A Survey of People Movement Analytics Studies in the Context of Smart Cities

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***Abstract*—With the advent of the newest emergency call mandates in US and Europe, with the advances in cellular-based and WiFi-based localization solutions, and with the developments of cloud computing and web-based social networks, the location information and movement-related data is becoming easier and easier to collect from the user mobile devices and from the user cloud data and it is more and more used in a variety of Location Based Services and for various network planning and management tasks. The last decade has seen significant research efforts dedicated to analyze the user location and movement data, to extract mobility patterns and features and to use the predicted patterns for a more efficient resource allocation and for better location-based services. In the context of what is called today 'the smart city', user mobility and location data are becoming key components of the smart city architecture and applications. The goal of this paper is to give a compact and comprehensive overview of the challenges and solutions related to collecting, storing, analyzing, visualizing, using or distributing people's movement data and to summarize the purposes of such data in the context of the smart cities and the Internet of Things.**

I. Introduction and motivation

The number of devices that nowadays allow the tracking of movement data and location patterns has been increasing at a fast pace in the last $5-10$ years and will continue to increase as we move towards the era of the Internet of (all) Things (IoT). Not only the majority of the smart hand-held devices are nowadays equipped with a positioning engine, but also transport devices, such as private cars or public buses are more and more relying on positioning technologies. For example, Europe has recently voted the eCall mandate, telling that all cars will be equipped with positioning technology to support emergency calls after April 2018. Some of the wireless devices and applications on the mobile devices are also uploading directly the collected user traces to public or private clouds. The result is that a huge amount of user mobility data is nowadays available in either open access or as proprietary data. Few examples of public data repositories with people's traces or other information related to people's movements are WikiLoc [16], geo-tagged Twitter pages, geo-tagged Flickr pages, Crawdad repository [18], CityBike [20] or OpenSteetMap [17]. Private repositories accessible via own accounts are for example Endomodo [19] or RunKeeper [21]. All this available data creates the need of powerful data mining methods and of efficient analysis tools to understand, interpret, visualize and find statistical meaning of the available data, and use such data for improved and more attractive Location Based Services (LBS). Applications of such analysis are multi-faceted and may range from physical activity monitoring for health purposes [22] or monitoring of the user activity on social networks [23] to movement-based analysis of economic well-being [8] or exposure to toxic factors in urban environments [9]. While a lot of research has been dedicated in the last decade to study the user mobility patterns and to derive laws that govern the people's movements and physical activity, comprehensive survey papers on the various aspects of analyzing the user mobility data are still hard to find. It is thus the purpose of this paper to give a comprehensive and unique overview of:

- The potential uses of user movement data in the context of the smart cities, Internet of Things (IoT) and Internet of People (IoP);
- Main mobility models and probability distribution functions of mobility-related parameters reported in the literature so far;
- The problems and challenges related to collecting, storing, analyzing, distributing and using in any way the movement data at both individual level or from large volumes;
- The existing solutions regarding movement analytics and location-based processing of user data, including a discussion about related European and international projects;
- The main public repositories of such data at the present moment and the international projects dealing with movement analytics and mobility-based applications and services;

The novelty of our papers comes from addressing in a comprehensive, structured and compact manner the problems and solutions related to user movement data analytics.

The rest of the paper is organized as follows. Section II gives the main definitions regarding the smart city environment and its connection to mobility studies. Section IV presents a summary of main existing mobility models in the literature and their related parameters. Section V discusses some of the main repositories of public data about user traces and user movements, as well as the most encountered data formats. Section VI presents an overview of the solutions regarding movement analytics and location-based processing of user data, such as the semantic interpretation of movementa data, the existing

ISSN 2305-7254

platforms for collecting movement data, and the main projects in Europe and outside Europe addressing the problem of user movements in the context of urban scenarios. Section VII discusses the current challenges and open problems in the considered research field. Section VIII summarizes the ideas and presents the conclusions.

II. Smart city concept

World population is increasing and people tend to move more towards urban areas. This general trend combined with the exponential increase of wireless devices, from smartphones and tablets to wearables and smart glasses creates a huge potential of interconnected wireless links between all wireless devices at close proximity from each other or in a certain geographical area served by cellular operators or other Internet service providers. The smart city concept is basically integrating this vision of interconnected devices or IoT with urban spaces, aiming at a better, more efficient and more secure way to manage the various city assets, such as public transport, community halls, schools, hospitals, traffic lights, parks, water supply networks or power plants [1].

