Coordination Dynamics: Centering and Hilbert Analysis of Environmental Dynamic Signals

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Abstract

This paper describes a method for analyzing the processing of environmental sensor data, with a focus on temperature and humidity signals. The dynamic nature of the data is explored by constructing phase diagrams, signal localization, and Hilbert transform and CPR-based analysis. This study reflects fundamental concepts from complex systems science, in particular coordination, attractor dynamics, and phase synchronization. This paper provides a foundation for further studies of system coordination.

1. Introduction

Coordination are fundamental issues in the study of complex systems. It is the manner in which the system parts unfold together over time. Phase-based analytical approaches that rely on CRP (continuous relative phase) computations based on the Hilbert transform also permit researchers to quantify and characterize the dynamic relationship between different system components (Lamb & Stöckl, 2014). These techniques are applied to temperature and humidity signal data from environmental sensors to extract local embedded dynamics associated with coordination patterns and attractor dynamics.

2. Data and Methods

2.1 Dataset Description

The sensor data analyzed in this study comes from an environmental monitoring system in a CSV file named "D1_sensor_data.csv". This dataset contains time series measurements of temperature and humidity. To ensure the uniformity of the data, we selected a subset corresponding to tag number 202204 for focused analysis.

2.2 Analytical Methods

Data Import and Filtration The raw dataset were imported to a Python environment using the library pandas. The raw data was filtered to keep only the rows for which tag_number = 202204, ensuring focus on the consistent subset of data.

Signal Extraction: Temperature and humidity were extracted as time series for individual and relative comparison.

Phase Plane Formation: The position x(t) and velocity, v(t) were calculated for each signal whereby, velocity was estimated using forward differencing (v(t)= x(t+1)-x(t)). The phase portraits were drawn using matplotlib, with x(t) on the x-axis and v(t) om the y-axis.

Phase Plot of Temperature and Humidity: For phase map based analysis, signals were biased to zero. This normalization is necessary to make symmetric distribution of amplitude oscillations such that a Hilbert Transform can be applied.

Hilbert transform analysis: To analyse the temperature and humidity signals, we apply the Hilbert transform. This method helps us to calculate two important values: continuous relative phase (CRP) and instantaneous phase. With this method, we can study two things: (1) how the frequency and phase of a signal change over time, and (2) how two signals interact with each other. For example, if one signal consistently ‘leads’ or ‘lags’ the other, this suggests a dynamic relationship between temperature and humidity. To make the results clearer, we use phase portraits to visualise the phase difference. These plots are like a map showing how the behaviour of the signal changes over time

Phase synchronisation analysis: Next, we focus on understanding the temporal relationship between temperature and humidity fluctuations. Using the instantaneous phase values obtained from the Hilbert transform, we calculated the phase difference between the two signals at each point in time. This difference is called the Continuous Relative Phase (CRP) and tells us whether the two signals are in sync (moving together) or out of sync (moving independently). For example, if the CRP remains close to 0°, the signals are highly synchronised. If the CRP fluctuates between -180° and +180°, the signals are out of sync. This analysis is critical because it reveals how temperature and humidity interact in real-world environments.

