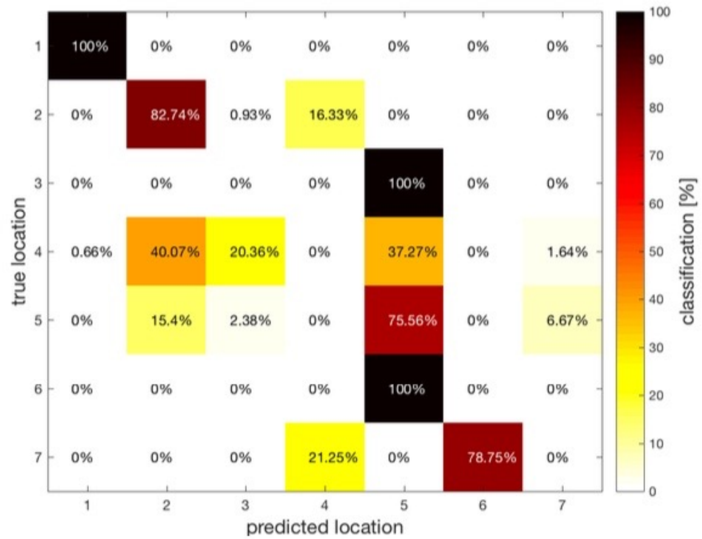
Indoor Localisation using Aroma Fingerprints

Philipp Müller
Tampere University

1. Olfactory navigation

2. Localisation using aroma fingerprints



3. Open questions and potential solutions

1. Olfactory navigation

What do salmon and homing pigeon have in common?

By Unknown - [1], Public Domain, https://commons.wikimedia.org/w/index.php?curid=17847705

Public Domain, https://commons.wikimedia.org/w/index.php?curid=446960

Evidence suggests that both species use olfaction for navigation.

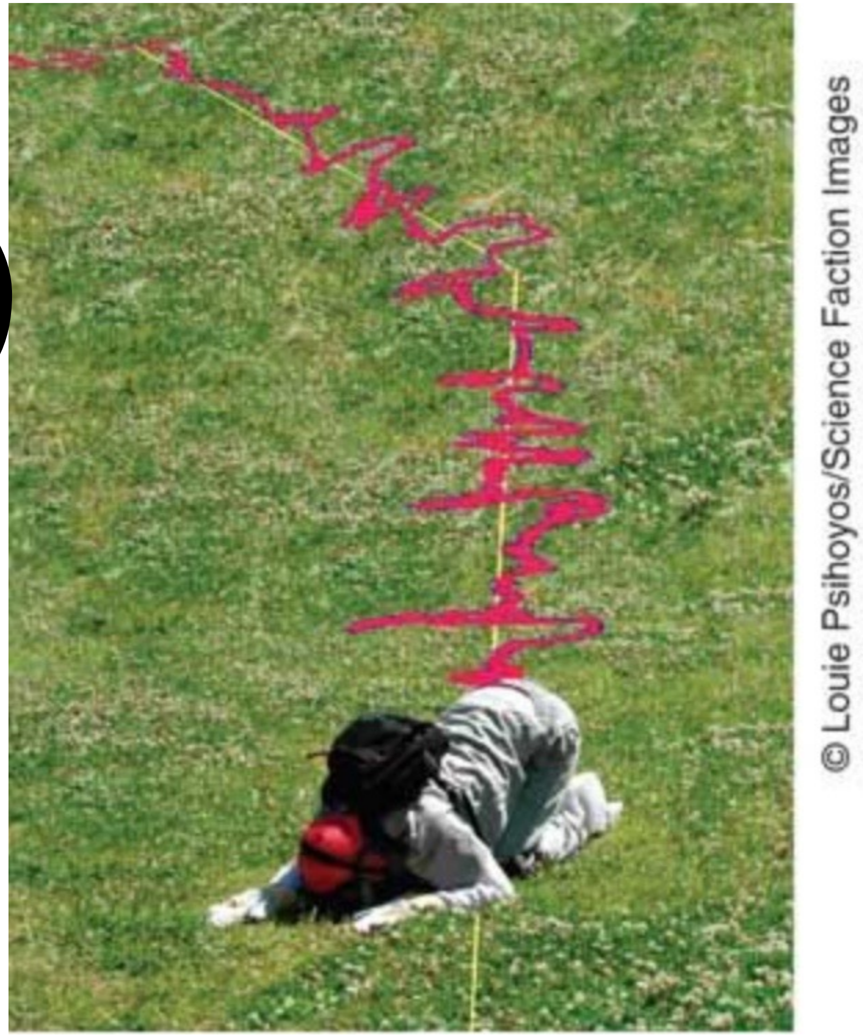
1. Olfactory navigation

Could humans use olfaction for localisation and navigation too?

Yes, they could.

But it might not be very practical as it requires
- crawling on the floor
- marking of different tracks with different scents

Is there a better solution?



