# Trajectory Mining for Smart Cities: A Focus on Indoor Localization using 5G Technology

Enea Vincenzo Napolitano

*Department of Electrical Engineering and Information Technology, University of Naples Federico II*

Abstract
This paper focuses on the use of Trajectory Mining techniques within Smart Cities. In particular, it is proposed the use of 5G technology for indoor localization and the use of trajectory mining techniques to analyze the trajectory data of users inside buildings. Thanks to the coverage and speed offered by the 5G network, you can improve the user experience and optimize space management. In this paper I describe one of the possible developments of my PhD research in order to develop optimized processes applicable in different contexts and adaptable within both public and private buildings.

**Keywords**
Smart City, Trajectory Mining, 5G, Indoor Localization

## 1. Introduction

Smart Cities are an urban environment that uses advanced technologies to improve citizens' quality of life, optimize efficiency and reduce environmental impact. Among the technologies used, Trajectory Mining has become increasingly popular in recent years thanks to the ability to provide valuable information about user activities within the city.
Trajectory Mining allows you to analyze the movements of individuals within the city, tracing their path and identifying areas of interest. This can be used to better understand user mobility patterns, to identify areas of the city with more traffic and to improve urban planning [1].
For example, Trajectory Mining can be used to identify areas of the city that require more security, analyzing routes taken by individuals in an emergency. In addition, it can be used to analyse public transport routes, identify the most popular routes and improve the service offered to citizens.
Trajectory Mining can also be used to improve the environmental sustainability of cities by identifying areas where energy efficiency can be improved and $CO_2$ emissions reduced.
There are many techniques available for trajectory Mining, each with its own advantages and limitations. Some of the most common Trajectory Mining techniques are the following:

- Trajectory Clustering: Trajectory clustering is a technique that groups similar trajectories into clusters based on different metrics, such as Euclidean distance or Hausdorff

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eneavincenzo.napolitano@unina.it (E. V. Napolitano)
0000-0002-6384-9891 (E. V. Napolitano)

distance[2]. This technique is useful for the analysis of the movement patterns of individuals[3].

- Trajectory segmentation: Trajectory segmentation is a technique that divides trajectories into smaller segments, each of which represents a particular behavior or event [4]. This technique is useful for analyzing the activities of individuals, such as work or shopping.

- Trajectory pattern mining: Trajectory pattern mining is a technique that analyzes recurrent patterns in the trajectories of individuals [5]. This technique is useful for identifying abnormal behaviors, such as unusual paths or unusual areas of interest[6].

- Spatio-temporal analysis of trajectories: Spatio-temporal analysis of trajectories is a technique that analyses trajectories in relation to space and time [7]. This technique is useful for identifying patterns of movement of individuals, such as speed and direction.

- Trajectory classification: Trajectory classification is a technique that assigns trajectories to certain classes or categories based on specific characteristics [8]. This technique is useful for the analysis of the movement patterns of individuals based on their activities or behaviors.

- Trajectory prediction models: Trajectory prediction models are a technique that uses past trajectories to predict the future trajectories of individuals [9]. This technique is useful for urban planning and traffic management.

In the literature, however, there are few references to the use of trajectory mining techniques inside buildings, this particular application could be a further increase in the efficiency of Smart Cities.

## 2. Indoor Trajectory Mining

Indoor trajectories Mining refers to the technique of extracting significant information from the trajectories of individuals within buildings or enclosed spaces. This technique uses different data sources, such as motion sensors, surveillance cameras, and users' mobile devices to acquire information about the activities of individuals [10].
The extraction of indoor trajectories is important for many applications, such as resource management, security, urban planning and operations optimization. For example, in the field of resource management, the extraction of indoor trajectories can help to optimize the use of spaces and improve the management of flows of people and resources. In security, extracting indoor trajectories can help identify abnormal behaviors of individuals within buildings and prevent security threats [11]. In urban planning, the extraction of indoor trajectories can help improve public space, service and transport planning.
The extraction of indoor trajectories can also help improve the user experience within buildings,

