INDOOR LOCATION SENSING AMBIENT MAGNETIC FIELD

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Positioning System
INTRODUCTION

- Indoor positioning system using magnetic field as location reference
  - Magnetic field inside building
Magnetic field distortion

A magnitude map (in units of μT) of the magnetic field.
Using magnetic field distortion as fingerprints

Some visualization of magnetic distortion signatures created while rotating an e-compass on a some distance circumferences.

Perfect circle of 100 steps

Outdoor

Indoor example 1

Indoor example 2
DEMO VIDEO CLIP 1
DEMO VIDEO CLIP 2

X4
DEMO VIDEO CLIP 3
DEMO VIDEO CLIP 4
Initial Investigation

Investigate the feasibility of using the magnetic field fingerprints as a localization reference for positioning system.

- How many sensors are needed to have a decent accuracy?
- How well the magnetic field aided positioning system would work?
- How can we correct the direction error from e-compasses?
Hardware setup
Rotating tower with a magnetic sensor

- Sensor Heading
- Magnetic Sensor
- Turn 360° in 100 steps
- Microcontroller and Bluetooth
- Stepper Motor

Step 0
Sensor Heading

Step 75
270°

Step 25
90°

Step 50
180°

5 cm
Data format

- At each step, three-dimensional vector \( m = \{m_x, m_y, m_z\} \) produced from a magnetic sensor (HMC6343).

- Locations and directions are indexed
  - Data set \( E = \{m_{0,0} \ldots m_{L,K}\} \) where
    - \( L \) is the location index
    - \( K \) is the rotation (step) index
Data collection process

- Every 2 feet (60 cm) along the corridor above 1 m on the floor.

- Total of 60 location points $\times$ 100 directions = 6,000 data features. (Data size = 84KB, 1 feature = 14 bytes)

- Two sets of data collected in a week apart.
  - Map dataset
  - Test dataset

A magnitude map (in $\mu$T) of the magnetic field.
DATA ANALYSIS

Angle correction
Accuracy as a function of a number of sensors
Confusion matrix & matrix of least RMS
Magnetic field distortion

\[ \parallel m \parallel \]
Fingerprint matching method

- 8 different combinations (fingerprints) of \( m \) in \( d \) where \( d^k = \{m_1...m_k\} \) with common denominator \( k = \{100, 50, 25, 20, 10, 5, 4, 2\} \) (location index is omitted)

- Least RMS based Nearest Neighborhood: given a map dataset \( E \) and target location fingerprint \( d \), then a nearest neighbor of \( d \), \( d' \) is defined as:

\[
\forall d'' \in E, |d \leftrightarrow d'| \leq |d \leftrightarrow d''|, |d \leftrightarrow d'| = \sqrt{\sum_{i=1}^{k} (d_i \leftrightarrow d'_i)^2}
\]

where \( E = \{m_{0,0}...m_{L,K}\} \) (\( L \) = location index, \( K \) = rotation index). Once it found \( d' \), get \( L \) and \( K \) of the \( d' \) as predicted location and direction.
Fingerprint matching method

- Root Mean Square Error

\[
\text{d}_k, \text{d}'_k, \text{d}''_k \] : observation – currently measured data
\[
\text{d}_k, \text{d}'_k, \text{d}''_k \] : map – previously collected data with geo tagged
\[
k \] : number of features (or dimension)

Compare the distances

Least RMS
Localization performance

Finding location index of $d'$ that has the least RMS error with $k=4$.

For example, $d^4$ can be

$\{m_1, m_{26}, m_{51}, m_{76}\}$, 
$\{m_2, m_{27}, m_{52}, m_{77}\}$, 
$\ldots$, 
$\{m_{25}, m_{50}, m_{75}, m_{100}\}$.

Err$_{\text{mean}} = 3.05$ m 
Err$_{\text{sd}} = 4.09$ m 
Err$_{\text{max}} = 15$ m,

70 % of the predicted data had errors of less than 2 meters.
Accuracy as a function of a number (k) of sensors

Average distance errors from every 8 different combinations (fingerprints) of $d^k$ where $k = \{100, 50, 25, 20, 10, 5, 4, 2\}$

$k =$ Number of features (sensors)
Angle correction

Finding direction index of fingerprint d’ that has the least RMS

<table>
<thead>
<tr>
<th>Corrected Prediction</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\text{Err}_{\text{mean}}$</td>
</tr>
<tr>
<td>$\text{Err}_{\text{sd}}$</td>
</tr>
<tr>
<td>$\text{Err}_{\text{max}}$</td>
</tr>
<tr>
<td>$\text{Err}_{\text{min}}$</td>
</tr>
<tr>
<td>$\text{Err}_{\text{range}}$</td>
</tr>
</tbody>
</table>
NEW SYSTEM DESIGN FOR PEDESTRIAN
New hardware design

