Comparison of floor detection approaches for suburban area

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Background

As a part of smart–buildings, indoor localisation systems bring constantly improving results. Several localisation methods works with a horizontal localisation error less than few meters.

However, for small suburban houses, horizontal localisation is not as important as detection of the current floor, which in is still a challenge in multi-storey buildings.

We compared several approaches that can be used in fingerprinting-based floor detection systems.

Previous works

- Possible data sources for floor detection
  - A cellular network fingerprints (Varshavsky 2007).
    - The tests were done in 9 to 16-storey buildings. The system classified the floor correctly up to 73 percent of cases and nearly 100 percent of measures were localised with an error less or equal tree floor.
  - Pressure (He 2012).
    - The proposed system could accurately determine the floor in a 4–storey building.
  - Wi–Fi (Karwowski 2013, Grzenda 2013).
- Possible classification methods
  - multilayer perceptron (Karwowski 2013)
  - k-Nearest Neighbours (Grzenda 2013)

Approaches

Signals and measures used for the floor detection

1. Pressure
2. Cellular Networks
   1. 2nd generation Global System for Mobile Communications (GSM) signals
   2. 3rd generation Universal Mobile Telecommunications System (UMTS) signals
3. Wireless computer network (Wi–Fi) signals

Classification method

The function $\mathcal{F} \to f$ that estimates the floor f on the base of a single fingerprint $\mathcal{F}$ was implemented as an ensemble of decision trees.

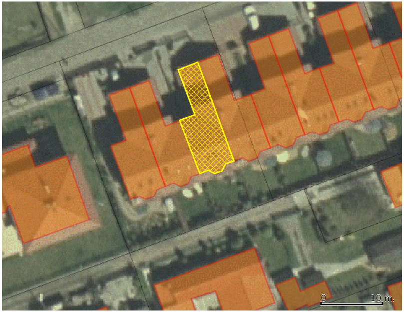
We used AdaBoostM2 (Freund 1997) algorithm, where weighted pseudo–loss are calculated for N observations and K classes

$$\epsilon_t = \frac{1}{2} \sum_{n=1}^{N} \sum_{k \neq y_n} d_{n,k}^{(t)} (1 - h_t(x_n, y_n) + h_t(x_n, k)),$$

where $h_t(x_n, k)$ is the confidence of prediction, $d_{n,k}^{(t)}$ are observation weights, and y_n is the true class label. Pseudo-loss is a measure of the classification accuracy from any classifier in an ensemble.

We fixed the number of trees in the random forest to 30. A further grow of trees did not improve the accuracy of the floor detection.

Measuring area



- The data were collected in a three floor suburban building (including the ground floor).
- The building has irregular shape and its outer dimensions are around 15 by 9 metres.

- LG Nexus 4 working with Android 4.2 Jelly Bean.
- The mobile phone was attached to a vacuum cleaning robot.
- The robot started separately on each floor. It was working the whole cleaning cycle by approximately one hour per floor.

Data

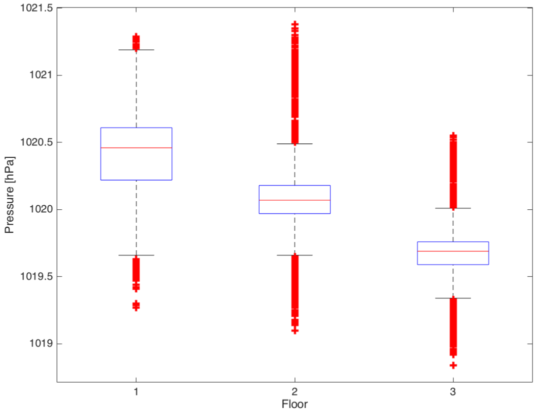
Data were collected in two days separately from two cellular telecommunication networks: 2G and 3G. During the measures we collected also Wi–Fi signals and pressure.

