On Integrating Robotic Data with GIS Tools in a Cloud Environment (Application Paper)

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Abstract

Merging robotic technologies, sensor networks, and Geographic Information Systems (GIS) offers significant potential across various domains, including agriculture and urban planning. However, a critical challenge lies in the lack of interoperability between data generated by these technologies and existing GIS tools. The EU-funded *GIS4IoRT* project addresses this gap by developing a plug-and-play and cloud-based middleware. This middleware facilitates seamless integration and visualization of multi-dimensional and multi-modal data within GIS environments. Key *GIS4IoRT* components include: a middleware architecture, a scalable cloud-based infrastructure, real-time robot querying capabilities, data quality assurance, spatio-temporal query support within the cloud, integration with GIS tools, and adherence to relevant standards. The middleware supports diverse data types, including LiDaR, imagery, and sensor data. This paper (1) presents an initial data integration architecture specifically designed for the sustainable architecture domain, (2) outlines the challenges encountered in designing such an architecture, and (3) explores novel data processing paradigms enabled by the architecture.

Keywords

data integration, geographical information system, robots, sensors, images, LiDaR, sustainable agriculture

1. Introduction and motivation

Complex, data-driven systems are inevitable in domains like agriculture and smart cities. Typically, these systems deploy computing and robotic machinery, including: sensors, cameras, laser 3D scanners (LiDaR devices) [1], installed on ground and air robots. These systems often rely on edge-fog-cloud architectures [2, 3, 4]. For example, in agriculture, such an architecture leverages a distributed computing paradigm to process data generated by sensors and devices deployed across farms. Initial data processing takes place at the devices, i.e., at the edge (e.g., sensors on robots). Fog nodes perform more complex data processing and analysis, based on data from multiple edge devices. Finally, cloud facilitates integrated long-term storage and advanced analytics, e.g., spatio-temporal, machine learning (ML) / artificial intelligence (AI).

The machinery at the edge level produces huge volumes of highly heterogeneous data (a.k.a. big data). The types of data include: text, dates, numbers - generated by simple sensors, 2D images and video in multiple formats - generated by cameras, and 3D images - generated by LiDaR devices. Notice that all the aforementioned data types are extended with timestamps and geographical coordinates, making new data types - *spatial time series* of numerical, images, video, and LiDaR data. To the best of our knowledge, techniques for analyzing and visualizing spatial time series of images, video, and LiDaR have not been researched or developed yet. Moreover, data of all these types collected from mobile robots are equipped with geographical coordinates, forming *trajectories*, which represent yet another data type to be analyzed.

It is evident that at the fog and cloud levels, heterogeneous data have to be integrated, to provide an overall view on the whole domain, based on various analytical and ML applications. To this end, *data integration architectures and processes* are applied [5, 6, 7]. Research and development works resulted in a few standard DI architectures, namely: federated [8] and mediated [9], lambda [10], data warehouse (DW) [11], data lake (DL) [12], data lake house (DLH) [13], and data mesh [14]. In all of these architectures, data are moved from DSs into

an integrated system by means of an integration layer. This layer is implemented by a sophisticated software, which runs the so-called DI processes.

This paper reports initial findings from an EU CHIST-ERA (https://www.chistera.eu) project on *Development of a plug-and-play middleware for integrating robot sensor data with GIS tools in a cloud environment* (further called *GIS4IoRT*), run by INRAE (France), Université de Liège (Belgium), Université de Rennes (France), Université Libre de Bruxelles (Belgium), and Poznan University of Technology (Poland). The focus of this paper is on the data integration architecture and challenges in processing and querying highly heterogeneous data.

2. Project contribution

The *GIS4IoRT* project challenges the existing research and technological paradigms in the field of data integration and processing in a few ways, discussed in this section.

Interoperability and integration: in the project we address the problem of integrating disjoint and often mobile and ephemeral data sources (DSs) by proposing a middleware solution that facilitates interoperability between robotic machinery, sensor networks, and GIS tools. By bridging this gap, the project aims to create a unified ecosystem where data from diverse sources can be seamlessly integrated, analyzed in the context of spatio-temporal dimensions, and visualized, enabling more comprehensive analysis and decision-making.