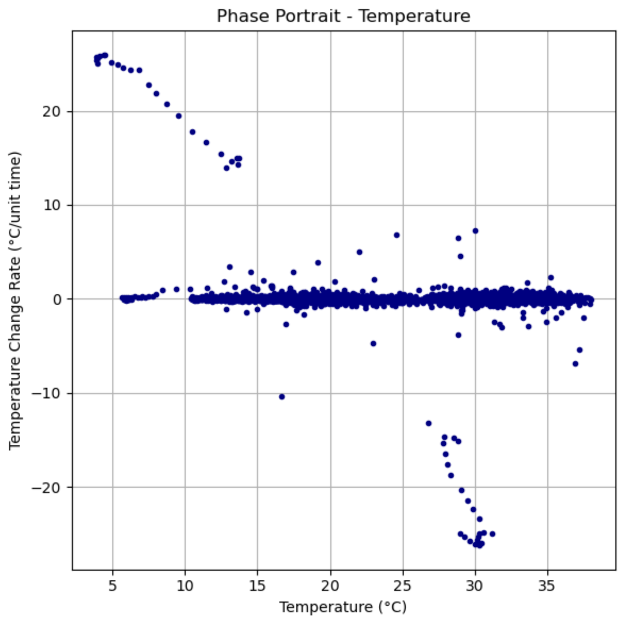
3. Results and Analysis

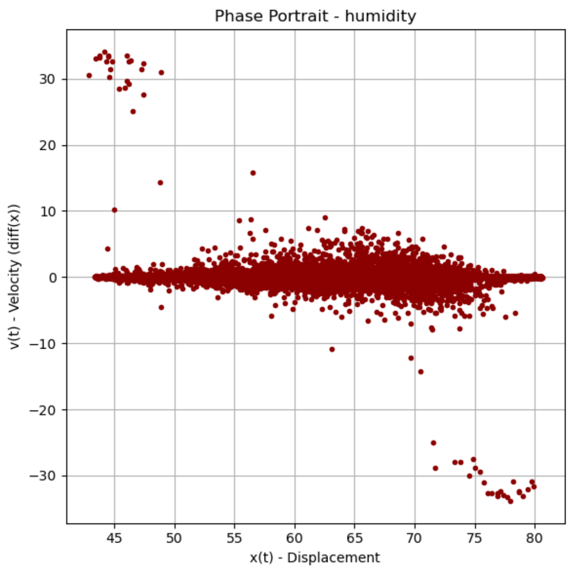
3.1 Phase Portrait of Temperature and Humidity

Temperature Signal Analysis: The phase portrait of temperature data revealed key dynamic patterns. Sharp transitions in the rate of change were observed near 10°C and 30°C, suggesting the system undergoes rapid shifts at these temperature thresholds. For example, when temperatures approached these critical points, the system behavior changed abruptly, similar to flipping a switch. Most data points clustered near zero rate of change, indicating long periods of stability across a wide temperature range. Together, these patterns suggest a multi-stable system—meaning the system can settle into multiple stable states depending on conditions.

Humidity Signal Analysis: In contrast, the humidity phase portrait showed strong nonlinear behavior and multi-stability. Sudden shifts in the rate of change occurred near 45% RH and between 75–80% RH, acting like "tipping points" where the system rapidly transitions between states. However, in the mid-range humidity (55–70% RH), the system remained relatively stable, with most data points clustering near zero rate of change. This implies humidity dynamics are more sensitive to extreme values but stable under moderate conditions.

Both temperature and humidity phase portraits highlight multi-stability, a feature where systems switch between stable states. For instance, temperature stabilizes broadly but shifts suddenly at thresholds, while humidity balances stability in mid-ranges with volatility at extremes. These findings help explain how environmental systems adapt to changing conditions..





3.2 Centering of Signals

Signal centering was applied to both temperature and humidity time series:

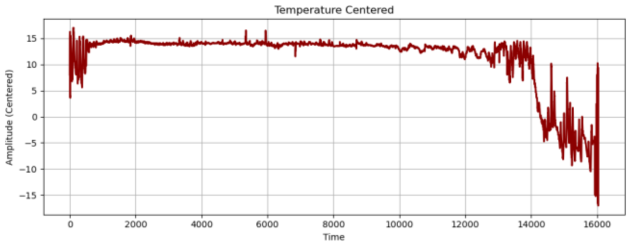
Temperature Centered Curve:

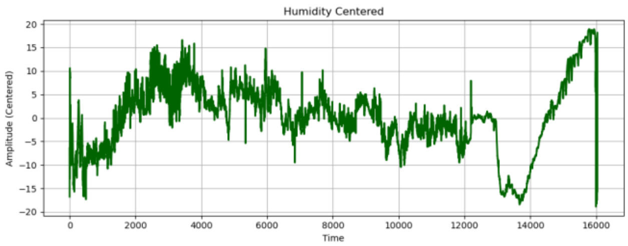
Initially, from 0 to around 2000 time units, the temperature rose quickly and then stabilized. For the majority of the recording period, fluctuations remained small until approximately 14,000 time units, when a dramatic decline and significant oscillations were observed.