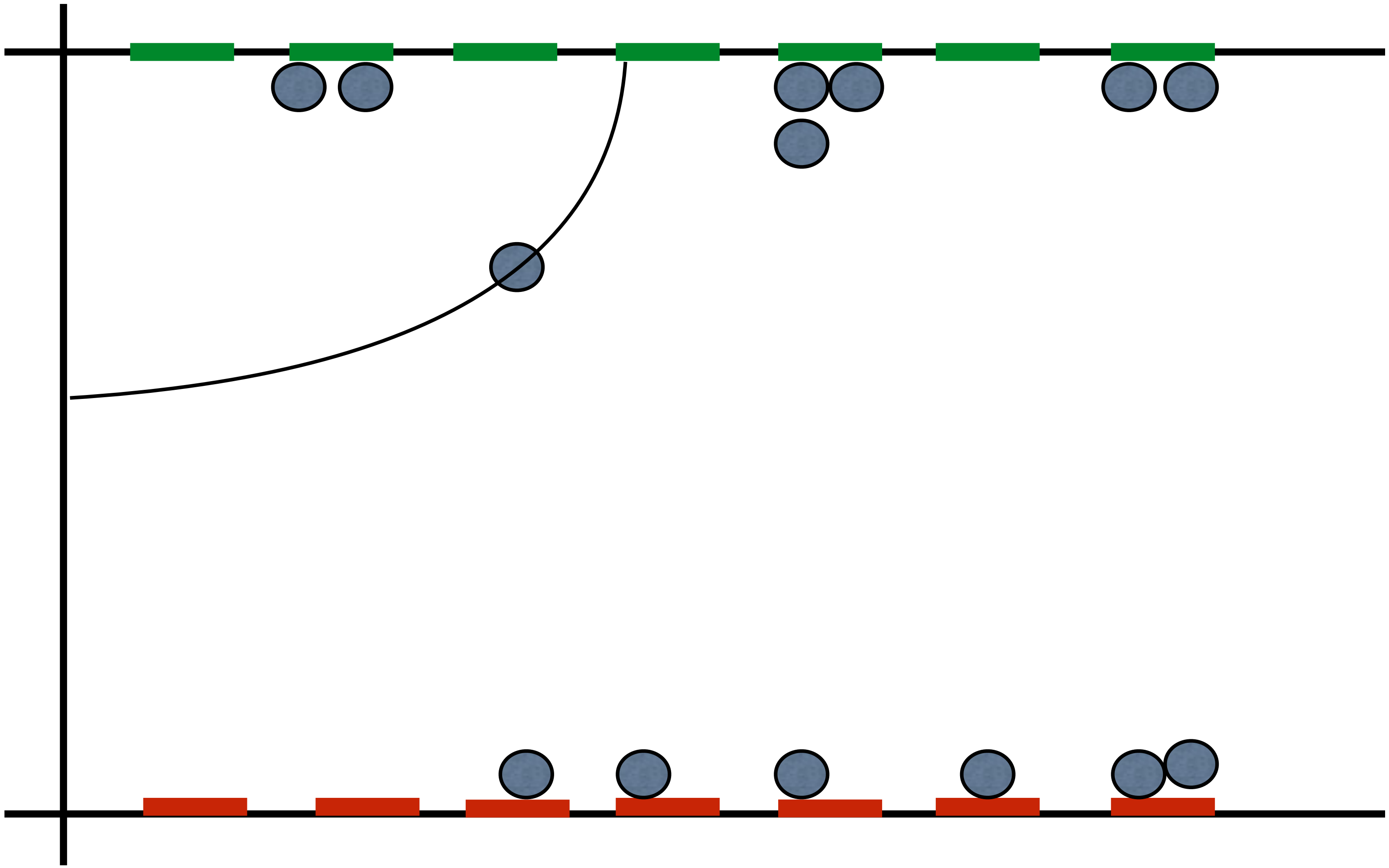
Porter et al. (2007)

Electronic noses perceive and quantify the scent of a location.

- Electronic noses (eNoses) mimic biological sense of smell & brain
- Different types of eNose sensor types exist
- IMS sensors do not age
- ChemPro100i yields usable measurements on 14 channels

Environics ChemPro100i

Ion mobility spectrometry based eNose works a little bit like coin sorting machine.



2. Localisation using aroma fingerprints

Measurements were collected at 7 locations under different conditions.


location 1

loc.	type	# empty	# crowded
1	office room	629	618
2	coffee room	643	631
3	open space	616	618
4	open space	609	614
5	corridor	630	646
6	open space	608	637
7	open space	626	611
Σ		4 361	4 375


