

INDOOR LOCATION SENSING USING GEO-MAGNETISM

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Presented by Jaewoo Chung

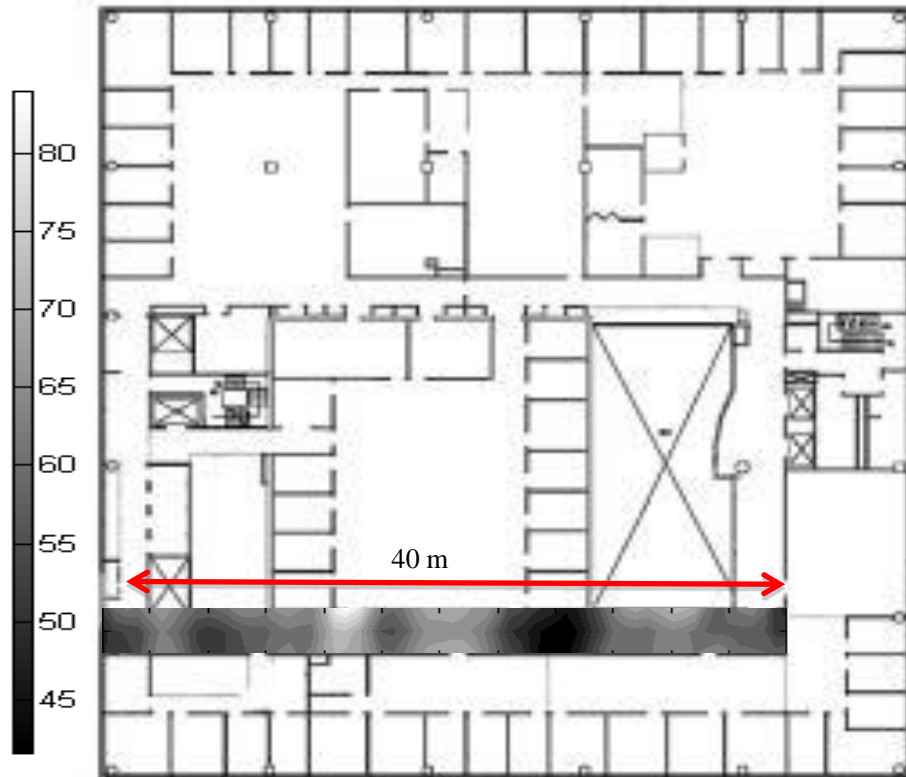
INTRODUCTION

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

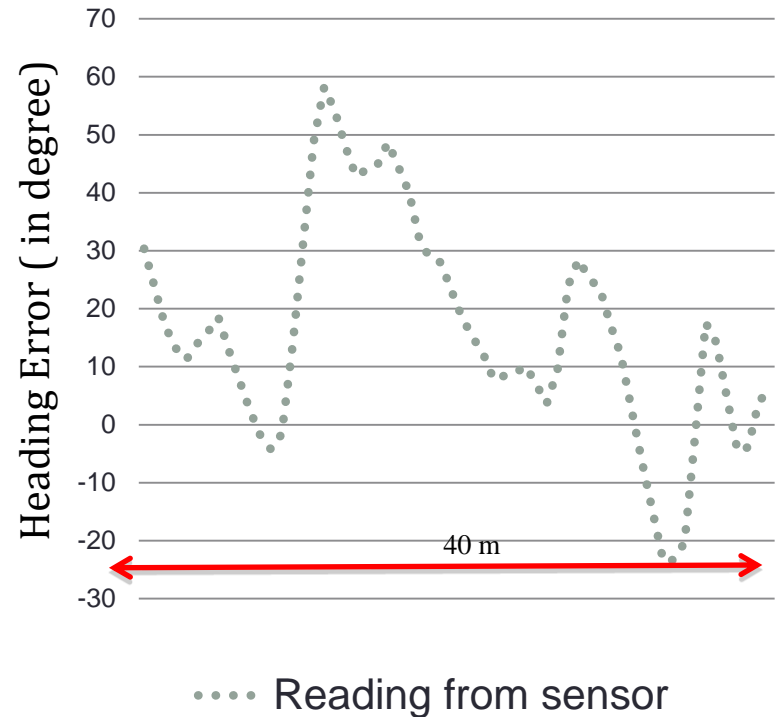
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Magnetic field distortion

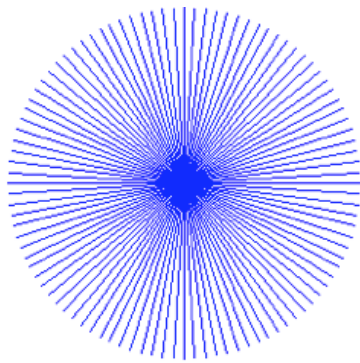


A magnitude map (in units of μT) of the magnetic field.

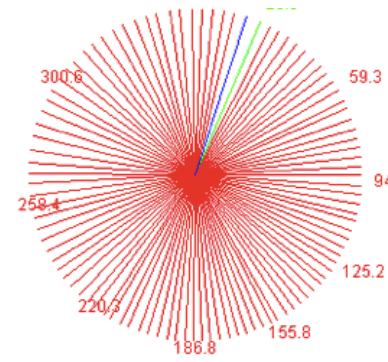


Using magnetic field distortion as fingerprints

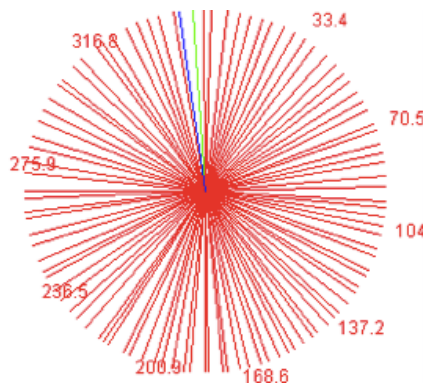
Some visualization of magnetic distortion signatures created while rotating an e-compass on a some distance circumferences.



