W-Air: Enabling Personal Air Pollution Monitoring on Wearables

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Personal Air Pollution Monitoring

- **Goal**: Allowing users to directly monitor quality of their surrounding air
- **Main motivation**: Personal air pollution monitoring
  - Quantitative health and well-being applications
  - Relationship: Physiological state ⇔ Environmental conditions?
- **Additional benefits**: Crowd-sourced air pollution monitoring
  - Leverage the power of the crowd: big data
  - Cheap high-resolution data

Personal Air Pollution Monitoring Devices

System	Pollutants	Usage	Scenario
Budde et al.	PM2.5, PM10	Carriable	Outdoor
AirSense	PM2.5	Carriable	In-&Outdoor
MyPart	PM10	Wearable	In-&Outdoor
MAQS	CO2	Carriable	Indoor
CitiSense	CO, NO2, O3	Carriable	In-&Outdoor
CommonSense	CO, NOx, O3	Handheld	Outdoor
Oletic et al.	CO, NO2, SO2	Handheld	Outdoor
Piedrahita et al.	CO, CO2, NO2, O3	Carriable	In-&Outdoor
W-Air	**CO2, O3**	**Wearable**	**In-&Outdoor**

Carriable: Handheld, attached to a backpack, bike etc.

See paper for full references

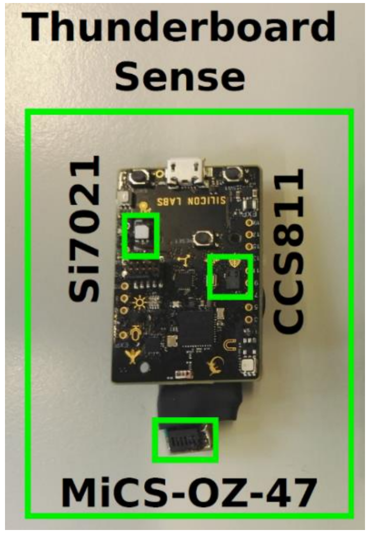
Wearables


- Many commercial products available (FitBit, Apple Watch etc.)
- Simple and compact devices ease user engagement
- Seamlessly integrated into peoples daily lives
- Biological or physiological parameters are commonly measured (e.g. heart rate, galvanic skin response)

Wearables look promising for personal air quality monitoring

W-Air: Wearable Prototype

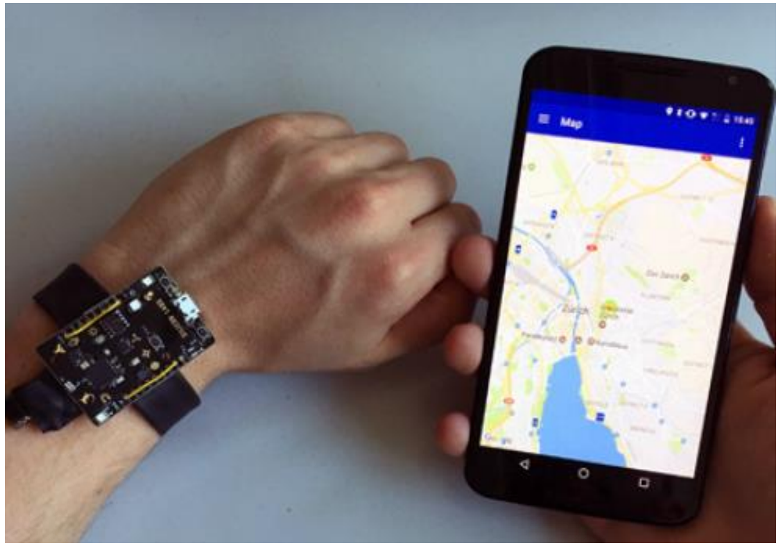
Temperature
& Rel.Humidity



SILICON LABS

VOC/eCO2
(metaloxide)

Ozone O3
(metaloxide)



W-Air ⟷ Bluetooth ⟷ Smartphone App:
Data logging
Calibration

Goal: Measure **ozone (O_3)** outdoors and **carbon dioxide (CO_2)** indoors
(eCO2 via VOC)

→ Can we use this prototype for accurate air pollution monitoring?

