE Proc of IROS 2015



# Proactive collision avoidance in intent space

## Recap of time scaled collision cone:

- ▶ Time scaled collision cone constraint takes the following form

$$f_i^s \geq 0$$

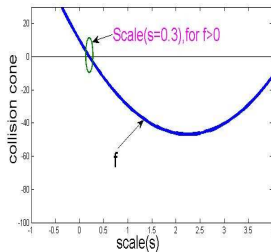
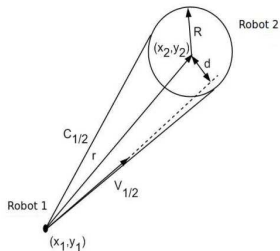
- ▶ where  $f_i^s$  is given by

$$f_i = (x^{t_c} - x_i^{t_c})^2 + (y^{t_c} - y_i^{t_c})^2 - R^2 \quad (1)$$
$$- \frac{(s\dot{x}^{t_c} - \dot{x}_i^{t_c})(x^{t_c} - x_i^{t_c}) + (s\dot{y}^{t_c} - \dot{y}_i^{t_c})(y^{t_c} - y_i^{t_c})^2}{(s\dot{x}^{t_c} - \dot{x}_i^{t_c})^2 + (s\dot{y}^{t_c} - \dot{y}_i^{t_c})^2}, \forall i = 1, 2 \dots n$$

- ▶  $f_i^s$  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

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

# Proactive collision avoidance in intent space



# Proactive collision avoidance in intent space

## Probabilistic version of time scaled collision cone

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

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

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

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

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

# Proactive collision avoidance in intent space

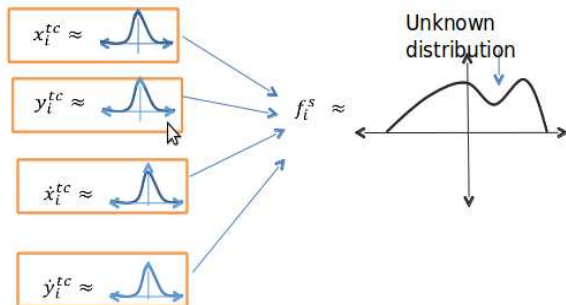
## Objective

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

## Challenge

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

# Proactive collision avoidance in intent space



# Proactive collision avoidance in intent space

## Solution

- ▶ Though the pdf of  $f_i^s$  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 ,  $\mu_i^1, \mu_i^2, \sigma_i^1, \sigma_i^2$

# Proactive collision avoidance in intent space

## Solution

- ▶ Similarly

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

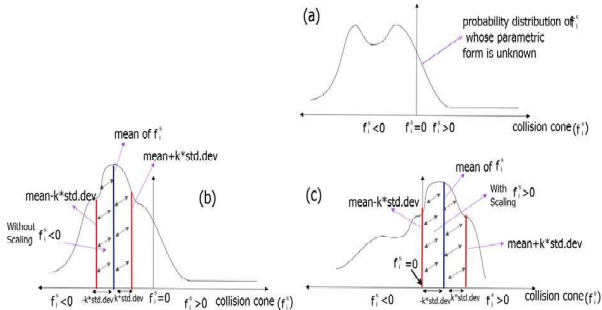
Where  $D_i, E_i, F_i, G_i$ , and  $H_i$  are the function of robot states and obstacle distribution parameters ,  $\mu_i^1, \mu_i^2, \sigma_i^1, \sigma_i^2$

# Proactive collision avoidance in intent space

## Solution

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

This can be suitably achieved by suitably changing the value of  $k$





# Proactive collision avoidance in intent space

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

- ▶ In the previous section we found out on how to obtain scale  $s$  for various values of  $k$  that would end up maximizing  $P(f_i^s) \geq 0$ .
- ▶ Since the pdf of  $P(f_i^s) \geq 0$  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  $P(f_i^s) \geq 0$  by a lower bound and this can be done by Cantelli's inequality.

