Sensor Fusion
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What is Sensor Fusion?

• Combination of different types of sensors to reach a better performance than possible with a single sensor

• Best sensor fusion system: The human brain

Why use it?

• To achieve better performance

• Extra sensors could work as backup if others fail (redundancy)
Complementary Sensors

Example:

FLIR profile

RADAR profile

Enemy plane

Ship
Fusion Levels

Increasing dataload

- Data Level
- Feature Level
- Decision Level

Increasing abstraction
## Applied Techniques

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Decentralized Fusion

a) Centralized fusion

b) Decentralized fusion
Extra Sensors

- Solar Sensor
- Magnetometer
- Rate Gyros
+ GPS
The Upgraded Testbed
Vector Matching

Wahba’s Problem:

\[
\text{minimize } J(A) = \sum_{i=1}^{n} \left\| \mathbf{v}_i^B - A\mathbf{v}_i^R \right\|^2
\]

Solution: Use the SVD method

1. Form B matrix of outer products

\[
\mathbf{B} = \sum_{i=1}^{n} \mathbf{v}_i^B (\mathbf{v}_i^R)^T
\]
Vector Matching

2. Split B into three matrices using Singular Value Decomposition

\[ B = U S V^T \]

3. The optimal attitude matrix best fitting the vector pairs can be found as:

\[ A_{opt} = U \text{diag}[1 \ 1 \ (\det U)(\det V)] V^T \]
Solar Cells

Working Principle:

Model:

\[ i_{sc} = i_{max} \cos \theta + v_s \]
Solar Cells

Temperature effects

![Graph showing temperature effects on solar cell intensity over time.](image)
Solar Cells

Calibration

• Sensitivity
• Mounting
• Cosine char.
Solar Cells

Mounting errors (adjustment of cell-axis)
Solar Cells

Cosine corrections
Sun Sensor

Performance

White Noise?
Magnetometer

Calibration

- Field bias
- Mounting uncertainties
Magnetometer

Calculating internal bias

At ‘zero’ attitude (A = I)

\[ \xi_{ref} = \xi_o + \xi_{bias} \]

Each measurement

\[ \xi_m = A \xi_o + \xi_{bias} \]

Least Square

\[ \xi_m = A \xi_o + (\xi_{ref} - \xi_o) \]

\[ \xi_m - \xi_{ref} = (A - I)\xi_o \]
Magnetometer

Mounting uncertainties calibrated by a small rotation, found using the SVD method

Result:
Rate Gyros

Working Principle:

Measures the state (angular rate) directly
Rate Gyros

Error sources:

- Noise
- Timevar. bias
- Scalefactor
- Accel. sensitivity
- Off-axis error
Data Fusion

Measurement model:

\[ x(t_k) = \begin{bmatrix} q \\ \omega \\ \beta \\ \beta_r \end{bmatrix}, \quad z(t_k) = \begin{bmatrix} \Delta \varphi_{11} \\ \Delta \varphi_{12} \\ \Delta \varphi_{13} \\ \vdots \\ \Delta \varphi_{N1} \\ \Delta \varphi_{N2} \\ \Delta \varphi_{N3} \\ \nu_2 \\ \nu_3 \\ e_m^B \\ e_s^B \end{bmatrix}, \quad h[x(t_k), t_k] = \begin{bmatrix} b_1^T A e_1^R + \beta_1 \\ b_1^T A e_2^R + \beta_2 \\ b_1^T A e_3^R + \beta_3 \\ \vdots \\ b_i^T A e_i^R + \beta_1 \\ b_i^T A e_i^R + \beta_2 \\ b_i^T A e_i^R + \beta_3 \\ \omega_2 + \beta_{r2} \\ \omega_3 + \beta_{r3} \\ A e_m^R \\ A e_s^R \end{bmatrix} \]
Data Fusion

