Optimizing Multi-floor Localization Efficiency

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ABSTRACT

Indoor localization through mobile devices is procuring interest from both academia and industry. Localization indoors becomes complicated in urban high-rise environments where the identification of an exact floor is strenuous. The pervasive presence of Wi-Fi in closed environments, such as buildings, allows it to be an ideal means of pinpointing an individual indoors. We analyzed specific WAPs associated with the building and compiled a dataset of more than 3,000 observations. Through the integration of Wi-Fi fingerprinting and various machine-learning algorithms we were able to detect the floor an individual is on based on RSSI values with 98% accuracy. Experimental results also show an accuracy of approximately 80% in determining the location of the individual within the specified floor.

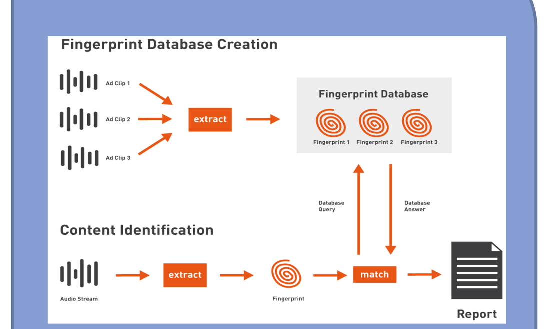
BACKGROUND

Location based services (LBS) in mobile devices enables a user to pinpoint their location

Global Positioning System (GPS) dominates outdoor localization

Vector of Received Signal Strength Indication (RSSI) values

These are stored into a database and used in identifying desired signals through comparison



PROBLEM & OBJECTIVE

Research Problem

- Difficulty in determining location in urban high rise environment
- Not in line of sight (LOS) of receiver
- Signal propagation is interrupted by building infrastructure
- Resource demands of fingerprinting data gathering
- Variability of devices
- Mutability of environment

Indoor positioning applications

- Inventory tracking
- Healthcare
- Security

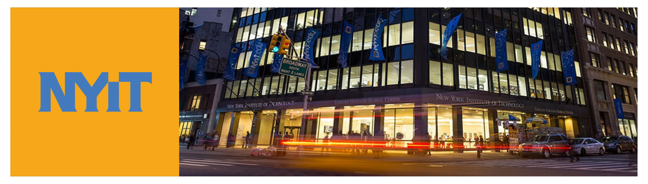
Objective

To show how simple localization models using existing Wireless Local Area Networks (WLANs) can predict the location of a mobile device in a multi-floor environment with a relatively high level of accuracy.

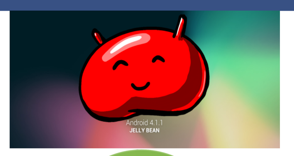
EXPERIMENTAL ENVIRONMENT

New York Institute of Technology, Manhattan, NY:

Edward Guiliano Global Center (EGGC) Building
RSSI were measured at 33 locations across the 6th, 7th, 8th, and 9th, floors



Create customized App to collect RSSI data and record location data.
- Google Nexus 10 Tablet operating on Android version 4.2.2, Jellybean



-Android Studio 2.0 and SDK tools

MATLAB for data processing and analysis.

METHODOLOGY

Data Collection → Data Processing → Data Classification → Verification

RESULTS

The testing results of our classifiers are summarized in Tables I, II, III. The results are the percentages of tested data points whose predicted floor matched their actual floor. Cross validation shows the average of the prediction accuracy among the 10-fold tests.

Basic Floor Classification Model Accuracies		
Classifier	Cross Validation	Testing Set Accuracy
KNN	99.2	97.6
Linear SVM	99.5	98.2
Decision Tree	98.7	98.5

Table I. Results of basic floor classifiers using various algorithms.

Basic Location Classification Model Accuracies		
Classifier	Cross Validation	Testing Set Accuracy
KNN	81.8	56.1
Linear SVM	86.4	78.8
Decision Tree	77.9	69.4

Table II. Results of basic location classifiers using various algorithms.