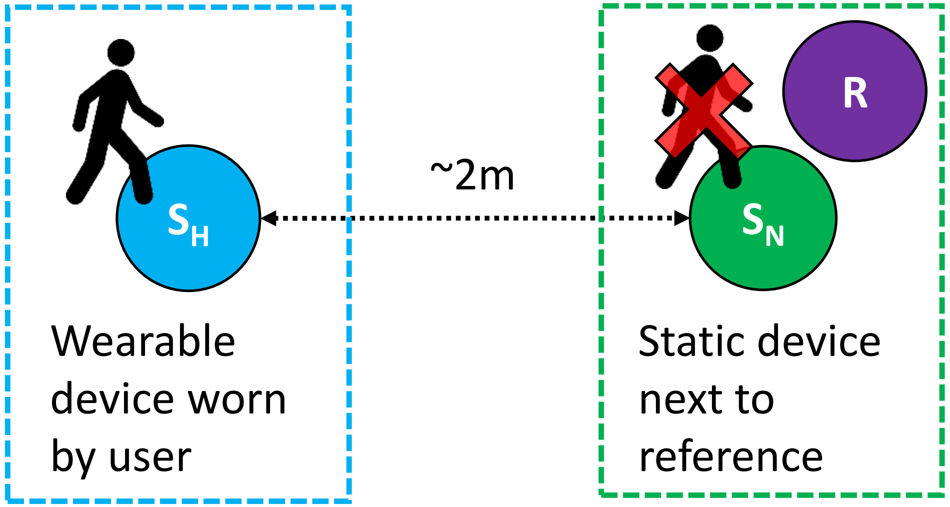
Measurement Study

Outdoor: Ozone (O_3)

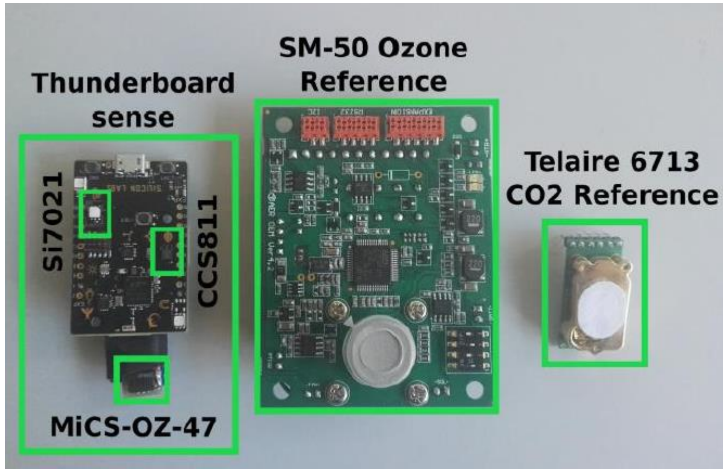
- City-center and residential area
- Reference: Aeroqual SM-50

Indoor: Carbondioxide (CO_2)