The main difficulty in addressing the concept of a smart city in a global and standardized manner stays in the fact that IoT environment is a highly dynamic environment, thus any smart city platform need to support massive heterogeneous devices and to be easily scalable and highly adaptive. Research about smart city proposed platforms can be found for example in [35], [36], [37], [41].

An European Smart City Model has been developed since 2007 by a team of researchers at the Technical University of Wien [42]. They have identified six indicators related to a smart city concept, namely smart economy, smart mobility, smart environment, smart people, smart living and smart governance and they have selected and classified 70 medium-sized European cities according to these indicators and to certain aggregation weights. According to their model, the top five smart cities in Europe are Luxembourg (LU), Aarhus (DK), Turku (FI), Aalborg (DK), and Odensee (DK).

III. Uses of movement analytics in the context of smart city

Mobility is an inherent part of a smart city [1], [2]. The use of the information about users' traces and their movement history is multi-faceted. A survey of the potential applications of the user mobility data in the context of smart cities points out towards 11 main classes of applications:

1) **Health-related** applications [38], such as LBS serving to increase the quality of life of elderly and disabled when mobility patterns are used for prevention of diseases or predicting the health status [10], fall detection methods [34], estimating the infectious disease dynamics according to human travel patterns [32], or for measuring the exposure to toxical factors [9];
2) **Social networking** applications, such as Facebook, Twitter, Flickr, Instagram or LinkedIn, where some form of geo-tagging is present [30], [40], social networks for mobile navigated tourism [31], estimating the economic well-being [8], or monitoring user activity on social networks [23], [4];
3) **Transportation** applications, for example by avoiding traffic congestion and crowded areas, for collective monitoring and prediction of user traffic [3], by adding a social layer of driving [30], urban transport fluidization [5], or optimized taxi sharing [6];
4) **Smart homes** applications, such as daily routine identification for mobile personal assistant [33] or smart lightening based on room occupancy;
5) **Smart shopping** applications [61], such as finding a desired item on a shelf inside a super-market or finding the nearest shop with looked-for items or seasonal discounts;
6) **Tracking** applications [62], [63], such as tracking a pet or a family member or sports trackers;
7) **Resource optimization** at the network operators side, such as radio resource and mobility management for more efficient network design [7] or analysis of the mobility's impact on device-to-device (D2D) communications for a better D2D architecture design [39], [64];
8) **Safety** applications [65], such as fast emergency response, crime prevention, fraud monitoring;
9) **Smart urban planning** [66], such as smart parking lots or automatic location-based fees at crowded concerts, museums, or shows;
10) **Cleaner/greener environment** [68], [67], such as decreased pollution, efficient waste management, and efficient water and electricity allocation;
11) **Infotainment and gamification** [69], such as Pokemón Go, RPG Diary Game Pain Squad or Zamzee Epic.

IV. Mobility models

The search for patterns and laws in the human and moving species, such as monkeys, birds or jackals [13], has started more than two decades ago. It was a famous article in Nature [24] in 2008 that first asserted that "human trajectories show a high degree of temporal and spatial regularity" and proved this by investigating user traces collected from 100000 anonymized mobile phone users. Since then, many studies focused on understanding better the movements of human beings and on using such derived patterns and laws into various context-aware and location-aware applications, such as radio resource and mobility management in cellular networks, traffic optimization in urban and sub-urban environments, or optimized taxi, bike or car sharing. Table I summarizes the most typical statistical distributions used in human mobility models in the past two decades.

As seen in Table I, the predominant distributions used to model user step, user angle and user speed are the Gaussian, the uniform and the truncated power law distributions. Few authors also suggested the use of other distributions, such as the boundary crossing distribution for angles and lognormal distribution for speeds. All these distributions are shown via their corresponding formulas and their corresponding parameters in Table II.

