An UWB Time-Difference-of-Arrival Model
For Mobile Robot Localization

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Outdoor

Global Navigation Satellite Systems

Indoor

?
UWB Positioning

Theoretical UWB ranging performance

Graph: courtesy Chung et al., Int. Conf. on Ultra Wideband Systems and Technologies, 2003
UWB for Mobile Robots
&
Mobile Robots for UWB
UWB for mobile robots

• Beats current localization technologies
  – Low power
  – High accuracy & update rate
  – Line-of-sight (LOS) insensitivity
  – Scalability

• Applications
  – Embedded systems / robots
    • Wireless sensor networks
    • Multi-robot systems
UWB error source: TOA multipath

- True TOA
- Attenuation by antenna pattern
- Attenuation by obstruction (NLOS)
- Attenuation & delay by obstr. (NLOS)

→ positive bias
Mobile robots for UWB

• **Systematic assessment tool**
  – Controlled trajectories
  – Real-time localization performance evaluation

• **Understanding & alleviating UWB shortcomings**
  – Algorithm development (sensor fusion, machine learning)
  – Distributed intelligence (multi-robot systems)

• **Test portability onto embedded systems**
State-of-Art

• UWB on robots
  – Little work done

• UWB for on-board localization
  – Roy et al. (2005); Gonzalez et al. (2009)
  – Augmented state particle filters (no explicit error models)

• UWB sensor fusion
  – With dead-reckoning sensors
  – Not done yet with exteroceptive sensors
How?
Single robot setup

On-board sensor information:

- odometry
- motion model
- UWB TDOA
- TDOA measurement model
Multi-robot setup

On-board sensor information:

- odometry
- motion model
- UWB TDOA
- TDOA measurement model
- Relative positions
- R&B model
The KIII mobile robot

- Embedded Linux, 400MHz CPU
- 802.11b WiFi
- High resolution odometry
- Ubisense 7000 Series Compact Tag
- Relative range & bearing (R&B) board

~10cm
Experimental arena

Robots exploit space through random movement

Data:
• UWB TDOA measurements
• Ground truth (overhead camera)
• Robot data (odometry, relative pos.)
The UWB Measurement Model
UWB range error model

\[ \hat{r}_{un} = r_{un} + \varepsilon_{un} + Yb_{un} \]

- \( \varepsilon \sim N(0, \sigma_{n}^{2}) \)
- \( b_{un} \sim \lnN(\mu_{\lnN,u}, \sigma_{\lnN,u}) \)
- \( Y \sim \text{Bernoulli}(1 - P_{L_{un}}) \)

[Alsindi and Alavi, IEEE VTC, 2009]
TOA error model

TOA (range) error:
\[ \Delta \hat{r}_{un} = \hat{r}_{un} - r_{un} \]

PDF of LOS error:
\[ p_{un}(\Delta \hat{r}_{un} | L_{un}) = p_N(\Delta \hat{r}_{un}) \]

PDF of NLOS error:
\[ p_{un}(\Delta \hat{r}_{un} | \bar{L}_{un}) = (p_{ln N,u} * p_N)(\Delta \hat{r}_{un}) \]

PDF of TOA error:
\[ p_{un}(\Delta \hat{r}_{un}) = P_{L_{un}} \cdot p_{un}(\Delta \hat{r}_{un} | L_{un}) + (1 - P_{L_{un}}) \cdot p_{un}(\Delta \hat{r}_{un} | \bar{L}_{un}) \]
TDOA error model

TDOA:
\[ \hat{\tau}_{uv,n} = \hat{r}_{un} - \hat{r}_{vn} \]

TDOA error:
\[ \Delta \hat{\tau}_{uv,n} = \Delta \hat{r}_{un} - \Delta \hat{r}_{vn} \]

PDF of TDOA error:
\[ p_{uv,n}(\Delta \hat{\tau}_{uv,n}) = (p_{un} \ast p_{vn})(\Delta \hat{\tau}_{uv,n}) \]
Illustration: TOA error model

LOS

NLOS
Illustration: TDOA error model

LOS - LOS

NLOS - LOS

NLOS - NLOS
Employing the UWB TDOA Model
Parameter estimation

\[ \Delta \hat{r}_{un} = r_{un} + \varepsilon_{un} + Yb_{un} \]

\[ \varepsilon \sim N(0, \sigma_{N}^2) \]

\[ b_{un} \sim \ln N(\mu_{\ln N,u}, \sigma_{\ln N,u}) \]

\[ Y \sim \text{Bernoulli}(1 - P_{Lun}) \]
TDOA error models

- 4000 data points per base-station pair
- Curve fitting: minimization of Kolmogorov-Smirnov distance between CDFs
- Final KS-distance of 0.036
TOA error models

<table>
<thead>
<tr>
<th>Base-station</th>
<th>Probability Density</th>
</tr>
</thead>
<tbody>
<tr>
<td>BS1</td>
<td>0.49</td>
</tr>
<tr>
<td>BS2</td>
<td>0.32</td>
</tr>
<tr>
<td>BS3</td>
<td>0.28</td>
</tr>
<tr>
<td>BS4</td>
<td>0.09</td>
</tr>
</tbody>
</table>

\[ P_L \]

- Probability density distribution for TOA error [m].
- Graph comparing error models for different base-stations.
Estimation of spatial LOS/NLOS

If ground truth available

Solve:
\[ \hat{\tau}_{uv,n} = \tau_{uv,n} + b_{un} - b_{vn} \]

and if: \( b_{xn} > T \)

\[ P_{L_{un},t} = 1 \]

else

\[ P_{L_{un},t} = 0 \]
Robot Detection Model
Multi-robot localization

• Distributed intelligence
  – Shared knowledge on positioning
  – Shared knowledge on environment
  – Robustness

• Potential performance improvement

• Heterogeneous multi-robot team
Range & bearing detection model

- Multivariate, multimodal Gaussian
- PDF is created according to R&B noise model

$$P_{mn}(x_n \mid D_{n,t})$$
Experimental Results
Experimental scenarios

1. Collaboration scheme
   a) Collaborative
   b) Non-collaborative

2. NLOS/LOS path conditions
   a) Naïve  no NLOS assumed
   b) Average estimated constant LOS proportion
   c) Spatial quasi-optimal spatial LOS/NLOS
Experimental results

Empirical Cumulative Density over all positioning errors

Non-collaborative

Collaborative
Conclusions

Summary
• Explicit, probabilistic UWB TDOA measurement model
• Model validated on real data
• Collaboration compensated for LOS/NLOS knowledge

Further work
• Online Estimation
• Spatial error models
Thank you for your attention.

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Experimental results

RMSE over all particle positions

Collaborative

Non-collaborative
Algorithm: Multi-robot Monte-Carlo Localization

1: for all particles do
2:  apply_motion_model(odometry, particles)
3:  apply_measurement_model(TDOA, particles)
4:  apply_detection_model(R&B, particles)
5: end for
6: for all particles do
7:  if (rand < (1-\alpha))
8:     resample(particles)
9:  else
10:     reciprocal_sample(R&B)
11: end if
12: end