Sensor Lag Correction for Mobile Air Temperature Measurements in an Urban Microclimate Context

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Introduction

During mobile transect measurements, it is imperative to relate the measured values to sensor surroundings, which vary quickly in urban areas.

- Problem:

Some sensors adapt slowly to the atmospheric conditions within the traversed microenvironments

- Measure for the inertia of a sensor:

The *time constant* τ_{63} - the time [s] that a sensor needs to adapt to 63 % of an impulse change

- The dynamical error:

Larger time constants *smooth* the recorded air temperature curve because local maxima and minima cannot be resolved [2, 3].

Research question and contribution

- How can measurements with a relatively slow sensor be corrected…

… in order to estimate high-resolution air temperature observations in an urban microclimate environment?

- Studies on sensor lag correction have been carried out in the context of radiosonde or airborne temperature measurements (e.g., [4, 5]), or in a micrometeorological context outside of urban areas (e.g., [2, 3])
- Studies on sensor lag correction in an urban setting are rare.

Instrumentation: The quest for ground truth

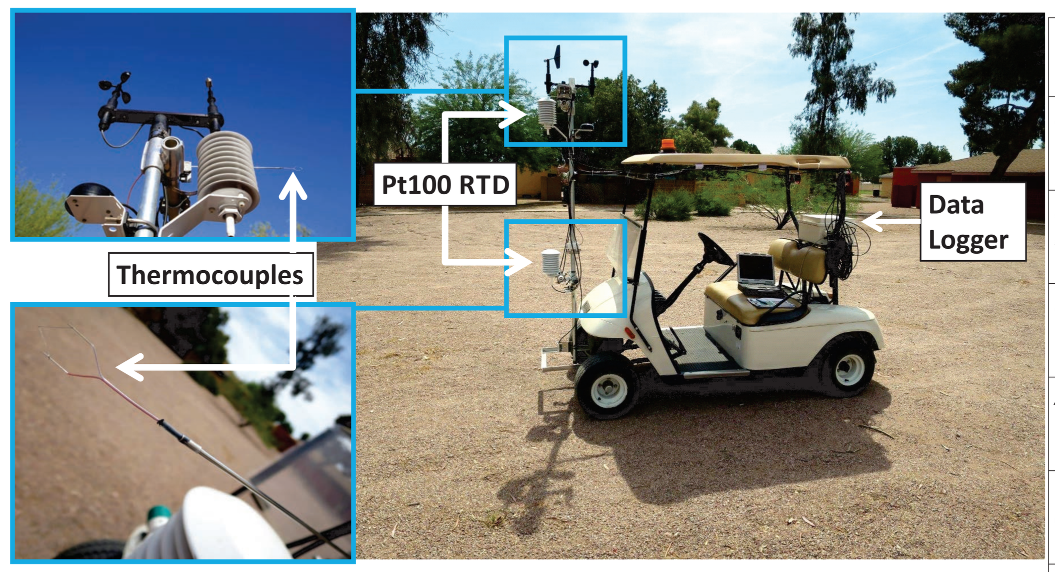

Fig. 1: The measurement platform. All sensors are mounted on a pole, which is attached to the front side of a golf cart. Data logger: Campbell Scientific CR1000.

	Fine-Wire Thermocouple (FWT)	Platinum Resistance Temperature Detector (RTD)
Model	Campbell Scientific Fw3, diameter: 0.0762 mm	Campbell Scientific HC2S3 (air temperature and rel. humidity probe)
Mounting height	1 m and 2 m	1 m and 2 m
Material	Chromel-Constantan	Platinum (resistance at 0°C = 100 Ω
Accuracy	± 0.1 °C (at 23 °C)	± 0.1 °C (between 0 °C and 40 °C)
Time constant τ_{63}	0.6 s in still air (typical value, see [7])	172.7 s in still air (stdv = 0.08 s); 46.2 s for wind speeds > 3.2 m/s (stdv = 3.7 s)
Sampling frequency	1 Hz	1 Hz

- The time constant of the Pt100 RTD was determined experimentally.
- Air temperature time series were time-detrended individually.
- Since the time constant of the applied FWTs is very low, their observations can be used as a ground truth for the evaluation of algorithmic parameter choices.

