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Human Trajectory Prediction in the Interaction between Human and Unmanned Vehicles

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Introduction

In the realm of shared spaces where humans and robots coexist, safeguarding interactions is vital. This study presents a data-driven trajectory prediction method that enhances robot action planning by integrating human danger awareness, promoting both safety and operational efficiency in human-robot environments.

Problem Formulation

Robot Model

- **State and Action:** The Robot's state and action at time t are represented by $x_R(t) \in R^{n_R}$ and $u_R(t) \in U_R \subset R^{m_R}$.
- **Dynamics:** The robot's dynamics are modeled by:

$$x_R(t+1) = f_R(x_R(t), u_R(t)) \tag{1}$$

This updates the robot's state based on its current state and action.

- **Objective Function:** The objective function, denoted as Q_R^g, incorporates the Euclidean distance from the robot's current state to its goal state and the action cost:

$$Q_R^g(x_R(t), u_R(t), g_R) = \theta_1 \|x_R(t) - g_R\|^2 + \theta_2 \|u_R(t)\|^2 \tag{2}$$

where θ_1 and θ_2 are weighting parameters.

- **Optimization Problem:** The robot solves the following optimization problem over the prediction horizon T_R:

$$u_R^*(t : t+T_R-1) = \begin{cases} \arg\min & \sum_{k=t}^{t+T_R-1} Q_R^g(\cdot) \\ \text{s.t.} & u_R(k) \in U_R \quad \forall k, \\ & Model(1) \\ & P_{\text{Coll}}(k) \le P_{\text{th}} \quad \forall k \end{cases} \tag{3}$$

where $k = t+1, \ldots, t+T_R$, $u_R^*(t : t+T_R-1) = [u_R^*(t) \ldots u_R^*(t+T_R-1)]^\top$, $P_{\text{Coll}}(k) \in [0,1]$ is the probability of a collision between the human and robot at prediction time instant k, and $P_{\text{th}} \in [0,1]$ is a threshold value.

Human Model

- **State and Action:** The Human's state and action at time t are represented by $x_H(t) \in R^{n_H}$ and $u_H(t) \in U_H \subset R^{m_H}$.
- **Dynamics:** The human's dynamics are modeled by:

$$x_H(t+1) = f_H(x_H(t), u_H(t)) \tag{4}$$

This updates the human's state based on its current state and action.

- **Objective Function:** The human's objective function is a weighted sum of two components—the goal-reaching and the safety objectives:

$$Q_H^g(x_H(t), u_H(t), g_H) = \theta_3 \|x_H(t) - g_H\|^2 + \theta_4 \|u_H(t)\|^2 \tag{5}$$

$$Q_H^s(x_H(t), u_H(t), x_R(t)) = \theta_5 e^{-\theta_6 \|x_H(t) - x_R(t)\|^2} \tag{6}$$

where $\theta_3, \theta_4, \theta_5$, and θ_6 are weighting parameters.

- **Action Selection:** The human selects the action that optimizes the combination of the goal and safety objectives:

$$u_H^*(t) = \arg\min_{u_H \in U_H} (\eta_1 Q_H^g(\cdot) + \beta \eta_2 Q_H^s(\cdot)) \tag{7}$$

where $\eta_1, \eta_2 \in R_{>0}$ are the weighting factors and $\beta \in \{0,1\}$ represents the human's danger awareness.