Complex Location Classification Model Accuracies			
Floor Classifier	Location Classifier	Cross Validation	Testing Set Accuracy
KNN	KNN	84.1	63.6
KNN	Linear SVM	86.3	79.1
KNN	Decision Tree	83.9	67.0
Linear SVM	KNN	84.1	64.2
Linear SVM	Linear SVM	86.8	79.7
Linear SVM	Decision Tree	83.0	67.9
Decision Tree	KNN	83.3	65.2
Decision Tree	Linear SVM	85.5	80.0
Decision Tree	Decision Tree	82.7	67.9

Table III. Results of combining floor classifiers with location classifiers.

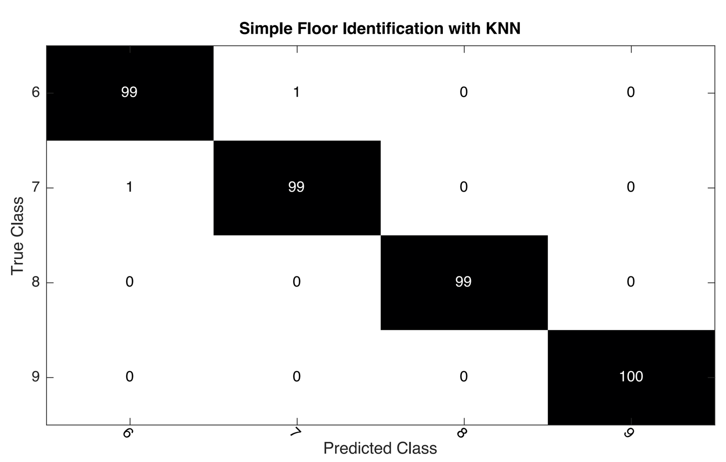
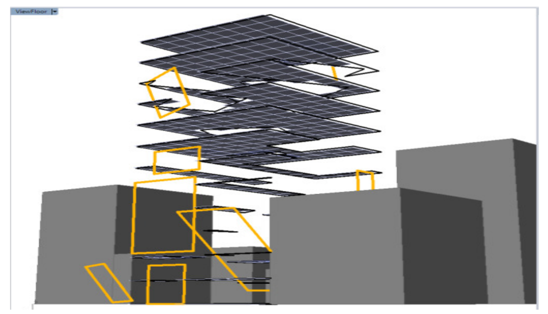


Figure I. Confusion matrix of floor classification.