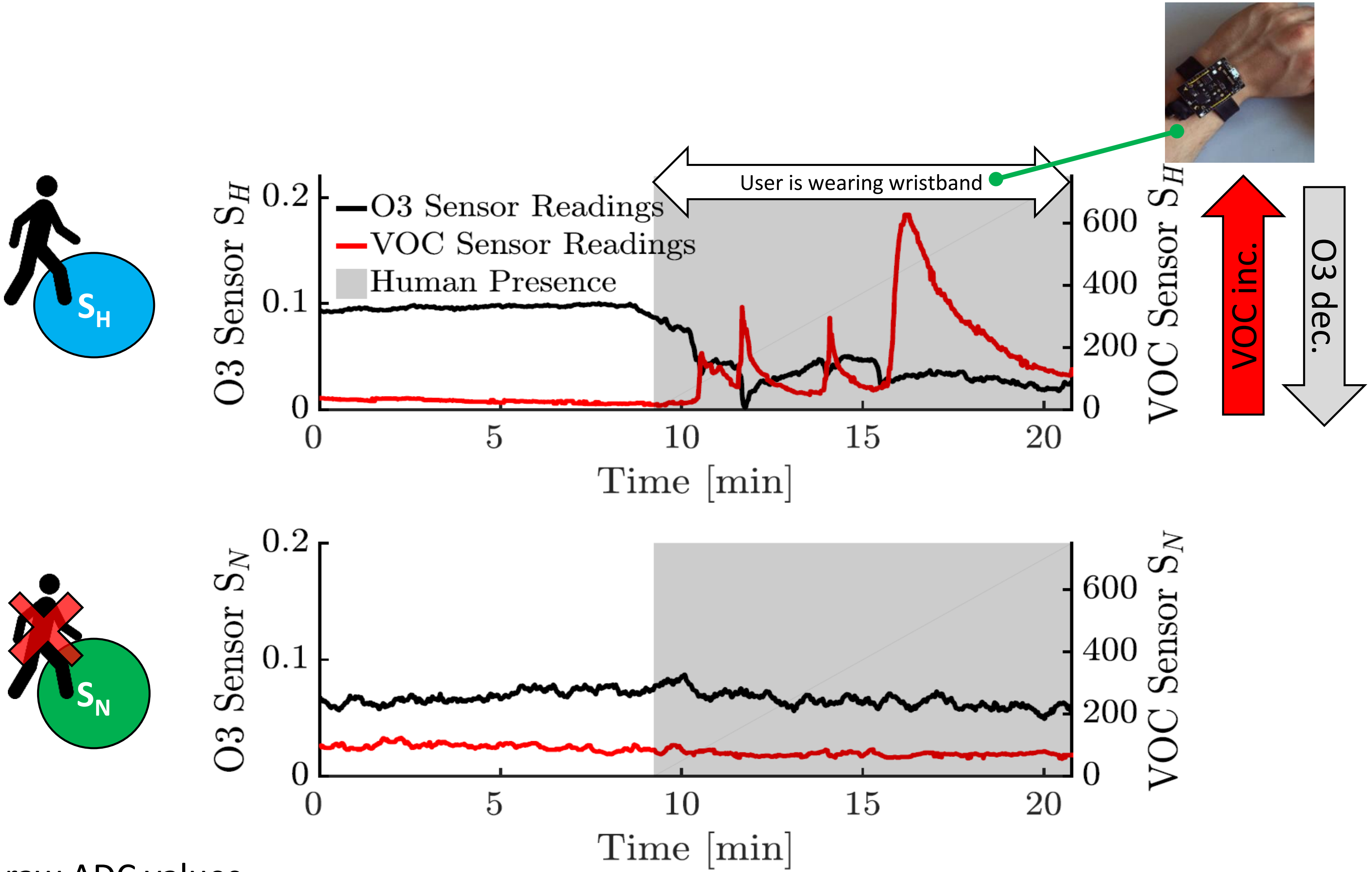
- Office, living- and bed-room
- Reference: Telair 6713



- ~100 hours recorded in each environment
- Distributed over 21 days between April and October 2017
- Basic data smoothing
- User was mainly sitting and reading/working