Measurement gradient matrix:

\[
H[x(t_k), t_k] = \begin{bmatrix}
-2(Ae_{1}^{R})^{T}B_1^x \\
-2(Ae_{1}^{R})^{T}B_2^x & 0_{3\times3} & 1_{3\times3} & 0_{3\times2} \\
-2(Ae_{1}^{R})^{T}B_3^x & 0_{3\times3} & 1_{3\times3} & 0_{3\times2} \\
\vdots & \vdots & \vdots & \vdots \\
-2(Ae_{N}^{R})^{T}B_1^x \\
-2(Ae_{N}^{R})^{T}B_2^x & 0_{3\times3} & 1_{3\times3} & 0_{3\times2} \\
-2(Ae_{N}^{R})^{T}B_3^x & 0_{3\times3} & 1_{3\times3} & 0_{3\times2} \\
0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 \\
2(Ae_{m}^{R})^x & 0_{3\times3} & 0_{3\times3} & 0_{3\times2} \\
2(Ae_{s}^{R})^x & 0_{3\times3} & 0_{3\times3} & 0_{3\times2}
\end{bmatrix}
\]
State Fusion

Using receiver solution as input measurement

\[ z_q(t_k) = \begin{bmatrix} \hat{q}_1 \\ \hat{q}_2 \\ \hat{q}_3 \\ \hat{q}_4 \end{bmatrix} \quad h[x(t_k), t_k] = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} \quad H_q[x(t_k), t_k] = \begin{bmatrix} 1_{3\times3} & 0_{3\times3} \\ 0_{3\times3} & 0_{3\times3} \end{bmatrix} \]

Residuals must be redefined:

\[ \delta x(t_k) \neq K(z_q(t_k) - h_q[x(t_k), t_k]) \]
\[ \Downarrow \]
\[ \delta x(t_k) = K(z_q(t_k) \otimes h_q[x(t_k), t_k]^*) \]
## Data fusion

### 5 Satellites

<table>
<thead>
<tr>
<th></th>
<th>GPS</th>
<th>GPS + Sun sensor</th>
<th>Improvement</th>
</tr>
</thead>
<tbody>
<tr>
<td>GPS</td>
<td>0.33 deg</td>
<td>0.30 deg</td>
<td>9 %</td>
</tr>
<tr>
<td>GPS + Magnetometer</td>
<td>0.32 deg</td>
<td></td>
<td>3 %</td>
</tr>
<tr>
<td>GPS + Rate gyros</td>
<td>0.32 deg</td>
<td></td>
<td>3 %</td>
</tr>
<tr>
<td>GPS + All</td>
<td>0.29 deg</td>
<td></td>
<td>12 %</td>
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</tbody>
</table>

### 3 Satellites

<table>
<thead>
<tr>
<th></th>
<th>GPS</th>
<th>GPS + All</th>
<th>Improvement</th>
</tr>
</thead>
<tbody>
<tr>
<td>GPS</td>
<td>0.48 deg</td>
<td>0.38 deg</td>
<td>21 %</td>
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</tbody>
</table>
## Results

### State fusion

<table>
<thead>
<tr>
<th>Situation</th>
<th>RSS error</th>
<th>MFLOPS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Raw attitude from receiver</td>
<td>0.49 deg</td>
<td>0</td>
</tr>
<tr>
<td>Raw attitude from receiver + Kalman</td>
<td>0.42 deg</td>
<td>5.9</td>
</tr>
<tr>
<td>Raw attitude from receiver + Kalman + Secondary sensors</td>
<td>0.37 deg</td>
<td>20.2</td>
</tr>
<tr>
<td>Phase data from receiver + Kalman</td>
<td>0.33 deg</td>
<td>18.6</td>
</tr>
<tr>
<td>Phase data from receiver + Kalman + Secondary sensors</td>
<td>0.29 deg</td>
<td>50.6</td>
</tr>
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Shadowed GPS

<table>
<thead>
<tr>
<th></th>
<th>GPS + All secondary</th>
<th>All secondary alone</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pitch (u)</td>
<td>0.13</td>
<td>0.26</td>
</tr>
<tr>
<td>Roll (v)</td>
<td>0.17</td>
<td>0.56</td>
</tr>
<tr>
<td>Yaw (w)</td>
<td>0.19</td>
<td>0.63</td>
</tr>
<tr>
<td>RSS</td>
<td>0.29</td>
<td>0.88</td>
</tr>
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</table>
Conclusion

• Sensor fusion techniques can be applied to GPS applications mainly on the data and feature level

• The gain in accuracy was however shown to be only moderate in this project

• Significant error sources include less than optimal sensors and mechanical alignment problems

• The accuracy achieved by secondary sensors alone was shown to be sufficient for many space missions