An example of the 3D indoor trajectory based on a syn-

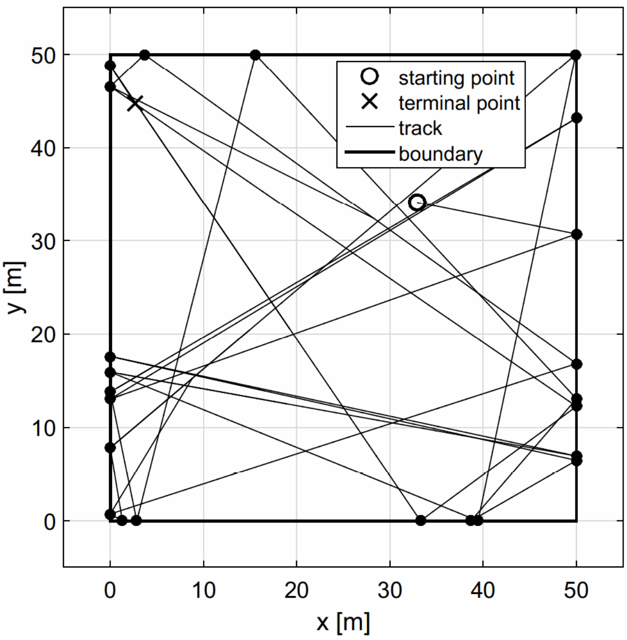

Fig. 1. Illustration of a 2D synthetic indoor trajectory according to the random direction mobility model

thetic modeling according to random direction mobility model [29] is shown in Fig. 1. Similarly, 2D traces based on a random walk outdoor mobility model are shown in Fig. 2.

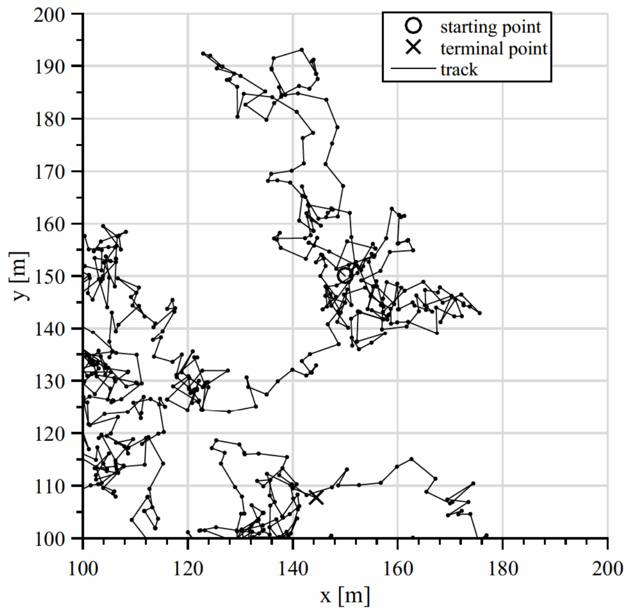

Fig. 2. Illustration of a 2D synthetic outdoor trajectory according to the random walk mobility model

The open-source distribution of several synthetic indoor mobility models, including the random direction and random walk mobility models can be found in [28].

Trajectory mining based on user traces, such as GNSS traces, usually has two components: trajectory clustering, where several user trajectories are group together according to common features, such as similarity based on Euclidian distances, and trajectory patterns extraction, where frequent patterns in time or space are discovered [45].

While human mobility is predictable to a certain extent, as several mobility models verified by measurements assert (e.g., [14], [24]), this movement is not determinic, and thus the use of random models such as Levy walk and Brownian motions is justified. More information about available movement traces and models and synthetic mobility models can be found in [44] and [45]. A taxonomy of movement patterns was published [53].

V. User traces open-access repositories

There is currently a huge amount of movement-related data in open access on web, but so far there are no centralized repositories with links to all the available user traces and movement-related data. In this section we will summarize the main open-access repositories where such data can be found and downloaded for research purposes.

The CRAWDAD [18] is the Community Resource for Archiving Wireless Data At Dartmouth, where users can upload their data after signing a licensing agreement with CRAWDAD site owners. The users can download the available data following a free registration process. Many different formats according to the user who input the data, see Table III, such as Extensible Markup Language (XML), Matlab MAT format or text (TXT) formats. Also various indoor measurements are available in there, which can be converted, with adequate processing into geo-tagged user data.