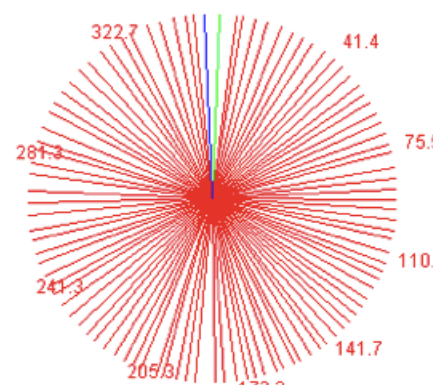
Perfect circle of 100 steps



Outdoor

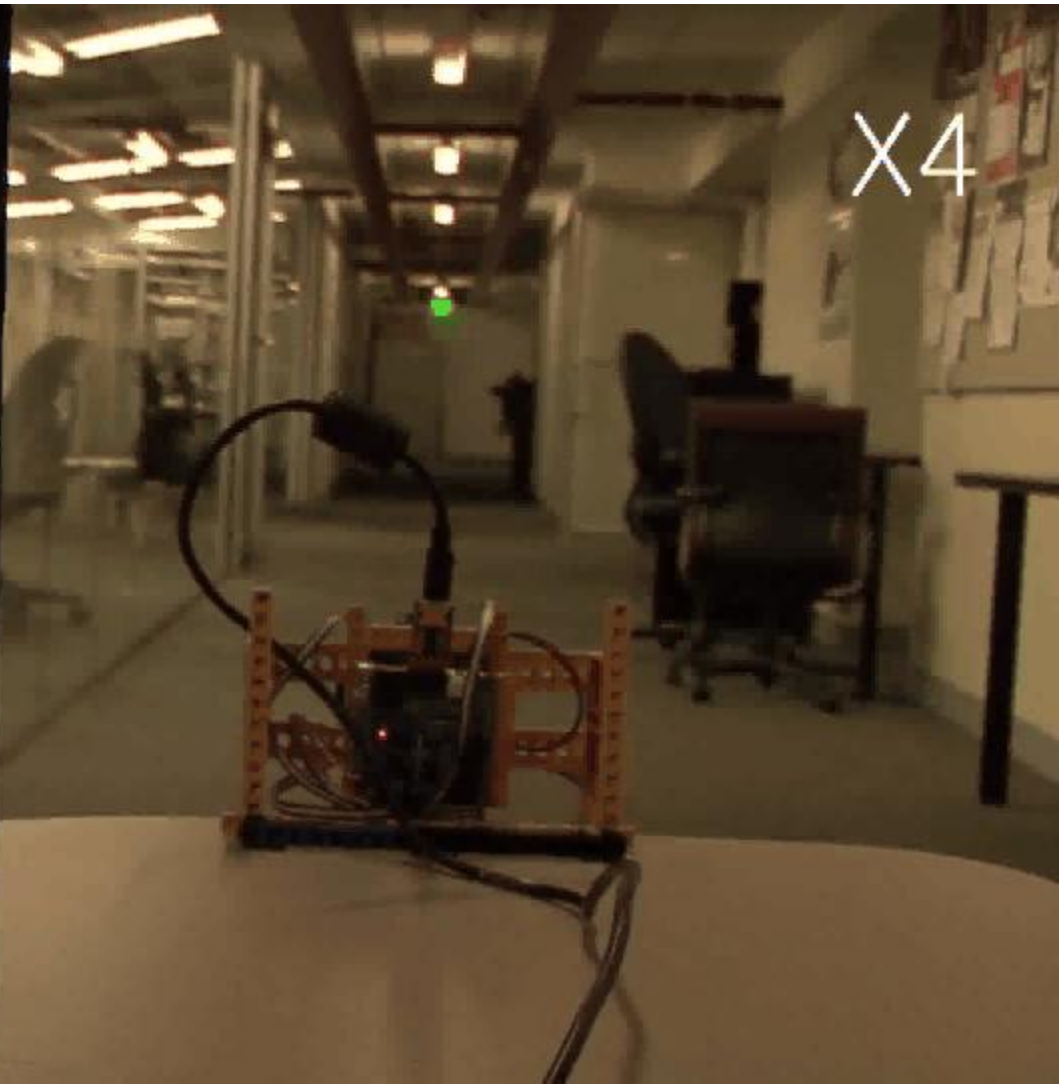


Indoor example 1



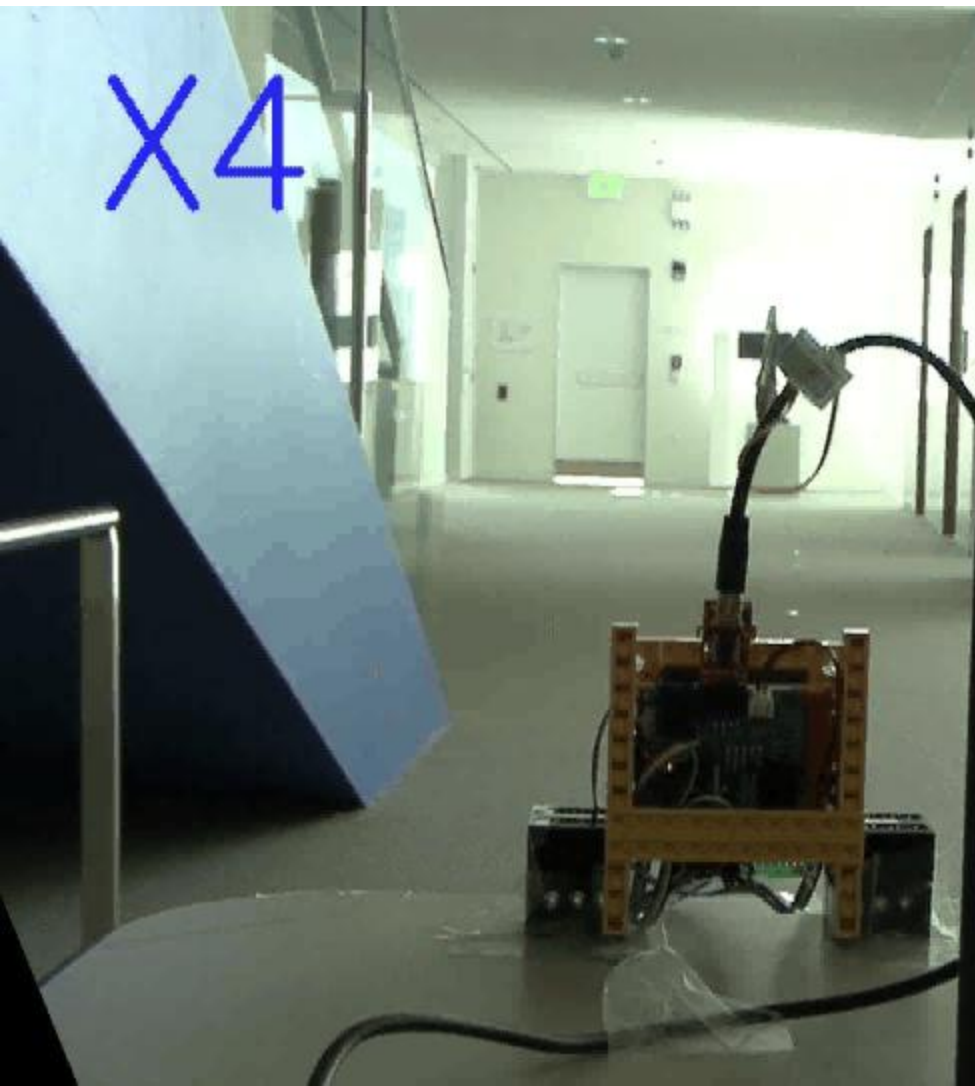
Indoor example 2

DEMO VIDEO CLIP 1

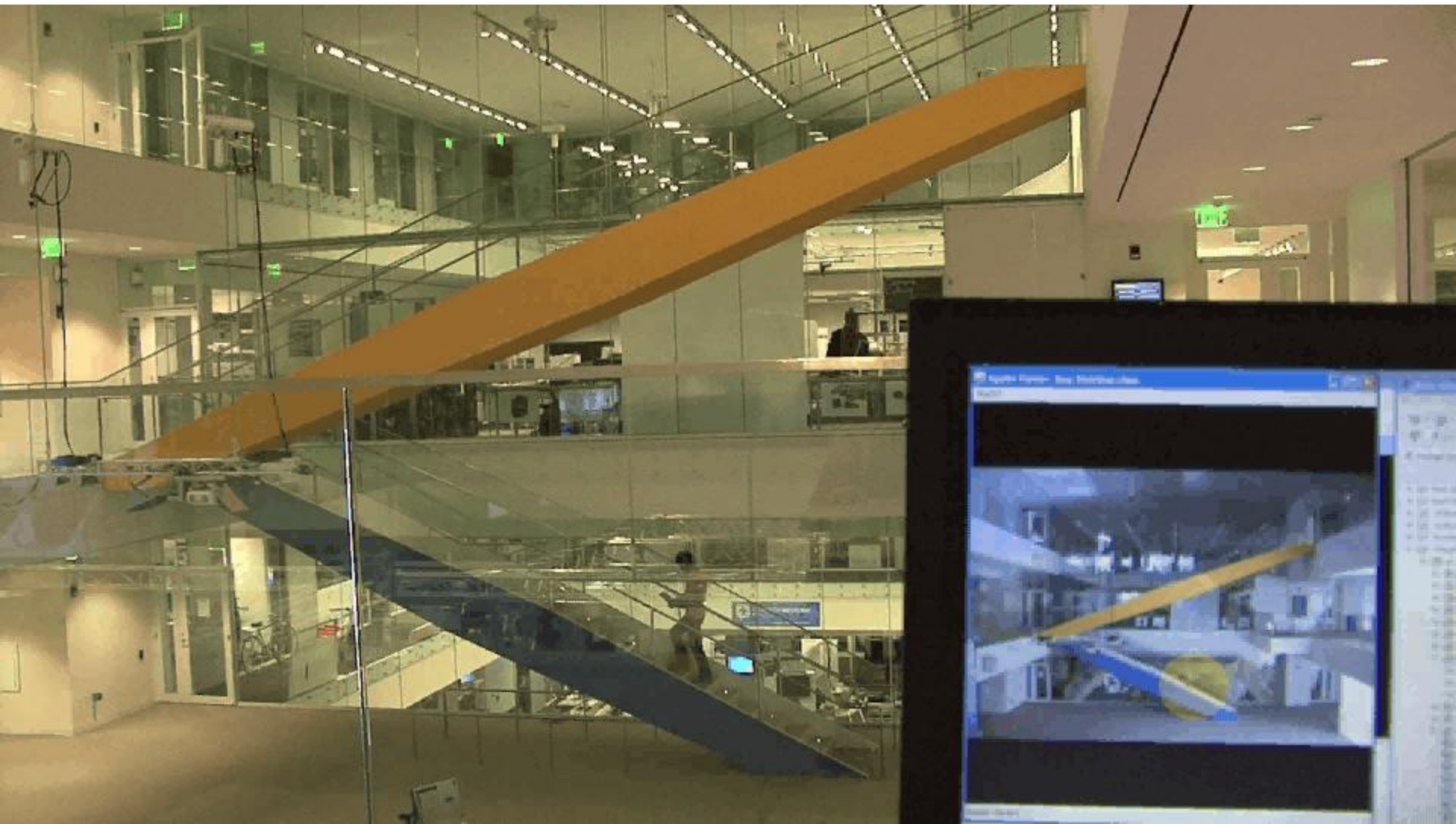


DEMO VIDEO CLIP 2

X4



DEMO VIDEO CLIP 3



DEMO VIDEO CLIP 4



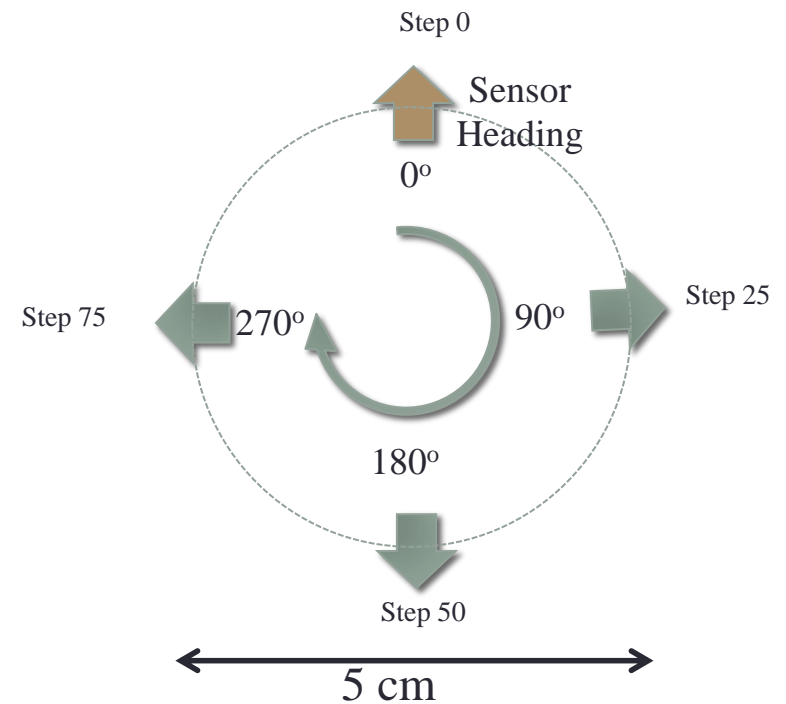
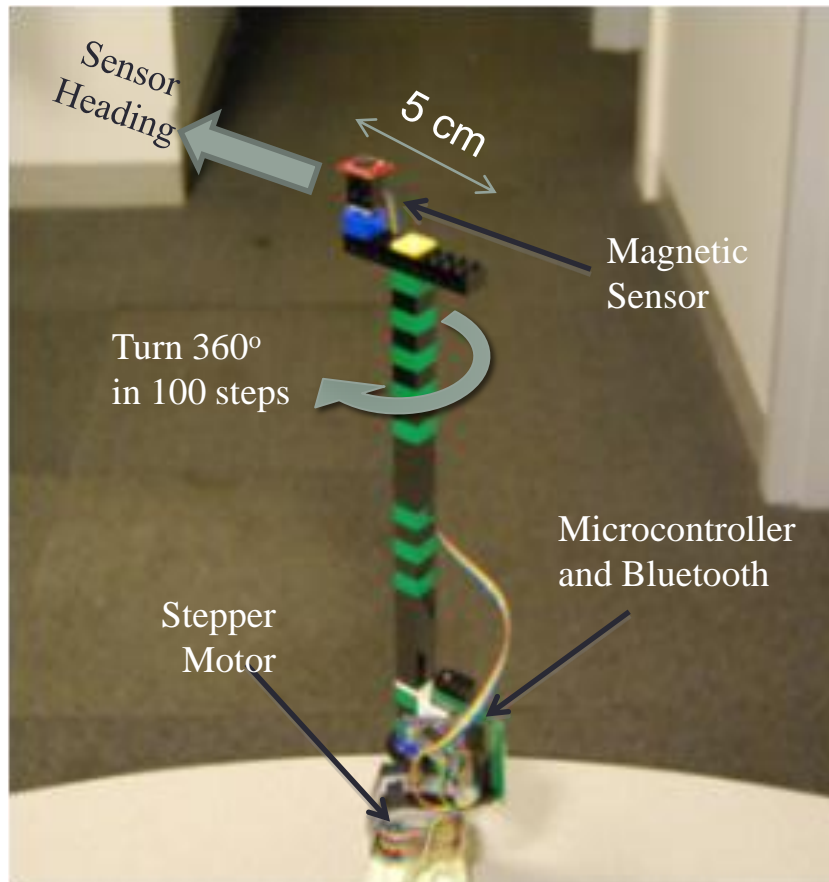
Initial Investigation

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?