Real-time querying and ML/AI-based approaches: by incorporating real-time querying of robots and ML/AI-based approaches, the project challenges traditional methods of data handling and processing. This enables the middleware to ensure data reliability and completeness, even in the face of challenges such as signal loss or missing data. The utilization of ML/AI algorithms for data quality assurance (e.g., profiling, anomaly detection, monitoring and alerting) and data processing (e.g., wrangling, analyzing, viusalizing) [15, 16] represents a departure from conventional approaches, highlighting the project's commitment to leveraging cutting-edge technologies for enhanced performance.

Spatio-temporal querying: the development of spatio-temporal query support and a user-friendly GIS client further challenges existing paradigms by enhancing accessibility and usability. This empowers users to efficiently browse available data and perform complex queries, involving space and time dimensions on highly heterogeneous, multi-modal, and ephemeral data, within the middleware. Spatio-temporal data introduce additional specific challenges, which are addressed in this project. The challenges include:

- *data pre-processing*: transforming, cleaning, and

detecting anomalies of spatio-temporal data require domain-specific knowledge;
- *complexity*: spatio-temporal data are complex, which requires specialized techniques to analyze the data across space and time dimensions;
- *pattern recognition*: discovering patterns and trends in trajectory data requires advanced machine learning techniques;
- *spatial and temporal granularities*: trajectory data often have varying levels of spatial and temporal granularities, which need advanced data analysis techniques to produce meaningful results;
- *spatial autocorrelation*: relationships and correlations in spatio-temporal data, which may be difficult to detect, can complicate their analysis;
- *temporal dynamics*: understanding how spatial patterns evolve over time and capturing dynamic relationships presents challenges in modeling trends and in building prediction models;
- *interpretation*: presenting findings spatio-temporal data analysis in a meaningful and easy to understand way is not straightforward, due to the complexity of dependencies between spatial and temporal dimensions.

3. Architecture

To address the aforementioned challenges, we proposed a data integration architecture, as shown in Figure 1. Data sources include various types of machinery, further called the Internet of Robotic Things (IoRT). They include: ground and air robots, sensors, cameras, and LiDaRs. The IoRT devices produce *streams of data* that are delivered in real-time to the GIS applications through the *GIS4IoRT middleware*. At the same time, these data are uploaded into a central *repository*. It stores also metadata and ontologies for mapping data from multiple IoRT, i.e., data in different modalities.

3.1. Data integration and querying layer

We based the architecture of the concept of a mediator [9]. Components marked as *DI process [ROS2]*, *DI process [sensors]*, *DI process [image, video]*, *DI process [LiDaR]*, and *DI process [data repository]* represent wrappers to DSs. Mobile robots are equipped with the ROS2 operating system, with its proper data formats and access interface. Data provided by these DSs are pre-processed, integrated (as much as possible), and correlated by the *data integration and querying layer*. The correlation applies to data of different modalities that are related to the same real-world phenomenon. For example, text data describing a field (geographical coordinates and dimensions, the type of a crop cultivated there, the type of soil) can be correlated with images of this field.
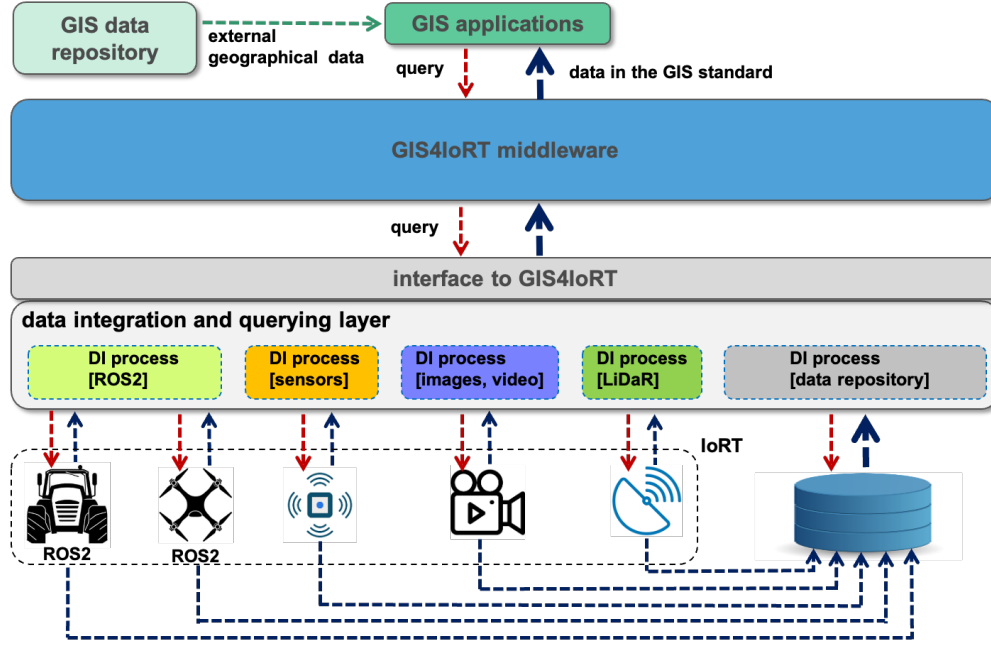
Figure 1: The architecture of the *GIS4IoRT* system