An example of a user trace collected from Rome taxi drivers during 2014 and available at [18] is shown in Fig. 3.

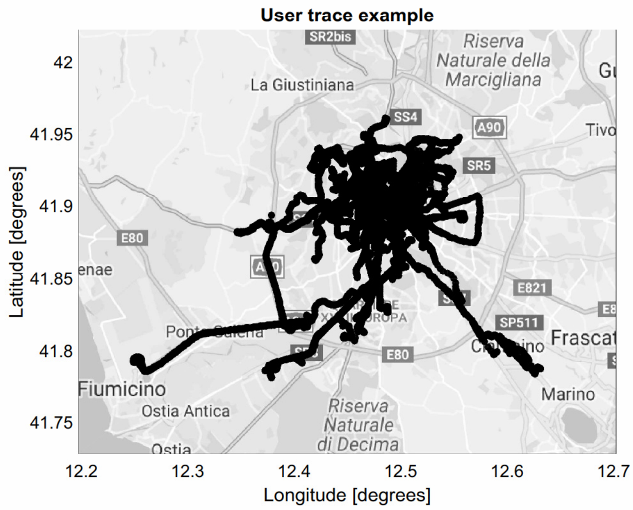

Fig. 3. Illustration of a taxi driver trace based on data in [15]

OpenStreetMap (OSM) [17] is a collaborative project where users can upload data in order to create a free editable map of the world. The raw data from OSM is available in either XML or Protocolbuffer Binary Format (PBF) formats. Metro Extracts [48] can automatically create snapshots of OpenStreetMap data into several user defined formats, such as XML, PBF, Shapefile of GeoJSON.

The CityPulse Dataset Collection [43] offers semantically annotated datasets, such as road traffic data, pollution and weather data, etc., collected from partners of the CityPulse EU FP7 project. The data is provided in the Comma Separated Values (CSV) format.

Wikiloc [16] repository contains a huge amount of trekking, walking, biking and other touristical routes, obtained via volunteer inputs. The data can be downloaded after creating a free user account. The data is typically provided in GPS Exchange Format (GPX) format, which is the default for storing GPS tracks.

The Open Data Institute (ODI), node Trento [47] has a huge smart city open dataset including more than 30 kinds of data, such as user traces, geolocalized tweets, mobile data, weather, energy, etc. The data is avaialble in GeoJSON format, a format for encoding a variety of geographic data structures.

The portal of open data from Malaga City hall [46] contains datasets such as data collected from CitiSense mobile application, bike stopping times for shared bikes, and so on. The data at this point is only available in Spanish, and the provided dataformats are GeoJSON and CSV.

The New York City Taxi and Limousine Commission (TLC) [49] Trip Record Data is a repository of billions of taxi trips in NYC in the past 5 years or more, including geo.tagged information such as pick-up and drop-off dates and times, pick-up and drop-off locations, trip distances, etc.

The Dan Work Open Datasets [50] is a repository with vehicle trajectories and fuel consumption from NYC, http://publish.illinois.edu/dbwork/open-data/.

The open-access available repositories discussed above and their associated data types and data formats are summarized in Table III.

In addition, geo-tagged stationary user positions are available on various social networks such as Twitter, Flickr, Instagram, Facebook, and there are several developer tools and applications that are able to extract and harness this geo-tagged data.

VI. EXISTING SOLUTIONS REGARDING MOVEMENT ANALYTICS AND LOCATION-BASED PROCESSING OF USER DATA

A. Semantic interpretation of movement data

The semantic analysis in the context of spatio-temporal data deals with deductive reasoning and conceptual representations of trajectory patterns [51]. For example, one could use such semantic analysis to guess based on available data is a person will choose the car or the bike at 8 o'clock to go to work. Similarly, one could support the information usability, i.e. via making of higher level representations of trajectory data (such as people driving with their bicycles) and linking it to other information sources (such information about shops, libraries, parks, or restaurants). Also, by gathering and analyzing human observations related to geo-tagged position, iuseful information for better urban planning can be derived, such as the coziness of spaces or the 'noise maps' of certain restaurants and pubs in a city. In addition, trajectory data could be looked at in new ways, such as via the means of augmented or virtual reality. The contextual geographical knowledge is very important for the semantic data interpretation [51], [52]. The linkages that can be discovered via spatial data mining and semantic reasoning could serve to improve the Location Based Services and context-aware applications and for various resource optimizations.