location 7


location 2

location 6


location 3


location 4


location 5

Tampereen yliopisto

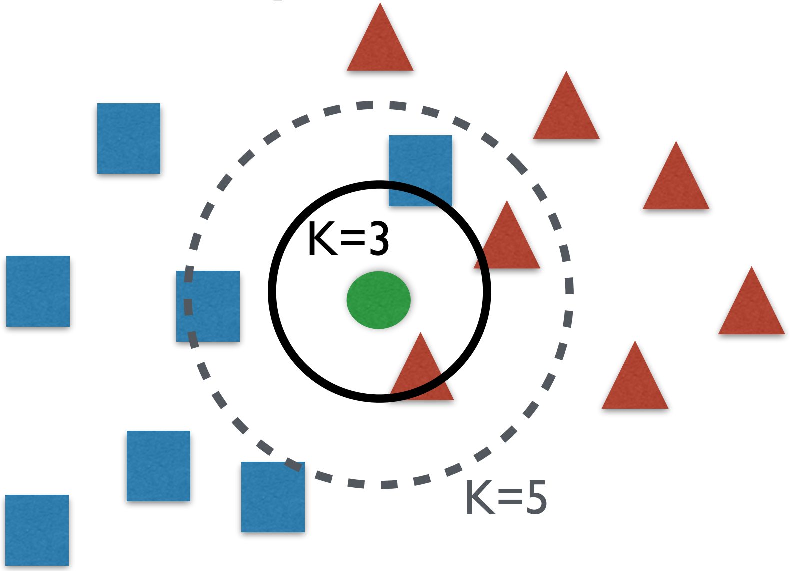
2. Localisation using aroma fingerprints

K Nearest Neighbour (KNN) classifier is used for localisation.

eNose measurements are standardised

Location estimate is label of K training samples closest to test sample

Closeness measured by Euclidean distance



$$\left(\sum_{i=1}^{N} |P_i - Q_i|^2\right)^{1/2}$$

P, Q..vectors
N..vector length

2. Localisation using aroma fingerprints

eNose-based localisation by K Nearest Neighbour algorithm has potential.