for example through the customization of services or the management of queues [12].
Unlike outdoor trajectories, the extraction of indoor trajectories requires the use of different technologies and data collection techniques, since the internal environment presents many obstacles.
The main challenges in extracting indoor trajectories are the poor availability of GPS signals, the lack of accurate indoor maps, the presence of obstacles limiting the accuracy of tracking and the lack of standardisation between different data collection systems.
To address these challenges and take full advantage of the opportunities offered by the extraction of indoor trajectories, it is necessary to continue to develop new technologies and data collection methodologies, as well as work to standardize data acquisition systems. In addition, the use of advanced data analysis techniques, such as machine learning [13, 14], can help process large amounts of trajectory data and extract useful information from it.
Among the various localization techniques that can be the basis of Trajectory mining, some are not yet used to the full of their potential. As in the case of advanced 5G telecommunications networks, they are a tool of great interest for indoor localization, which requires an interdisciplinary approach and constant technological innovation to reach its full potential.

## 3. 5G-based Localization

There are many indoor localization techniques, such as Wi-Fi, Bluetooth and UWB (Ultra Wide Band) technology, which have been used successfully in many applications. Today the most used techniques are:

1. GPS (Global Positioning System): GPS technology is used to capture the exact location of a moving object. GPS uses a system of satellites orbiting the Earth to determine its location. Satellites send radio signals to the GPS device, which uses them to calculate its position based on the distance from the satellites. GPS can provide a very precise location, but can be affected by obstacles such as tall buildings, trees or tunnels. [15]
2. Motion sensors: Motion sensors such as the accelerometer, gyroscope, and orientation sensor can be used to detect the movement and position of an object [16]. Accelerometers measure the accelerating force of the moving object, gyroscopes measure its rotation, and the orientation sensor measures its position relative to the magnetic north.
3. Wi-Fi: Wi-Fi can be used to detect the location of an object based on its location relative to the available Wi-Fi access points. This technology leverages the fact that each Wi-Fi access point has a unique identity, called BSSID, which can be used to identify its location [17]. The Wi-Fi device of the moving device uses the signal strength received from the surrounding Wi-Fi access points to calculate its approximate location.
4. RFID (Radio Frequency Identification): RFID technology can be used to detect the location of an object through the use of RFID tags and readers. An RFID tag is a device that can be attached to an object and contains a unique identity. An RFID reader can detect the presence of the tag and its location [18]. This technology is often used in environments such as warehouses or airports to track the location of objects.
5. Bluetooth: Bluetooth technology can be used to detect the location of an object via its Bluetooth signal.This technology takes advantage of the fact that the Bluetooth sig-

nal strength decreases as the distance between devices increases [19]. Using multiple Bluetooth detection points, you can triangulate the position of a moving device.

6. Environmental sensors: Environmental sensors such as temperature sensors, humidity sensors, and light sensors can be used to detect the location of an object based on its surroundings. For example, if an object moves from a hot area to a cold area, the temperature sensor can detect this change and infer the location of the object. This technology is less precise than other localization techniques, but may be useful in some specific scenarios.