This layer is also responsible for translating queries arriving from GIS applications via *GIS4IoRT middleware*, like in a mediated architecture. As compared to the standard mediated architecture, the challenge here is to translate queries for very diverse data sources that offer different functionalities. To make it more challenging, these data sources are ephemeral as they may be temporarily unavailable and may provide data of qualities changing in time.

3.2. GIS4IoRT middleware

Serverless computing at the edge and fog requires particular functionality, which is provided by the *GIS4IoRT middleware*, namely: (1) dynamic resource orchestration, (2) a fine-grained data caching, to optimize data transfers between storage (e.g., MinIO, S3), via the *data integration and querying* layer, (3) data caching at the edge, to enable the most efficient processing and energy usage, and (4) producing data that conform to GIS standards.

Particular innovation is in considering: (1) caching not only on traditional CPU, but also on FPGA, to reduce response time and energy consumption, (2) smart resources allocation, to manage data and functions with respect to different objectives like data quality, response time, and energy consumption.

In addition to optimizing data transfers and processing at the edge and fog, the *GIS4IoRT middleware* enables spatio-temporal querying of IoRT data. GIS applications execute queries in the context of GIS external data (e.g., the map of a given area) from *GIS data repository*, based on input GIS data from end-users. This supports users in running complex spatio-temporal queries, leveraging both IoRT-generated data and external GIS data, to gain deeper insights and make informed decisions.

Notice that in such a system, multiple IoRT devices may provide the same or similar data, e.g., a drone flying over a given field and a ground robot traversing the same field. Both of them may provide images from two different perspectives, in two different formats, and in two different resolutions.

Notice also that the system architecture is highly dynamic. The dynamicity results from: (1) new devices that can be dynamically deployed in fields and (2) unstable, limited, or unavailable WiFi in fields, causing that devices moving into areas without network coverage disappear temporarily from the system. As a consequence, querying them is limited or impossible.

3.3. Challenges in querying IoRT

In such a setup, it is necessary to equip the user of the system with options allowing to manage queries and understand their results. To this end, two standard parameters, namely the *quality of service* (QoS) and the *quality of data* (QoD) must be extended with the following notions.

QoS execution time - a given query has a parameter specified by the user that limits the time to retrieve results. After exceeding the time, either the query is aborted or partial results are provided - this depends on another parameter provided by the user. To handle this type of QoS, the system must be able to dynamically estimate the execution time and be able to re-route a query to the appropriate data source (IoRT device or data repository). The query should be executed on an agent that offers the fastest response and transmits the lowest volume of data, at the price of lower quality of the results (e.g., lower image resolution, data from sensors sample at a lower frequency).

QoD freshness - notice that fresh data come from the machinery deployed in fields. With a certain delay, these data are also transmitted to the central repository. Thus, the freshness parameter guides the system to which data source send a query.

QoD resolution - the machinery may provide data fast but of lower quality. For example, simple sensors may transmit their measurements in real-time with a given frequency, but they may buffer their measurements taken at a much higher frequency. The buffered data are transmitted to the central repository when WiFi allows it. While transmitting images in real-time, a device may downgrade its resolution to assure acceptable *QoS execution time*. The same image is transmitted to the repository at the highest possible resolution, when a suitable bandwidth is available.

To provide the aforementioned QoS and QoD, the system must be able to dynamically select DSs on which a given query will be executed. To this end, models for managing *QoS execution time*, *QoD freshness*, *QoD resolution* will be built, based on ML/AI techniques.

As mentioned before, the results of queries in such a system must be equipped with metadata describing the quality of the result. Such metadata include: (1) percentage of result completeness – it allows to estimate how much data is missing, due to the unavailability of DSs, (2) downgraded quality of data, due to either low network throughput or assuring *QoS execution time*.