All standardised eNose measurements are used

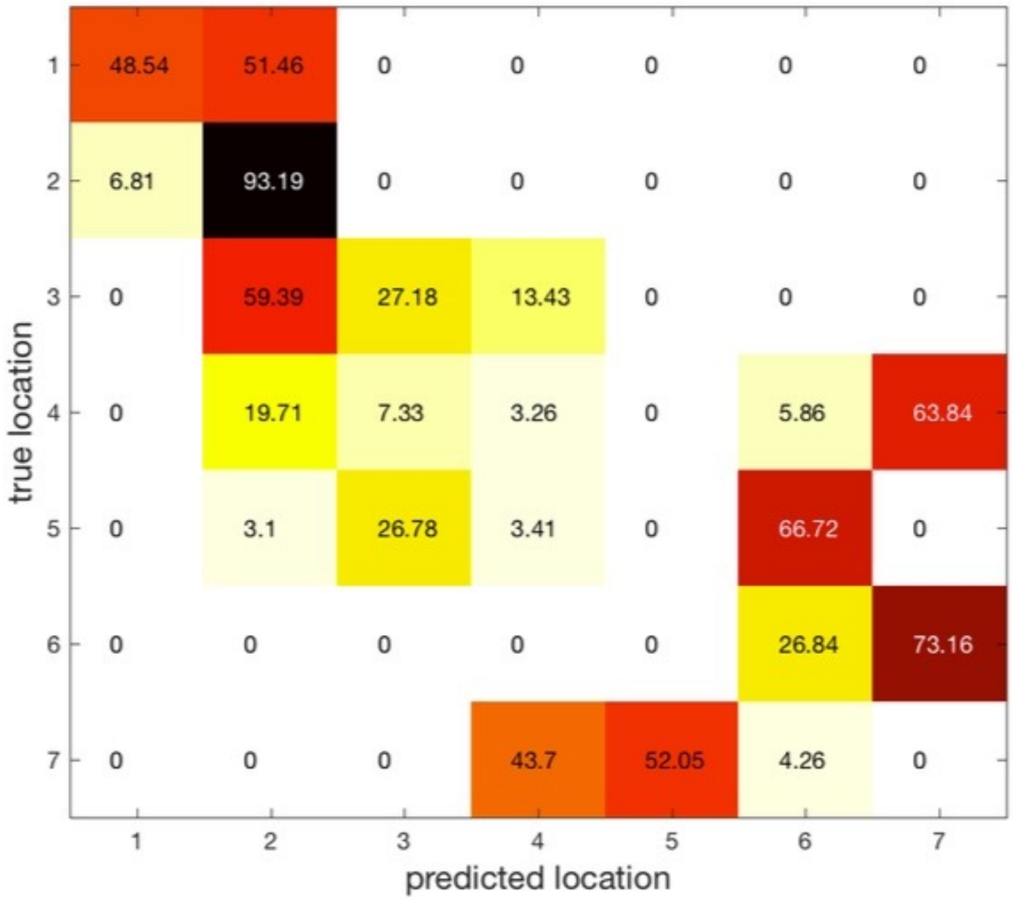
10-fold cross validation is used

Average over validation accuracies of 10 runs

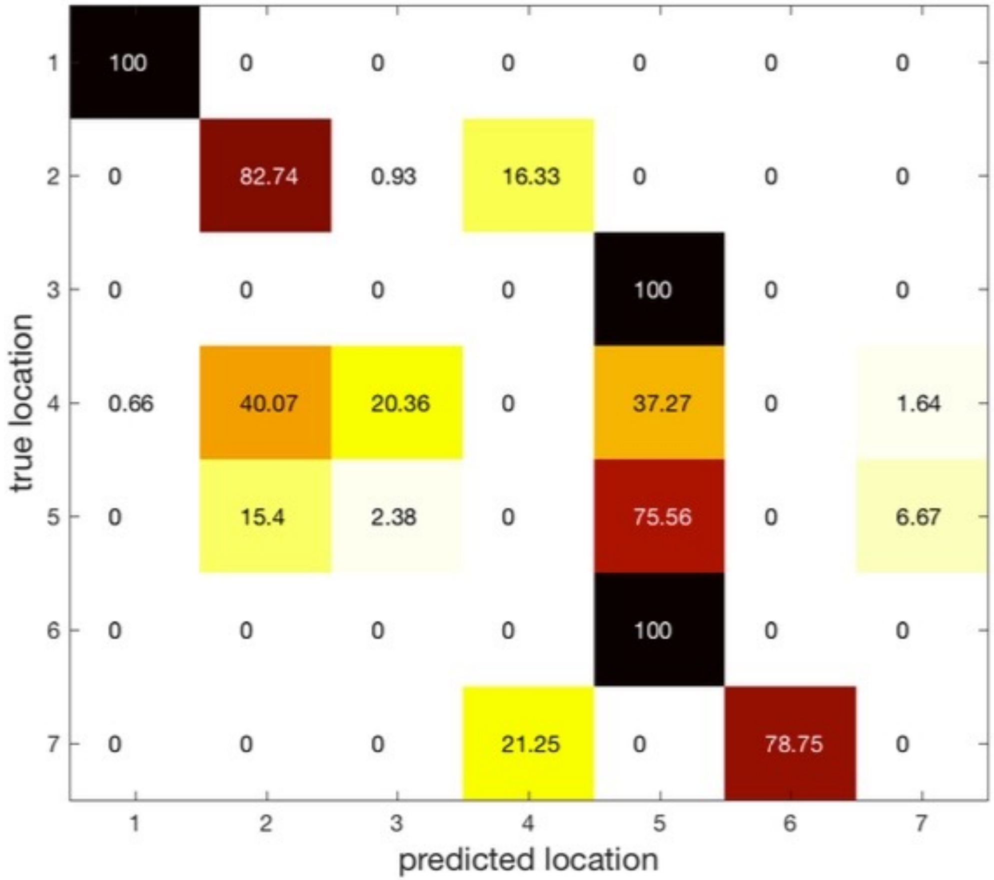
K	validation accuracy
1	99.98%
3	99.91%
5	99.87%
7	99.84%

2. Localisation using aroma fingerprints

Presence of people changes eNose readings.



Classification rate (%) for NN trained in empty spaces and tested in crowded spaces



Classification rate (%) for NN trained in crowded spaces and tested in empty spaces

IMS channels are correlated. Principal Component Analysis (PCA) removes correlation.

For the training data $\mathbf{X} = \{\mathbf{x}_1, .., \mathbf{x}_N\}$ with $d = 14$ dimensions PCA works as follow [9, p. 568]:

1) Compute d-dimensional mean vector $\boldsymbol{\mu}$ and d-by-d covariance matrix $\mathbf{C}$ of data set $\mathbf{X}$.
2) Compute eigenvectors and eigenvalues of $\mathbf{C}$, and sort them according to decreasing eigenvalues.
3) Choose a subset of these eigenvalues, for example, the first k eigenvalues and form d-by-k matrix $\mathbf{A}$ (k eigenvectors as columns of $\mathbf{A}$).
4) PCA-transformed data $\mathbf{Y} = \{\mathbf{y}_1, .., \mathbf{y}_N\}$ is now defined as $\mathbf{y}_i = \mathbf{A}^T(\mathbf{x}_i - \boldsymbol{\mu})$, where each $\mathbf{y}_i$ has $\mathbf{k}$ variables.

$$\mathbf{y}_{\text{test}} = \mathbf{A}^{\mathbf{T}}(\mathbf{x}_{\text{test}} - \mu)$$

G. Minaev et al. (2018). *Indoor localisation using aroma fingerprints: Comparing nearest neighbour classification accuracy using different distance measures*

2. Localisation using aroma fingerprints

IMS channels are correlated. Choice of channels used for localisation affects accuracy.

Principal Component Analysis showed that channels are correlated

First 2 components explain 95% of variance

First 4 components explain 99% of variance

Classification accuracy in percent

room	IMS	PCA 95%	PCA 99%
1	48.54	52.10	53.07
2	93.19	93.19	100.00
3	27.18	34.30	27.51
4	3.26	0.00	2.93
5	0.00	0.00	0.00
6	26.84	27.63	26.53
7	0.00	0.00	0.00

Choice of distance measure influences classification accuracy and computation time.