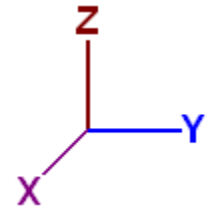
Hardware setup

Rotating tower with a magnetic sensor

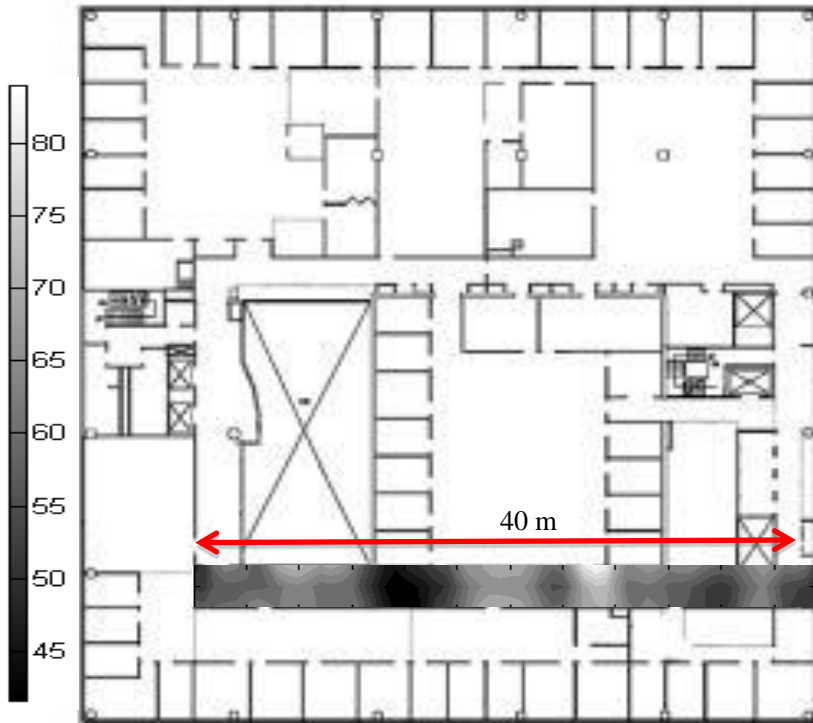


Data format

- At each step, three-dimensional vector $\mathbf{m} = \{m_x \ m_y \ m_z\}$ produced from a magnetic sensor (HMC6343).
- Locations and directions are indexed
 - **Data set** $E = \{\mathbf{m}_{0,0} \dots \mathbf{m}_{L,K}\}$ where
 - L is the location index
 - K is the rotation (step) index



Data collection process



A magnitude map (in μT) of the magnetic field.

- Every 2 feet (60 cm) along the corridor above 1 m on the floor.
- Total of 60 _{location points} X 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

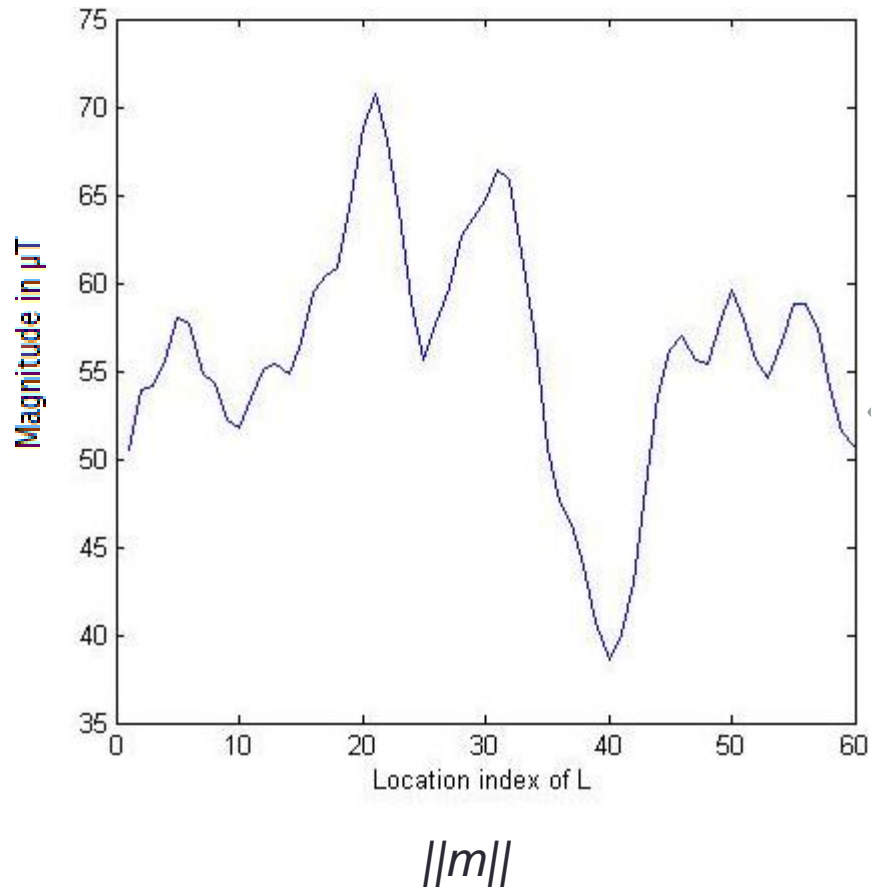
DATA ANALYSIS

Angle correction

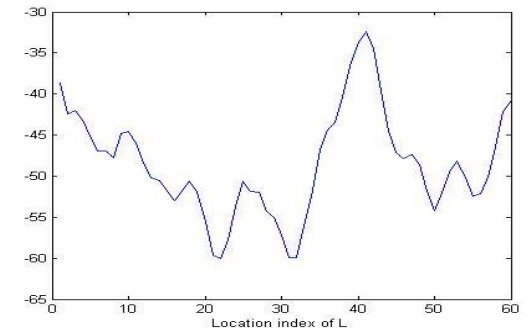
Accuracy as a function of a number of sensors

Confusion matrix & matrix of least RMS

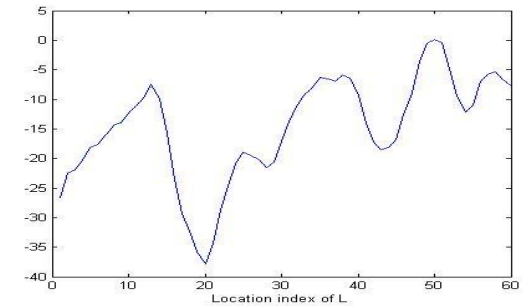
Magnetic field distortion



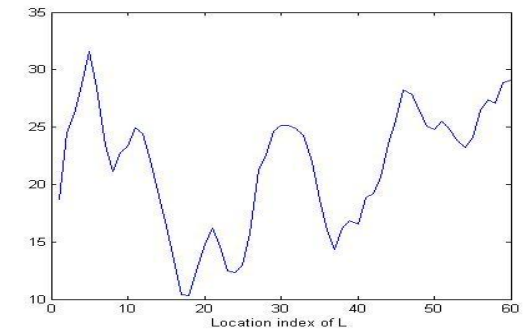
m_x



m_y



m_z



Fingerprint matching method

- 8 different combinations (fingerprints) of \mathbf{m} in \mathbf{d} where $\mathbf{d}^k = \{\mathbf{m}_1 \dots \mathbf{m}_k\}$ 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 \mathbf{E} and target location fingerprint \mathbf{d} , then a nearest neighbor of \mathbf{d} , \mathbf{d}' is defined as:

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

where $\mathbf{E} = \{\mathbf{m}_{0,0} \dots \mathbf{m}_{L,K}\}$ (L = location index, K = rotation index).

Once it found \mathbf{d}' , get L and K of the \mathbf{d}' as predicted location and direction.

Localization performance

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

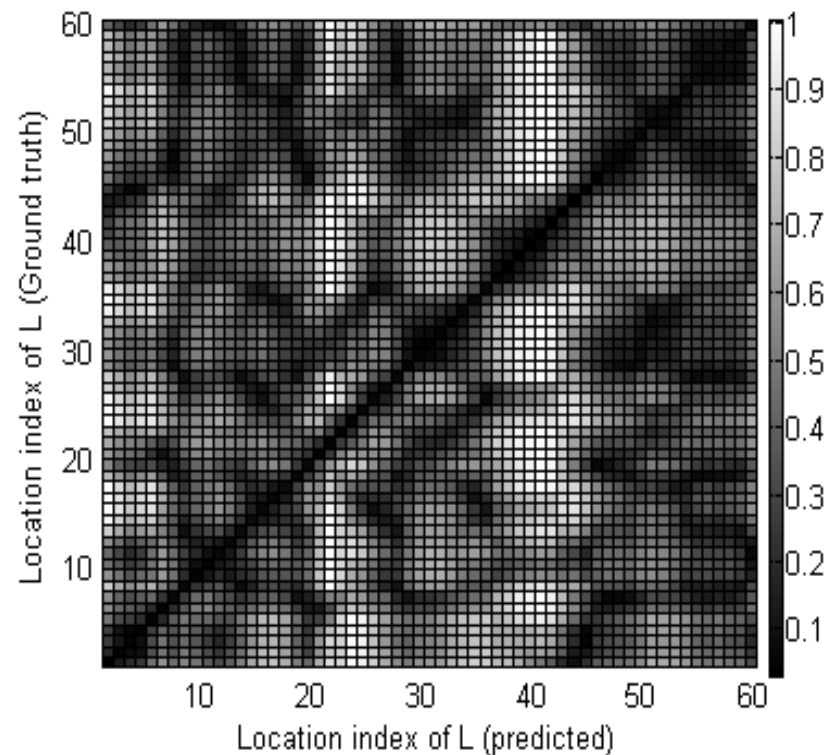
For example, d^4 can be
 $\{m_1, m_{26}, m_{51}, m_{76}\}$,
 $\{m_2, m_{27}, m_{52}, m_{77}\}$,
 \dots ,
 $\{m_{25}, m_{50}, m_{75}, m_{100}\}$.

