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Why Study (Cooperative) Crowd Navigation?

**Science:**

• “Cooperation” prerequisite for autonomous robot navigation in crowds
• Model extends to shared autonomy

**Applications:**

• AFRL/Human Performance Wing

  Former AF/ST Werner Dahm:
  “two key areas [for AF S&T investment, next 10 years]:
  (i) increased use of autonomy …
  (ii) augmentation of human performance… need to [certify] the high levels of adaptability and autonomy”

• Industry: Boeing assembly line

**Goal: probabilistic tools for “certifiable” HRI**
Starting Point: Modeling Interaction

Prediction without interaction

Interaction

Prediction with interaction
The Interaction Density

- \( f^{(i)} \) is agent \( i \)'s continuous path in the plane \( \mathbb{R}^2 \):

\[
\begin{align*}
  f^{(i)} : [0, \infty] & \rightarrow \mathbb{R}^2 \\
  : t & \rightarrow [x(t)^{(i)}, y(t)^{(i)}]
\end{align*}
\]

- \( f = (f^{(1)}, f^{(2)}, \ldots, f^{(n)}) \) is concatenation of \( n \) agent paths

\[
p(f^{(R)}, f^{(1)}, f^{(2)}, \ldots, f^{(n)} | z_{1:t})
\]
But how should we construct this \textit{joint} density?

We’ll start with independent agent trajectory models (interaction free models)
Want to model *multiple goals, probabilistic duration*
Deriving the Interaction Free Density

(Recall) \[ p(f^{(R)}, f^{(1)}, f^{(2)}, \ldots, f^{(n)} \mid z_{1:t}) \]

\[
p(f^{(i)} \mid z_{1:t}) = \sum_{\bar{g}_{m}} \int_{\bar{T}_{m}} p(f^{(i)}, \bar{g}_{m}, \bar{T}_{m} \mid z_{1:t})
\]

\[
= \sum_{\bar{g}_{m}} \int_{\bar{T}_{m}} p(f^{(i)} \mid z_{1:t}, \bar{g}_{m}, \bar{T}_{m}) p(\bar{g}_{m}, \bar{T}_{m} \mid z_{1:t})
\]

\[
\approx \sum_{\bar{g}_{m}} \int_{\bar{T}_{m}} p(f^{(i)} \mid z_{1:t}, \bar{g}_{k}, \bar{T}_{k}) \sum_{k=1}^{N_{p}} w_{k} \delta \left[ (\bar{g}_{m}, \bar{T}_{m})_{k} - (\bar{g}_{m}, \bar{T}_{m}) \right]
\]

\[
= \sum_{k=1}^{N_{p}} w_{k} p(f^{(i)} \mid z_{1:t}, \bar{g}_{k}, \bar{T}_{k}).
\]
Visualization of the Interaction Free Density
Including the Interaction

\[ p(f^{(R)}, f^{(1)}, f^{(2)}, \ldots, f^{(n)} \mid z_{1:t}) \approx \prod_{i=1}^{n} p(f^{(i)} \mid z_{1:t}) \]

non-interacting GPs

\[ \psi \times \text{GPs:} \]

\[ \psi(f^{(R)}, f) \]
Putting it all together: *Interacting Gaussian Processes*

\[
p(f^{(R)}, f^{(1)}, f^{(2)}, \ldots, f^{(n)} \mid z_{1:t}) = \frac{1}{Z} \psi(f^{(R)}, f) \prod_{i=1}^{n} p(f^{(i)} \mid z_{1:t})
\]

\[
p(f^{(i)} \mid z_{1:t}) = \sum_{k=1}^{N_p} w_k p(f^{(i)} \mid z_{1:t}, \bar{g}_k, \bar{T}_k)
\]

\[
p_{IGP}(f^{(R)}, f \mid z_{1:t}) \xrightarrow{\text{argmax}} (f^{(R)}, f)^ *
\]
Overhead Stereo Tracking System
Results!
Efficiency vs Density: human tele-op, reactive, IGP

Time to Travel 6 meters (seconds)

Average Crowd Density Over Duration of Run (people/m²)

- Reactive performance, n = 60
- Human driver, n = 85
- IGP performance, n = 80

Sparse data bin region
- IGP: Binned from 0.6 to 1.0
- Human: Binned from 0.6 to 1.0
Contribution of interaction term: IGP vs GP

<table>
<thead>
<tr>
<th>Number of Runs Failed</th>
<th>Average Crowd Density Over Duration of Run (people/m²)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0</td>
</tr>
<tr>
<td>GP, times GP failed = 80, Overall % GP failed: 0.63492</td>
<td></td>
</tr>
<tr>
<td>IGP, times IGP failed = 21, Overall % IGP failed: 0.19444</td>
<td></td>
</tr>
</tbody>
</table>

- GP failed runs, given density: 2/10, 3/8, 3/9, 7/11, 5/7, 5/7, 11/15, 7/9, 8/8, 11/12, 3/5, 5/5, 2/2, 5/5, 3/3
- IGP failed runs, given density: 1/16, 1/13, 2/12, 3/16, 2/7, 1/5, 0/6, 1/2, 3/6, 1/3, 2/2, 0/0, 3/3, 0/0, 1/1

No failures
Efficiency vs Density: IGP, GP, human tele-op

Average Crowd Density Over Duration of Run (people/m²) vs Time to Travel 6 meters (seconds)

- Human driver, n = 85
- GP Performance, n = 40
- IGP performance, n = 80

Sparse data bin region
- IGP: Binned from 0.6 to 1.0
- GP: Binned from 0.6 to 1.0
- Human: Binned from 0.6 to 1.0

Monday, March 5, 2012
Future Work

- **Shared autonomy: Fuse human and machine decision making**

\[
p(h, f^{(R)}, f | z_{1:t}) = \frac{\psi(h, f^{(R)}, f)}{Z} p(h | z_{1:t}) p(f^{(R)} | z_{1:t}) \prod_{i=1}^{n} p(f^{(i)} | z_{1:t})
\]

\[
(h, f^{(R)}, f)^* = \arg \max_{h, f^{(R)}, f} p(h, f^{(R)}, f | z_{1:t})
\]

- **Verification and Validation of Human Robot Interaction?**
  - what can we say about performance probabilistically?

- **Improve approximation procedure**
  - Gibbs sampling with modified Metropolis-Hastings for inference of nonlinearly coupled Gaussian Processes
Future Work

- Data driven methods of determining interaction function
  - Tree representation of pedestrian clusters?
  - Incorporating game theory for interaction learning (Waugh, et al)

Thanks!
Instrumenting the cafeteria: *new dataset*

Now have a huge store of decent quality crowd interaction data!

- Around 80 hours of tracks (collecting more each day!)
- Potential machine learning database for crowd prediction algorithms
  - Dirk Helbing and Luc Van Gool at ETH, Drew Bagnell at CMU
- Explore dataset for interaction “modes”
  - like Perona’s fly experiments at Caltech
Instrumenting the cafeteria: ongoing work

- Histogram navigation (Shuo Han)
  - collect data about current situation
  - navigate according to most similar situation in database of crowds
- Behavior anomaly recognition (Ozay, Tsuei)
  - using pan-tilt zoom camera, detect abnormal behavior
- Shared autonomy (Topcu, Livingston, Trautman)
  - multiple robots controlled by one operator