67 distance measures tested (full list available at:
http://butler.cc.tut.fi/~piche/misc/distanceMeasures.pdf)

Euclidean ($p = 2, r = 2$) $$\left(\sum_{i=1}^{N} |P_i - Q_i|^p\right)^{1/r}$$ P, Q..vectors
N..vector length

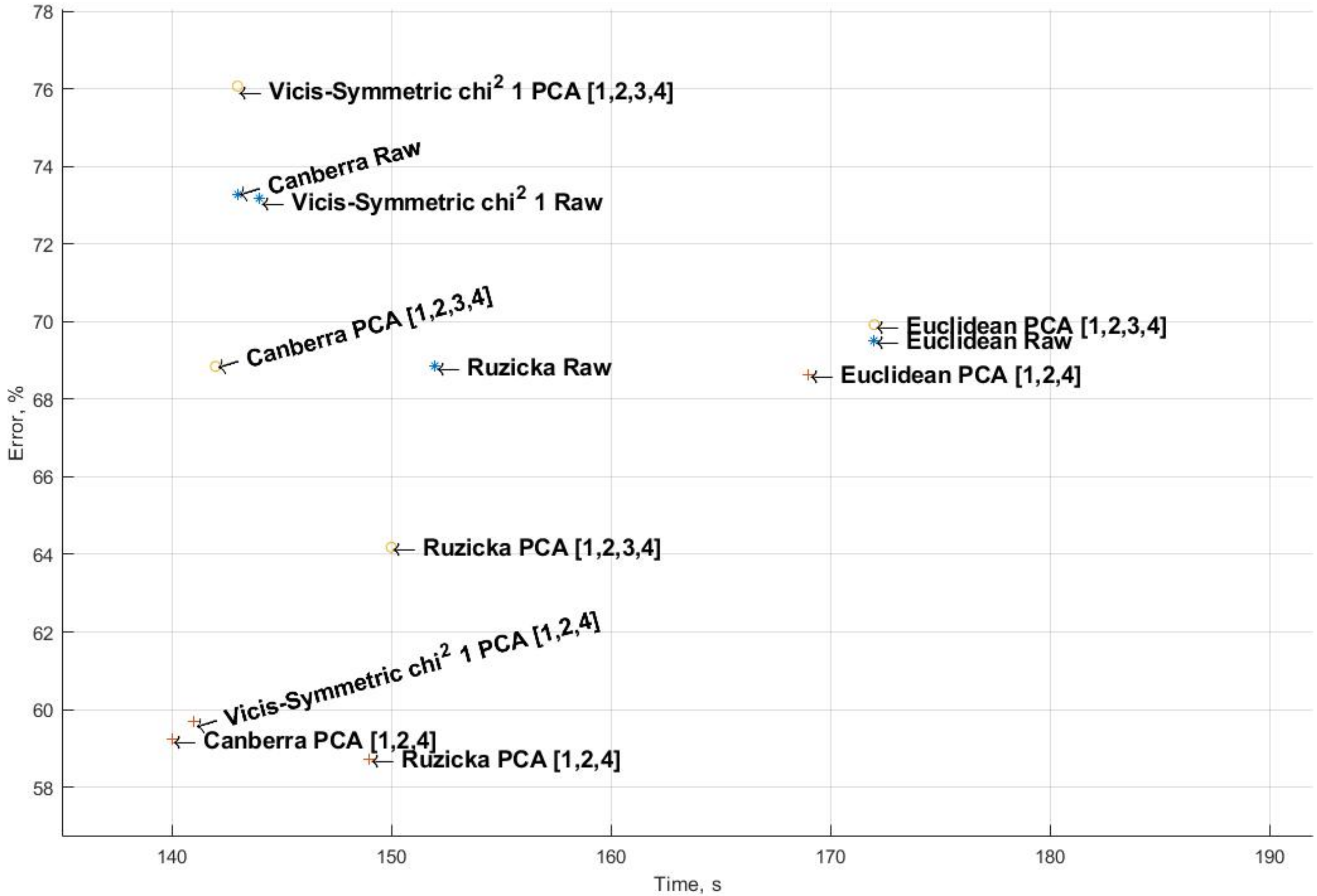
Ruzicka $$\sum_{i=1}^{N} |P_i - Q_i| \,/\, \sum_{i=1}^{N} \max(P_i, Q_i)$$

Canberra $$\sum_{i=1}^{N} (|P_i - Q_i| \,/\, |P_i| + |Q_i|)$$

Vicis-Symmetric χ^2 $$\sum_{i=1}^{N} \frac{(P_i - Q_i)^2}{\min(P_i, Q_i)^2}$$

2. Localisation using aroma fingerprints

Choice of distance measure and PCA influence classification accuracy and computation time.



Tampereen yliopisto

Choice of distance measure and PCA influence classification accuracy and computation time.

