Spatio-temporal interpolation of urban mobile sensing data

Carmine Colarusso
Dept. of Engineering
University of Sannio
Benevento, Italy
ccolarusso@unisannio.it

Ida Falco
Dept. of Engineering
University of Sannio
Benevento, Italy
i.falco@studenti.unisannio.it

Eugenio Zimeo
Dept. of Engineering
University of Sannio and CINI
Benevento, Italy
zimeo@unisannio.it

***Abstract*—This extended abstract introduces a strategy for urban environmental mapping that leverages mobile sensing and interpolation techniques across the temporal dimension. The framework interpolates sparse, time-staggered measurements to generate full-area maps, improving spatial coverage without the need for dense sensor deployment. With temporal-aware strategies, we improve estimation in unsampled areas and times.**

***Index Terms*—mobile sensing, temporal interpolation, monitoring, Edge-Fog-Cloud.**

I. Introduction

The growing complexity of smart cities has led to an increasing reliance on IoT devices to gather georeferenced data for key urban applications, such as traffic management, environmental monitoring, and emergency response.

In mobile sensing scenarios, data collection points continuously shift due to vehicle movement. Only some parts of the city are sampled during any particular time window. Mobile sensing, in contrast to static sensor networks, requires dynamic techniques that adjust to changing spatial coverage. Adaptive interpolation methods that can manage irregular temporal sampling, forecast values in unsampled regions, and integrate previous data to overcome this difficulty are needed.

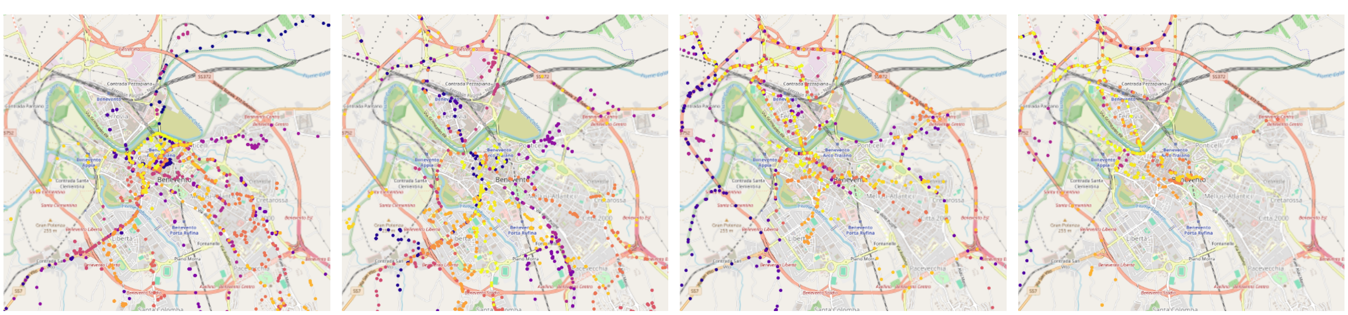
In our case, IoT nodes are installed on public utility vehicles. To better understand the time impact on mobile sensing, Fig. 1 illustrates the collected samples considering the first, second, third, and fourth hours of the waste collection vehicles' shifts. The spatial coverage changes; for example, during the 4^{th} hour, few data samples are available.

In this abstract, we address the integration of the time dimension into interpolation models, emphasizing the importance of capturing how environmental parameters evolve over time in urban settings to augment the spatial coverage. We propose strategies that adapt to the irregular and asynchronous nature of mobile data collection, accounting for the changing spatial coverage over time due to sensor mobility. We explore how the use of historical information can improve interpolation accuracy in unsampled regions and time slots. Experimental results confirm that incorporating the temporal dynamics improves the reconstruction of highly variable pollutants.

II. Methodology

By integrating temporal modeling with spatial mesh generation and leveraging historical data when necessary, we can estimate environmental parameters in unsampled regions with improved accuracy. The ST-product [1] approach performs linear temporal interpolation between consecutive measurements and then applies spatial interpolation at each time slice.

The overall process is schematized in Fig. 2. The spatial domain is first discretized into a regular grid of small cells, with dimensions of approximately 100 meters per side. Each cell acts as a localized spatial unit where measurements are collected over time whenever a mobile sensor (e.g., a vehicle) traverses the area. As a result of the irregular movement patterns of the sensors, the temporal sampling within each cell is sparse and unevenly distributed. To reconstruct a continuous temporal profile for each cell, interpolation techniques



(a) 1^{st} hour (b) 2^{nd} hour (c) 3^{rd} hour (d) 4^{th} hour

Fig. 1: Problem statement. Different colors refer to different vehicles.

