Enhancing urban monitoring through Fog-Cloud interpolation of mobile sensing data

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***Abstract*—The increasing deployment of distributed sensor networks for urban monitoring introduces challenges in data interpolation. This extended abstract proposes a Fog-based interpolation and Cloud aggregation framework that distributes computational tasks across Fog and Cloud layers. This way, we enhance the efficiency of smart sensing applications. Our approach exploits localized spatial interpolation methods directly at Fog nodes, allowing for reduced computation at the Cloud, which remains only in charge of merging the interpolated meshes.**

***Index Terms*—interpolation, Fog computing, Cloud integration, Edge-Fog-Cloud, geographical data.**

I. Introduction

Air quality monitoring is a crucial component of smart cities, enabling countermeasures and contributing to improved urban livability. Building a detailed environmental map would traditionally require a dense network of static sensors across the entire urban area, which can be cost-prohibitive. To address this, we propose a cost-effective framework that leverages data from mobile sensors mounted on utility vehicles. These sensors transmit data via LoRaWAN, a low-power wide-area communication protocol suitable for covering large urban regions. Once the data is collected at the Fog layer, accurately reconstructing a continuous and reliable environmental map from discrete and non-uniform measurements requires the application of advanced interpolation techniques capable of handling spatial sparsity, ensuring that the resulting map captures the underlying environmental patterns while maintaining high accuracy and responsiveness for real-time urban monitoring. Typically, the computational complexity of these techniques is cubic with respect to the input. For this reason, we distributed the computation across multiple Fog nodes, each handling local data interpolation independently. Only a lightweight aggregation step is performed in the Cloud, enabling faster and more scalable processing tailored to real-time urban monitoring needs.

II. Methodology

The proposed approach leverages distributed resources in the smart city across multiple Fog nodes. In this way, the system decomposes the problem, ensuring scalability and reducing latency using a hierarchical three-layer system.

In the Edge layer, multiple sensors on vehicles collect geo-referenced environmental data. IoT devices collect information and handle data transmission to the Fog; in our configuration, LoRaWAN communication was employed.

In Fog, the collected data are interpolated. **Inverse distance weighting (IDW)** [1] is a deterministic interpolation method where nearby points have more influence on the estimated value than distant ones. **Radial basis function (RBF)** interpolation [2] models values using radial functions centered at known points. The interpolation is performed independently on each Fog server, resulting in multiple interpolated meshes corresponding to the different coverage areas of the gateways. Moreover, the Fog computes a boolean matrix to track the position (lat, lon) where real measurements are available and a weight matrix using the inverse of the Euclidean distance transform to the nearest nonzero element for each point to support the Cloud's aggregation phase.

In the Cloud, the global mesh is generated, providing a comprehensive view of the urban environment. In case of overlapping areas, some aggregation technique must be applied. We proposed four different aggregation techniques:

- Average Aggregation (**A**): computes the simple average of all available values for each position.
- Pairwise Average Aggregation (**PA**): iteratively merges two interpolated maps at a time by averaging corresponding cells using a simple mean.
- Weighted Average Aggregation (**W**): calculates the weighted mean of values, where each value is assigned a specific weight from the weight matrix.
- Pairwise Weighted Average Aggregation (**PW**): combines two maps at a time using a weighted mean on each cell and proceeds iteratively, updating the weighted matrix.

The pairwise versions have been proposed to enable early computation. As soon as the first two meshes arrive in the Cloud, the aggregation process can begin immediately, without waiting for all meshes to be available. This approach enhances efficiency by progressively integrating new data, reducing latency, and improving real-time processing performance.

III. Evaluation

Our evaluation is based on the city of Benevento, Italy, where a dedicated coverage analysis was conducted to determine the optimal placement of five LoRaWAN gateways to ensure full urban coverage. Based on these positions, we