K Nearest Neighbour (KNN) classifier
  using different values for K and distance measures

Linear Discriminant Analysis (LDA)

Support Vector Machine (SVM)
  Multiclass SVM to distinguish between 7 locations

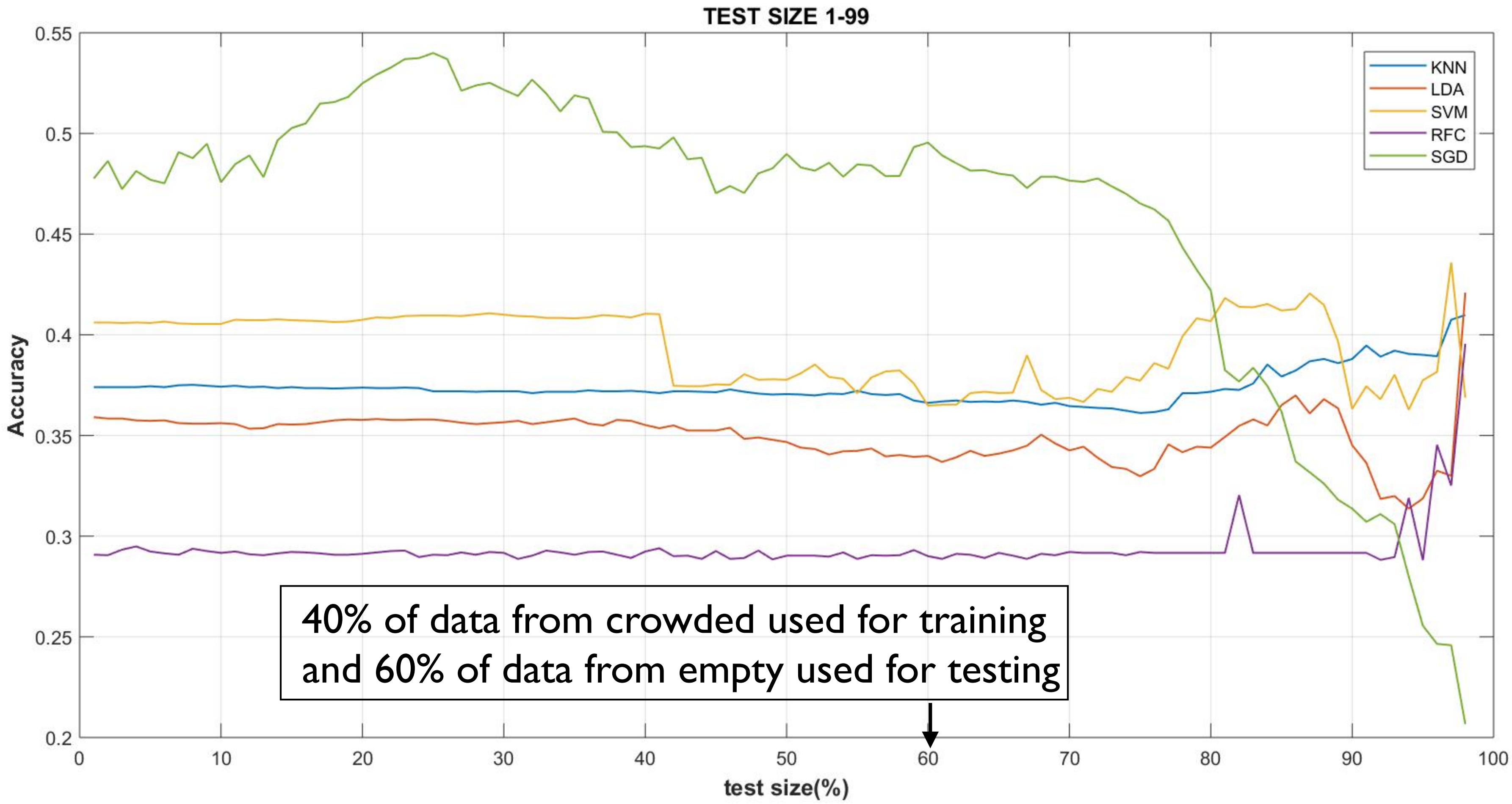
Random Forest (RF) classifier

Stochastic Gradient Descent (SGD)

S. Islam et al. (2019). *Aroma based localisation in GNSS-denied environments*, in Proceedings of XXXV Finnish URSI Convention on Radio Science, *https://urn.fi/URN:NBN:fi:tuni-202001311703*

2. **Localisation using aroma fingerprints**

Choice of classifier influences classification accuracy (and computation time).



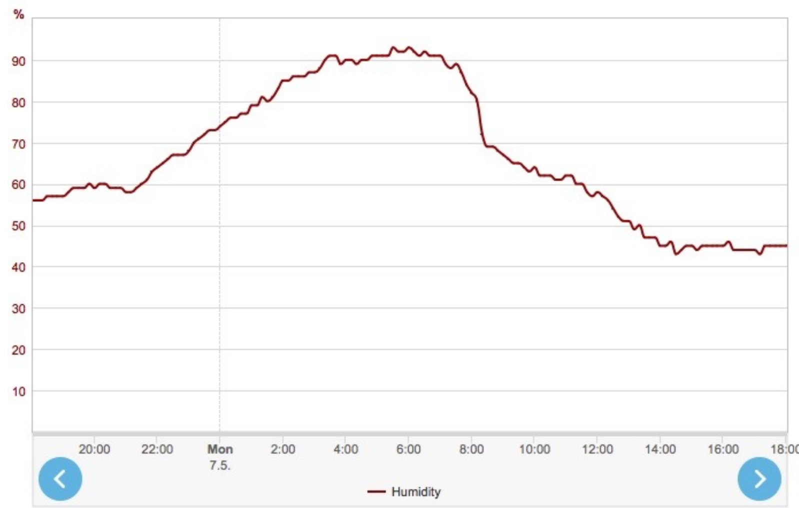
Training data from crowded conditions, test data from empty conditions

3. Open questions and potential solutions

Environmental factors affect the mobility of ionised molecules.

