The gap between cycling practices and mapping services for smart cycling

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***Abstract*—Cycling is gaining priority in urban mobility policies and smart cities should be prepared to offer smart cycling services that help to promote such transition. A key element for many of those services is a Geographic Information System and particularly a road network model that represents all the possible roads in a city. The main contribution of this work is the identification and characterization of an important gap between the GPS traces corresponding to the real routes made by cyclists and their representation in the road network model of Open Street Map (OSM). More specifically, there are parts of the GPS traces that cannot be mapped into the road network of OSM, because they have no matching representation. We call these segments, ad-hoc segments. To develop a deeper understanding about this problem, we collected data from a specially designed route and analysed how the respective trace was mapped into OSM. We identified all the occurrences of ad-hoc segments and categorized them according to their root cause. The results suggest that the main overall cause of these problems is directly linked with limitations of the road network model, such as missing roads. This seems to indicate that road network models, as commonly used in OSM, do not properly address the specificities of cycling, or micro-mobility in general. This problem has a major impact in the quality of the services provided to urban cyclists and in the value of the data available for micro-mobility planning and management.**

***Index Terms*—Cycling Routes, OSM, map-matching, smart cycling, micro-mobility, urban mobility**

I. Introduction

Urban mobility is critical for urban competitiveness and a key enabler for smart and sustainable cities. As cities strive to meet sustainability goals [1] and deliver solutions that promote public health [2] and quality-of-life in urban space [3], the development of cycling is increasing its policy priority across the entire European Union, at both local and national levels [4]. Information technology plays a major role in this transition, with Smart Cycling [5] emerging as a broad concept that aims to capture the shared, real-time, and collaborative application of data, communications and services, to help best move people individually, and collectively, across the urban environment [6].

A Smart City should thus empower cyclists with digital tools that allow them to select routes offering them the best combination between ride safety, comfort and efficiency to maximise bikeability [7]. It should also empower municipalities and transit authorities with strong insights about the reality of micro-mobility to inform mobility planning and operational processes.

A common element across all these services is the road network model representing the set of all routes available in a city. This is a key component of Geographical Information Systems, providing core information for all sorts of mobility services. For example, when analysing the route of a vehicle, the trace of positions representing the trajectory of that vehicle is mapped into the road network, the assumption being that positions outside an existing road are positioning errors.

This process of mapping a GPS trace to the most suitable route on the road network is called map-matching [8]. It aligns the multiple individual traces into a finite set of road segments, which is essential for supporting navigation features or to aggregate dispersed analytics data under specific segments within the road network. The efficacy of this map-matching process may vary considerably, depending on the complexity of the road network and the accuracy of the points composing the trace. In some cases, the process may not be able to unambiguously identify a suitable match, either because of positioning errors or because the trace follows a path that is not represented in the road network model.

A. Cycling and road network models

In general, road networks are not restricted to motorized traffic, and all sorts of roads may be considered, such as cycle paths, pedestrian trails, private roads, forest tracks or roads that are only occasionally open. However, the primary use case for road network models has always been automotive traffic and this has had a major impact on the basic assumptions upon which these models are created and managed.

When we consider cycling, the common approach is to assume that bicycles will either share the road with cars or they follow some type of cycle path. However, with bicycles and other micro-mobility modes, the concept of road network is much fuzzier. Simply creating a road network composed of cycle paths would be simple, but it would not be a realistic solution. Even for the most bicycle-friendly cities, there is no such thing as a fully segregated bicycle network. Bicycle trips end-up being the result of a multi-objective optimisation process that comprises the selection of cycling tracks, but also many other types of roads [7]. Route selection can be a strongly personal choice, as cyclists may combine very diverse criteria for their route selection [9]. Cyclists may often use footpaths, parks and other unconventional paths that often are not represented on a road network model [10]. A realistic journey may thus imply frequent switching between very heterogeneous roads with very different profiles and purposes.

Other micro-mobility modes essentially have the same problem, but each of them with their own specificities. The ideal route for cycling will not necessarily be the ideal route for e-scooters, eBikes, electric wheelchairs or cargo-bikes. This diversity dilutes even further the boundaries between car roads and pedestrian sidewalks, creating endless new movement patterns that cannot be matched by basic road network models.