- Extend the system to provide a human wearable device
- Data update rate 10 Hz
Fingerprint matching method

- **Data format**
  - At each step, 3-dimensional X4 vector \( \mathbf{d}_{\text{raw}} = [m_{x1}, m_{y1}, m_{z1}, m_{x2}, m_{y2}, m_{z2}, m_{x3}, m_{y3}, m_{z3}, m_{x4}, m_{y4}, m_{z4}] \) is produced from a magnetic sensor badge.
  - Locations and directions are indexed
    - \textbf{Map} \( E = \{d_{1,1} \ldots d_{L,K}\} \) where
      - \( L \) is the location index
      - \( K \) is the rotation index

- **Least RMS based Nearest Neighborhood:**
  - Given a map dataset \( E \) and target location fingerprint \( d \), then a nearest neighbor of \( d \), \( d' \) is defined as
    \[
    \forall d'' \in E, \, |d \leftrightarrow d' | \leq |d \leftrightarrow d''|, \, |d \leftrightarrow d'| = \sqrt{\sum_{i=1}^{k} (d_i \leftrightarrow d'_i)^2}
    \]
    - \( L \) and \( K \) of the \( d' \) are predicted location and direction.
Data collection process

• Map fingerprints were collected at every 2 feet (60 cm) on the floor rotating sensor attached chair at the height of 4 feet above ground.

• The test data set was collected in a similar manner, sampling one fingerprint per step (2 feet), a week later than the creation of the fingerprint map.
New hardware design

- Inertial Measurement Unit (IMU) + 4 magnetic sensors

Magnetic sensor (M): 3 axes HMC5843
Gyroscope sensor (G): 3 axes ITG-3200
Accelerometer sensor (G): 3 axes ADXL345
MPU: ATmega328
Evaluation of localization performance

• Measure localization performance in two different structural environments:
  • Corridors
  • Atrium
Corridors

Corridor map data: Total of 37200 fingerprint = 868KB, (1 fingerprint data = 28 bytes)
Dimension = 187.2 m x 1.85 m
Atrium map data: Total of 40800 fingerprints = 979.2 KB. (1 fingerprint data = 28 bytes)

Dimension = 13.8 m x 9.9 m
DATA ANALYSIS
Least RMS errors in Corridors using least RMS with NN

75.7% of the predicted positions have an error less than 1m.
Err_{mean} = 6.28 m (Err_{sd} = 12.80 m, Err_{max} = 52.60 m)
Least RMS errors in Atrium
using least RMS with NN

72 % of the predicted positions have an error less than 1m.
Err_{mean} = 2.84 m (Err_{sd} = 3.39 m, Err_{max} = 12.82 m)
Method for filtering outliers

- Algorithm using least RMS of raw, unit, and intensity vectors
- $|L_{raw}' \leftrightarrow L_{norm}'| \leq 1$ or $|L_{raw}' \leftrightarrow L_{unit\_vector}'| \leq 1$, where $L'$ is a location index of $d'$

\[
d_{raw} = [m_1, m_2, m_3, m_4], \text{ where } m = \{m_x, m_y, m_z\}
\]
\[
d_{norm} = [n_1, n_2, n_3, n_4], \text{ where } n = \sqrt{m_{xk}^2 + m_{yk}^2 + m_{zk}^2}
\]
\[
d_{unit\_vector} = [u_{x1}, u_{y1}, u_{z1}, u_{x2}, u_{y2}, u_{z2}, u_{x3}, u_{y3}, u_{z3}, u_{x4}, u_{y4}, u_{z4}],
\]
where $u_{(x,y,z)} = m_{(x,y,z)k}/n_k,$
Least RMS errors in corridors using least RMS with NN

88 % of the predictions fall under 1 meter of error.
Least RMS errors in Atrium
Algorithm using least RMS of raw, unit, and intensity vectors

86.6 % of the predictions fall under 1 meter of error

Histogram of distance error in meters.

CDF of distance error in meters.
## Result with varying search area

<table>
<thead>
<tr>
<th>Search area in diameter</th>
<th>$\text{Err}_{\text{mean}}$ (m)</th>
<th>$\text{Err}_{\text{SD}}$ (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Corridor</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>40 meter</td>
<td>1.65 meter</td>
<td>6.15 meter</td>
</tr>
<tr>
<td>30 meter</td>
<td>0.66 meter</td>
<td>3.22 meter</td>
</tr>
<tr>
<td>20 meter</td>
<td>0.32 meter</td>
<td>1.15 meter</td>
</tr>
<tr>
<td><strong>Atrium</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>&gt;15 meter</td>
<td>0.96 meter</td>
<td>2.17 meter</td>
</tr>
<tr>
<td>9 meter</td>
<td>0.61 meter</td>
<td>1.75 meter</td>
</tr>
</tbody>
</table>
DEMO VIDEO CLIP 5
Other outlier filtering methods (recent updates)