According to [54], [58], we can group the movement patterns into three semantic categories:

1) convergence/divergence patterns [55] or hot motion paths [58] referring, for example, to routes and places that are frequently visited by people;
2) flock patterns, convoys or moving clusters, referring to patterns and law that govern the movements of persons found spatially close to each other for certain time periods, such as family members, groups of friends, work colleagues, etc. [55], [56];
3) trajectory patterns, referring to patterns and laws that can be derived from individual user or vehicle traces [57]

The challenges stay in deriving semantic frameworks able to support large-scale data sets, while having good usability.

B. Existing platforms for collecting movement data

Many industrial units worldwide have been developing indoor and outdoor positioning and navigation platforms that enable user data collection, and its possibly visualization and analysis. Few examples are: Nokia High Accuracy Indoor Positioning (HAIP), Quuppa indoor location platform for shopping malls and retail places, Estimote and Pozyx indoor location platforms, NAO Cloud of PoleStar, or SPREO cloud platform for shopping centers.

On the other hand, open-access platforms for the collection of user movements and other and geo-tagged information are much harder to find. Several initiatives to build such platforms have recently started, for example in Barcelona, Spain [60] and in Nova Friburgo, Brazil [59].

C. European and other international projects

A search in the European and non-European project landscape dealing with the user mobility traces, movement analytics, and user trajectories in the context of urban scenarios or smart city shows that considerable effort worldwide has been dedicated and continues to be dedicated to these aspects. The projects and their main goals related to movement analytics in smart cities are summarized in Table IV.

VII. OPEN CHALLENGES

The challenges regarding the end-user movement analytics are grouped into the following classes and they refer to the issues encountered when trying to collect, process, interpret and visualize the movement user data:

1) Indoor user traces: while GNSS solutions can nowadays offer high location accuracy in most outdoor scenarios and GNSS receivers are more and more used in wireless devices, the indoor positioning has still many open challenges and there is not much

data available in open access regarding users indoor movements.

2) 3D analysis: while 2D analysis involving latitude and longitude of user traces is nowadays widespread, 3D analysis based on user traces is still hard to be found in the literature, mostly likely due to the difficulty in estimating accurately the altitude, both in outdoors (especially in flat environments) and indoors (especially in buildings with open spaces, where floor detection is very challenging)
3) Ontology approaches: developing formal ontologies-based approaches and ontology formalisms to enable the semantics of both raw trajectory data and mined trajectory patterns
4) Privacy issues: the anonymization of data when users traces are collected is an important step towards preserving the user privacy, but this might be not enough to protect the users' whereabouts, especially when context analysis is performed, such as most visited places, usual night location that can be associated with the home place and usual day location which can be associated with the work place, and so on. The legislation covering the privacy of user location data is also not yet here and efforts have to be made for a better understanding of the privacy concerns and a better protection of data.
5) Indoor maps: unlike the outdoor maps, which are highly accurate and widely available in open-access, from providers such as Google and Here maps, indoor maps are still scarce and there are many legal, social and administrative impediments in creating them. Simultaneous Location and Mapping (SLAM) technologies are likely to be needed for accurate mapping of the indoor environments and particular attention has to be paid to the security aspects when mapping commuting halls or large area of public interest, such as airports, railway stations or shopping malls.
6) Open-access platforms: in order to better engage the citizens into databases creation through crowdsourcing and volunteer inputs, new platforms have to be created and made available to the public through technological efforts combined with City halls efforts.

VIII. Conclusions

Finding the right tools for the collection, interpretation, analysis, visualization and semantic processing of user movement data is an important step towards developing better Location Based Services, which will contribute to the end-users well-being and towards an engaging smart city that puts the citizens first. People spatio-temporal context and history of movements offer important information to support a variety of services and applications, from better localization to personal assistant and disease prevention. The research in this area is multi-disciplinary and wide-encompassing. Our paper aimed at giving some unified overview of the different aspects of the movement analytics in the context of smart cities, by emphasizing the open-access aspect of such a research and by providing a collection of mobility models, open-access repositories, available platforms and past and present consortium projects. The open challenges and further research directions have also been discussed.