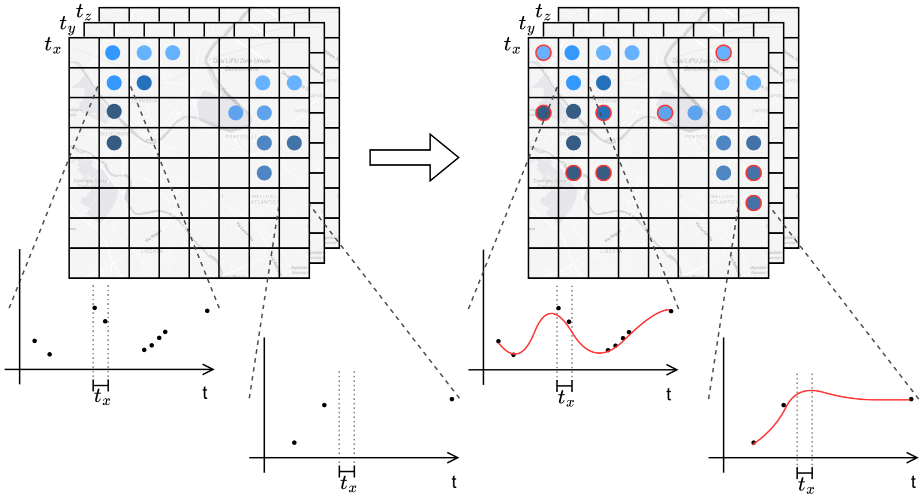


Fig. 2: Methodology overview

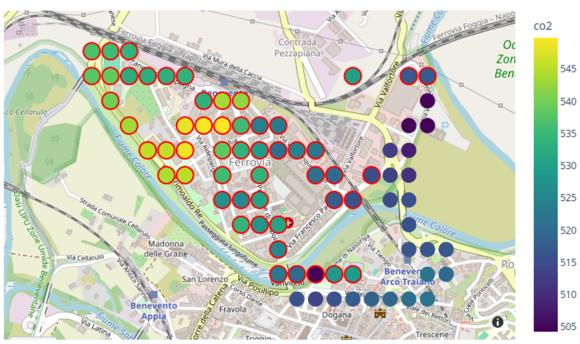


Fig. 3: Real and temporal interpolated $CO2$ measures

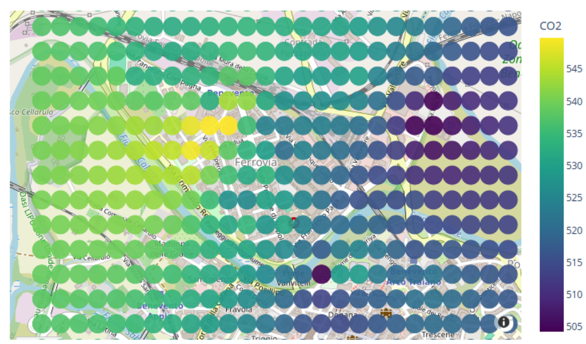


Fig. 4: Spatio-temporal $CO2$ interpolation

are employed to generate regularly sampled time series (red lines). Interpolation is applied selectively; it is performed only when sufficient temporal coverage exists within a reasonable proximity, thereby minimizing the risk of introducing artificial trends or erroneous estimates. This procedure substantially increases the number of spatial locations with available observations at each time step (e.g., t_x), effectively achieving a form of temporal data augmentation (circles with red boundary in the figures). The resulting dataset exhibits a much higher spatial density of measurements compared to the original sparse observations. Consequently, when spatial interpolation methods such as Kriging or IDW are subsequently applied, the denser and more uniformly distributed dataset leads to a significant improvement in the accuracy and reliability of the reconstructed spatial fields. This enhanced framework supports a more precise characterization of the underlying spatiotemporal dynamics of the phenomenon under investigation.

III. Experiments

We conducted a drive through the city of Benevento with a $CO2$ and temperature sensor securely mounted on the roof of a vehicle to ensure undisturbed data collection. Following the methodology described, we applied temporal interpolation to the recorded measurements. This way, at a specific timestamp, we obtained values for different spatial positions, as shown in Fig. 3. We then used these temporally enriched points to perform spatial interpolation, resulting in the environmental map presented in Fig. 4.

We used two instrumented vehicles, one to generate the interpolated map and the other as ground-truth to calculate the error between the interpolated and the measured value in the locations it passed through. The temperature error is very low. In contrast, $CO2$ concentrations can vary significantly over short time scales and spatial locations due to factors like local emissions and ventilation, leading to a higher error, $\sim 7\%$.

References

[1] P. Revesz, *Spatiotemporal Interpolation Algorithms*. Boston, MA: Springer US, 2009, pp. 2736–2739. [Online]. Available: https://doi.org/10.1007/978-0-387-39940-9_803