PREDICTING FLOOR-LEVEL FOR 911 CALLS WITH NEURAL NETWORKS AND SMARTPHONE SENSOR DATA

William Falcon, Henning Schulzrinne
Columbia University

Introduction

In cities with tall buildings, emergency responders need an accurate floor level to find 911 callers quickly. We develop a system which identified the correct floor level with 100% accuracy across 63 trials in NYC.

Our system consists of three parts:
1. Indoors/Outdoors classifier.
2. Indoors/Outdoors transition detector.
3. Barometric pressure based height estimator and unsupervised floor level clustering.

Conclusion

By marrying an LSTM with mobile device sensor data and repeated visit clustering, we predicted the correct floor level with 100% accuracy across 63 trials in NYC buildings.

17 floors

12 floors

19 floors

14 floors

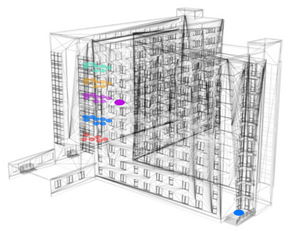
13 floors

References

[1] Seung-Seok Choi, Sung-Hyuk Cha, and Charles C Tappert. A survey of binary similarity and distance measures. Journal of Systemics, Cybernetics and Informatics, 8(1):43–48, 2010.

[2] Sepp Hochreiter and Jurgen Schmidhuber. Long short-term memory. ¨ Neural Computation, 9(8): 1735–1780, 1997.

Approach part 3: Floor Level Estimator



estimate floor number via cluster index ~3

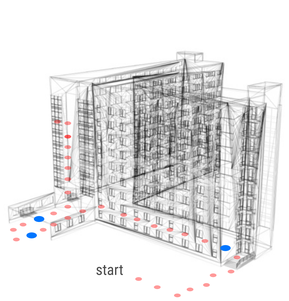
find nearest height cluster from previous visits [3.0, 2.9, 4.0, 5.0, **5.1**, ..., 12.0, 12.2]

compute elevation from predicted entrance p_0 and current location p_1

$$m_\Delta = f_{floor}(p_0, p_1) = 44330(1 - (\frac{p_1}{p_0})^{\frac{1}{5.255}})$$

normalize by weather pressure at nearby station $p_0 \approx |w_i - w_0| + p_i$

Approach part 2: Indoor/Outdoor Transition Detector



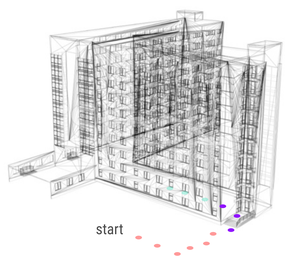
Indexes of indoors/outdoors transitions $B_{i,k}$ = [8, 22, 25]

Jaccard distance [1]

$$J_j = J(s_i, V_j) = \frac{|s_i \cap V_j|}{|s_i| + |V_j| - |s_i \cap V_j|}$$

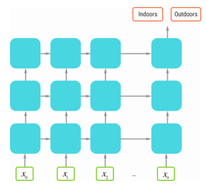
outdoors = 0 indoors = 1 $\hat{Y}_{i,k}$ = [0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1]

Approach part 1: Indoor/Outdoor Classifier: LSTM

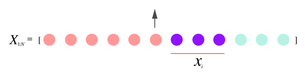


outdoors = 0 indoors = 1 $\hat{Y}_{i,k}$ = [0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1]

LSTM [2]



movement time series $X_{i,k}$ =



sensor data = [baro pressure, GPS vert acc GPS hor acc, GPS speed, RSSI, magnetometer]

Results: Floor level prediction

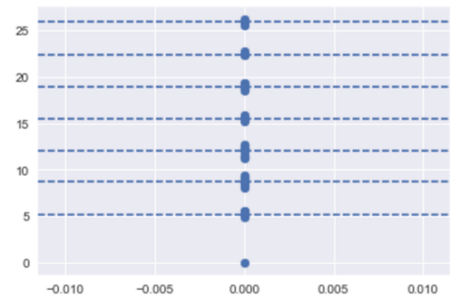
Floor number prediction accuracy

Classifier (m=4.02 | m=bldg conditional)	Exact Floor	± 1 floor	> ± 1 floor
LSTM	0.65 | 1.0	0.33 | 0	0.016 | 0
Feedforward	0.65 | 1.0	0.33 | 0	0.016 | 0
SVM	0.65 | 1.0	0.33 | 0	0.016 | 0
Random Forest	0.65 | 1.0	0.33 | 0	0.016 | 0
Logistic Regression	0.65 | 1.0	0.33 | 0	0.016 | 0
HMM	0.619 | 0.984	0.365 | 0	0.016 | 0.015

Estimated distribution of floor heights via repeated visit clustering

Floor range	Estimated $d_{i,j}$	Actual $d_{i,j}$
1-2	5.17	5.46
2-3	3.5	3.66
3-4	3.4	3.66
4-5	3.45	3.5
5-6	3.38	3.5
6-7	3.5	3.5
7-8	3.47	3.5

Floor level detection via repeated visit clustering



Results: Indoors/Outdoors classification

Table 1: Model performance on validation and training set.

Model	Validation Accuracy	Test Accuracy
LSTM	0.923	**0.903**
Feedforward	**0.954**	0.903
SVM	0.956	0.876
Random Forest	0.974	0.845
Logistic Regression	0.921	0.676
HMM	0.976	0.631

Code and data available at:
http://bit.ly/floor911