An indirect consequence of these specific mobility patterns is that map-matching can become particularly difficult. In particular, any part of a route that does not follow a conventional path is very likely to fail the map-matching process. This means that the system will not be able to provide a realistic account of cycling activity. Moreover, when the map-matching fails, the segment data that could not be matched is normally eliminated [11], which corresponds to a huge loss of information that could otherwise have been used to progressively improve the model itself.

This mismatch between the reality of the routes used by cyclists and the mobility models that should represent them has important implications for the ability of those systems to properly address the specific needs of micro-mobility services. An incomplete road network will have a negative impact on routing services that use it as a data source [12]. Cyclists, will not get accurate navigation directions or insightful information about all possible routes. The added value of cycling navigation services becomes very reduced and cyclist will not have confidence in the information provided.

For urban planners and transit authorities, a focus on micro-mobility needs a more fine-grained scale than what is normally relevant for automotive traffic. Working with an overly simplified version of reality will lead to misinformation and to decisions that are most likely to fail their goals or even to cause negative unintended consequences.

B. Objectives

In this work, we aim to develop a deeper understanding about the concrete nature and extent of this problem. More specifically, we aim to study the concrete situations leading to possible mismatches, assess their potential impacts and explore alternatives that may help to mitigate or eliminate the negative consequences. These general objectives can be instantiated by the following research question:

1) What are the concrete causes and the main properties associated with these mismatches between real cycling routes and their mapping into a road network model?

The remainder of this paper is organised as follows. In chapter II, we summarise some of the most relevant work in this topic. In chapter III, we describe the methodology used for the execution of this study. In chapter IV, we present the results. In Chapter V, we discuss the implications of those results and what they mean for smart cycling. In chapter VI, we summarise the conclusions of this work and describe opportunities for extending this research.

II. Related Work

Previous work has addressed the limitations of map-matching for cycling mobility by proposing new map-matching algorithms that can be more efficient with this particular type of routes. Bergman and Oksanen [12] proposed a method based on Hidden Markov Model (HMM), which preferred bikeways extracted from Open Street Map (OSM) to perform map-matching. In addition, cyclists can go through open areas, such as parks, instead of exclusively following the road network, also known as semi-restricted trajectories [13]. Behr et al proposed an approach that allows map-matching of trajectories that possibly contain on- and off-road sections. Moreover, if the road data is incomplete, general map matching does not work well. To address this problem, Sasaki et al [14] proposed an algorithm to interpolate missing road segments by using vehicle trajectories based on map matching and clustering techniques. Dong et al proposed the use of mapillary data to generate bike network information [15].

Previous work has also considered the specificities of route selection for cyclist. While car navigation is essentially optimised for time, cycling routes need to consider a trade-off between multiple objectives, such as safety, distance or comfort. The best route is always a personal and subjective decision of each cyclist [16]. Nunes et al. [16] proposed a meta-heuristic approach to solve the multi-objective bike routing. They use A-Star algorithm to create an initial solution, and then a perturbation method to generate a higher diversity of solutions. Matos et al. [17] developed an information system for cycling navigation based on seven indicators, including energy expenditure, comfort, or infrastructure, among others. They computed the optimal path between different OD pairs for each indicator and analyzed their trade-offs.

Schirck-Matthews et al. [18] compared GPS traces with suggestions of online trip planners. In general, cyclists go through fewer traffic signals, and use more cycleways, footways, or bike lanes than suggested routes from Google and MapQuest. This shows that routing engines are still missing on crucial details, resulting in suggestions that are still far from optimal.

The analysis of related work shows that there has been considerable work on dealing with the implications of incomplete road networks. In this work, we aim to gain a better understanding on the concrete causes of the problem and generate some early insights into what can be done differently so that road networks may more faithfully represent the reality of cycling patterns.

III. Methodology

Our methodology involved the deliberate identification of cycling scenarios that were likely to originate a mismatch between the route effectively taken by cyclists and the mapping of that route to the road network model. We called ad-hoc segments to those route sections where the map-matching process fails to provide a correct match. This includes cases where the map-matching process proposes a route that does not represent the real route made by the cyclist or when it simply fails with the indication that it is not confident enough to propose any match.

To identify a broad range of these ad-hoc segments, we explored our own experience of common cycling routes in the city of Braga. This is a city with reduced cycling infrastructure, where cyclists often take less conventional routes to avoid sharing the roads with cars. We analyzed those routes in search for sections that could correspond to mismatch cases. The result was the initial list of seed cases in table I.

