Human Intention Prediction

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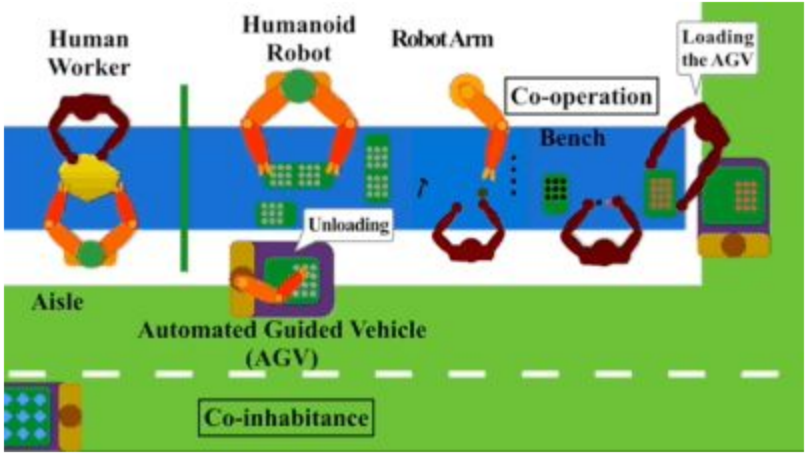
Motivation

There are two challenges for mobile robots in dense pedestrian environments(shopping malls, schools and airports):(1)The robot may get frozen;(2)The robot may behave intrusively.

However, if robots could predict people's intention, it will be easier for them to interact with humans socially.

Application Scenarios



Scenario 1.[1]

Scenario 2.[2]

Related Works

Social-LSTM[3]: considering others' influence

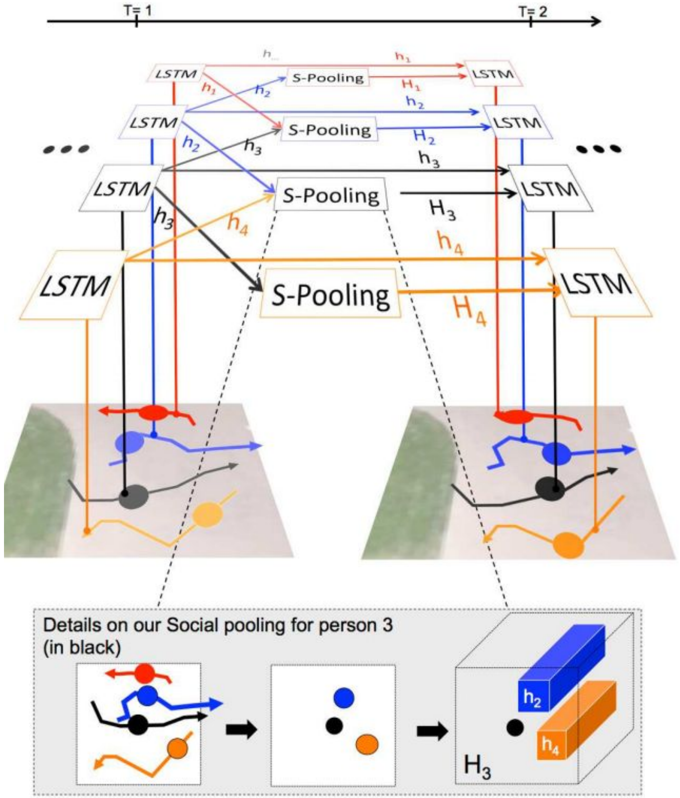
(1)Social pooling of hidden states

$$H_i^t(m,n,:) = \sum_{j \in \mathcal{N}_i} 1_{mn}[x_j^t - x_i^t, y_j^t - y_i^t] h_j^{t-1}$$

(2)Pose estimation

$$[\mu_i^t, \sigma_i^t, \rho_i^t] = W_p h_i^{t-1}$$

$$L^i(W_e, W_l, W_p) = -\sum_{t=T_{obs}+1}^{T_{pred}} \log(\mathbb{P}(x_i^t, y_i^t | \sigma_i^t, \mu_i^t, \rho_i^t))$$