Observations Outdoor

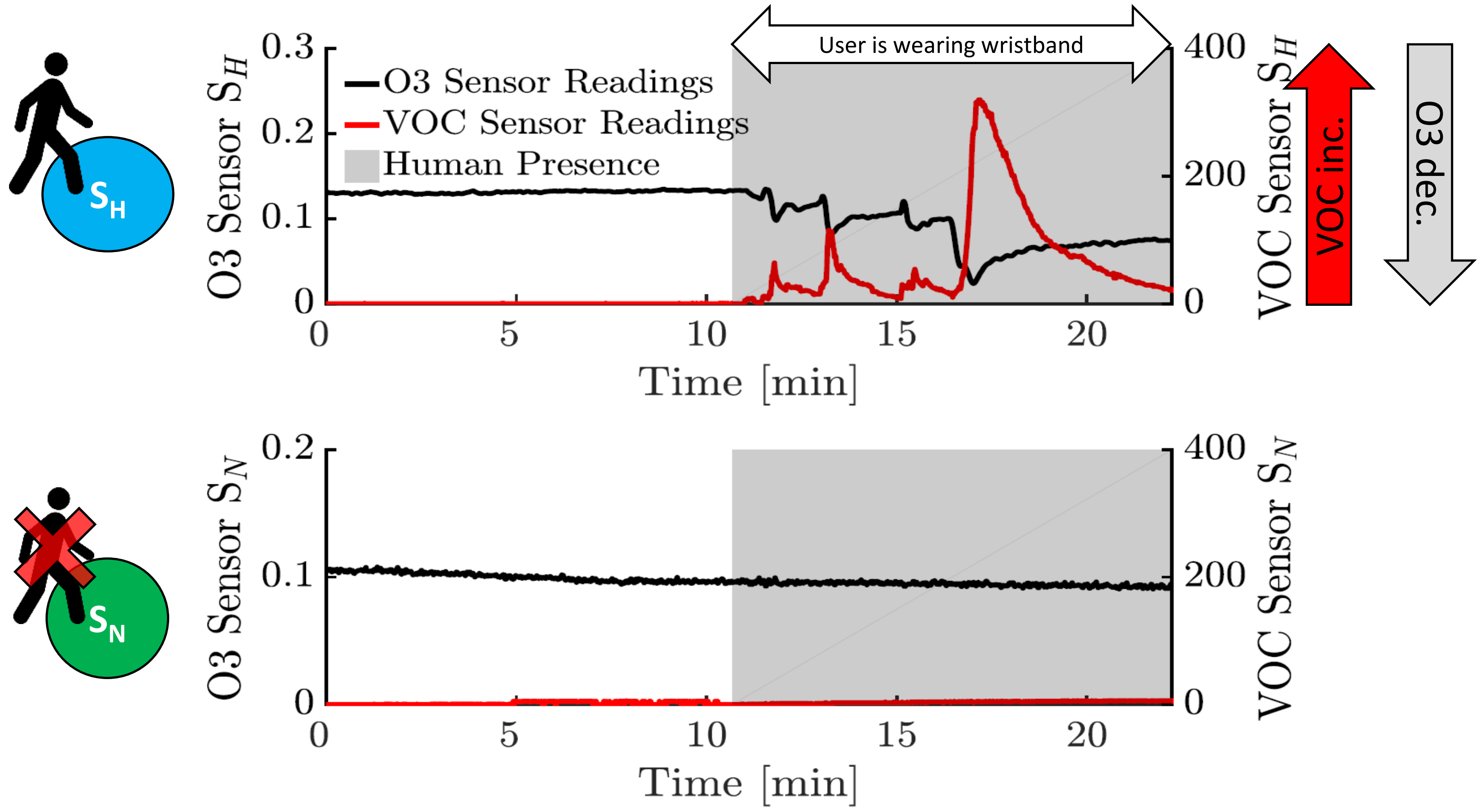


O3: Uncalibrated, raw ADC values

VOC: Factory calibrated VOC measurements

Observations Indoor

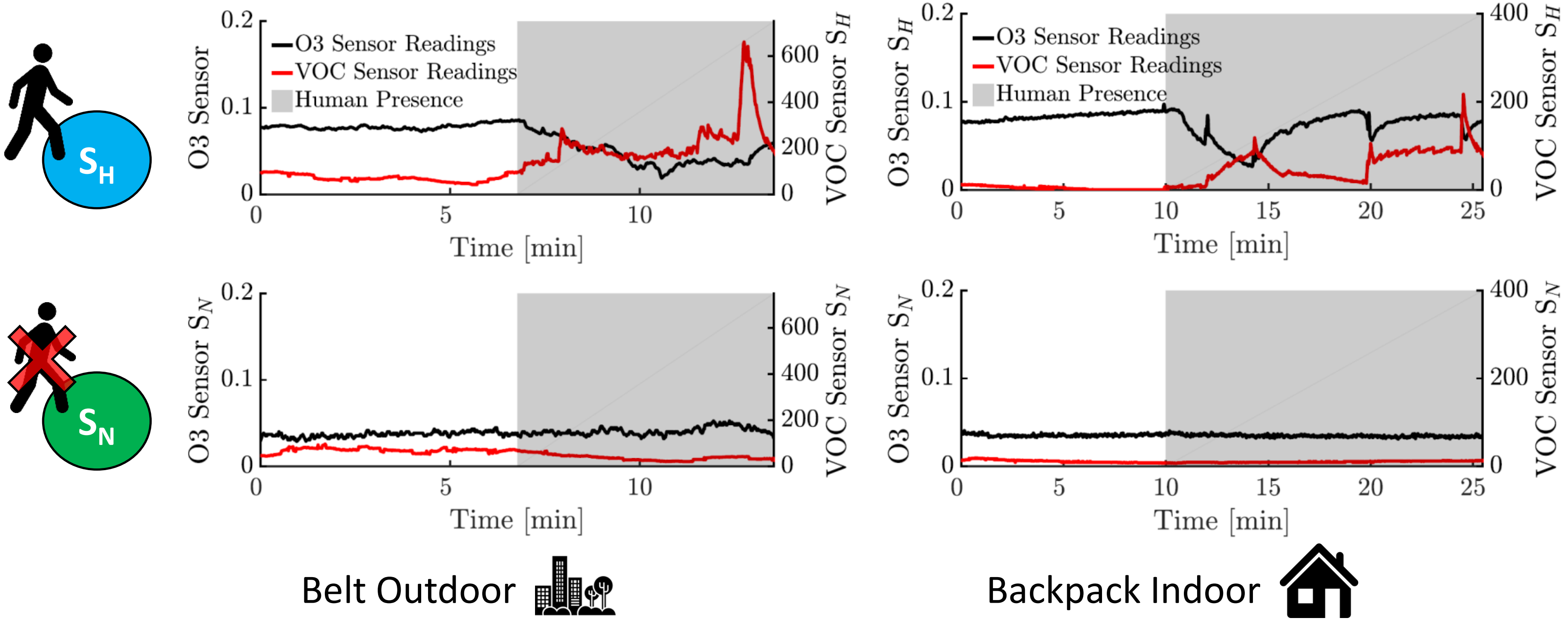
We observe the same human interference indoors!