4. Related works and technologies

Compared to existing GIS and IoT integration architectures surveyed in [17], the *GIS4IoRT middleware* introduces a novel approach by emphasizing real-time data acquisition from mobile robotic platforms and integrating it seamlessly with GIS tools. While traditional architectures primarily focus on static sensor networks and cloud-based GIS processing, *GIS4IoRT* extends these capabilities by incorporating dynamic, ephemeral data sources from ground and aerial robots, addressing key challenges in data quality, latency, and interoperability.

Additionally, *GIS4IoRT* enhances spatial-temporal query support and optimizes resource management through intelligent caching and processing at the edge and fog layers. Unlike previous works that rely on centralized architectures, the proposed system leverages a flexible middleware approach to dynamically adapt to different IoT infrastructures, making it more suitable for applications requiring on-demand, real-time robotic sensing and decision-making.

4.1. Cloud computing

During the last decade, cloud computing has enabled (big) data processing in various domains, e.g., healthcare, fleet management, banking, sales, social networks. Cloud computing offers Infrastructure (IaaS), Platform (PaaS), and Software (SaaS) as a Service. IaaS and PaaS rely on rented resources, following a pay-as-you-go model, enabling elasticity (scale-up and scale-out). In SaaS, software hosted on cloud is made available in the form of a subscription. Recently, Function-as-a-Service, as an implementation of serverless computing, has been proposed to offer higher elasticity and more fine-grained energy consumption and billing [18].

Serverless computing is a recent research field with few projects. For example, in Europe, (1) *CloudButton* (cloudbutton.eu) provides a serverless data analysis platform, with high performance runtime and a mutable data middleware; *EDGELESS* (www.hipeac.net/network/projects/7247/edgeless/) tackles efficient processing with resource-constrained edge-devices, *MELODIC* (h2020.melodic.cloud/the-project/) supports data-intensive applications to run within security, cost, and performance boundaries on distributed cloud computing, and *RADON* (radon-h2020.eu/overview/) supports a DevOps framework to create and manage micro-service applications.

Commercial solutions have been proposed, for: (1) simple functions, but have shown their limits for stateful processing [19], (2) extending cloud computing tools, such as *Spark* [20], or (3) using in serverless environments, such as *Spark-IO*. Other contributions, like *Pocket* or *Apache Crail*, investigated the management of ephemeral data.

4.2. Robotics and IoT

The consolidation of ML/AI techniques, IoRT, and geo-spatial technologies is revolutionizing spatial data analysis and interpretation. Advancements in this area enable automated geo-spatial feature extraction [21], enhancing precision and insight in geographical interpretations. ML algorithms analyze LiDaR data and satellite imagery for automatic identification and classification of features (e.g., buildings, vegetation) and for providing dynamic views of Earth's surface changes over time. Autonomous GIS systems, powered by AI, aim for natural language

task acceptance and minimal human intervention in spatial problem-solving, enhancing accessibility and user-friendliness [22]. Additionally, AI plays a crucial role in managing vast geo-spatial data from sensors, drones, and satellites, enabling efficient processing beyond human capacity.

However, there is still a huge research gap in integrating GIS solutions and the robotic technology in an fully automated system. Such a system not only applies ML/AI techniques to data previously collected (also using robots), but also can answer GIS user queries dynamically, by asking the IoRT machinery for highly specific data and managing the operation of the IoRT subsystems in (nearly) real-time. The body of existing literature offers works on GIS supporting UAVs [23], integration with BIM systems and construction applications [24], and support for robot navigation [25]. Also a ROS-based plugin for the popular *QGIS* system was developed [26], but it is based on outdated ROS1 and is no longer maintained.

These examples show that although the existing research has explored aspects of integrating IoRT with GIS systems, but comprehensive solutions addressing dynamic data integration and real-time processing are still to be developed. This is the gap we bridge in the *GIS4IoRT* project, providing the low-level software agents to make the IoRT machinery "understand" the standards and requirements of GIS. We develop the middleware in order to effectively manage the data flow and system configuration in the cloud/fog environment, and implement the GIS adoption layer that will make the GIS systems (e.g., *QGIS*) aware of the functionalities provided by *GIS4IoRT*.