$\text{Err}_{\text{mean}} = 3.05 \text{ m}$

$\text{Err}_{\text{sd}} = 4.09 \text{ m}$

$\text{Err}_{\text{max}} = 15 \text{ m}$,

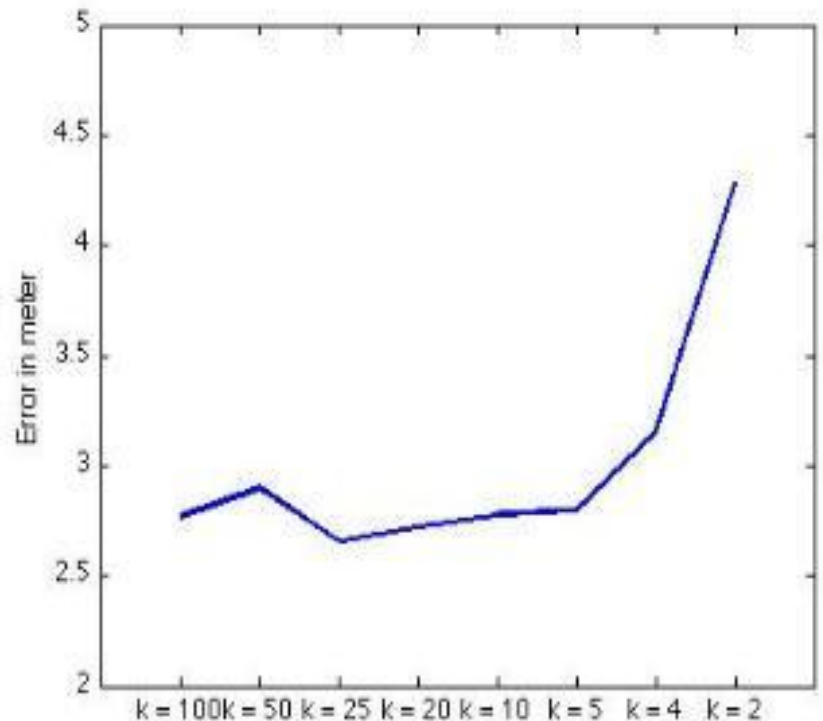
70 % of the predicted data had errors of less than 2 meters.



Normalized confusion matrix of RMS error with $k=4$.

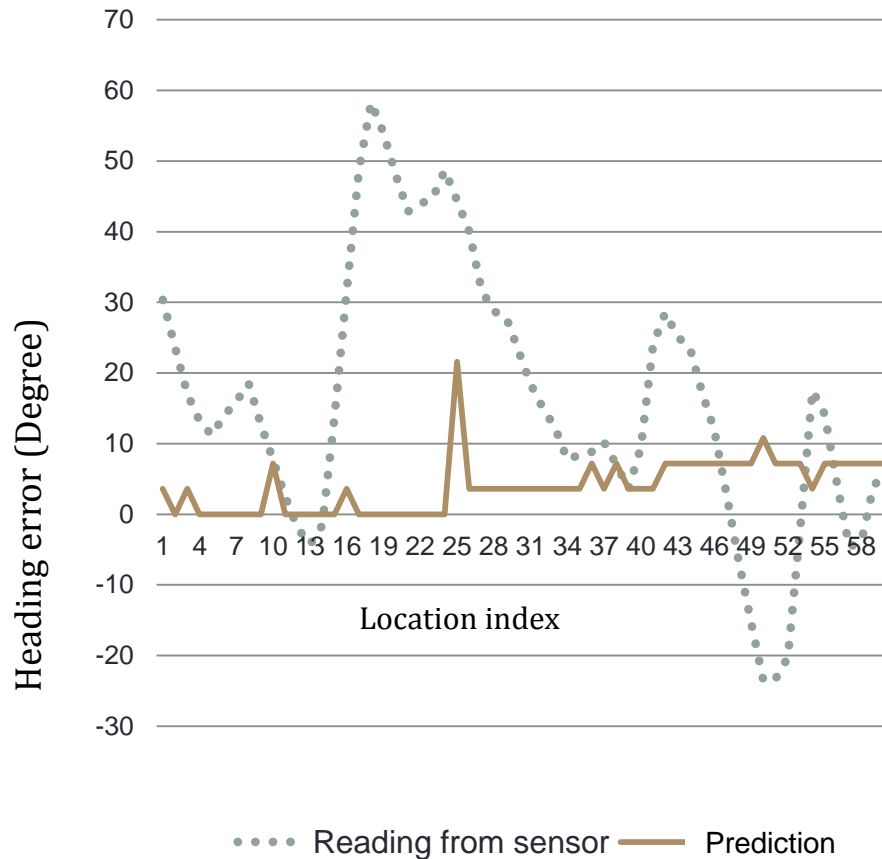
Accuracy as a function of a number (k) of sensors

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



Number of sensors (k)

Angle correction



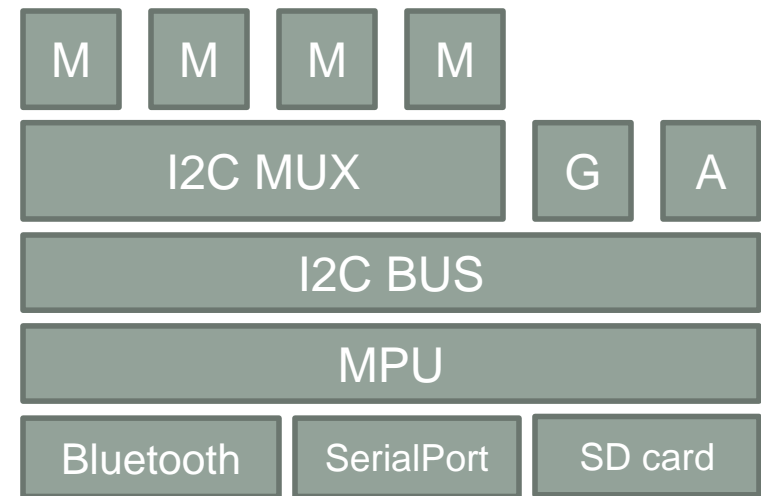
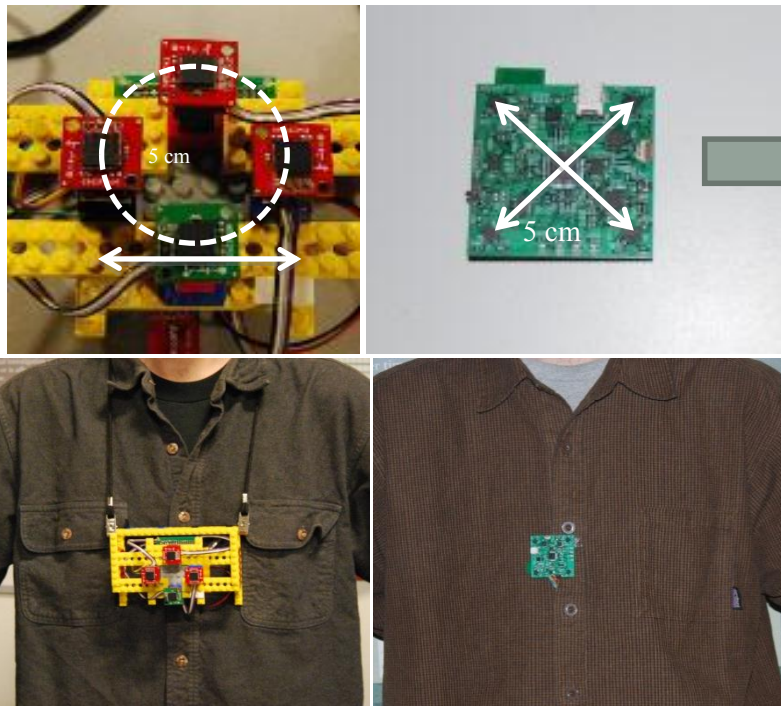
Finding direction index of fingerprint d' that has the least RMS

	Sensor	Prediction
Err_{mean}	20.38°	4.6°
Err_{sd}	15.32°	4.017°
Err_{max}	59.31°	21.6°
Err_{min}	-22.62°	0°
Err_{range}	81.93°	21.6°

NEW SYSTEM DESIGN FOR PEDESTRIAN

New hardware design

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

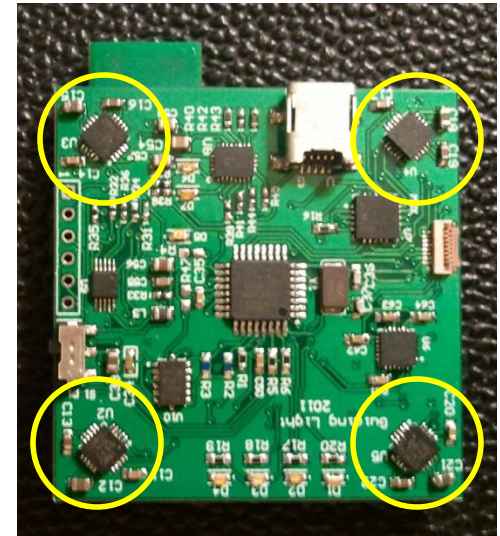


Magnetic sensor (M): 3 axes HMC5843
Gyroscope sensor (G): 3 axes ITG-3200
Accelerometer sensor (G): 3 axes ADXL345
MPU : ATmega328

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
 - **Map $E = \{\mathbf{d}_{1,1} \dots \mathbf{d}_{L,K}\}$** 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

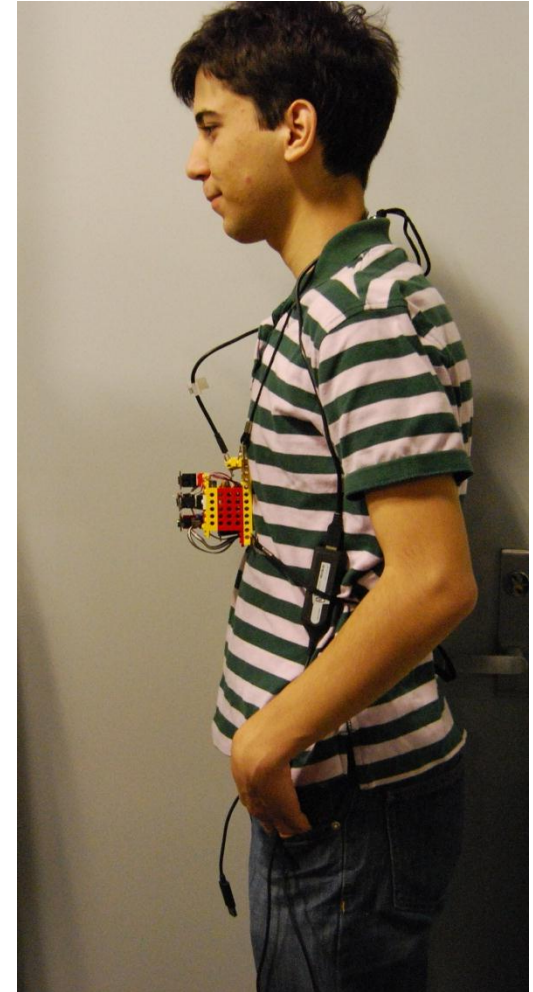
$$\forall d'' \in E, |d \leftrightarrow d'| \leq |d \leftrightarrow d''|, |d \leftrightarrow d'| = \sqrt{\sum_{i=1}^k (d_i \leftrightarrow d'_i)^2}$$

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.