The potential uses of user movement data in the context of the smart cities was classified in 11 large classes in Section III, and examples from each class were emphasized.

The main mobility models and probability distribution functions of mobility-related parameters reported in the literature so far were summarized in Section IV and Table I. It was shown that Gaussian, uniform and the truncated power law distributions are the predominant ones in modeling users' movements and movement-associated parameters, such as step, angle changes, oause times, speed or acceleration.

We pointed out that some of the main problems and challenges related to collecting, storing, analyzing, distributing and using in the movement data are: the existence of many standards and formats of data storage and many repositories without a unified database to enable a fast and easy access; the distribution terms of many of such repositories which may prohibit their use in certain contexts or without express permission of the users who uploaded the data in cloud repositories such as Wikiloc, the semantic interpretation of data and the insufficient coverage of sematic rules and categories in todays' literature, and the lack of open-access platforms for the collection of user movements and other and geo-tagged information.

We also discussed some of the existing solutions regarding movement analytics and location-based processing of user data, such as: grouping movement data in one of the three semantic categories: convergence/divergence patterns, flock patterns or trajectory patterns, building platforms for collecting movement data, preferable in standardized formats such as GPX format, and the solutions provided in several European and international projects, as summarized in Table IV.

Last but not least, we have summarized in Table III the main public repositories of such data at the present moment and the international projects dealing with movement analytics and mobility-based applications and services, which can serve as a reference table for researchers interested in studying large-scale mobility models and movement patterns.

Our analysis show that, despite of an already large pool of existing solutions and databases in the field of the movement analytics of human beings, there are still many open and interesting challenges to address, and researchers have a wide mixture of available tools to start their investigations.

Acknowledgment

The authors express their warm thanks to the Academy of Finland (project 303576) for its nancial support.

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TABLE I. STATISTICAL DISTRIBUTIONS OF USER MOBILITY PARAMETERS FOUND IN THE LITERATURE

Model Type	Model name	Distributions
Synthetic	Brownian motion[11]	Gaussian distribution of user speeds; Uniform distribution of azimuth angles
Synthetic	Random waypoint model[11]	Uniform distribution of user speeds; Uniform distribution of azimuth angles
Synthetic	Levy walk [12], [14]	Constant user speeds
Synthetic	Mobility models for terminal [11], [25] mobility in cellular systems	Either Uniform distribution or boundary crossing distribution of azimuth angles (scenario dependent)
Synthetic	Slaw model [26]	Truncated Power Law (TPL) distribution of flight times and pause times
Traced-based	Barabasi et al. [14], [24]	Truncated power law distribution of user steps
Traced-based	Kim et al. [27]	Lognormal distribution of user speed; non-uniform distribution of angles, reflecting the direction of roads and walkways
Traced-based	Lee et al. [12], [13]	Mostly uniform distribution for azimuth angles, but some cases with stronger biases at -90 and $+90$ degrees; Truncated Pareto distribution for flight lengths; Gaussian distribution for mean square displacements

TABLE II. MOST COMMONLY USED DISTRIBUTIONS FOR THE USER MOBILITY PARAMETERS

Distribution	Probability distribution function $p(x)$	Model parameters
Exponential	$\frac{1}{\mu} exp\left(-\frac{x}{\mu}\right)$	μ
Gaussian	$\frac{1}{\sqrt{2\pi\sigma^2}} exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)$	μ, σ
TPL	$(x+1500)^{-\beta} exp(-\frac{x}{k})$	β, k
Log-normal	$\frac{1}{\sqrt{2\pi\sigma^2}} exp\left(-\frac{(ln(x)-\mu)^2}{2\sigma^2}\right)$	μ, σ
Extreme value	$\frac{1}{\sqrt{\sigma^2}} exp\left(-\frac{x-\mu}{\sigma}\right) exp\left(-exp(\frac{x-\mu}{\sigma})\right)$	μ, σ
Gamma	$\frac{1}{b^a\Gamma(a)} x^{a-1} exp\left(-\frac{x}{b}\right)$	a, b
Uniform	$\frac{1}{2max(x)}, -max(x) \leq x \leq max(x)$	$-$