Belt and Backpack Settings

- Q: Is the human interference a wrist-usage problem?
  A: No!
- Belt and backpack usage have been used before in related work (Budde et al., MAQS, clarity.io etc.)

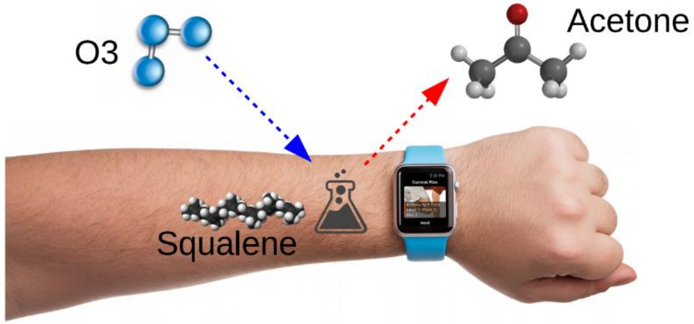
Observations Belt and Backpack



We observed human interference for all settings (wrist, belt and backpack) in both outdoor and indoor environments!

Human interference

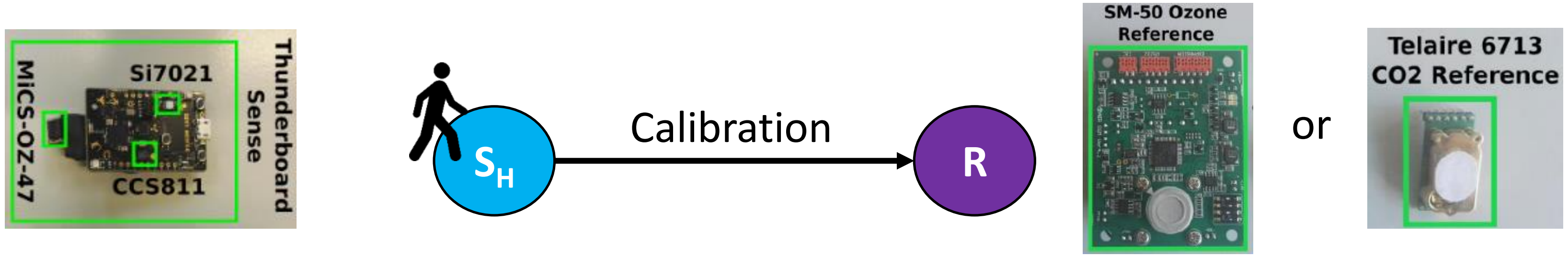
- General observation during human presence situations:
  - VOC concentration increases
  - O_3 concentration decreases
- Possible reasons are different VOC emissions from:
  - Human skin: natural skin oils and cosmetic products
  - Clothing
  - Human breath
  - Chemical reactions with ambient O_3



Problem: Both gas sensors are affected by the human generated interference. This is a possible error source for ambient air quality monitoring in a wearable setup!

Calibration of Human Interference

- Can we counteract the human interference and therefore reconstruct the true O_3 & CO_2 concentrations by calibrating the air quality sensors?



