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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 $x_R(t) \in \mathbb{R}^m$ and $u_R(t) \in U_R \subset \mathbb{R}^m$.

- **Dynamics**: The robot's dynamics are modeled by:
  \[
  x_R(t+1) = f_R(x_R(t), u_R(t))
  \]

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

- **Objective Function**: The objective function, denoted as $Q^R_{\beta}$, incorporates the Euclidean distance from the robot's current state to its goal state and the action cost:
  \[
  Q^R_{\beta}(x_R(t), u_R(t), g_R) = \theta_1 ||x_R(t) - g_R||^2 + \theta_2 ||u_R(t)||^2
  \]

where $\theta_1$ and $\theta_2$ are weighting parameters.

- **Optimization Problem**: The robot solves the following optimization problem over the prediction horizon $T_R$:
  \[
  a_R^*(t : t + T_R - 1) = \arg \min_{a_R(t)} \sum_{k=t}^{t+T_R-1} Q^R_{\beta}(a_R(t))
  \text{ s.t. }\]

where $k = t+1, \ldots, t+T_R$, $a_R(t) = [a_R(t+1), \ldots, a_R(t+T_R-1)]^T$, $P_{\text{coll}}(k) \leq P_h \forall k$ and $P_h \in [0, 1]$ is a threshold value.

Human Model

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

- **Dynamics**: The human's dynamics are modeled by:
  \[
  x_H(t+1) = f_H(x_H(t), u_H(t))
  \]

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

- **Objective Function**: The human's objective function is weighted sum of two components—the goal-reaching and the safety objectives:
  \[
  Q^H_{\beta}(x_H(t), u_H(t), g_H) = \theta_3 ||x_H(t) - g_H||^2 + \theta_4 ||u_H(t)||^2
  \]
  \[
  Q^H_{\beta}(x_H(t), u_H(t), g_H) = \theta_5 ||g_H - g_H(t)||^2
  \]
  \[
  \text{where } \theta_3, \theta_4, \theta_5, \text{ and } \theta_6 \text{ are weighting parameters.}
  \]

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 $N_{\text{sim}}$ time steps. For each time step $t$, the dataset includes past observations over a horizon of $T_H$ and future positions over a horizon of $T_H$. 

Experiment Results

- **Action Selection**: The human selects the action that optimizes the combination of the goal and safety objectives:
  \[
  u^*_H(t) = \arg \min_{a_H(t)} (\eta_1 Q^H_{\beta}(a_H(t)) + \eta_2 Q^H_{\beta}(a_H(t)))
  \]
  \[
  \text{where } \eta_1, \eta_2 \in \mathbb{R}^m \text{ are the weighting factors and } \beta \in (0, 1) \text{ represents the human's danger awareness.}
  \]

Trajectory Prediction

- **Model Structure**: The model consists of an encoder-decoder architecture with an LSTM network.

- **Inputs**:
  - Robot's Past Positions: $p_R^T(t)$, from time $t - T_R$ to current time $t$.
  - Human's Past Positions: $p_H^T(t)$, from time $t - T_H$ to current time $t$.
  - Danger Awareness Coefficient: $\beta$, indicating the human's perception of potential risks.

- **Outputs**: A sequence of predicted future positions of the human over the prediction horizon, denoted by $p_H^{T_R}$.

- **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 ground truth human trajectory $z_H$.

  - **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.

Conclusions

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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