Trajectory Prediction

Model Structure

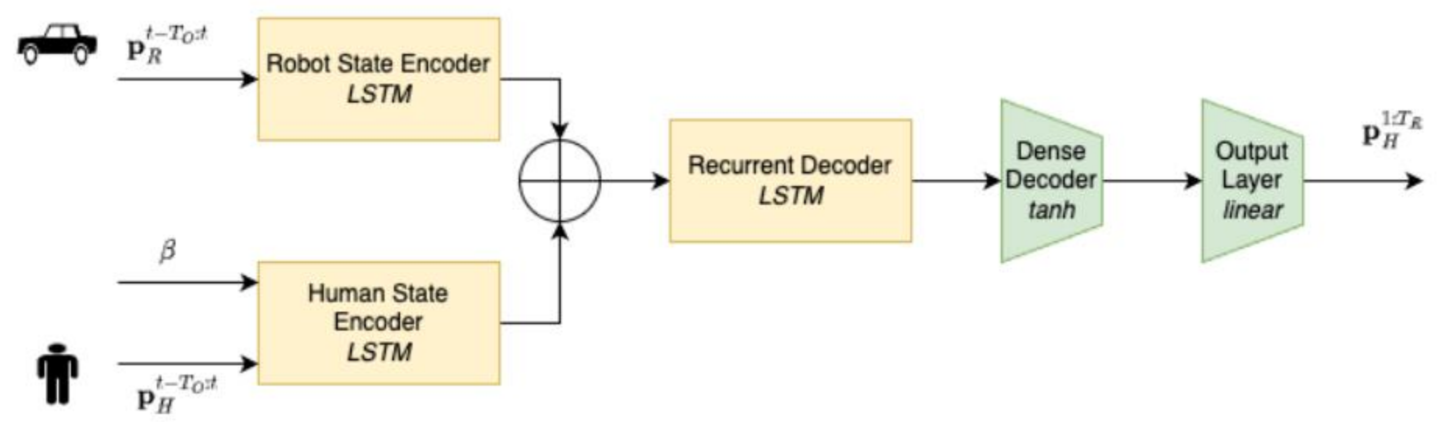


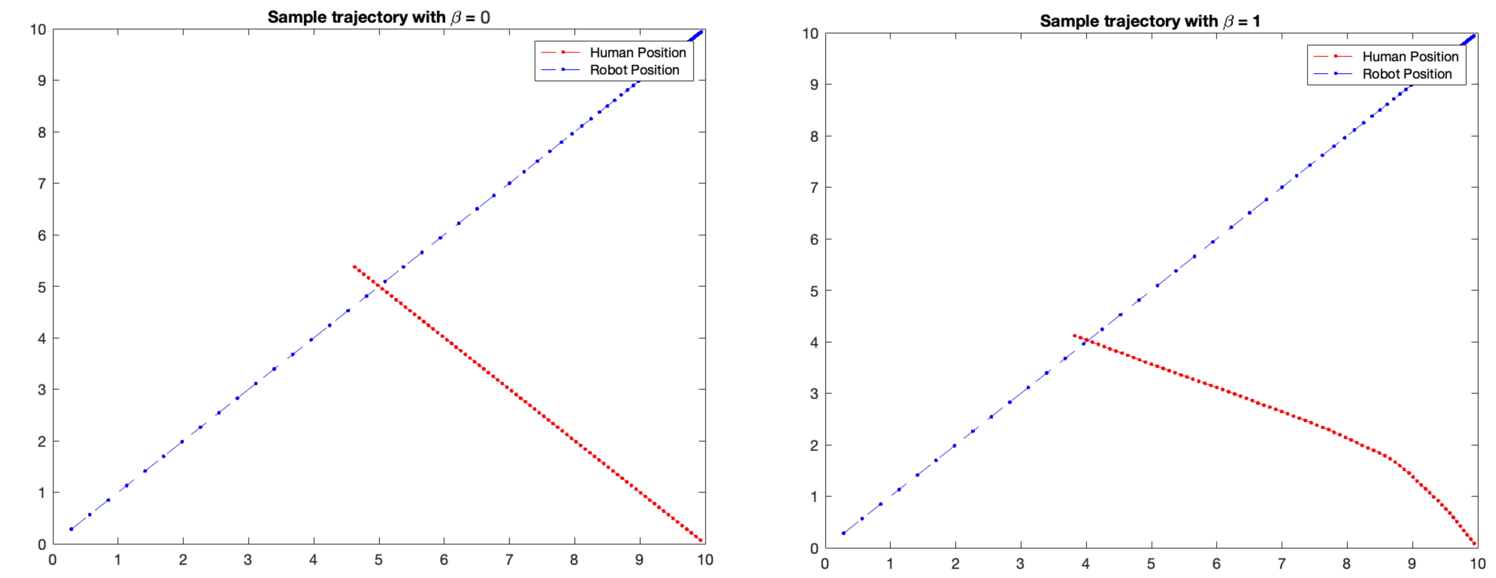
Fig. 1. Recurrent Neural Network (RNN) model for trajectory prediction