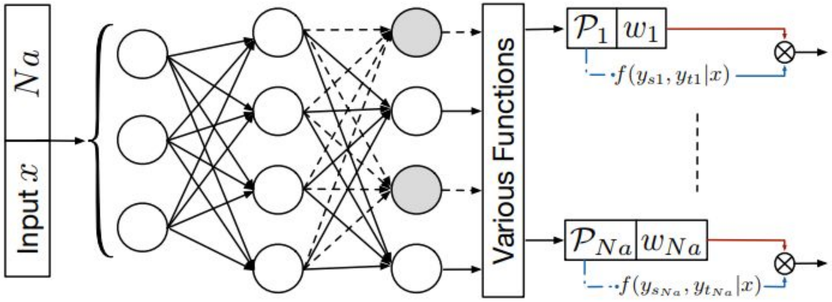
Related Works

Mixture Density Networks[4]: Probabilistic Prediction of Vehicle Semantic Intention and Motion. -- Interindependent Prediction

（1）Inputs：current state features x

（2）Outputs:y = [ys, yt] ,location and

time information.



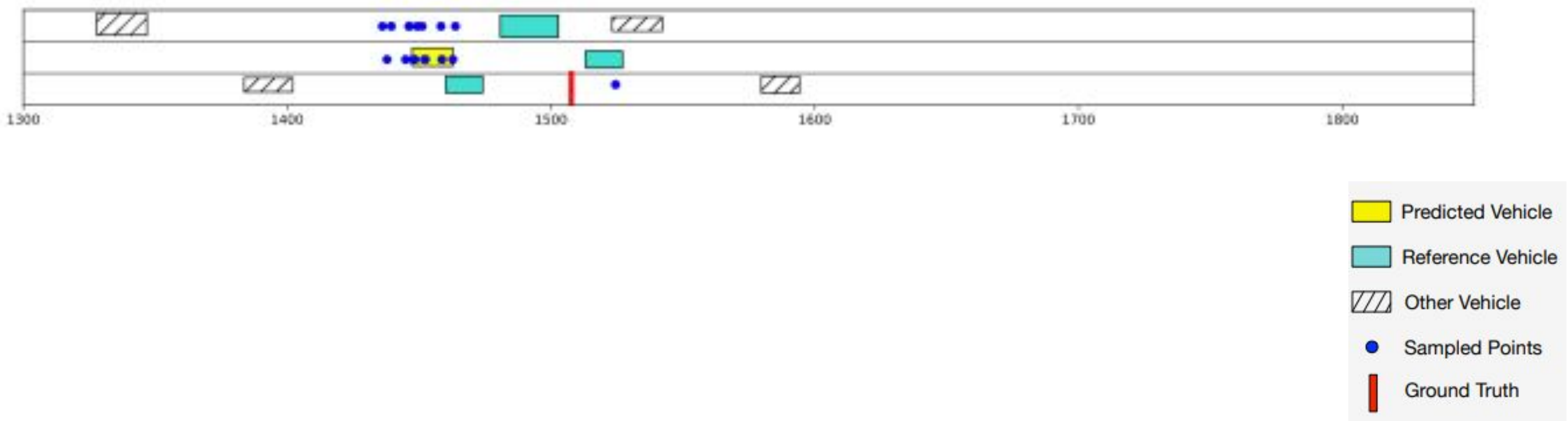
(3)Loss function:

$$L = W_1\Big(-\sum_n log\Big\{\sum_{a=1}^{N_a} \hat{w}_a^n f(\boldsymbol{y}_a^n|\boldsymbol{x})\Big\}\Big) + W_2\Big(-\sum_n \sum_{a=1}^{N_a} \hat{w}_a^n log(w_a^n)\Big),$$