TABLE I
SEED CASES FOR ROUTE PLANNING

Case	Case Description
Recent roads	The cyclist rides on a street that was recently subjected to traffic changes, which may not yet be represented.
Shortcut	The cyclist takes a shortcut, i.e a non-official but convenient path that may not be represented in OSM.
Wrong direction in one-way street	The cyclist rides against traffic on a one-way street.
Pedestrian	The cyclist rides on a sidewalk or pedestrian path.
Dirt track	The cyclist takes an dirty road, possibly created through the passage of pedestrians over time.
Zebra crossing	The cyclist uses a zebra crossing to go from one side of the road to another (either dismounting or not).
Pedestrian Bridge	The cyclist takes a pedestrian bridge over a busy road.
Semi-public roads	The cyclist takes a road located in a semi-public area, such as a University.
Adjacent roads	Car and cycle roads are adjacent and even minor positioning errors may result in an incorrect matching.

We then conceived an experimental route containing 19 situations that were likely to produce ad-hoc segments. All the seed cases in table I were represented by at least of one these situations. Having been designed specifically for this purpose, this experimental route did not aim to be representative of the number of potential problems that may occur on real cycling routes. However, all the ad-hoc segments included in this route corresponded to realistic cycling trajectories that are commonly used by actual cyclists as part of their journeys. The potential ad-hoc segments are thus genuine, even if their concentration within this route was artificially created for the purpose of this study.

We collected data by cycling the designated route with a bicycle equipped with a mobile phone and an action video camera, both of which were attached to the bicycle handlebar. On the mobile phone, we used the GPS logger application [1], to register the GPS trace. To avoid unintended effects on the mapmatching algorithms, we configured the application to avoid usage of battery optimization and avoid filtering noisy GPS signals. The video feed was used as complementary data source, especially for clarification on cases where some additional knowledge about the trajectories could become necessary for the correct interpretation of the results. The video also allowed us to generate images to illustrate the various ad-hoc situations embedded in our experimental route. Figure 1 represents a map view of the trace used for this study.

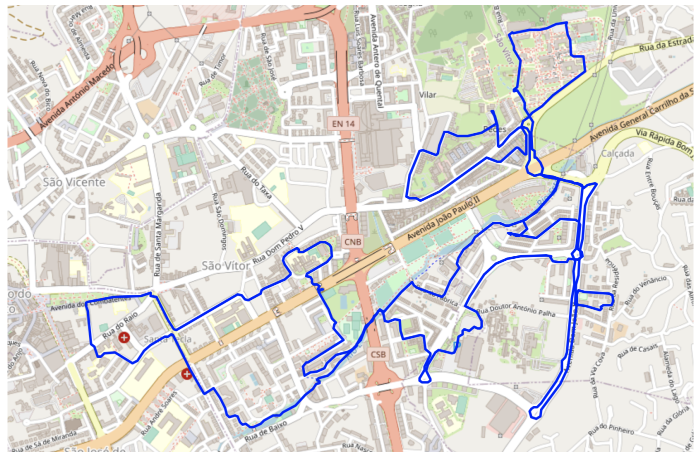

Fig. 1. Map view of the original bike trace recorded in Braga.

A. *Route processing – map-matching*

To analyse the trace data, we started by executing the respective map-matching process. We selected Open Street Map (OSM) as the mapping context for this study. OSM is a collaborative mapping project aggregating geographical data all over the globe, including information about the road network, administrative limits, and infrastructures. While the problem is common to many other Geographical Information Systems, OSM offers the extra benefit of open access to all the road network details, thus providing a much deeper insight into the possible causes of the problem.

To execute the map-matching itself, we used the map-matching engine developed by Mapbox [19]. This engine is OSM-based and offers 100.000 free requests per month. A single request can have between 2 and 100 coordinates, and should be framed by a specific mobility profile: driving, cycling, or walking. The results of the process include not only the proposed route over the existing road network, but also a confidence level that can be used to identify uncertainty situations. We should emphasize that our objective is not to evaluate the performance of any map-matching algorithm. Mapbox was chosen just as a representative example of what to expect in general from a map-matching tool.

The execution of the map-matching process was made for the entire trace and was totally independent from any initial considerations about possible ad-hoc segments or seed cases. Following on mapbox guidelines, the points were filtered so that every point in the request should be at least 15 meters apart from the previous one and should have been registered at least 5 seconds after the previous one.