# Proactive collision avoidance in intent space

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

- ▶ The lower bound are thus obtained through

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

- ▶ Thus solving for larger  $k$  increases the lower bounds and thus improves the confidence measures

# Proactive collision avoidance in intent space

## Collision Avoidance in Multiple Intent space

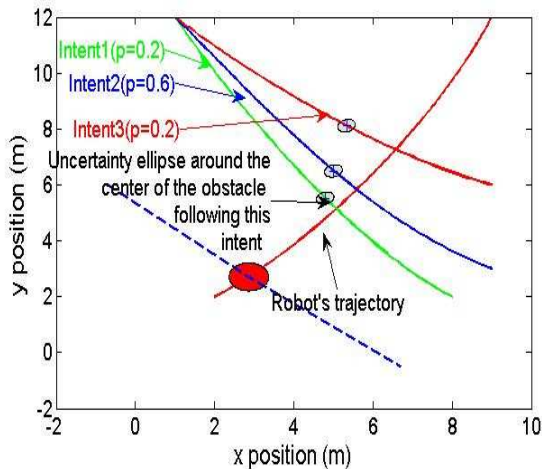
- ▶ As stated earlier, the objective is to Find maneuvers that maximize the confidence of safety for more probable intents.
- ▶ As seen in formulation one, the expression on the Lower bound of confidence is.

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

- ▶ Hence confidence of safety is directly related to variable  $k$

# Proactive collision avoidance in intent space

## Collision Avoidance in Multiple Intent space



# Proactive collision avoidance in intent space

## Cost function for Collision Avoidance in Multiple Intent space

### ► Optimization Formulation

$$\text{minimize} \quad w_t \Delta t + w_r \Delta r$$

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

- Where  $\Delta t = (s - 1)^2$  and  $\Delta r = -\sum_i^n \gamma_i * k_i$
- 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.
- $\gamma_i$  is the probability of intent  $i$

# Proactive collision avoidance in intent space

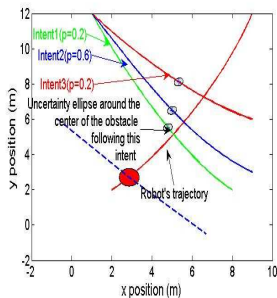
## Cost function for Collision Avoidance in Multiple Intent space

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

# Proactive collision avoidance in intent space

## Illustration, Scale along the current robot path

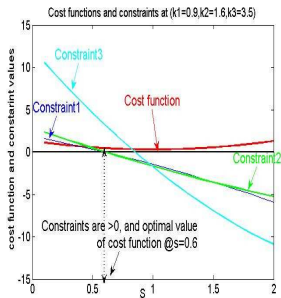
- Consider the Scenario shown in the following figure



# Proactive collision avoidance in intent space

## Illustration, Scale along the current robot path

- ▶ The cost function and the constraint for the above scenario is shown in the following figure

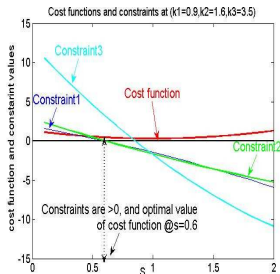




# Proactive collision avoidance in intent space

## 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  $s = 0.6$ ,  $k_1 = 0.9, k_2 = 1.6, k_3 = 2$

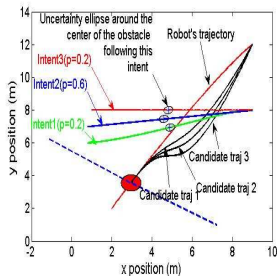


- From the values of  $k_1, k_2, k_3$ , we can say that the scale  $s = 0.6$  corresponds to 75% of safety/confidence for intent two (most probable) and 30% confidence / safety for intent one

# Proactive collision avoidance in intent space

## 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).

# Proactive collision avoidance in intent space

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