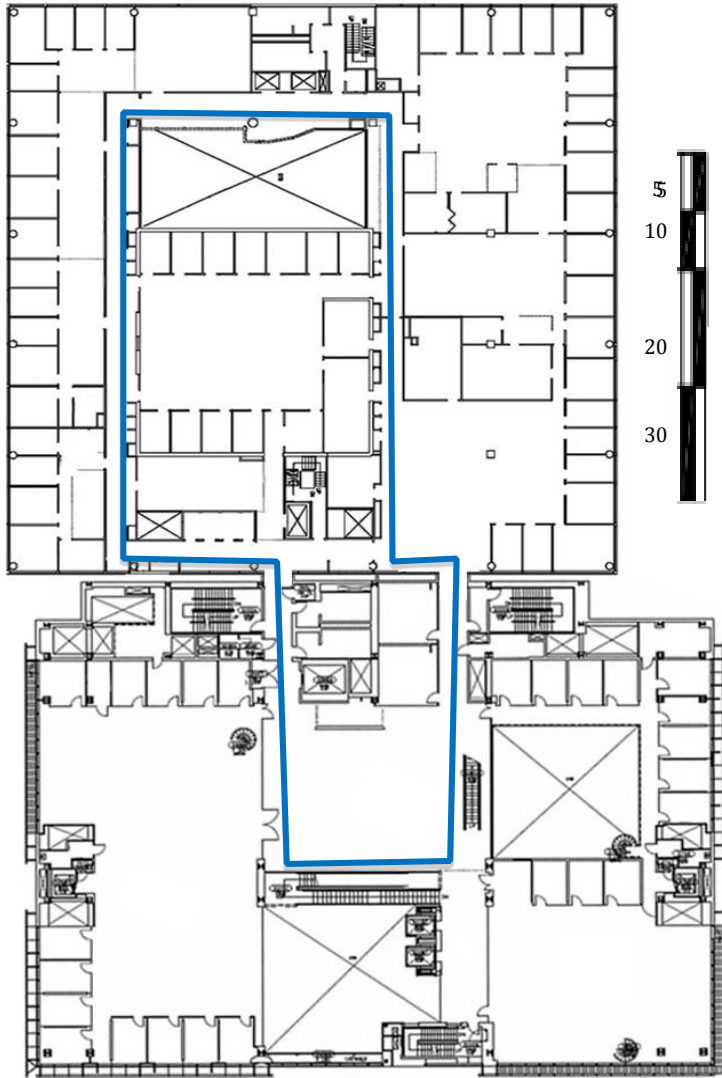


Evaluation of localization performance

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

Corridors

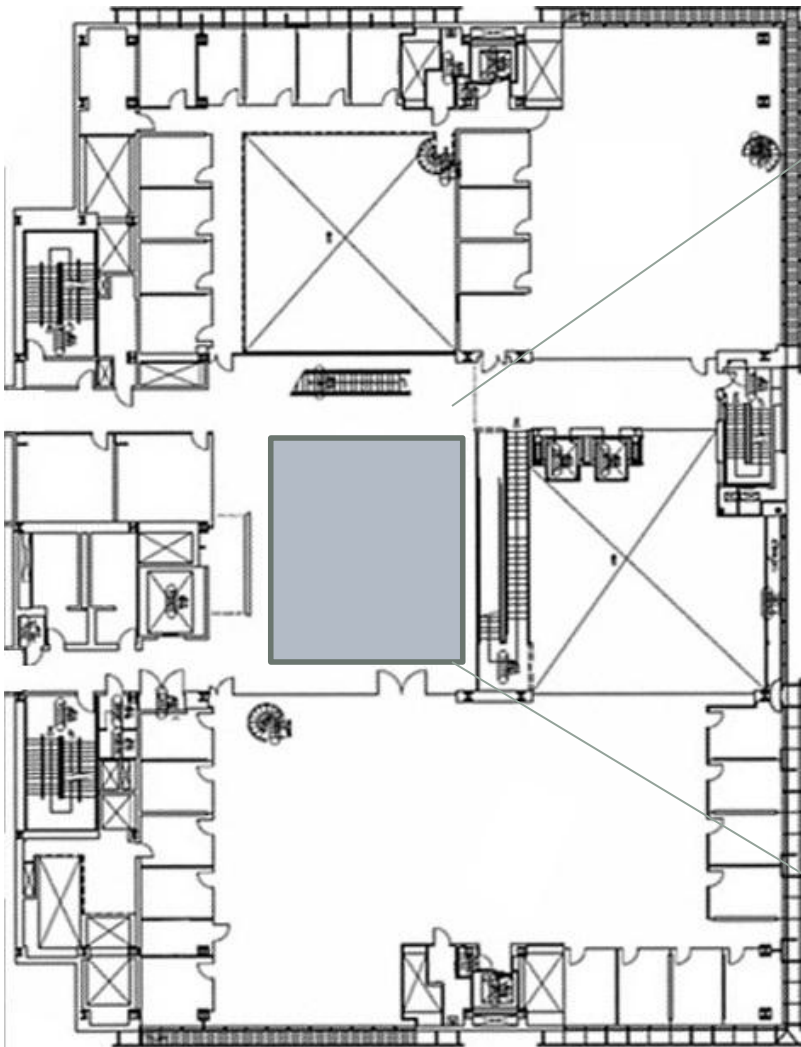
Corridor map data: Total of 37200 fingerprint =
868KB, (1 fingerprint data = 28 bytes)
Dimension = 187.2 m x 1.85 m



Atrium

Atrium map data: Total of 40800 fingerprints = 979.2 KB. (1 fingerprint data = 28 bytes)

Dimension = 13.8 m x 9.9 m



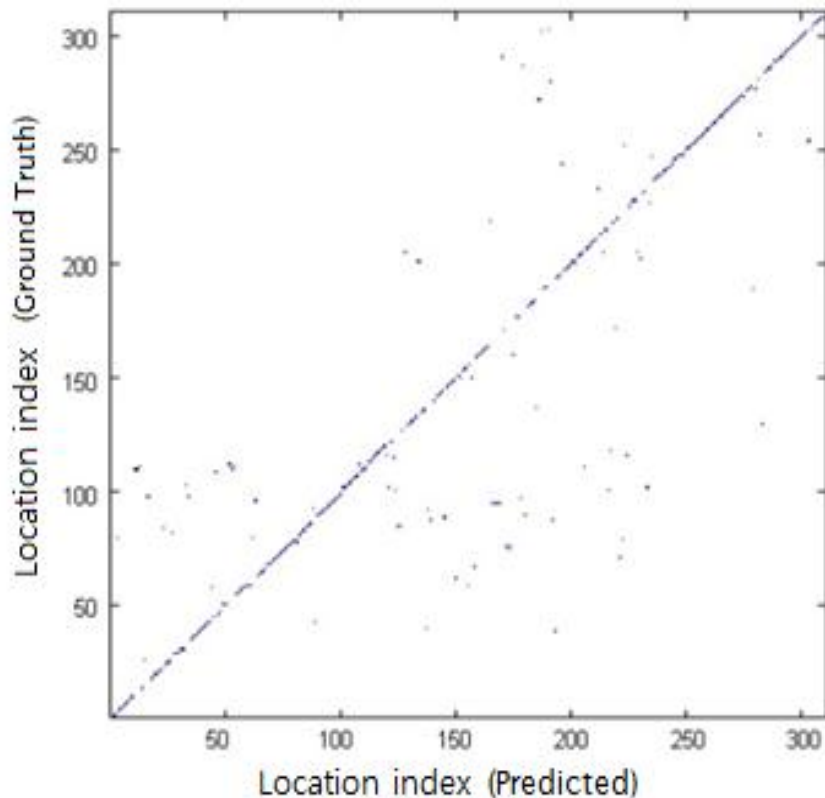
DATA ANALYSIS

Least RMS errors in Corridors

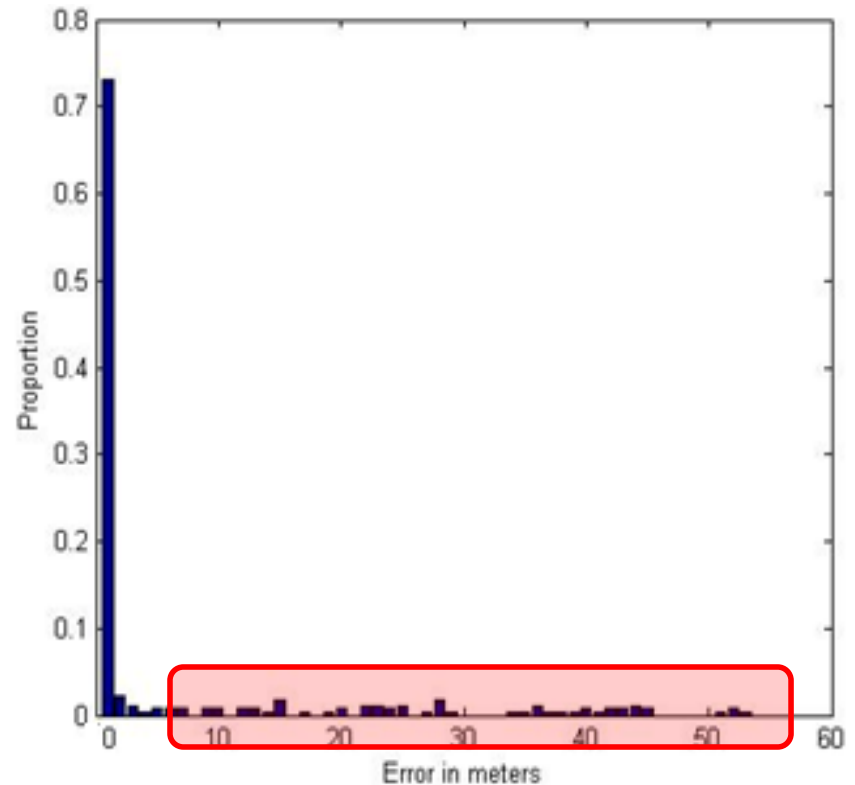
using least RMS with NN

75.7 % of the predicted positions have an error less than 1m.