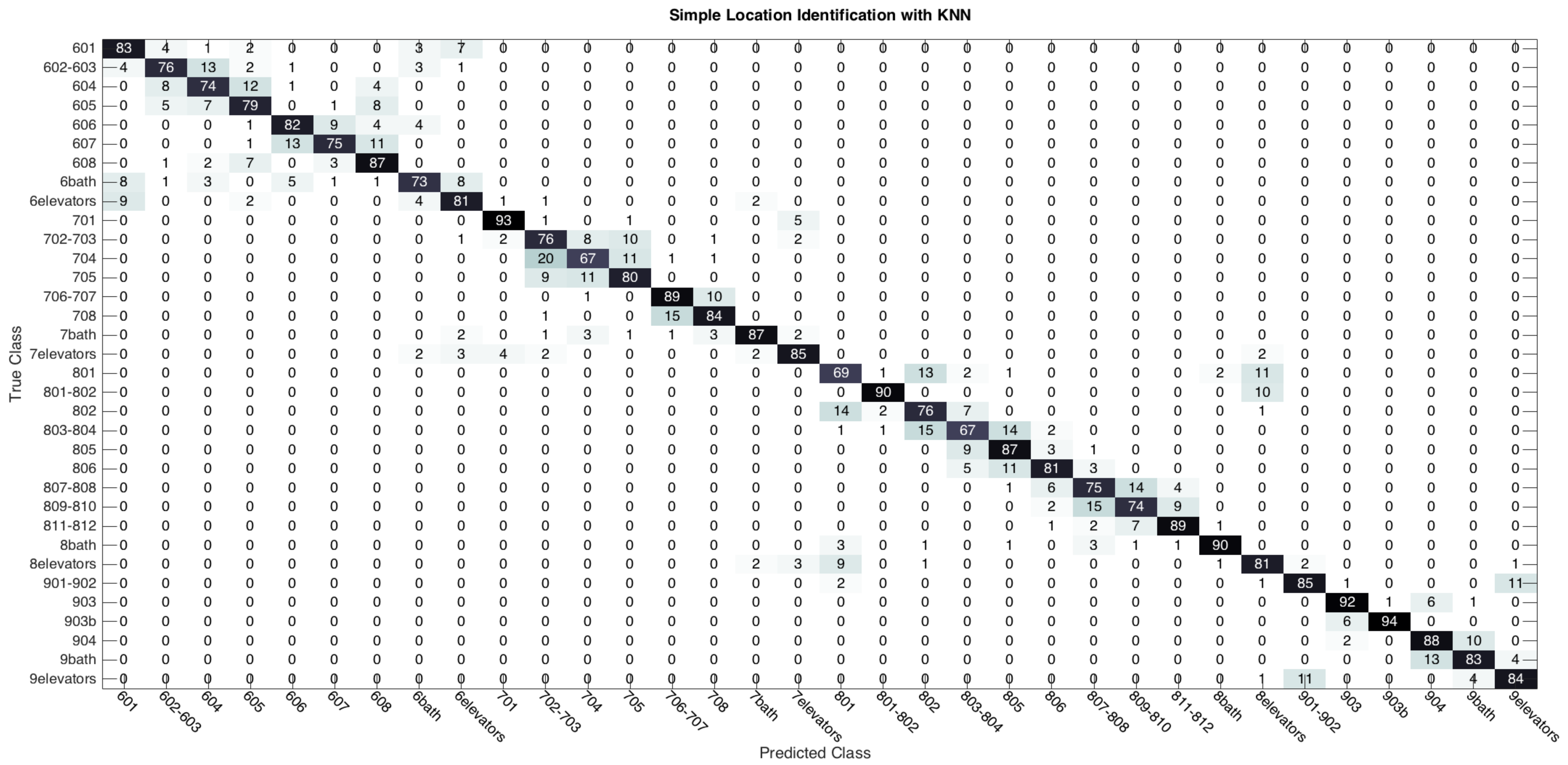


Figure II. Confusion matrix of location classification.

DISCUSSION

- Floor classification models yielded accuracies of approximately 98% demonstrating our system's effectiveness. Location classification models did not give high accuracies because of limitations in the environment, varying levels of network congestion, the presence of more classes, and greater path loss across floors as opposed to across rooms.
- Due to the success of the floor classification model, we proposed to classify the data through a complex location model. This would first determine the floor followed by the respective location. The results generated were largely similar to the ones produced by the simple location model due to the high prediction accuracy by the floor classification.
- Average accuracy was higher when using a combination of classifiers. The strongest classifier in our study was Linear SVM.
- Access to various visible WAPs provided a radio map to identify features.

CONCLUSION

Through our research and experimentation we were able to efficiently determine the floor location of a mobile device in the EGGC building with an accuracy of 98%. Localization within a specific floor did not yield comparable results, approximately 84%. The attempts made to improve this accuracy through the integration of various machine learning algorithms were of little success. However, predicting the location of a mobile device in a multi-story environment was achieved.

FUTURE WORK

Future Work:
- Investigating accuracy loss due to environmental variables such as time of day and network congestion
- Testing feasibility of finer location labels
- Testing accuracy of other classifier types or variations of classification algorithm parameters
- Finer data processing, reduction of outliers, and feature selection to improve training classification models

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