Preliminary results from the project consortium demonstrate the successful integration of diverse hardware devices [27] and initial algorithms for data processing [21, 28, 29, 30] and quality assurance.

4.3. GIS and IoRT

GIS systems play a pivotal role in integrating spatial data for analysis, visualization, and decision-making across various domains. With the emergence of the IoT and the IoRT, there is a growing need for standards that facilitate the interoperability and integration of geo-spatial data with sensor networks and robotic technologies. Here, we explore the state of the art in GIS standards related to IoT and IoRT.

OGC standards: the Open Geospatial Consortium (OGC) is a leading authority in developing standards for geo-spatial data interoperability. OGC has developed a few standards relevant to IoT/IoRT, such as Sensor Web Enablement, which provides protocols and encodings for the exchange of sensor data over the Web. Additionally, OGC SensorThings API standardizes the way IoT sensor data are published and accessed.

ISO standards: the International Organization for Standardization (ISO) has also contributed to the development of standards for geo-spatial data interoperability. ISO 19156, also known as Observations and Measurements, provides a framework for describing and encoding sensor observations, supporting the integration of IoT data into GIS environments. ISO 19115-1 specifies metadata standards for describing geographic information and services, including metadata elements relevant to IoT/IoRT DSs. Also IEEE has contributed to the standardization of robot map data representation through IEEE 1873-2015, which defines a common format for exchanging 2D metric and topological maps among robots, computers, and GIS platforms. Unlike proprietary formats, IEEE 1873-2015 facilitates long-term comparability and evaluation of maps across different systems, making it particularly relevant for robotic navigation and collaborative mapping applications [31].

Semantic interoperability: achieving semantic interoperability between geo-spatial data and IoT/IoRT devices is essential for meaningful data integration and analysis. Standards such as the Semantic Sensor Network Ontology developed by the World Wide Web Consortium provide a common semantic framework for describing sensor observations and capabilities, enabling effective communication between IoT devices and GIS systems.

Geo-spatial data formats: standardized geo-spatial data formats are crucial for interoperability between GIS and IoT/IoRT systems. Formats such as *GeoJSON*, *Shapefile*, or *KML* provide common encodings for representing geographic data and sensor observations.

4.4. Adaptability to Other Domains

The *GIS4IoRT* project leverages precision agriculture as a testbed for the proposed architecture, given the growing need for smart, sustainable farming solutions to address economic and environmental challenges in Europe. However, the modular design of the *GIS4IoRT middleware* enables adaptation beyond agriculture—extending to disaster response, autonomous navigation, and urban planning.

In disaster response, real-time sensor data integration facilitates damage assessment and resource coordination [32, 33, 34], yet ensuring reliable data transmission in disrupted networks remains a challenge. While the concept of using distributed sensors for disaster management is well established [35], its effective deployment requires integrating recent advancements in IoRT and GIS technologies. Similarly, autonomous navigation demands low-latency processing and seamless fusion of multi-modal sensor data for precise localization and obstacle avoidance [27].

In urban planning and architecture, scalable data handling and interoperability with existing GIS frameworks

are essential for integrating diverse spatial data sources used in traffic analysis, infrastructure monitoring, and environmental assessment [36, 37]. Despite its potential to enhance urban automation and data-driven decision-making, the integration of robots with smart city infrastructure remains underexplored. Recent efforts, such as the Smart City Component in a Robotic Competition [38], demonstrate how robots can act as both consumers and producers of smart city data, underscoring the need for seamless interoperability between robotic systems and urban GIS platforms.

5. Summary and future work

In this paper we outline research challenges encountered while designing an integration architecture for dynamic spatio-temporal, heterogeneous, and multi-modal data generated by IoRT machinery, with GIS analytical tools, within the EU *GIS4IoRT* project. The fundamental challenges include: (1) correlating multi-modal data within a user query, (2) providing query results according to QoS and QoD parameters, (3) dynamically re-routing queries to appropriate DSs, to assure QoS and QoD, (4) building cost models for managing QoS and QoD, and (5) analyzing spatial time-series of non-standard data.

Open issues that further will be investigated in the project include among others: (1) dynamic resource provisioning for QoS and QoD, (2) reactive heterogeneous data caching at the edge, fog, and cloud, (3) proactive data caching, (4) building ontologies for semantic data annotations and correlations, (5) novel visualization techniques at the GIS level.

Acknowledgments

Declaration on Generative AI

The authors have not employed any Generative AI tools.

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