[1]https://play.google.com/store/apps/details?id=com.peterhohsy.gpsloggerlite

IV. Results and Discussion

A. *Identification of anomalies*

To analyse the map-matching results, we created an OSM map representation in QGIS, overlaying the original trace and the route proposed by the map-matching process. We then analysed the whole route to identify any cases that could correspond to a mismatch situation. For this analysis, we did not take into account the 19 cases that have been used to create the route. All the ad-hoc segments reported were identified by visually inspecting the map. More specifically, we signaled for further analysis any situations where the trace and the route proposed by the map-matching seemed to either diverge or follow parallel directions. We also used our own field knowledge about each concrete situations, and the video feed whenever needed, to assess in more detail the characteristics of each of those situations and decide whether or not they qualified as ad-hoc segments. The selection criteria was that an ad-hoc segment should correspond to a failed mapping or to a mapping made to a road segment that was not representative of the trace section that it was meant to model. For example, a segment made on a sidewalk that was mapped to the main road, would qualify as an ad-hoc segment.

In total, we identified 16 situations that corresponded to our definition of an ad-hoc segment. To support subsequent analysis, we registered, for each of those route segments, a unique id (1-16), its start and endpoint and a problem description. Figure 2 shows an example of one of those 16 situations. The real route is represented by the blue continuous line, while the mapped segment in represented by the dashed red line. In this example, the cyclist used the sidewalk next to a one-way road and in the opposite direction to traffic.

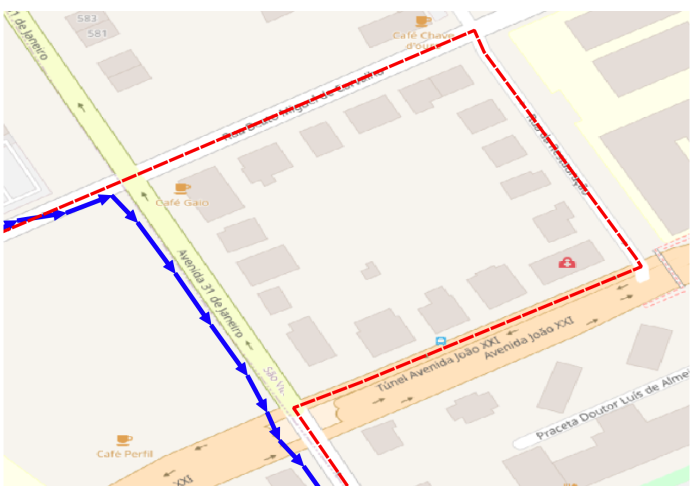

Fig. 2. ID12 - Map-matching a trace performed on a forbidden direction.

B. *Occurrences Categories*

Following on the identification and description of anomalies, we then aggregated those anomalies into categories according to the assessment of the respective cause. This resulted in the categorisation represented in table II with six major causes for ad-hoc segments

Among these categories, the most common were related to missing road network elements, such as roads or intersections. They have an impact on routing, by inducing huge detours or suggesting more dangerous roads, and they also impact mobility models through the loss of relevant information or through its association with the wrong roads.

Another common category considers the cases when cyclists ride against the traffic in a one-way road. In these cases, the cyclists used either a pedestrian sidewalk or a road with low motorized traffic in order to ride with relative safety. However, the map-matching results differ. In case 12, the map-matching returned a wrong segment, and in cases 13 and 14 it returned the correct segments. This may be due to the road tags and their use by the Mapbox algorithm. In case 12, the road was tagged as ”secondary” as in 13 and 14 the roads were ”tertiary” and ”residential”. We can adapt the map-matching algorithm to consider these roads, in order to have a better understanding of cyclist behavior and their preferences, but, at least for the purpose of routing it could mean pushing cyclists to ride on dangerous conditions.

The last category regards competing roads. These paths may be represented as different parts of the same road or as different roads next to each other, such as a cycle-way parallel to the main road. Unlike cars, cyclists have the ability to use the road and the cycle path, which significantly increases the complexity of the map-matching algorithm when both roads are next to each other. In these cases, even minor GPS errors might be enough to cause the mismatch.