Mobility depends on humidity, temperature, barometric pressure, air currents

Day time affects humidity and temperature at least outdoors



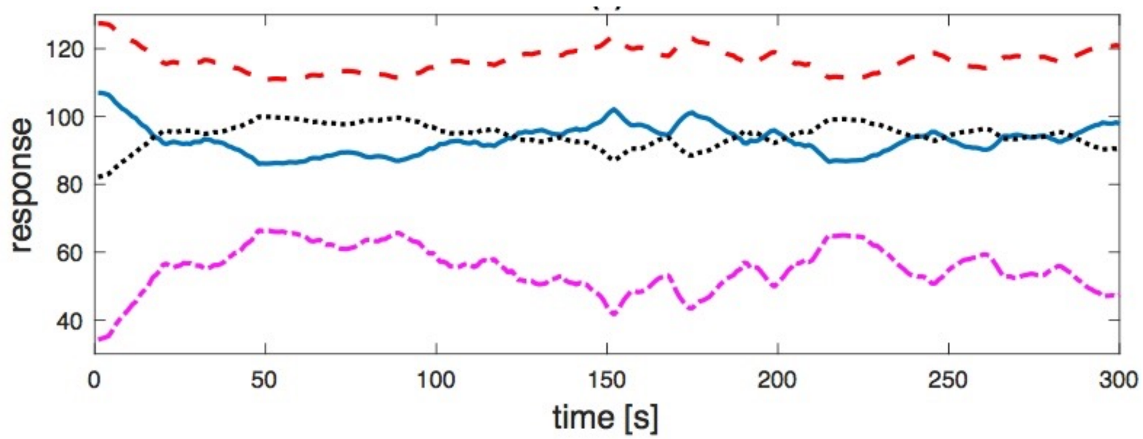
Indoors people affect humidity and temperature

Presence of people brings in additional molecules

3. Open questions and potential solutions

Data post-processing and using sequences of measurements could improve accuracy.

Channel responses show significant fluctuations



Noise mitigation using sliding moving average

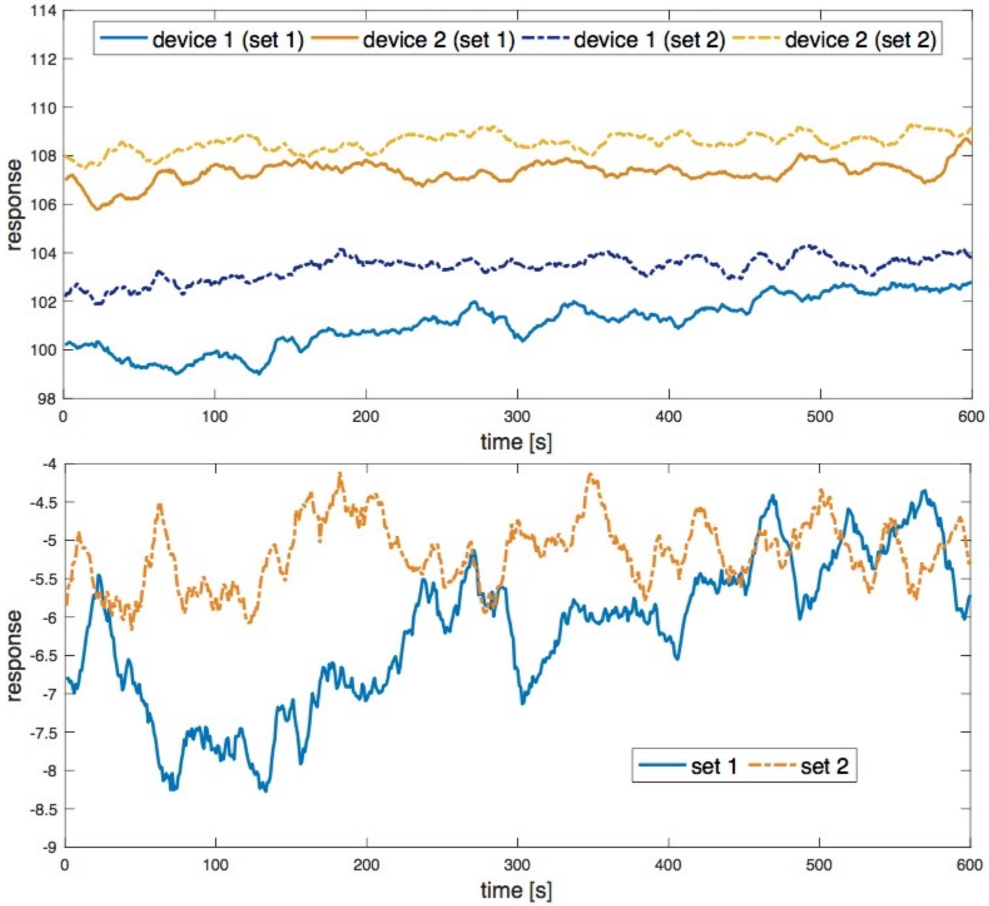
Bayesian filtering and smoothing should improve classification accuracy

Device heterogeneity is present for IMS sensors, but its influence needs to be studied.