Study site and transect runs

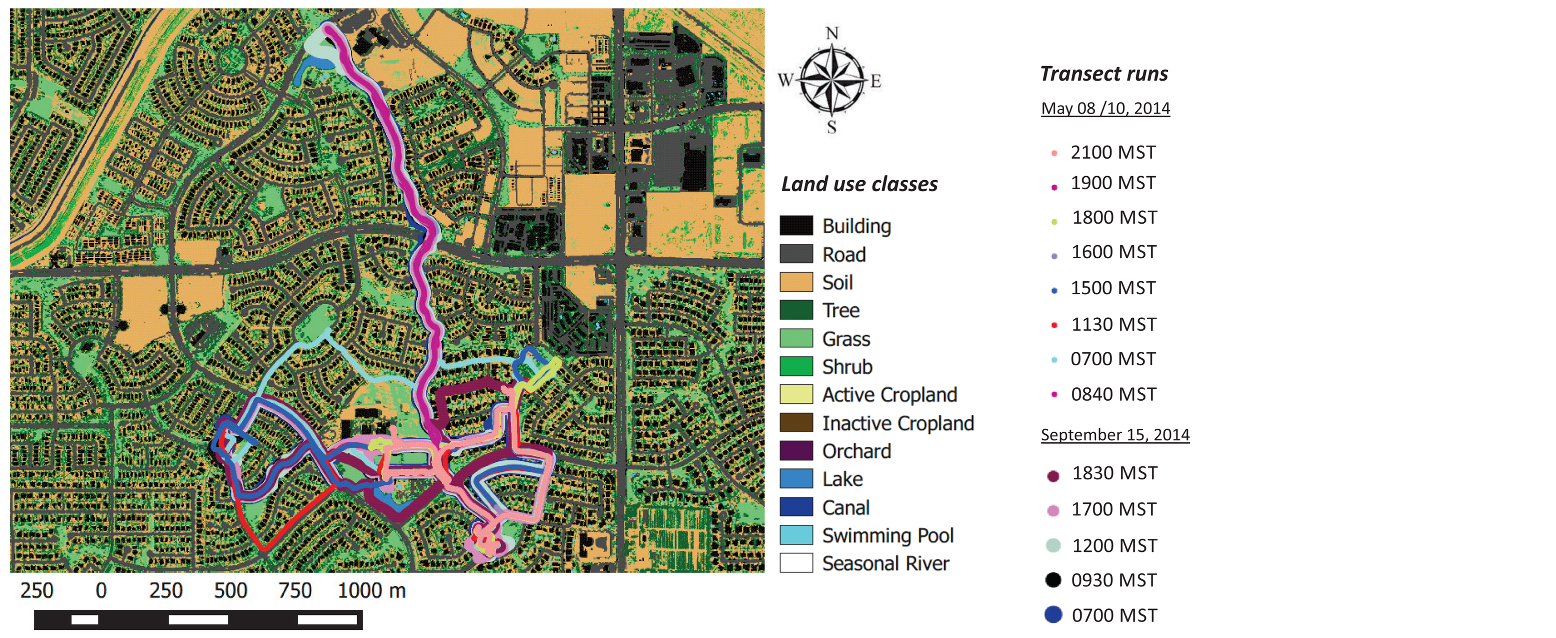

Fig. 2: The study site in **Power Ranch, Gilbert, Arizona**. The sample transect runs are plotted on top of a high-resolution land-use map [1].

Methodology

- Basic assumption:

The measured temperature is the true temperature, convoluted with the time-derivative of the impulse-response function [2, 3, 4, 6].

- Solution: Deconvolution!

Deconvolution procedures are described in [2, 3, 4, 6]. We base our approach mainly on [2], while optimizing the choice for two algorithmic parameters.