V. Discussion

The results confirm a clear mismatch between real cycling traces and the way they are represented when mapped into an OSM road network. More specifically, they seem to indicate that the main overall cause of this problem is directly linked with limitations of the road network model. From all the six categories of ad-hoc segments identified in this study, only one, competing roads, cannot be linked to those limitations. Two roads adjacent to one another, is a worst-case scenario for map-matching of cycling routes. As cyclists may potentially use any of those roads, both possibilities need to be considered and even small positioning errors may be enough to produce a wrong match. For all the other cases, however, the problem is not associated with any complexity of the map-matching process. It is always a direct consequence of a mismatch between the real routes and the routes represented in OSM. Since there is not a suitable match, the map-matching process could never provide one.

We can thus conclude that road network models, as commonly used in OSM, do not properly address the specificities of cycling, or micro-mobility in general. Even if this is not necessarily a limitation of OSM itself, the prevailing road network models seem to assume that cyclists can either use normal roads or the official cycle paths. As a consequence, it fails to consider all sorts of shortcuts, alternative paths

TABLE II
CASE CATEGORIES

Case Categories	IDs	#	Category Description
Missing Road	3, 7, 8, 9, 15, 16	6	Fall in this categories the occurrences where the cyclist rode on segments that were not defined in the OSM road network.
Missing intersections	15	1	Fall on this category occurrences where the intersections between two or more roads are not defined in the OSM road network.
Wrong Direction	12,13,14	3	Fall on this category the occurrences where the cyclist rode on a one-way road but contrary to traffic direction.
Semi-public Roads	4, 5	2	Cases where the cyclist used semi-public roads, tagged as private on OSM road network. A ”semi-private” tag should be considered to differentiate roads where cycling or walking are possible. This would improve modelling cycling behaviour.
Complex Crossing	10	1	Complex crossings are situations where the cyclist must change its course in order to avoid dangerous situations at crossings, such as by taking pedestrian zebra crossings or other pedestrian facilities. These trajectory adjustments cannot be mapmatch into the road network since it is designed primarily for cars.
Competing Roads	1,2,6,11	4	Fall in this category occurrences where the map-matching was not able to correctly match the real trace segment due multiple viable alternatives that the cyclist can ride on. Even small interferences on GPS signal can result in wrong map-matching outputs.

or specific crossing strategies at complex intersections that cyclists daily resort to in an attempt to make their journeys more efficient and safer.

Given this mismatch between the reality of cycling traces and the road network models that are expected to represented them, it comes as no surprise that map-matching processes may often fail. The problem is that each of those failed segments represents a major loss of valuable information, with important consequences for the ability of cycling information systems to provide a realistic account of cycling activity.

This has a twofold impact. The first is the impact on the accuracy of the models that can be created based on the road network information. Those models can be very valuable for urban planning and mobility management, but if they are based on a road network that is inaccurate, then, they will also be inaccurate or even misleading. Also, if the road network does not represent all the possibilities, and particularly those that cyclists seem to prefer, navigation services will necessarily suggest routes that are not ideal. If a cyclist systematically receives route suggestions that seems to ignore what the cyclist perceives as some obviously better alternatives, then the confidence on that navigation service is broken. This can be particularly negative for beginner cyclists or tourists, who are less knowledgeable about the shortcuts or alternative roads that could offer them more comfort, safety or efficiency.

As suggested by previous work on pedestrian networks, the root causes for this problem might be a reflection of a car-oriented mindset and the much higher demand for car navigation services [20]. Assumptions associated with the automotive, are so deeply embedded that they are never even perceived as such. They are just seen as what is expected to work with any mobility mode. A contribution of this work is thus to highlight a very specific way in which those assumptions fail when applied to urban cycling.

We can also discuss whether these limitations arise from limitations in the OSM model itself, or from common practices around OSM mapping. In general, it can be argued that the OSM model is so generic that it should not be a limitation in itself. However, abstraction also has its price, which, in this case, might be the added challenge of promoting convergence on specific practices. This is not a major problem for car road networks, as they have always been the major use case for OSM and their mapping practices are well established. However, when considering other types of road networks, there are no special constraints on how to represent them, but there are also no well-defined practices on how to do it. This is a problem for any road network, which is expected to be co-created by multiple entities and serve multiple independent services. Without some level of convergence on basic principles, such as which tags to use, or which roads to represent, a road network model will not be able to serve this core role in mapping services.