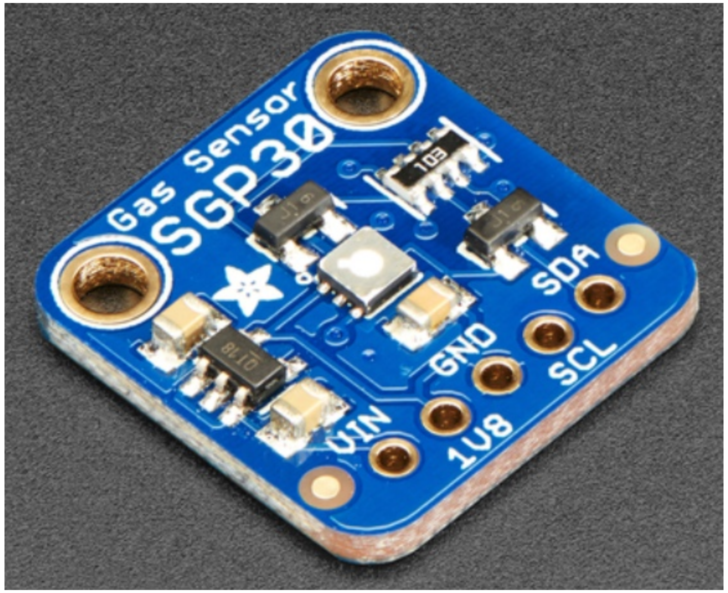
IMS experience no signal drift due to ageing

Device heterogeneity can be observed

Calibration could be done in different ways



Sensors that are safer and more affordable need to be tested.

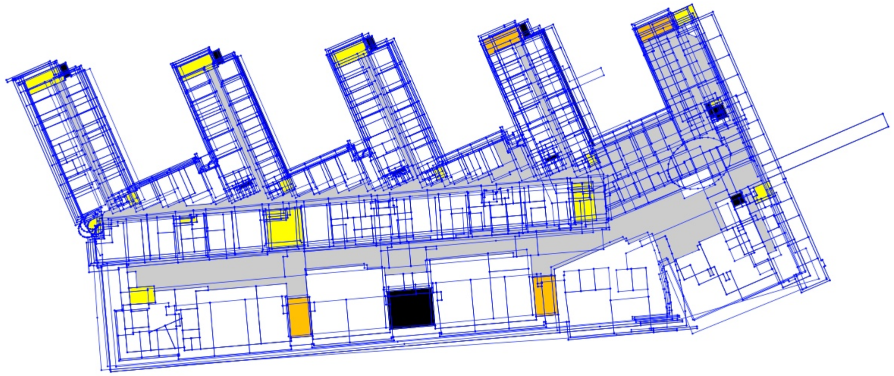


IMS sensors are expensive

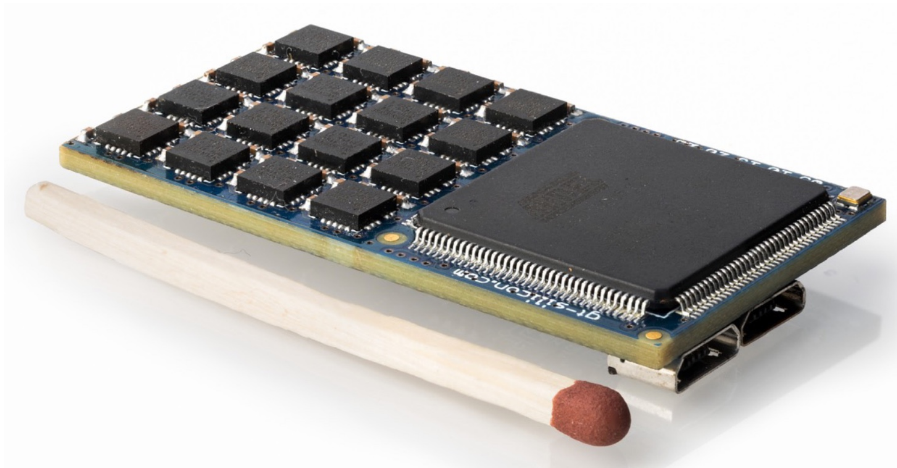
Most IMS sensors use radioactive source for ionisation

Advanced metal oxide sensors experience (almost) no ageing and are affordable

Aroma fingerprints should be combined with other means of localisation.



Conditional information for better accuracy and faster classification



Technique should be fused with other indoor locali-sation techniques

Localisation using aroma fingerprints has potential but requires further research.

eNose-based localisation using KNN classifier can yield high validation accuracy

Various sensor for analysing gases still need to be tested and compared

Fusion of aroma fingerprints with other sensors and information is highly recommended

Thank you!
Questions?

Philipp Müller
Senior Research Fellow, D.Sc. (Tech.)
philipp.muller@tuni.fi