5G, the latest generation of wireless technologies for mobile communication, holds the promise of delivering ultra-fast and reliable connectivity [20]. By utilizing higher frequency bands (700 MHz, 3700 MHz, and 27 GHz) compared to its predecessors, 5G enables the transmission of large amounts of data at exceptionally high speeds, reaching up to 10 Gbps.
This technology has the potential to revolutionize indoor localization by offering unparalleled accuracy, enhanced reliability, and wider coverage when compared to previous technologies like Wi-Fi and Bluetooth. Specifically, 5G can leverage a combination of localization techniques, including multi-antenna access, radio pulse analysis, and the utilization of external sensors, to achieve precise localization.
Moreover, 5G brings forth a myriad of advanced features, such as ultra-low latency and the ability to handle massive data volumes, making it highly suitable for high-precision indoor location applications like indoor navigation and device monitoring [20].
To compare the effectiveness of 5G with existing indoor localization techniques, several factors can be considered, including accuracy, coverage, speed, and system complexity. For example, Wi-Fi and Bluetooth are extensively used for indoor localization due to their relatively low cost. However, their accuracy may be limited in crowded or noisy environments. On the other hand, Ultra-Wideband (UWB) technology offers exceptional precision but can be expensive and power-intensive.
In contrast, 5G stands out by providing superior accuracy owing to its advanced location features such as multi-antenna access and radio pulse analysis.
The indoor localization capabilities of 5G are facilitated by various techniques. One of these techniques is beamforming technology, which employs antennas to direct signals towards specific devices. Additionally, Massive Multiple Input Multiple Output (MIMO) technology utilizes multiple antennas to deliver stronger and more accurate signals. Another approach involves utilizing millimeter waves within the 5G framework, which offer high spatial and temporal resolution.
Advanced Telecommunication Networks, encompassing 5G technology, can support sophisticated indoor location technologies like Time Difference of Arrival (TDOA) and Angle of Arrival (AoA) [20]:

- TDOA is a technology that determines the location of a device by analyzing the difference in signal arrival time from a series of base stations. This technology necessitates exceptionally high time accuracy.
- AoA is a technology that determines the location of a device by analyzing the arrival angle of the signal from a series of base stations. Real-time processing of large data volumes is required for this technology [20].

## 4. Potential Applications

The use of 5G technology for indoor localization can provide important solutions to improve signal accuracy and coverage, paving the way for new opportunities for indoor Trajectory Data Mining.
Inside buildings, localization and Trajectory mining can be used in different contexts, such as:

1. Indoor navigation: Indoor localization can be used to help people navigate inside large buildings such as airports, shopping malls, hospitals, museums and train stations.
2. Safety: Indoor location can be used to improve building safety. For example, location tracking can be used to track the movement of staff and guests and report suspicious behavior. In addition, localization can be used to quickly evacuate people in an emergency.
3. Resource Management: Indoor localization can be used to manage resources within buildings such as valuables, equipment, goods, and people. For example, localization can be used to track the location of objects within a warehouse and optimize the distribution of goods.
4. Marketing: Indoor localization can be used to offer customized marketing services to building visitors. For example, stores can use localization to send personalized offers to customers within the store.

In addition, the combination of indoor Trajectory data and other data sources such as weather, traffic data and environmental data can provide additional valuable information for Smart City management and optimization.
The combination of 5G-based indoor localization and indoor Trajectory Mining can open up new perspectives for Smart City management, improving the efficiency of public services and the quality of life of citizens.

## 5. Conclusion

Smart Cities are increasingly present in people's lives and represent a new frontier for the intelligent management of cities and public services. Indoor localization is a fundamental technology for Smart Cities, as it allows you to monitor and track the movements of users within buildings and public facilities. The use of 5G technology for indoor localization can provide important solutions to improve signal accuracy and coverage, paving the way for new opportunities for indoor Trajectory data mining.
In this paper, we evaluated an approach to indoor Trajectory Mining using 5G-based localization in smart cities. The methodology involves the use of Machine Learning algorithms to analyze Trajectory data and identify user mobility patterns, with potential applications in the field of optimizing the flow of people in public environments, vehicle traffic monitoring, identification of points of interest and prevention and emergency management.
The combination of 5G-based indoor localization and indoor Trajectory Mining can open up new perspectives for Smart City management, improving the efficiency of public services and the quality of life of citizens.

In conclusion, I believe that the use of 5G technology for the indoor localization and Data Mining of indoor trajectories represents a new frontier in the intelligent management of Smart Cities and can provide important solutions to improve the quality of life of citizens and the efficiency of public services.

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