$\text{Err}_{\text{mean}} = 6.28 \text{ m}$ ($\text{Err}_{\text{sd}} = 12.80 \text{ m}$, $\text{Err}_{\text{max}} = 52.60 \text{ m}$)



Least RMS errors



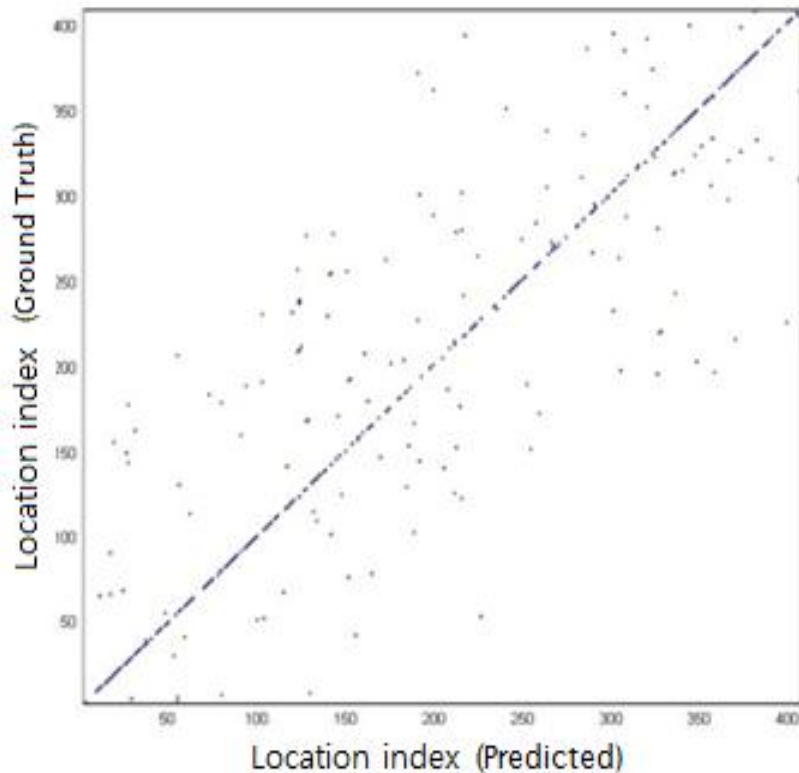
Histogram of distance error.

Least RMS errors in Atrium

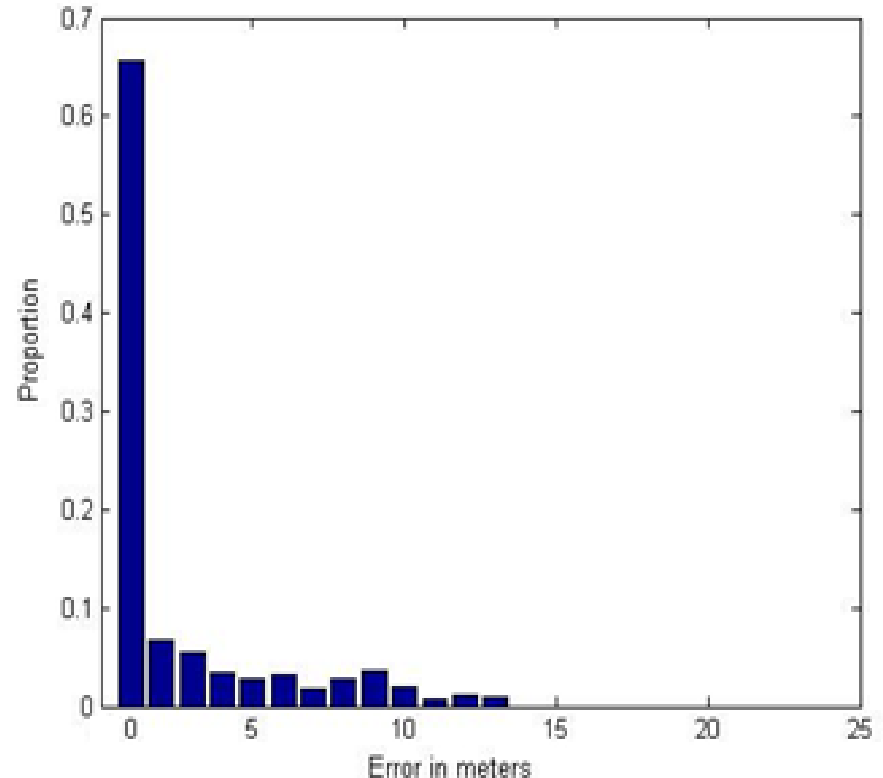
using least RMS with NN

72 % of the predicted positions have an error less than 1m.

$\text{Err}_{\text{mean}} = 2.84 \text{ m}$ ($\text{Err}_{\text{sd}} = 3.39 \text{ m}$, $\text{Err}_{\text{max}} = 12.82 \text{ m}$)



Least RMS errors



Histogram of distance error.

Method for filtering outliers

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

$$\mathbf{d}_{\text{raw}} = [m_1, m_2, m_3, m_4], \text{ where } \mathbf{m} = \{m_x, m_y, m_z\}$$

$$\mathbf{d}_{\text{norm}} = [n_1, n_2, n_3, n_4], \text{ where } n = \sqrt{m_{xk}^2 + m_{yk}^2 + m_{zk}^2}$$

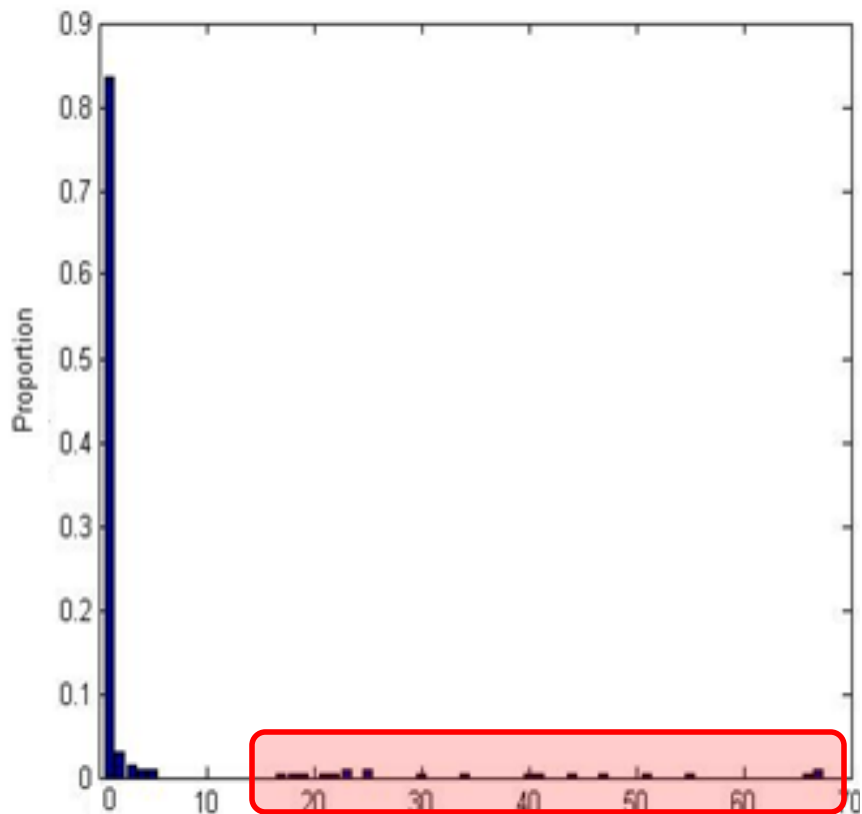
$$\mathbf{d}_{\text{unit_vector}} = [u_{x1}, u_{y1}, u_{z1}, u_{x2}, u_{y2}, u_{z2}, u_{x3}, u_{y3}, u_{z3}, u_{x4}, u_{y4}, u_{z4}],$$

$$\text{where } \mathbf{u}_{(x,y,z)} = m_{(x,y,z)k} / n_k,$$

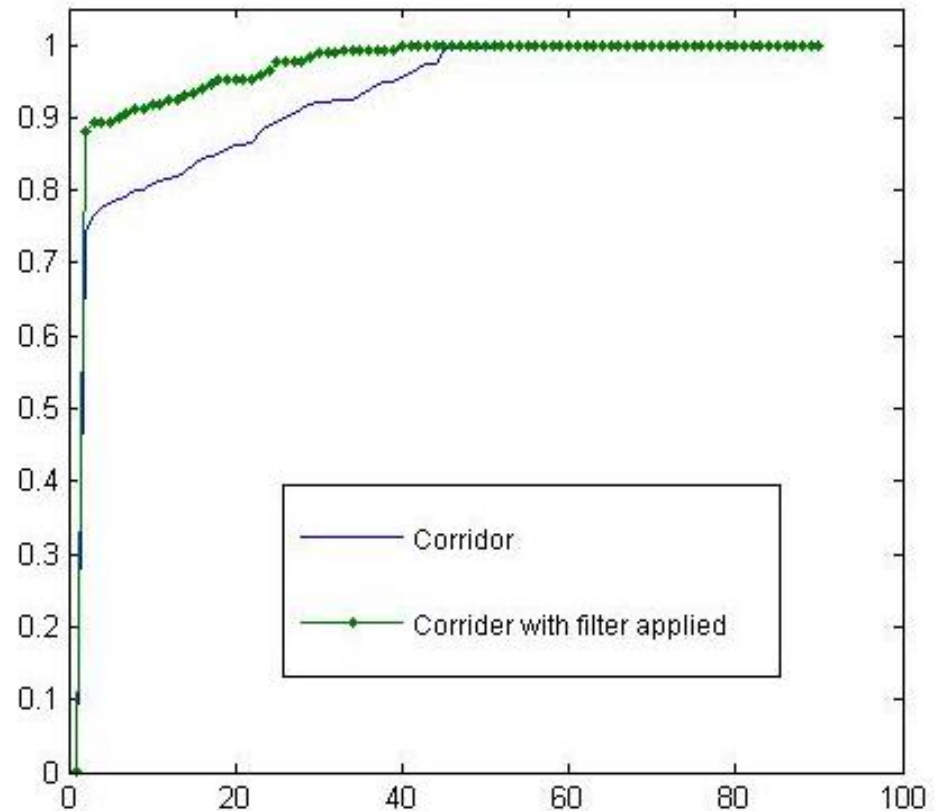
Least RMS errors in corridors

using least RMS with NN

88 % of the predictions fall under 1 meter of error.