• Combined with WiFi localization [1]
  • $\text{Err}_{\text{mean}} = 0.92$ meter
  • $\text{Err}_{\text{SD}} = 1.91$ meter
  • $\text{Err}_{\text{max}} = 9.6$ meter

• Applying particle filter
  • 1000 particles with particle motion models used in (Haverinen et al 2009).
  • Particles converge after 3 meters of travel.
    • $\text{Err}_{\text{mean}} = 0.7$ meter
    • $\text{Err}_{\text{SD}} = 0.89$ meter
    • $\text{Err}_{\text{max}} = 7.1$ meter

Comparison between two different floors

<table>
<thead>
<tr>
<th>True location</th>
<th>Predicted location</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2\textsuperscript{nd} Floor</td>
</tr>
<tr>
<td>2\textsuperscript{nd} Floor</td>
<td>1.0</td>
</tr>
<tr>
<td>3\textsuperscript{rd} Floor</td>
<td>0</td>
</tr>
</tbody>
</table>
INDOOR MAGNETIC FIELD STABILITY

The magnetic field’s stability inside of a building over time
The effect of moving objects on system performance
The effect of objects carried by the user
The magnetic field’s stability inside of a building over time

Method:

- \( \text{CosineSimilarity} (A, B) = \frac{1}{n} \sum_{i=1}^{n} \frac{(A_i \cdot B_i)}{|A_i||B_i|} \), where \( n = 60 \);
- \( \text{Magnitude} (A, B) = \frac{\sum_{i=1}^{n} |A_i||B_i|}{\sum_{i=1}^{n} |B_i|} \), where \( n = 60 \).

Results:

- \( \text{CosineSimilarity}(M_{\text{init}}, M_{2\_week}) = 0.9997 \), and \( \text{CosineSimilarity}(M_{\text{init}}, M_{6\_month}) = 0.9977 \).
- \( \text{Magnitude}(M_{6\_month}, M_{\text{init}}) = 0.99 \) and \( \text{Magnitude}(M_{2\_week}, M_{\text{init}}) = 1.01 \).
The effect of moving objects on system performance

The minimum RMS distance between any two locations in our map data = 1.96 µT. Error tolerance < 0.98 µT
The effect of moving objects on system performance

Errors measured in a room, with and without furniture, was also not significant. 
(RMS error = 0.71 µT)
Previous Work

• Infrastructure based
  • GPS (Radio, Satellites)
  • Active Badge (IR, IR beacons)
  • Active Bat (Ultrasound, beacons)
  • WLAN based positioning (Radio, WLAN stations)

• Without Infrastructure System
  • Vision based (vSLAM and PTAM)
  • Magnetic field based (single magnetic sensor + statistical & probabilistic approaches)
    • Siiksakulchai et al. 2000
    • Haverinen et al. 2009
    • Navarro et al. 2009
Discussion

- Limitations
  - Cost of constructing magnetic field maps
    - Map data collection method needs to be improved.
  - Works in buildings based on metallic skeletons
  - Influences of dynamically changing magnetic fields generated by large devices.
# Conclusion

<table>
<thead>
<tr>
<th>System</th>
<th>Wireless Technology</th>
<th>Positioning Algorithm</th>
<th>Precision</th>
<th>Cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>Our system</td>
<td>Magnetic Fingerprints</td>
<td>Nearest Neighborhood with least RMS</td>
<td>90% within 1.64 m (88% within 1.0 m) 50% within 0.71 m</td>
<td>Low - Medium</td>
</tr>
<tr>
<td>RADAR</td>
<td>WLAN RSS fingerprints</td>
<td>kNN, Viterbi-like algorithm</td>
<td>90% within 5.9 m 50% within 2.5 m</td>
<td>Low</td>
</tr>
<tr>
<td>Horus</td>
<td>WLAN RSS fingerprints</td>
<td>Probabilistic method</td>
<td>90% within 2.1 m</td>
<td>Low</td>
</tr>
<tr>
<td>Where Net</td>
<td>UHF TDOA</td>
<td>Least Square/RWGH</td>
<td>50% within 3m</td>
<td>Low</td>
</tr>
<tr>
<td>Ubisense</td>
<td>Uni-directional UWB TDOA + AOA</td>
<td>Least Square</td>
<td>99% within 0.3m</td>
<td>High</td>
</tr>
<tr>
<td>GSM fingerprinting</td>
<td>GSM cellular network (RSS)</td>
<td>Weighted kNN</td>
<td>80% within 10m</td>
<td>Medium</td>
</tr>
</tbody>
</table>