Related Works

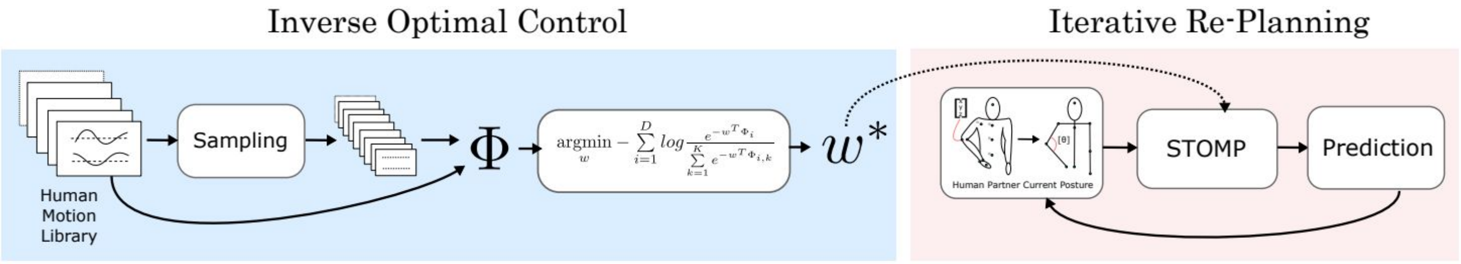
Mixture Density Networks[4]:

(4)Results



Related Works

Inverse reinforcement learning(inverse optimal control)[5]: learn a cost function which "explains" the motion of the human.



Related Works

Inverse reinforcement learning(inverse optimal control)[5]:

Feature functions:

$$C(\tau) = w^T \Phi(\tau) \; , \Phi(\tau) = \begin{bmatrix} G(\tau) \\ A(\tau) \end{bmatrix}$$

(1) Distance between human links.

(2)Smoothness: These features ensure that the trajectory remains smooth. We measure configuration and task space length, squared velocities, squared accelerations and squared jerks along the trajectory using finite differencing.

Related Works

Inverse reinforcement learning(inverse optimal control)[5]:

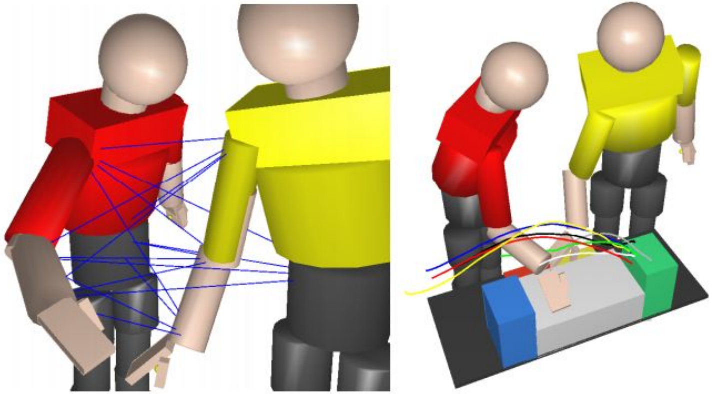
Optimal weights(convex optimization):

$$w^* = \underset{w}{\operatorname{argmin}} - \sum_{i=1}^{D} log \frac{e^{-w^T \Phi_i}}{\sum\limits_{k=1}^{K} e^{-w^T \Phi_{i,k}}}$$

Related Works

Inverse reinforcement learning(inverse optimal control)[5]:

Interative Replanning: dynamic obstacle avoidance



Hot Topics

(1)Reactive Prediction: “what … if ... ”;

(2)Multi-agent motion prediction;

(3)Viewpoint influence:local, global as well as occlusion;

(4)Taking use of the semantic infomation and traffic rules.

… ...

Bibliography

[1]https://bair.berkeley.edu/blog/2017/12/12/corobots/

[2]Liu C, Chen J, Nguyen T D, et al. The robustly-safe automated driving system for enhanced active safety[R]. SAE Technical Paper, 2017.

[3]Alahi A, Goel K, Ramanathan V, et al. Social lstm: Human trajectory prediction in crowded spaces[C]//Proceedings of the IEEE conference on computer vision and pattern recognition. 2016: 961-971.

[4]Hu Y, Zhan W, Tomizuka M. Probabilistic prediction of vehicle semantic intention and motion[C]//2018 IEEE Intelligent Vehicles Symposium (IV). IEEE, 2018: 307-313.

[5]Mainprice J, Hayne R, Berenson D. Predicting human reaching motion in collaborative tasks using inverse optimal control and iterative re-planning[C]//2015 IEEE International Conference on Robotics and Automation (ICRA). IEEE, 2015: 885-892.

Tanks for your listening! Advice?