Histogram of distance error in meters.

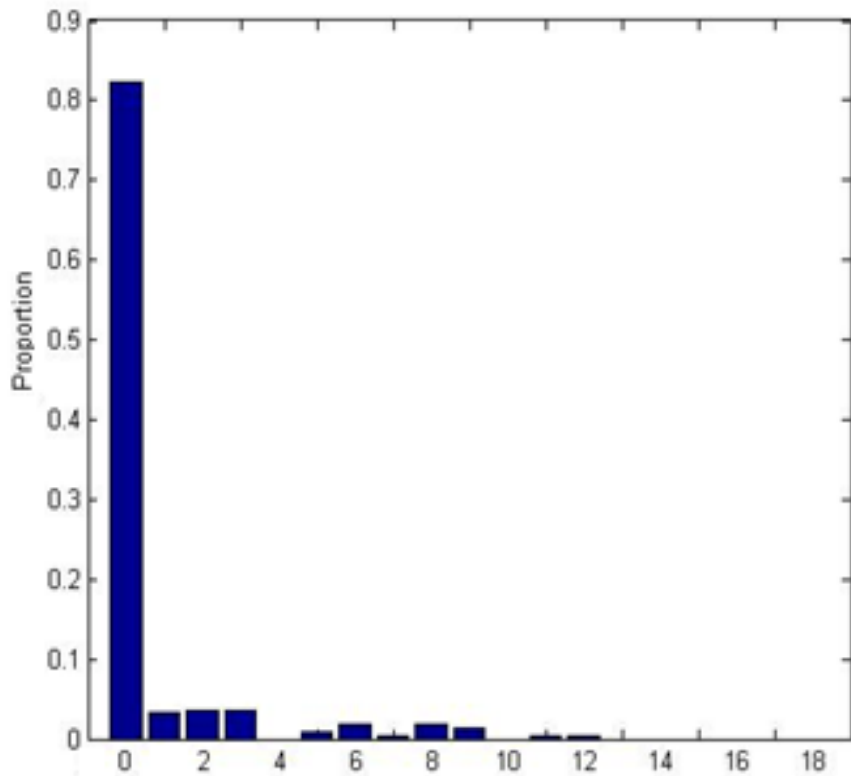


CDF of distance error in meters.

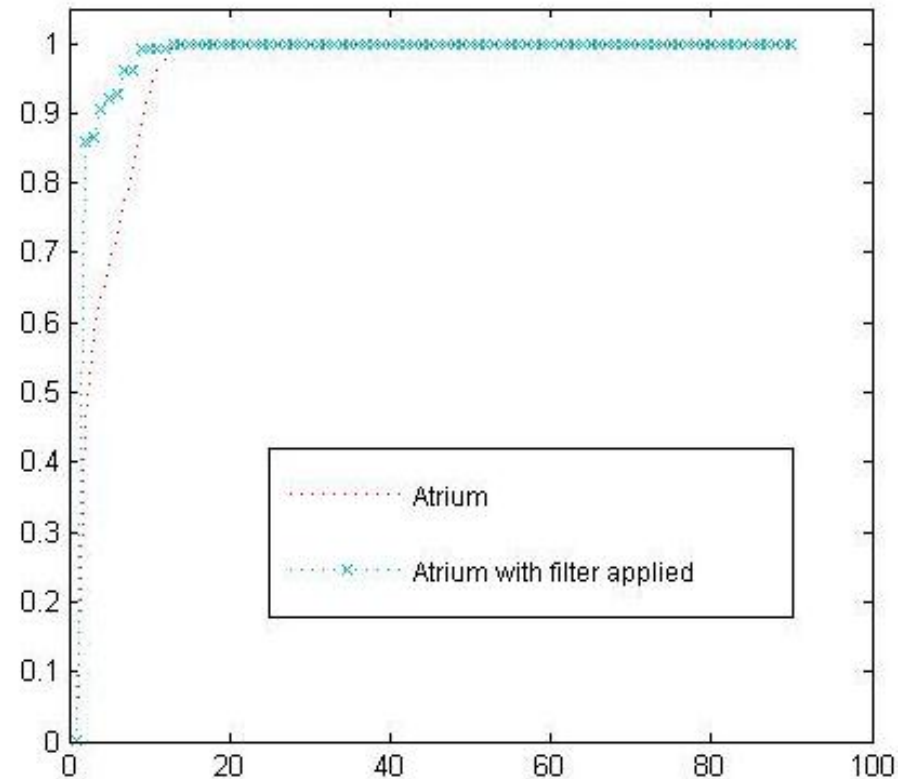
Least RMS errors in Atrium

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.

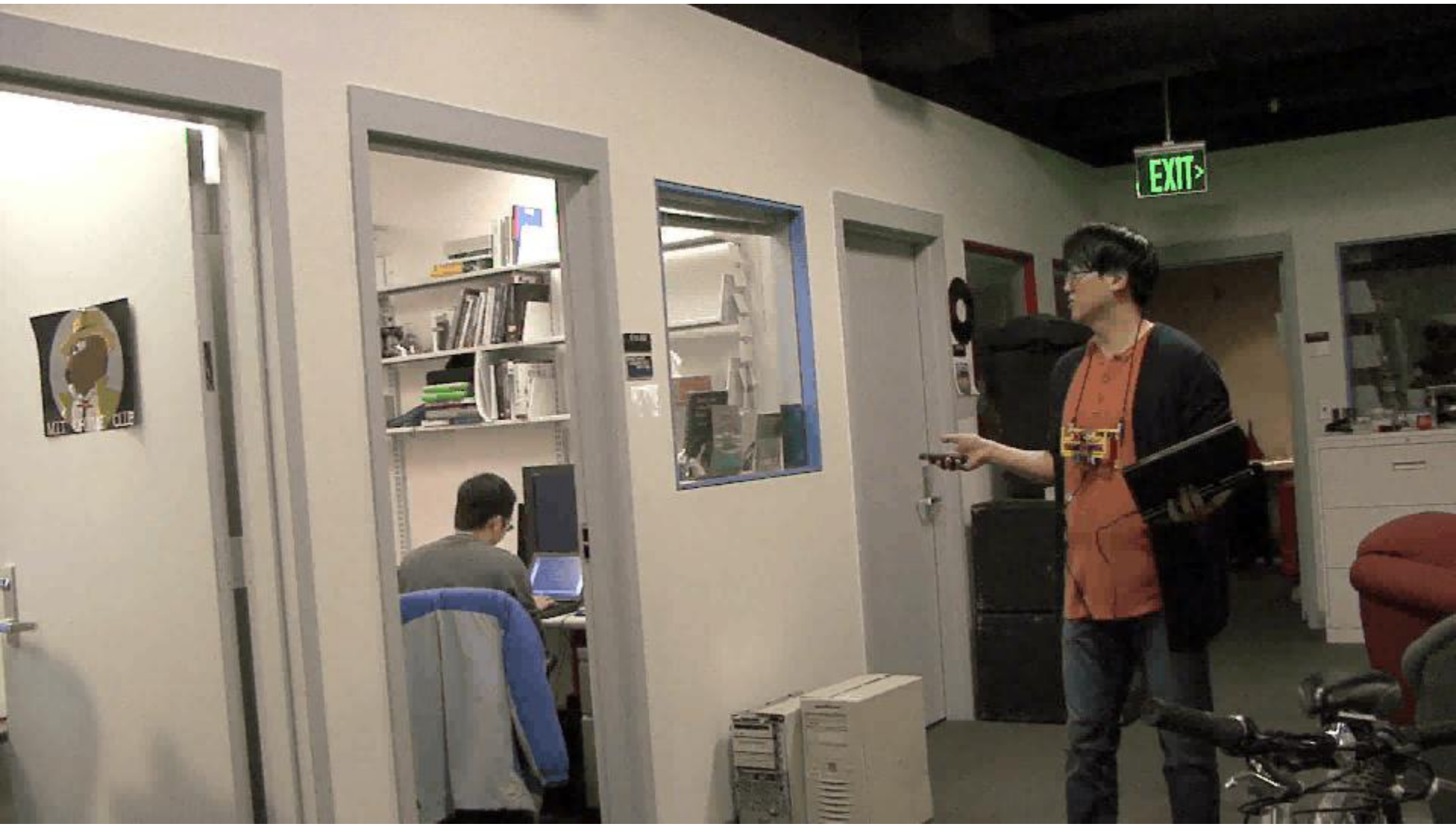


CDF of distance error in meters.