- Sensor array:
  - Measurements from both gas sensors and temperature sensor are calibrated to reference measurements
- Approach
  - Method 1: Linear Multiple Least-Squares (MLS)
  - Method 2: Non-Linear Artificial Neural Network
  - 10-fold CV on 2000 random samples from dataset

Results

Root-Mean-Squared-Error

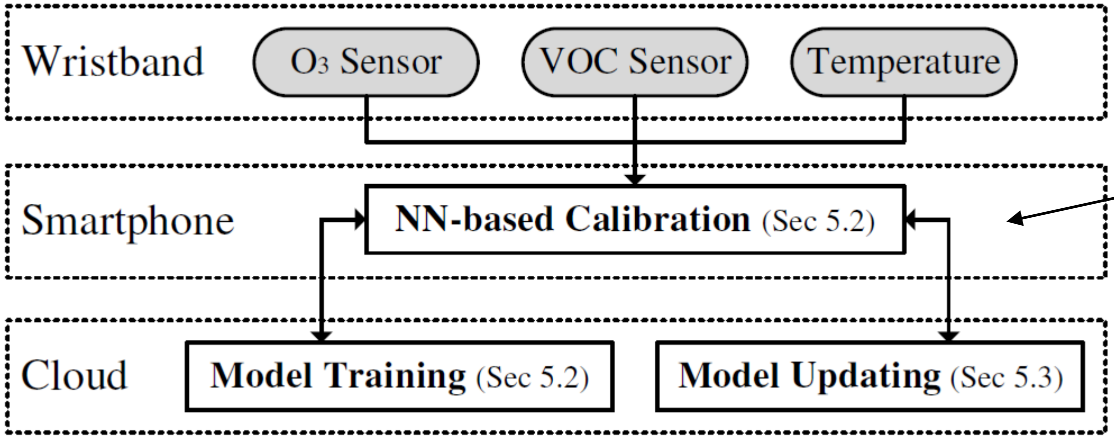
Normalized Error, according to European Data-quality Objective (DQO) for O_3:
<1: Sufficient for any application
<2: Sufficient for indicative meas.
>2: Quality too bad for any appli.

Goodness-of-fit

	Target	Method	RMSE	$RMSE_\sigma$	R^2
Outdoor 	O_3	Linear MLS	10.7ppb	2.24	0.15
	O_3	Non-Linear NN	3.5ppb	0.72	0.91
Indoor 	CO_2	Linear MLS	135ppm	1.17	0.49
	CO_2	Non-Linear NN	44ppm	0.38	0.94

Non-linear **neural networks** are able to compensate for the human interference and recover the true O3 and CO_2 concentrations with high accuracy

