

Geomagnetic Field Based Indoor Localization Using Recurrent Neural Network

2018 SURF Project

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Outline

- Project introduction
- Motivation
- Overview
- Method background
- Indoor positioning techniques
- Geomagnetic filed
 - K Nearest Neighbor (KNN)

System Design

- Geomagnetic Field Map Generation
- RNN model
- Data Generation for Training

■ Conclusion

- Experimentation Environment
- Neural Network Training
- Experiment results

Evaluation & Improvements



Project introduction

- Motivation
- Commercial interests and demand for indoor localization increases.
- *RF signal-based systems are the most common due to convenience and cost saving.*
- *However*, the unstable nature of RF signals limited the accuracy of RF-based indoor localization.



Project introduction

- Overview
- 1. Build a geomagnetic map (as well as BLE fingerprinting map).
- 2. Generate 50,000 traces of various pedestrian walking pattern from the map by *Linear Interpolation algorithm*.

3. Use Google Tensorflow with NVIDIA cuDNN library as a Deep Learning framework. 95% of the traces are used for training and 5% (2500) of the traces are used for localization evaluation.

4. Result: Average positioning error of 1.062 meters compared to the average error of 3.14 meters of our BLE (Blue Tooth Low Energy) fingerprinting results.



Method background

- Geomagnetic filed
- Indoor positioning techniques
 - K Nearest Neighbor (KNN)



Geomagnetic filed

■ Geomagnetic field

Centrosphere produces the magnetic field that extends from the Earth's interior out into space.





GM filed based vs. RF signal-based localization

RF signal based localization

Unstable nature caused by <u>interference</u>, <u>diffraction</u>, and <u>reflection</u> in indoor environment.

In indoor environment, the signal strength varies as the it gets further away from the ratio transmitter terminal.





GM filed based vs. RF signal-based localization

GM filed based localization

The geomagnetic field is influenced by metal, thus the fixed space owns its specific geomagnetic field.





GM filed based vs. RF signal-based localization



Measurements of geomagnetic field, wireless LAN, and sound waves according to time



Geomagnetic filed

Detection

Working principle: Hall Effect

Device: Smart phone magnetic field sensors; Standalone magnetic field sensors.





Geomagnetic filed map



Fig. 3. Geomagnetic field variation according to movement



Indoor positioning techniques

Absolute positioning

The estimated location is only derived from the current signal strength. (CNN)

■ Relative positioning

It calculates the next position relative to the current position, which leads to incremental and contiguous location tracking. (RNN)



■ The method for <u>classification</u> and <u>regression</u>

By computing the <u>Euclidean distance</u> among the values with K-NN (Nearest Neighbor) algorithm, it finds the closest K neighbors and estimates the location that is actually the weighted center of those K neighbors.

In Cartesian coordinates, if $\mathbf{p} = (p_1, p_2, ..., p_n)$ and $\mathbf{q} = (q_1, q_2, ..., q_n)$ are two points in Euclidean n-space, then the distance (d) from \mathbf{p} to \mathbf{q} is given by

$$d(\mathbf{p},\mathbf{q}) = d(\mathbf{q},\mathbf{p}) = \sqrt{(q_1-p_1)^2 + (q_2-p_2)^2 + \dots + (q_n-p_n)^2}$$

$$=\sqrt{\sum_{i=1}^n (q_i-p_i)^2}.$$

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■ Application in this project

For KNN regression, whose labels are X-Y coordinates. The output is derived by averaging K coordinates.

Reference point location		
(1,3)	(2,3)	(3,3)
(1,2)	(2,2)	(3,2)
(1,1)	(2,1)	(3,1)

Reference point Geomagnetic strength		
12	24	6
48	33	26
42	18	38



■ Application in this project

For KNN regression, whose labels are X-Y coordinates. The output is derived by averaging K coordinates.

eg: If detected geomagnetic field value is 25.

K = *2*, *location* (*2*.*5*, *2*.*5*);

Reference point location		
(1,3)	(2,3)	(3,3)
(1,2)	(2,2)	(3,2)
(1,1)	(2,1)	(3,1)

Reference point Geomagnetic strength		
12	24	6
48	33	26
42	18	38



■ Application in this project

For KNN regression, whose labels are X-Y coordinates. The output is derived by averaging K coordinates.

eg: If detected geomagnetic field value is 25.

K = 2, location (2.5, 2.5); K = 3, location (2.33, 2);

Reference point location		
(1,3)	(2,3)	(3,3)
(1,2)	(2,2)	(3,2)
(1,1)	(2,1)	(3,1)

Reference point Geomagnetic strength		
12	24	6
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System Design

- Geomagnetic Field Map Generation
- RNN model
- Data Generation for Training

By Zhenghang Zhong (Klaus)



◆ Geomagnetic Field Map Generation



X: the northly intensityY: the easterly intensityZ: the vertical intensity

H: the horizontal intensity

F: the total intensity

I: the inclination angle

D: declination angle

Figure: The seven elements of geomagnetic field vector B_m **associated** with an arbitrary point in space.