The perception of this problem, and the need to confront this mismatch between road network representations and cycling traces, raises the obvious question of what can be done about it. The answer may not be so obvious because the root of the problem lies in a fundamental flaw of the current model. The results suggest a clear conflict between cyclists and mobility authorities about what constitutes an official or a de facto cycling route. For cyclists, many of these unofficial routes may simply be obvious choices based on their field knowledge and their situated assessment of current circumstances. Mobility authorities, however, might tolerate these de facto routes because they understand their value for cyclists, but they are bound by regulatory and legal responsibilities that may stop them from acknowledging those routes as suitable cycling routes.

In the end, this dilemma ends up as a content management challenge for OSM. The idea that everyone can create and enrich OSM, so that OSM data may become a faithful representation of the physical world as seen by the collective view of multiple contributors, is at the core of the OSM model. It also matches very well cycling practices, where route sharing is very popular. This inside knowledge that cyclists have about the best ways to cycle in their city, could allow the OSM road network to evolve continuously, as any viable routes would eventually become part of the model. However, this open paradigm relies on the implicit assumption that, if people go to the field, they can assert the correction of information, and it should thus be simple to agree about the existence of a road and its basic properties. The idea that there might be de facto cycling routes that cannot be officially classified as cycling routes creates an ambiguity that may challenges those basic assumptions and the simplicity of OSM abstractions.

From a more technical perspective, it should be possible to automate the identification and characterisation of these ad-hoc segments on a large scale. This would create awareness about their existence and could serve to trigger revision processes that included an official assessment of concrete situations. Unmatched road segments would no longer be wasted information. They would become the core input for the progressive alignment between OSM and the reality it intends to represent. Some cases could be addressed by simply updating OSM representations. Others could serve as a sign for the need to perform small interventions in the physical infrastructure to either prevent people from taking specific ad-hoc segments that might be considered dangerous, or to make any necessary adjustments so that they could be officially recognised as cycling routes. Yet another alternative might involve the creation of new OSM tags to signal de facto routes, possibly making them an option that users, may or not consider, when using mapping services.

VI. Conclusion

All over the world, in high-profile cycling cities or in cities just trying to make their first steps towards sustainable urban mobility, local cyclists apply their local knowledge to identify the best possible routes across a complex and heterogeneous network of roads. The main contribution of this work is the identification and characterisation of an important gap between those routes that are effectively taken by cyclists and their representation in the road networks of geographic systems. More specifically, there are parts of the traces that represent the cyclist trip that cannot be mapped into the road network of OSM, because they have no matching representation. We call these segments, ad-hoc segments, and discuss their impact in the quality of the services provided to urban cyclists and in the value of the data available for micro-mobility planning and management.

A. Limitations

There are two major limitations in this study, which are somewhat related. The first is the use of visual inspection as a technique for the identification and characterisation of ad-hoc segments. This was needed because we had to start by gaining a deeper understanding about the specific ways in these mismatches occur, before we could be ready for more automated and quantitative methods of analysis. The second limitation, which largely derives from the first one, is the use of a single GPS trace as input. Even though this trace was specifically conceived for triggering multiple situations where we expected the process to fail, we do not claim to have captured the full spectrum of potentially ad-hoc segments. Also, this single trace cannot provides us with any sense of the frequency of the problem and the relative weight of the various types of ad-hoc segments.

B. Future Work

As future work, we plan to address the main limitations of this study by developing automated methods to detect ad-hoc segments and by conducting large scale studies based on quantitative methods. The automatic detection of ad-hoc segments will benefit from the methodological and assessment approaches defined in the current work. We plan to start by defining metrics that can characterise the very diverse nature of these ad-hoc segments. The formalization associated with these metrics will become a building block for the automation processes, which will use those metrics for classification purposes. This ability to perform automated detection will be a fundamental enabler for large scale studies, possibly involving data from multiple cities. For this, we plan to use many real-world traces shared by cyclist communities in public cycling platforms, e.g. wikiloc. Unlike what we did in the current study, those routes will not be created specifically for this purpose and therefore their results will allow us to gain a realistic sense of the dimension of the problem. By considering a diverse and representative set of routes, we will be able to make a quantitative assessment of the problem, more specifically by measuring the relative frequency of those ad-hoc segments in regard to all the routes considered and the relative frequency of each of the specific types of ad-hoc segments. It should also be possible to analyse possible correlations between those frequencies and particular characteristics of the respective urban spaces.

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