TABLE III. OPEN-ACCESS REPOSITORIES WITH MOVEMENT-RELATED USER DATA

Repository	Data types	Data formats
CRAWDAD [18]	user traces, e.g. from taxi drivers and geo-tagged stationary positions	Various (e.g., XML, TXT, MAT, etc)
OSM [17]	user traces and geo-tagged stationary positions	XML, PBF
WikiLoc [16]	user traces, under various activities (walking, trekking, biking, running, ...)	GPX
CityPulse [43]	geo-tagged stationary positions	CSV
ODI, Trento node [47]	geo-tagged stationary positions	GeoJSON
Malaga City hall [46]	user traces and geo-tagged stationary positions	GeoJSON , CSV
TLC [49]	geo-tagged stationary positions	CSV
Dan Work [50]	vehicle traces	CSV, MAT

TABLE IV. OVERVIEW OF MAJOR PROJECTS DEALING WITH URBAN MOBILITY, USER MOVEMENT ANALYTICS AND LOCATION-BASED DATA

Project name	**Brief description of goals related to movement analytics**
EU FP6 GeoPKDD http://www.geopkdd.eu (2005 – 2008)	Spatio-temporal knowledge discovery and data mining methods for moving objects and their trajectories
EU FP7 URBANMOB http://cordis.europa.eu/result/rcn/166344_en.html (2013 – 2014)	Utilising the data produced by Oulus Urban Pervasive Infrastructure and other sources for modelling and exploiting urban flows and networks; work based on wireless traces
EU FP7 Urban Sensing http://urban-sensing.eu (2012 – 2015)	Data collected from social media for analyzing patterns of use and citizens' perceptions related or concerning city spaces;
EU FP7 EUNOIA http://eunoia-project.eu (2012 – 2013)	Investigates how new data available in the context of smart cities can be exploited to understand mobility and location patterns in cities; compares mobility and location patterns in different European cities
EU FP7 CitySense (2013 – 2016)	provided innovative smart city applications and offers a number of semantically annotated datasets in open access [43]
EU Open-Cube www.opencube-project.eu (2013 – 2015)	Developing software tools that facilitate publishing of high-quality Linked Statistical Data and reusing distributed Linked Statistical Data in data analytics and visualisations; focusing on economic and social indicators in cities
EU FP7 MULTI-POS www.multi-pos.eu (2012 – 2016)	Initial Training Network in the field of multi-technology positioning; reduced-scope analysis of indoor mobility models in the context of signals of opportunity
EU H2020 ETN GEO-C http://www.geo-c.eu (2015 – 2018)	Training Network of PhD researchers focusing on how people can understand the processes driving smart cities and their services, and how they can gain a sense of control rather than being controlled by the services provided by a smart city
EU H2020 EOpen4Citizens http://open4citizens.eu (2016 – 2018)	Project focusing on how to empower the citizens to make meaningful use of open data
Future Urban Mobility Singapore National Research Foundation http://ares.lids.mit.edu/fm/index.html (2010 – 2015)	Developing a new paradigm for the planning, design and operation of future urban mobility systems, aiming at both passengers and freight, in order to enhance sustainability and societal well-being on a global scale
US NSF 0335244 ORBIT http://www.orbit-lab.org/ (2003 – 2008)	Building an open access research testbed for next-generation wireless networks, and covering also location-based mobile network services
US NSF 0643322 Exploring dynamics of pedestrians http://www.nsf.gov/awardsearch (2007 – 2012)	Producing new techniques for extracting features, processes, and phenomena from movement data-sets generated by agent-based models
US NSF 1441177 Human Geography Motifs http://nsf.gov/awardsearch (2014 – 2016)	Examining how shifting motifs in the everyday rhythms and tempo of people form interdependently, with mobile transport and communications infrastructure
US NSF 1421325 Published network mobility traces http://nsf.gov/awardsearch (2014 – 2017)	Developing and evaluating techniques for manipulating and then publishing mobility traces formally proven and with high accuracy
US NSF 1320694 MobiBench http://nsf.gov/awardsearch (2013 – 2017)	Producing benchmarks in the form of evaluation scenarios and test-suites for mobile networking protocols and services for user and vehicular mobility