◆ Geomagnetic Field Map Generation

Geomagnetic field Distribution (indoor & outdoor)

Outdoor --- locally similar, worldwide different

- Liquid-iron outer core --- strongest
- Magnetic minerals in the crust and upper mantle --- locally significant
- Electric sea water (current) flow

Indoor --- complex and wider difference

• Various structures

(steel structures, steel shelter doors, elevators, and generators)





◆ Geomagnetic Field Map Generation

World Magnetic Model (WMM)

The Republic of Korea is positioned in the 50μ T zone

- Core field changes perceptibly from year to year --- secular variation
- Unpredictable and non-linear changes in core field
- WMM coefficients update every five years, WMM2015 is valid from 2015.0 to 2020.0

What about in Suzhou, China?



Main field total intensity (F). Contour interval is 1000 nT. Mercator projection.



System Design

◆ Geomagnetic Field Map Generation

Measurement



Hardware



Figure: Geomagnetic Hall Effect

Figure: magnetic field sensor in smart phone





◆ Linear Interpolation --- improve resolution





Fig. 6. Geomagnetic field creation process

Figure: (WiKi) Linear interpolation

Figure: Data storage



System Design

◆ Geomagnetic Field Map Generation



Figure: Geomagnetic field maps of the first and the second floor in EE building of Korea University



RNN model

■X^t ■Z^t ■W_{in} ■W

Weights applied to the links from input nodes to hidden nodes, hidden nodes to hidden nodes, and hidden nodes to output nodes.



Fig. 7. The structure of a basic Recurrent Neural Network

♦ Output

 $Z_{j}{}^{t} = f_{out}(W_{out}(f(W_{in}X_{i}{}^{t} + WY^{t-1})) \ (i \in \ \{1, \ 2, \ 3\}, \ j \in \ \{1, \ 2\})$



Data Generation for Training

➤ Method

- Geomagnetic field map
- Model of pedestrian movements confined in one map
- Supervised training

Data

- Total distance of movements: 750 KM
- Total steps: 1,000,000 steps
- Data size: 67.9 MB
- Training data: 20-step movement as a single trace (50,000 traces)
- 95% for training, 5% for evaluation

Using a modified version of random waypoint model

What is random waypoint model?



- Two important factors decide performance: algorithm & training data
 - Random waypoint model

In mobility management, the **random waypoint model** is a random model for the movement of mobile users, and how their location, velocity and acceleration change over time.

Firstly used to evaluate mobile ad hoc network routing protocols.





A temporary network without the aid of any established **infrastructure** or centralized **administration**, just use **mobile hosts**.



System Design

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Data sample



57 282719 2065. \mathbf{v} : 091910 v: 59 y: 101 v: -25 391242 v: 0292 v: -25 061164 18590, 9483 -24 V÷ 776. -24 62 328674 -12.876650312239 72 v÷. x: -12.773212, y: -23.956657 x: -12.681461, y: -23.613662 63 724408, y: 72.137865 64 706035 y: 71.947056 Fig. 8. Experimental data sample 1 unit = 11.4 cm

809191

427573

236764

855146

664337

61

v:

8382

15955

840187,

794736.

0318,

925,

72,

4508.

737921

502744,

-25

-25

-25

-25

-25

V÷.

VC.

V÷.

γ÷.

V÷

V÷

V÷.

v:

661308

678593

701187

24

-36.

-32.

-31

Z :

Z)

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950DB

517505

660978

748646

538463

255061

-32.12145

-25.671062

-25.66474

61 2549

μT



- Experimentation Environment
- Neural Network Training
- Experiment results



Experimentation Environment

Category	Machine / Tools
CPU	Intel i7-6900K 3.2GHz (8C16T)
GPU	NVIDIA Geforce GTX1080 8GB
RAM	DDR3 32GB 2133MHz
OS	Ubuntu Server 16.04 LTS
Language	Python 3.5
Library	Google Tensorflow 1.2
	NVIDIA cuDNN v5.1



Neural Network Training

Parameters

- Hidden nodes
- Mini-batch size
- Execution epochs (iteration over entire dataset)
- Learning rate

Methods

- Standard normal distribution (biases and weights)
- Optimizer: Adam
- Loss function: MSE(mean square error)
- Repeated feed-forward propagation of inputs, back propagation of errors



Neural Network Training

D The number of hidden nodes

The mini-batch size





Neural Network Training

Overall parameters

Category	Value
Neural model	Recurrent Neural Network
Loss function	Mean Squared Error (MSE)
Optimizer	Adam
Hidden node	200
Learning Rate	0.001
Mini-batch size	20



Experiment results

Test:

 5% evaluation data (50,000 steps = 2500 traces) of modeled traces

• RNN model

Results:





• Experiment results



Figure: Evaluation results for a sample path



Experiment results



Localization performance in terms of the number of hidden nodes



300 hidden nodes: Overfitting



Evaluation

Achievements

- Error range: 0.441m 3.874m
- Average error: 1.062m ٠
- Smooth and continuous movement tracking ٠

Drawbacks

- WMM coefficients update every five years
- Strong environment dependence

Advantage

- Rather stable geomagnetic value ٠
- Very low cost ٠
- Less collection work



Improvements

- Advanced RNN model (LSTM, bidirectional RNN)
- Mapping ٠ (e.g. multi-floor, multi-building)
- Data collection and traces generation (improved ٠ random waypoint model) (e.g. random walk model, random direction model)



Questions?



END