Table: Collected measures

Method	All	1st floor	2nd floor	3rd floor	length
Pressure	13061	5457	4275	3329	1
GSM	39321	16001	10420	12900	12
UMTS	20311	4996	12381	2934	9
Wi–Fi	29459	12074	8327	9058	13

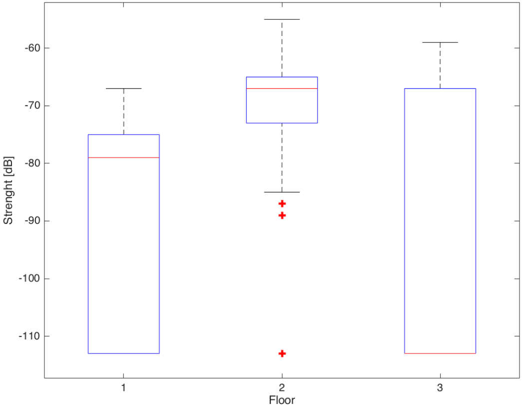
All data were randomly split into two equal parts: the learning set and the testing set.

Pressure



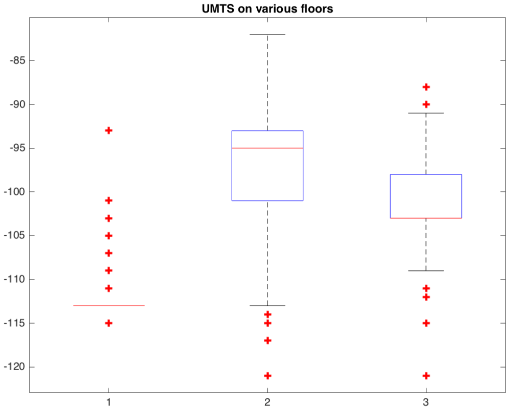
The the 25th and 75th percentiles boxes are well separated, but we observe many outliers.

GSM – the strongest signal



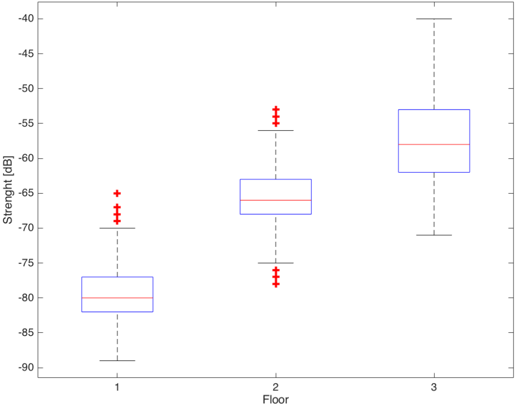
For all floors we can observe a disappearance of signals: the outliers that lie on the level -113 dBm

UMTS – the strongest signal



The mobile device did not allow the user to choose 3G permanently. Therefore the signals are missing on the ground floor.

Wi–Fi – the strongest signal



The measures are well separated and without far outliers.

Accuracy

Table: Accuracy and errors for various types of signals

Method	Accuracy [%]	one–floor error [%]	two–floor error [%]
Pressure	74	24	3
GSM	98	2	0
Wi–Fi	99	1	0
UMTS	100	0	0

Accuracy for single signal

Table: Accuracy and errors for single signal

Method	Accuracy [%]	one–floor error [%]	two–floor error [%]
Pressure	74	24	3
GSM	78	20	2
Wi–Fi	84	16	0
UMTS	89	10	1

Only the best signal source was selected on the base of Gini coefficient.

The Gini coefficient equals $2(AUC) - 1$. Where AUC is the area underneath the Receiver Operating Characteristic Curve (ROC Curve).

Accuracy for equal number of measures

Table: Accuracy and errors for equal number of measures

Method	Accuracy [%]	one–floor error [%]	two–floor error [%]
Pressure	72	26	2
GSM	97	3	0
Wi–Fi	99	1	0
UMTS	100	0	0

The number of measures was limited to 10900.
Among them 4000 were taken on the ground floor, 4000 were taken on the first floor and 2900 were taken in the attic.

Conclusions

- We compared several approaches to recognise on which floor a mobile device is in the 3-storey building at suburban area. In all tests the random forest were used as a detection model.
- The obtained accuracy was 74 percent for pressure and 98–99 percent for GSM and Wi-Fi,
- The UMTS signals were ambiguous, because of automatic change between 2G and 3G cellular network, but this approach recognised all measures without any mistake.
- In future work we want to improve pressure localisation results, check a stability of the system among time, and examine an area–base localisation.

Acknowledgement

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