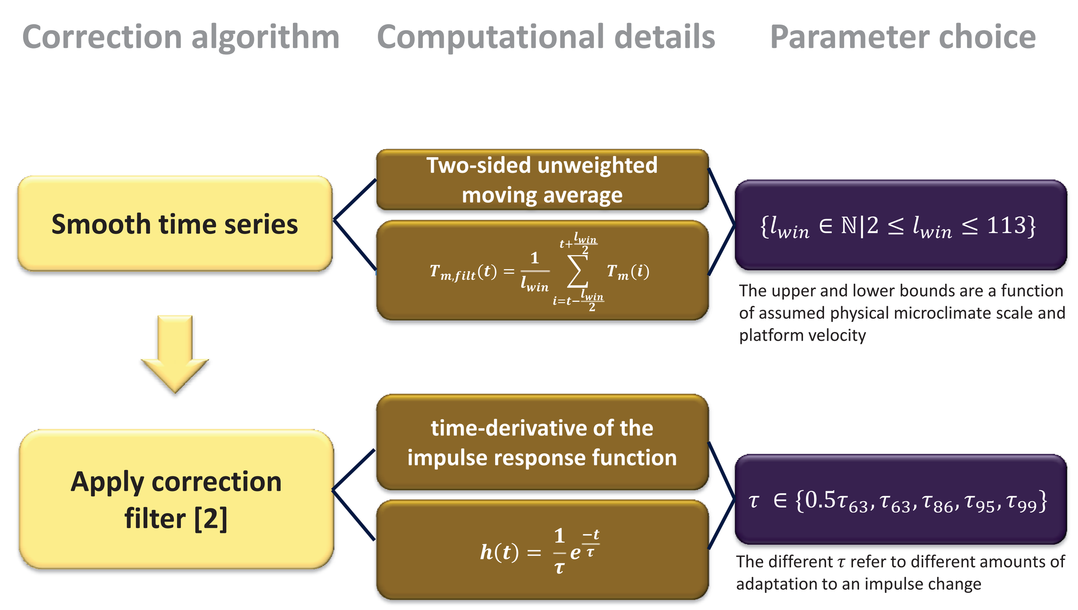

Fig. 3: Finding the optimal parameter choice for the correction algorithm by computing the root mean square error (RMSE), the mean absolute error (MAE), the maximum absolute error (Ae_{max}), and the index of agreement (d, as described in [5]) between corrected PRT data and the data from the fast FWT sensor.

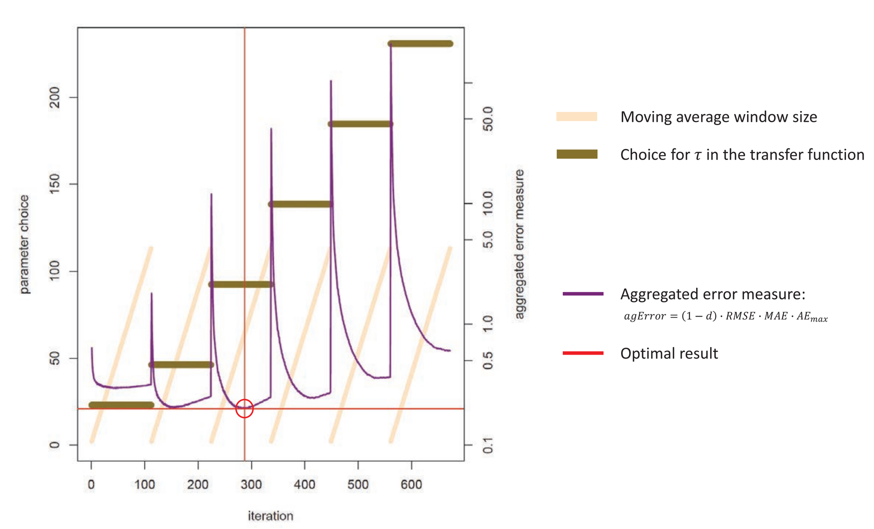

Fig. 4: Results of the parameter optimization experiment, averaged over all available data sets.

The final method follows 5 steps:
(based on the parameter study result

1. Smooth time series using *lwin* = 64
2. Apply correction filter using $\tau_{86} = 2*\tau_{63} = 92.42$
3. Fast Fourier Transform of both the time-derivative of the impulse response funtion (= *H(f)*) and the smoothed PRT data (= *G(f)*) [2]
4. Division of G(f) by H(f) to retrieve the true temperature spectrum [2]
5. Inverse Fast Fourier Transform [2]