Result with varying search area

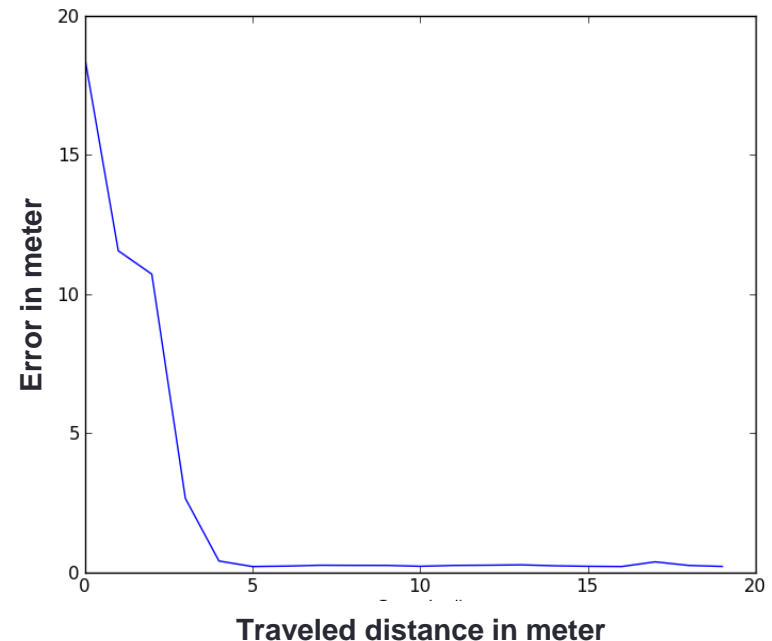
Search area in diameter	Err _{mean} (m)	Err _{SD} (m)
Corridor		
>72 meter	4.96 meter	13.94 meter
40 meter	1.65 meter	6.15 meter
30 meter	0.66 meter	3.22 meter
20 meter	0.32 meter	1.15 meter
Atrium		
>15 meter	0.96 meter	2.17 meter
9 meter	0.61 meter	1.75 meter

DEMO VIDEO CLIP 5



Other outlier filtering methods (recent updates)

- Combined with WiFi localization [1]
 - $Err_{mean} = 0.92$ meter
 - $Err_{SD} = 1.91$ meter
 - $Err_{max} = 9.6$ meter
- Applying particle filter
 - 1000 particles with particle motion models used in (Haverinen et al 2009).
 - Particles converge after 3 meters of travel.
 - $Err_{mean} = 0.7$ meter
 - $Err_{SD} = 0.89$ meter
 - $Err_{max} = 7.1$ meter



[1] Place Engin <http://www.placeengine.com>

[2] Haverinen, J.; Kemppainen, A. , "A global self-localization technique utilizing local anomalies of the ambient magnetic field," Robotics and Automation, 2009. ICRA '09. IEEE International Conference

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

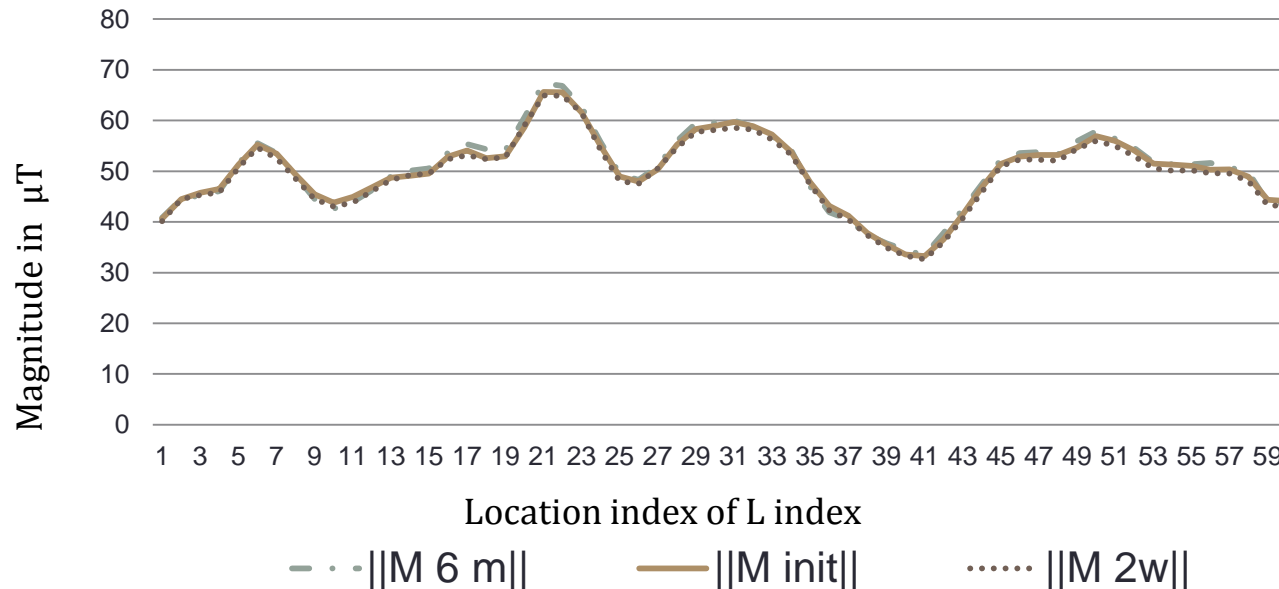
The magnetic field's stability inside of a building over time

Method:

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

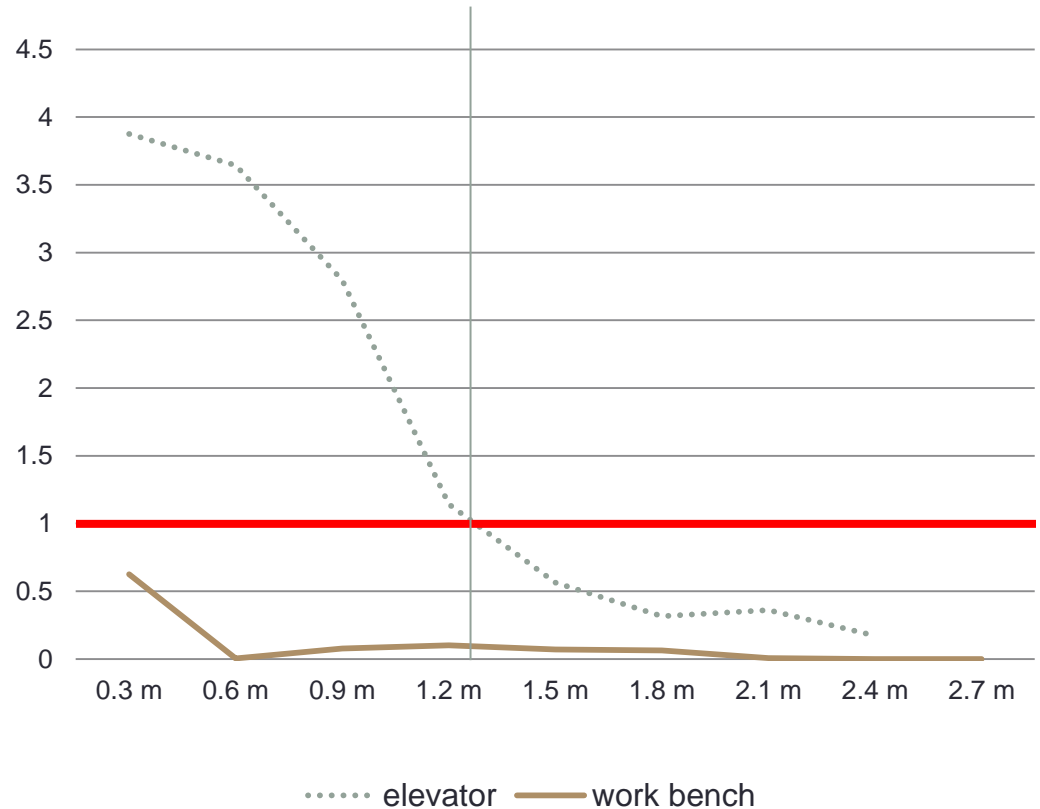
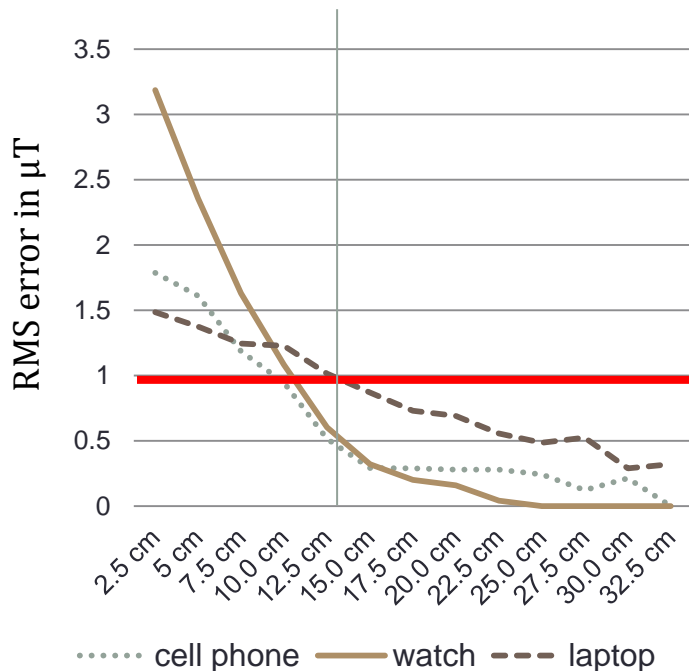
Results:

- $\text{CosineSimilarity}(M_{\text{init}}, M_{2_week}) = \mathbf{0.9997}$, and $\text{CosineSimilarity}(M_{\text{init}}, M_{6_month}) = \mathbf{0.9977}$.
- $\text{Magnitude}(M_{6_month}, M_{\text{init}}) = \mathbf{0.99}$ and $\text{Magnitude}(M_{2_week}, M_{\text{init}}) = \mathbf{1.01}$



The effect of moving objects on system performance

The minimum RMS distance between any two locations in our map data = $1.96 \mu\text{T}$.
Error tolerance < $0.98 \mu\text{T}$



The effect of moving objects on system performance



Errors measured in a room, with and without furniture, was also not significant.
(RMS error = $0.71 \mu\text{T}$)

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

System	Wireless Technology	Positioning Algorithm	Accuracy	Precision	Cost
Our system	Magnetic Fingerprints	Nearest Neighborhood with least RMS	4.7 m	90% within 1.64 m 50 % within 0.71 m	Medium
RADAR	WLAN RSS fingerprints	kNN, Viterbi-like algorithm	3-5 m	90% within 5.9 m 50% within 2.5 m	Low
Horus	WLAN RSS fingerprints	Probabilistic method	2 m	90% within 2.1 m	Low
Where Net	UHF TDOA	Least Square/RWGH	2-3 m	50% within 3m	Low
Ubisense	Uni-directional UWB TDOA + AOA	Least Square	15 cm	99% within 0.3m	High
GSM finger-printing	GSM cellular network (RSS)	Weighted kNN	5m	80% within 10m	Medium