Humidity Centered Curve:

Although the detailed plot is not shown here, the centered humidity signal was expected to exhibit similar behavior, characterized by long periods of stability interspersed with sudden shifts, indicating possible critical transitions or responses to external disturbances.

Centering the signals allowed for clearer observation of internal dynamics and enhanced the reliability of subsequent dynamic analyses. This step follows best practices as outlined in complex systems and phase analysis methodologies (*Lamb & Stöckl, 2014*).





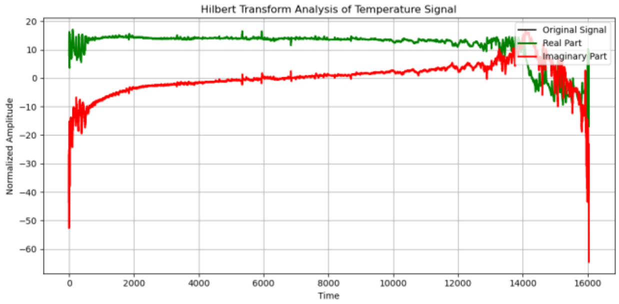
3.3 Hilbert Transform Analysis of Temperature and Humidity Signals

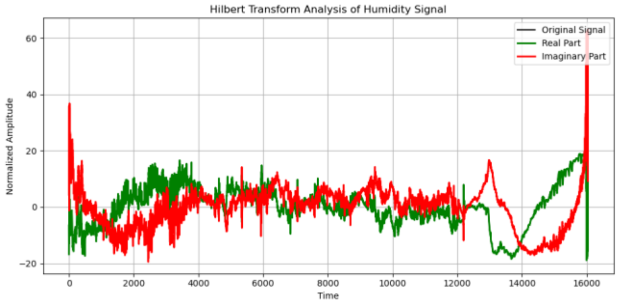
The Hilbert Transform was applied to the centered temperature and humidity signals to generate complex analytic signals:

Temperature Signal Hilbert Transform: The original signal (black curve) and the real part of the analytic signal (green) closely align. The imaginary part (red) captures local oscillatory behaviors and provides insights into instantaneous phase variations.

Humidity Signal Hilbert Transform: Similarly, for humidity, the real part followed the original signal's shape, while the imaginary part captured dynamic variations, especially during abrupt changes.

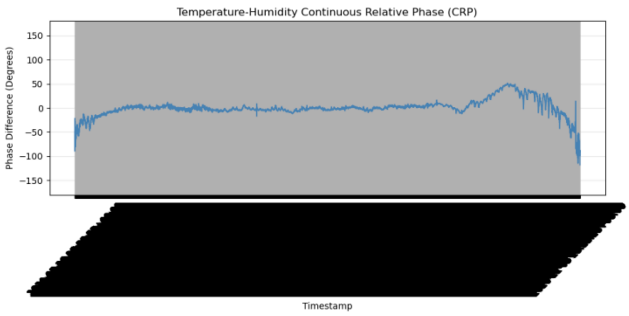
Applying the Hilbert Transform enabled the extraction of local dynamic structures not visible in the raw signals, laying the groundwork for further phase-based synchronization analyses.