- **Inputs:**
  - *Robot's Past Positions:* $p_R^{t-T_O:t}$, from time $t - T_O$ to current time t.
  - *Human's Past Positions:* $p_H^{t-T_O:t}$, from time $t - T_O$ to current time t.
  - *Danger Awareness Coefficient:* β, indicating the human's perception of potential risks.
- **Outputs:**
  - A sequence of predicted future positions of the human over the prediction horizon, denoted by $p_H^{1:T_R}$.
- **Main Modules of the Danger-Informed Model:**
  - *Robot State Encoder:* An LSTM module that processes the sequence of past robot positions and encodes it into a state representation, z_R.
  - *Human State Encoder:* An LSTM module that processes the sequence of past human positions and encodes it into a state representation, z_H. This module also incorporates the estimated value of the danger awareness coefficient, β.
  - *Decoder Module:* An LSTM module that takes the concatenated state representations of the robot and human, z_R and z_H, and predicts the future trajectory of the human.

Experiments & Results

Experiment Setup and Data Generation

- **Simulation Environment:** A two-dimensional space where both the human and robot navigate towards dynamically updating goal positions.
- **Past and Future Data:** Positions and velocities of the human and robot are recorded over N_{sim} time steps. For each time step t, the dataset includes past observations over a horizon of T_O and future positions over a horizon of T_H.



(a) $\beta = 0$, Unconcerned Human (b) $\beta = 1$, Concerned Human

Fig 2. Human Robot Interaction sample trajectories.

Prediction Results

- Feed the trajectory data into the prediction model.
- Generate the human trajectory prediction.
- Compare with the ground truth human future position to evaluate the performance of the prediction model.

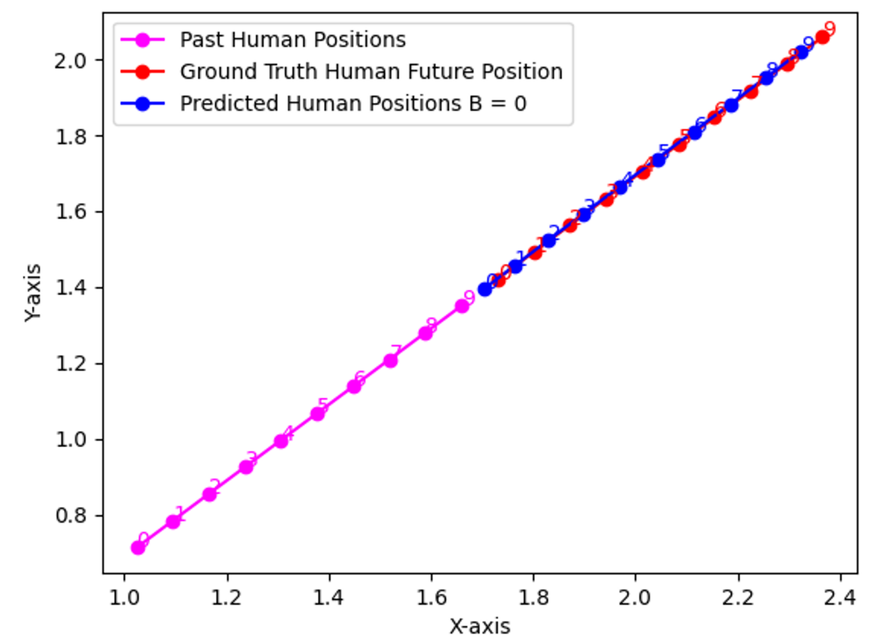


Fig 3. Sample output of the prediction system.

Conclusion

This research advances the predictive modeling of human trajectories with a data-driven approach that accounts for human danger awareness. The resulting model demonstrates potential for enhancing robot decision-making, fostering safer and more efficient human-robot interactions. Future integration into action planning schemes promises significant improvements in the cohabitation of humans and autonomous systems in shared environments.

References

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