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 $\tau_{63}$ - 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 microclimatic 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 micrometeoro logical 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

- 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. 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.

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.

<table>
<thead>
<tr>
<th>Correction algorithm</th>
<th>Computational details</th>
<th>Parameter choice</th>
</tr>
</thead>
<tbody>
<tr>
<td>Smooth time series</td>
<td></td>
<td>$\tau_{63}$</td>
</tr>
<tr>
<td>Two-sided moving average</td>
<td></td>
<td>$\tau_{63}$</td>
</tr>
<tr>
<td>Apply correction filter [2]</td>
<td></td>
<td>$\tau_{63}$</td>
</tr>
<tr>
<td>Time derivative of the impulse response function</td>
<td></td>
<td>$\tau_{63}$</td>
</tr>
</tbody>
</table>

The final method follows 5 steps:

1. Smooth time series using $\text{box} = 64$
2. Apply correction filter using $\tau_{63} = 21.46$
3. Fast Fourier Transform of both: the time-derivative of the impulse response function ($\tau_{63}$) and the smoothed RTD data ($\tau_{63}$) [2]
4. Division of (2) by (3) to retrieve the true temperature spectrum [2]
5. Inverse fast Fourier Transform [2]

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 residual absolute error (r.e.), and the index of agreement (IA) are used as error metrics [2] between corrected PRT data and the data from the fast FWT sensor.

Correlation results

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

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 illustrates a best and a worst case scenario.

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).