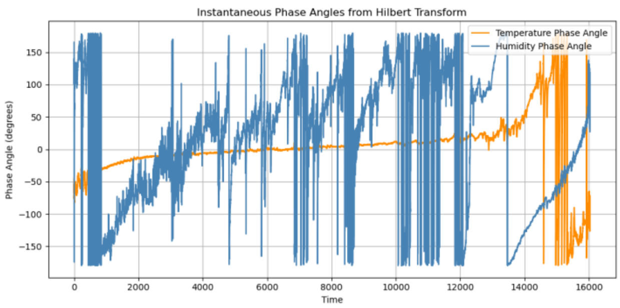




3.4 Continuous Relative Phase and Instantaneous Phase Extraction Analysis

Subtracting the instantaneous phase of humidity from the instantaneous phase of temperature yields the Continuous Relative Phase (CRP), which measures the synchronicity of the two signals. For instance, a CRP of 0° indicates that the temperature and humidity peaks coincide perfectly. When the CRP varies between -180° and +180°, it suggests that one signal consistently leads or lags behind the other. To ensure clarity in the results, all CRP values are adjusted to fall within the range of [−180°, +180°]. By monitoring the CRP over time, we can discern patterns in the interaction between temperature and humidity. For example, if the CRP remains stable during a heat wave, it implies that humidity changes in a predictable manner in response to temperature fluctuations. Conversely, if the CRP exhibits significant fluctuations, it may indicate that external factors, such as rainfall, are affecting their relationship.





4. Discussion

The phase portrait analyses provided valuable insights into the dynamical organization of the temperature and humidity systems:

Temperature Dynamics: The compact and organized structure of the temperature phase portrait suggests a strong internal regulatory mechanism, akin to homeostatic control. This behavior aligns with the attractor concept in dynamical systems theory, where the system tends toward stable configurations.

Humidity Dynamics: In contrast, the more dispersed structure of the humidity phase portrait indicates greater sensitivity to external influences or more complex intrinsic dynamics. These findings suggest that humidity may be subject to more intricate control mechanisms or environmental perturbations.

Preparation for Hilbert Transform-based phase analysis positions this study to explore synchronization and coordination patterns in greater detail, concepts that are central to both complex systems science and interpersonal dynamics studies (*Butler, 2011*).

5. Conclusion

With the systematic work-paperwork, dynamic visualization is shown the simple methods of the science of complex systems — in particular, the handling of phase partners, the signal centering and development stages in the analysis of synchronization phases — can be successfully applied to national level data. These approaches expose latent dynamic structures and constitute effective means for monitoring the stability, switching and coordination of complex natural and engineered systems.

References

Lamb, P. F., & Stöckl, M. (2014). On the use of continuous relative phase: Review of current approaches and outline for a new standard. Clinical Biomechanics, 29(5), 484-49

Rosenblum, M. G., Pikovsky, A. S., & Kurths, J. (1996). Phase synchronization of chaotic oscillators. Physical Review Letters, 76(11), 1804–1807. https://doi.org/10.1103/PhysRevLett.76.1804

Rosenblum, M., & Kurths, J. (1998). Analysing Synchronization Phenomena from Bivariate Data by Means of the Hilbert Transform. In H. Kantz, J. Kurths, & G. Mayer-Kress (Eds.), Nonlinear Analysis of Physiological Data (pp. 91–99). Springer. https://doi.org/10.1007/978-3-642-71949-3_6

Granados-Lieberman, D., Valtierra-Rodriguez, M., Morales-Hernandez, L. A., Romero-Troncoso, R. J., & Osornio-Rios, R. A. (2013). A Hilbert Transform-Based Smart Sensor for Detection, Classification, and Quantification of Power Quality Disturbances. Sensors, 13(5), 5507–5527. https://doi.org/10.3390/s130505507

Shiju, S., & Sriram, K. (2019). Hilbert transform-based time-series analysis of the circadian gene regulatory network. IET Systems Biology, 13(4), 159–168. https://doi.org/10.1049/iet-syb.2018.5088

Gengel, E., & Pikovsky, A. (2021). Phase reconstruction from oscillatory data with iterated Hilbert transform embeddings—benefits and limitations. Physica D: Nonlinear Phenomena, 429, 133070. https://doi.org/10.1016/j.physd.2021.133070

On the use of continuous relative phase: Review of current approaches and outline for a new standard. Clinical Biomechanics, 29(5), 484–493. https://doi.org/10.1016/j.clinbiomech.2014.03.008