Correction results

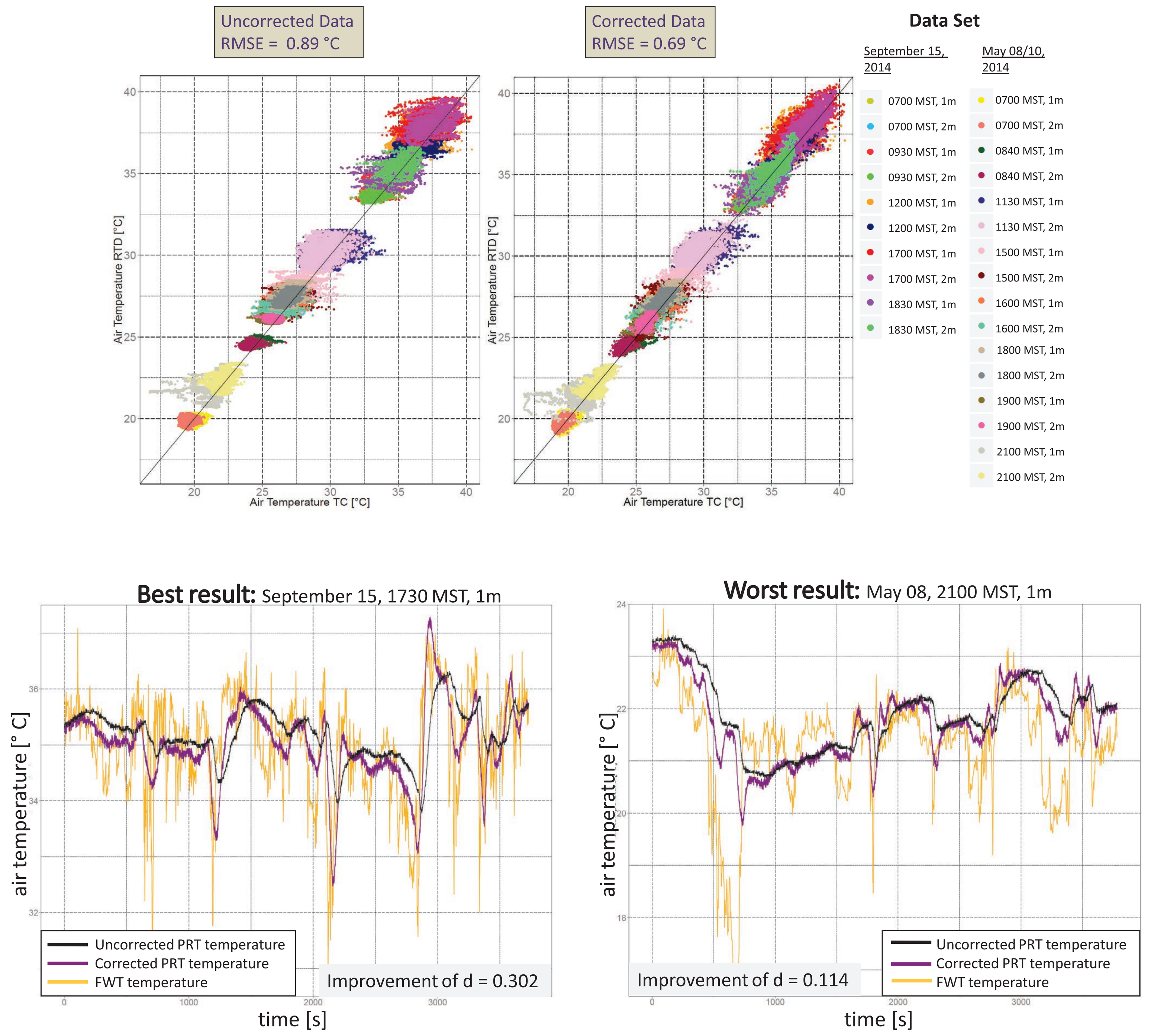

Fig. 5: Correction results when applying the algorithm as outlined above. The scatterplots show the improvement of the RMSE between PRT and FWT data after applying the correction. The time series below illustrate a best and a worst case scenario. FWT data was smoothed dependend on the minimal physical microclimate scale and platform velocity.

Conclusion and future work

- Applying the determined sensor lag correction procedure improves the agreement between PRT data (slow sensor) and FWT data (fast sensor) in all investigated settings.
- The results need to be verified for data sets representing different settings, e.g. in terms of sensor setup (other time constants) or season (winter / spring).

References

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