Adaptive Cloud-based Indoor Positioning System Using Wi-fi Fingerprints Mahesh Gaya, David Mascharka, Joel Afriyie, Jennifer Steffens, Dominic Sherman, and Eric Manley Department of Computer Science and Mathematics, Drake University UNIVERSITY

Abstract

Global Positioning Systems (GPS) are highly accurate at predicting outdoor locations; however, due to signal attenuation, they are unreliable in indoor locations. Wireless mobile devices can be used to collect location fingerprints based on sensor readings and Wi-Fi signal strengths, and we have demonstrated the uses of machine learning algorithms to predict indoor locations based on these fingerprints within 2 meter accuracy.

We propose an adaptive indoor positioning system that integrates with Google Maps and maintains a cloud-based database of Wi-Fi fingerprints. This system allows for both manual and passive collection of training points, automatic training, and seamless switching between the indoor models and other location services.



- App sends Wi-Fi fingerprints and location data to the Firebase Realtime Database
- App also sends a request for machine learning to the App Engine
- One of the servlet instances accepts the request and replies with an estimated indoor location
- App updates the location accordingly

Data Collection



- Sensors: Accelerometer, Rotation vector, Magnetic field, Wireless Wi-Fi
- Data collected from different buildings
- User is stationary or walking at a steady pace

Methodology

- Wi-Fi fingerprints and location data are sent to the Firebase Realtime Database as training data Models are consistently trained on the AppEngine Each building will have their own model parameters Training models will be tuned using Grid Search

- (Hyperparameter tuning)



Instance-based Approach

- and the training instances
- accuracy of 2 meters
- divided into small sections

Artificial Neural Networks

- ANN works best with big data



- cloud-based approach
- better for big data

- beginners-guide
- **Mobile Phone-Based Sensors**

• Instance-based learners predict values for a new instance by comparing the distance between the new instance

• From our previous research^[2], k-Nearest Neighbor (k-NN) algorithm was the best performing algorithm with an

• However, to improve the speed of k-NN, data need to be

• Artificial Neural Network (ANN) consists of an input layer, some hidden layers and an output layer

• Several characteristics can be considered for training

Conclusions

• Training models can be consistently tuned if we adopt a

• k-NN performs better for small data, but ANN performs

Data from more buildings need to be collected

References

1. Alice Zheng, 2015, Evaluating Machine Learning Models -- A Beginner's Guide, https://www.slideshare.net/AliceZheng3/evaluating-machine-learning-models-a-

2. David Mascharka, and Eric Manley, 2016, Machine Learning for Indoor LocalizationUsing