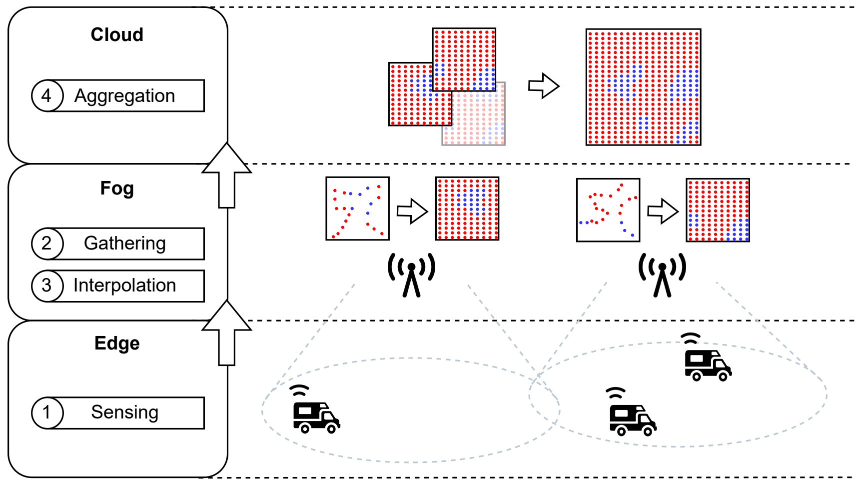

Fig. 1. Proposed methodology

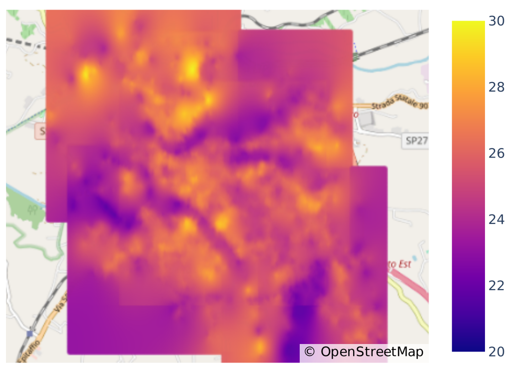

Fig. 2. Mesh computed with WA aggregation

TABLE I
COMPUTATION TIMES [S]

Interpolation	ϕ_{cloud}	min(ϕ_k)	max(ϕ_k)	μ_{PA}	μ_{PW}	μ_A	μ_W
IDW	0.821	0.156	0.236	1.941	0.440	1.207	0.887
RBF-linear	46.314	3.004	10.029	11.734	10.233	11.000	10.680
RBF-tps	87.870	5.214	16.395	18.100	16.599	17.366	17.046
RBF-cubic	44.652	1.745	8.931	10.636	9.135	9.902	9.582

defined five circular areas with a 2 km radius to approximate each gateway's coverage. While real-world coverage is not perfectly circular due to urban morphology and signal propagation constraints, this approximation does not affect the validity of our analysis. We used actual waste collection vehicle routes within the city and intersected them with land surface temperature data provided by the Landsat 8 TIRS satellite [3]. This allowed us to simulate mobile temperature data collection. Using the predefined gateway coverage zones, we processed data points separately at the Fog level to generate five interpolated meshes, which were then sent to the Cloud for final aggregation. Fig. 2 shows the final temperature map using WA aggregation.

To evaluate the proposed methodology, we conducted a

TABLE II
INTERPOLATION RMSE

Method	IDW	RBF-linear	RBF-tps	RBF-cubic
Cloud	2.814	2.447	**2.537**	3.529
Fog	1.815	**1.597**	1.953	3.089
PA	2.272	**2.083**	2.304	3.201
PW	2.316	**2.101**	2.321	3.369
A	2.263	**2.080**	2.302	3.195
W	2.211	**2.024**	2.207	3.070

latency and accuracy analysis.

We distinguished latency into the following components: ϕ_k represents the k-th Fog's time to perform local interpolation. η denotes the time required for computing meshes aggregation in the Cloud. μ is the time for the complete distributed computation, defined as $\mu = max(\phi_k)+\eta$. Finally, ϕ_{cloud} represents the time for the Cloud to perform a single global interpolation on all data in a centralized manner. Tab. I compares ϕ_{cloud} with the times μ for each aggregation technique, which includes the time required for the slowest interpolation at the Fog level plus the time needed to merge all the meshes in the Cloud.

Tab II shows the Root Mean Squared Error for all the tested interpolation techniques, performed directly in the Cloud with all the data, and in Fog. Finally, it shows the global results with the different aggregation techniques.

IDW is the fastest method, but it suffers from higher error rates, so RBF with a linear kernel is a more balanced choice.

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