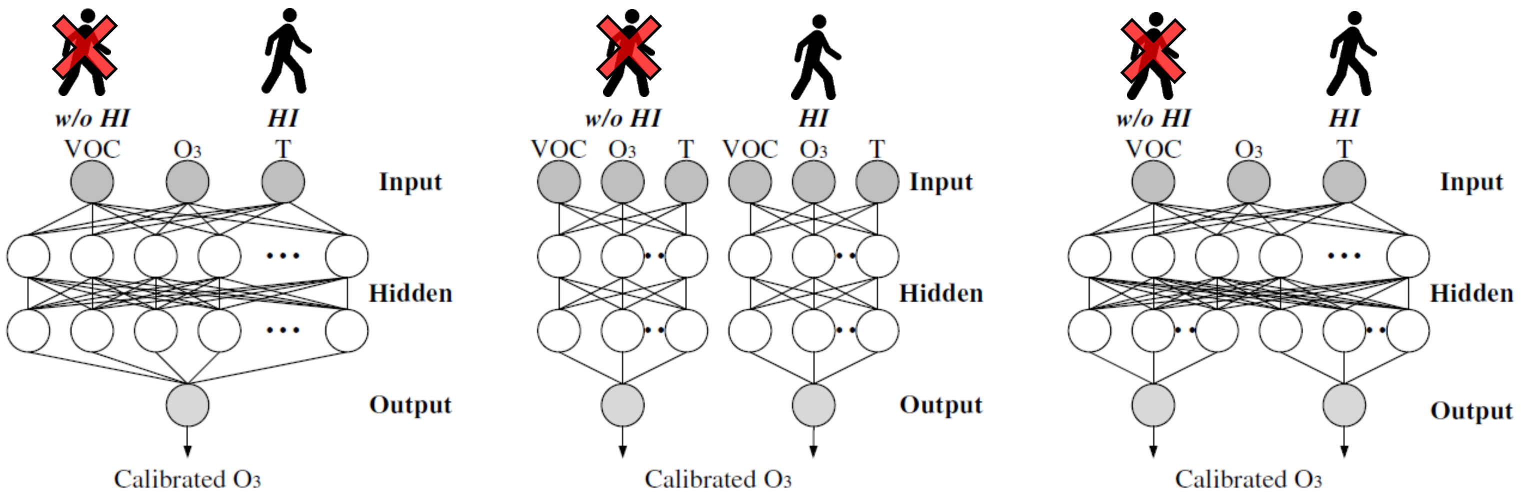
W-Air Work Flow



Separate NN for each environment

- Challenges
  - Calibration should work in situations with and without human interference
  - Training efforts should be small (e.g. training dataset size)
- Our approach to tackle these challenges
  - Shared hidden layer neural network architecture
  - Semi-supervised model updating
- Assumption: The calibration process knows if the user is wearing W-Air and if she/he is out- or indoors

Neural Network Architectures



Unified NN | Two independent NNs | Shared layer NNs

- Unified NN: no distinction between human and non-human interference
- Two independent NNs: Individual training with data from only one case
- Shared layer NN: one shared hidden layer and two individual layers
  - Exploit potential shared features between HI and w/o HI data to reduce training dataset requirements → Also known as *multi-task learning*
- Shared layer NN improves accuracy up to 12% compared to other two architectures

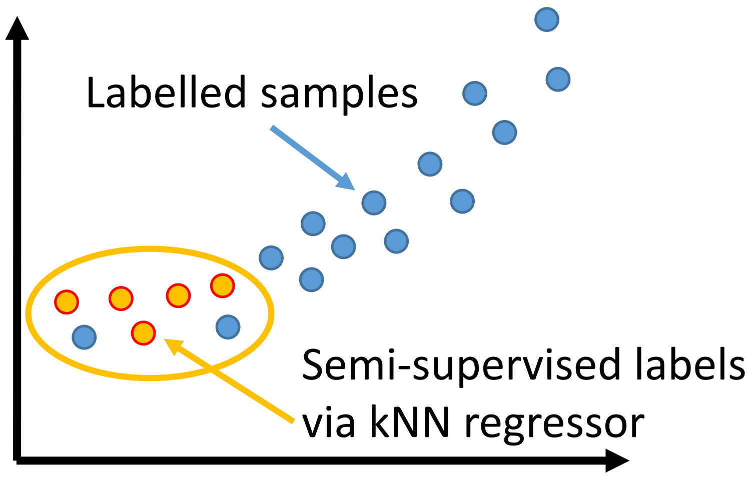
Overall Calibration Performance

- Baseline: Linear MLS calibration trained on data w/o HI
  - Represents a typical factory calibration
- Shared hidden layer architecture
- 10^3 training samples, 10^4 testing samples
- Results RMSE ($RMSE_\sigma$) :

Environment	Test Case	Baseline	NN-based
Outdoor (O_3)	No Human Interference	10 ppb (2.0)	4.3 ppb (0.86)
	With Human Interference	16.8 ppb (3.7)	4.3 ppb (0.94)
Indoor (CO_2)	No Human Interference	177 ppm (1.5)	64 ppm (0.57)
	With Human Interference	325 ppm (2.3)	38 ppm (0.29)

Model Updating

- We need to be able to update our calibration model:
  - Abundant and diverse data covering different environmental conditions
- **Problem**: Acquiring ground-truth during usage by un-trained users is impractical
  - Requires high-quality reference measurements
- **Our solution**: Semi-supervised learning based on the COREG [1] algorithm to generate our own artificial ground-truth



- Basic idea: Boost situations during training with only a few samples by adding artificial ground-truth
- In average 20% accuracy improvement for semi-supervised model updates
- Details in paper and [1]

[1] Zhou et al. Semisupervised regression with cotraining-style algorithms.

Conclusion

- W-Air enables personal and accurate air pollution monitoring on Wearables
- Human interference affects metaloxide based gas sensors and significantly decrease measurement accuracy
- Our solution: neural network based calibration
- We boost the training process by using
  - Shared-hidden layer architecture
  - COREG Semi-superviced learning