A data visualization interactive exploration of human mobility data during the COVID-19 outbreak: a case study

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***Abstract*—In this paper, we present a real-world study where a community-based tracking infrastructure has been put to good use for understanding human mobility during the COVID-19 outbreak, in order to contrast its diffusion. In particular, the infrastructure, deployed in 81 points of interests (POIs) across the Madeira Islands (Portugal), can collect a massive amount of spatio-temporal data, that can be enriched with potentially independent data sources of additional values (such as the official number of people affected by the coronavirus disease), and crowdsourced data collected by citizens. These enriched hyper-local data can be manipulated to provide i) stakeholders with a visual tool to contrast COVID-19 diffusion through human mobility monitoring, and ii) citizens with an interactive tool to visualize, in real-time, how crowded is a POI and plan their daily activities, and contribute to the data acquisition. Here we present the deployed community-based infrastructure and the data visualization interactive web application, designed to extract meaningful information from human mobility data during the COVID-19 outbreak.**

***Index Terms*—Spatio-temporal data, data visualization, COVID-19, passive Wi-Fi tracking, human mobility data**

I. Introduction

Mobile computing can be defined as the set of IT technologies (products and services) that enable users to gain access to computation, information, and related resources when they are in movement [1]. In this definition, the concepts of mobility and wireless connectivity play a key role, providing users with the ability to keep connected while moving. In recent years, the fast-paced evolution of ICT has made mobile technologies and wireless computing pervasive, enabling the emergence of the pervasive computing paradigm. This paradigm, also known as ubiquitous computing, bolsters up the need to have computing and communication gracefully integrated with human users into the environment, including an emphasis on ease and naturalness of use, and unobtrusiveness is paramount [2]. Mark Weiser was a pioneer in describing this concept in his seminal 1991 paper, that begins with the following words: *The most profound technologies are those that disappear. They weave themselves into the fabric of everyday life until they are indistinguishable from it* [3]. Nowadays, pervasive computing is crucial for a broad range of applications: using a wide range of sensors, and exploiting pervasive technologies and communication, researchers and practitioners can collect data unobtrusively and cost-effectively [4]. One relevant area that strongly benefit of this scenario is related to understanding human mobility.

Understanding human mobility is a relevant issue in modern society, as witnessed by the wide range of studies focusing on this topic [5], [6]. The collection of human mobility data often resorts to social sensing, which refers to a set of sensing and data collection paradigms where data are collected from humans or devices on their behalf [7]–[9]. Several are the applications that can benefit from understanding human mobility via social sensing, ranging from understanding individual mobility patterns [10], to traffic forecasting [11], [12], including urban planning [13], and sustainability issues [14], [15]. Another investigated issue concerns the understanding of human mobility for epidemic modeling and human virus spread prediction [16], [17]. This issue seems more actual than ever due to the coronavirus 2019 disease (COVID-19) and the pandemic the world is experiencing. Several researchers already started to investigate COVID-19 tracing infection from mobility data, to understand the effect of control measures [18].

Motivated by the rapid spread of COVID-19 and its critical impact on our lives, and inspired by the social sensing paradigm, the contribution of this paper lies in the design of an interactive data visualization web application implemented to provide real-time spatio-temporal data, collected exploiting a low-cost passive Wi-Fi tracking community-based infrastructure. In particular, we here present how the existing infrastructure [19] can be put to good use to collect data that can be manipulated to visualize hyper-local flows of people. This kind of data can be put to a variety of uses, from planning where and when to visit monitored locations to help contain the diffusion of COVID-19 disease and its (real-time) effect on human mobility in Madeira Island (Portugal).

The remainder of this paper is organized as follows. Section II describes some relevant studies related to Wi-Fi tracking systems considering large scale scenario, and data visualization related to COVID-19. Section III details the deployment of the low-cost passive Wi-Fi tracking community infrastructure, while Section IV describes the interactive data visualization application. Finally, the paper concludes with final remarks and considerations for future work.

II. Related Work

In this section, we present an overview of studies focusing i) on understanding human mobility via social sensing, and ii) on data visualization related to the COVID-19 pandemic.

A. Understating human mobility via social sensing

Human mobility data can be gathered exploiting different approaches, but the more common ones concern the use of sensors and pervasive technologies, or the extraction of meaningful information from social media [20], [21]. In this analysis, we focus on the former approach, that allows obtaining high-resolution spatio-temporal mobility trajectories and patterns of individuals and entire social systems using a variety of sensors and sensing technologies. Currently, we can define three main categories of approaches. The most common method is crowdsourcing data from smartphones, including GPS and sensing of nearby Wi-Fi APs (access points or routers) and cell towers [19], [22]. Additionally, mobility data may be collected from systems designed to enable communication and connectivity, such as mobile phone networks or Wi-Fi systems [23], [24]. Finally, large corporations such as Google, Apple, Microsoft, combine Wi-Fi APs with GPS data to improve location accuracy, a practice known as *wardriving* [25].

Focusing on studies related to Wi-Fi APs, the authors of [26] inferred mobility data from Wi-Fi logs in a University campus, using the RADIUS protocol. The movement data were analyzed concerning stays, leaps, and moves, i.e., the time a user remained in the proximity of one Wi-Fi station and movements or leaps between stations depending on the time differences one device was observed in each station. A similar approach has been investigated in [27] where the authors used Wi-Fi access log data and tried to characterize a University Campus activity. In [28] the authors present a study of human mobility using six months of high temporal resolution Wi-Fi and GSM traces. Interestingly, the authors demonstrate how it is possible to estimate the location and use of Wi-Fi access points using only one GPS observation per day, per person, revealing an opportunity for using ubiquitous Wi-Fi routers for high-resolution outdoor positioning. An advanced method used the information broadcast from 8000 Wi-Fi devices in Australia to perform what the authors called SSID profiling [28]. This technique involves analyzing the captured information, focusing on the SSIDs (names of the saved networks on the devices) to associate different devices with social connections. More recently, an attempt has been done to localize crowds with Wi-Fi probes, applying location fingerprinting interpolations from the received signal strength (RSSI) values from previously scanned indoor locations [29].

Our passive Wi-Fi infrastructure uses the same technologies above presented, but providing a long term study in the wild, over a large geographical area, and across multiple location typologies. Moreover, our infrastructure engages the community, both in the infrastructure deployment and data collection (as explained in detail in the next section).

B. Data visualization and COVID-19

Data Visualization can be defined as the graphical representation of information and data, making data visible [30]. Data visualizations have gained a key role in the process of trying to understand the world and are being employed in a varied number of fields and aspects of life (e.g., [31]). During the COVID-19 outbreak, data visualization has been strongly exploited to present the numbers, constantly updated, of the COVID-19 pandemic diffusion in terms of different cases reported (confirmed, death, and recovered), focusing on a specific country or providing global information (see, for example, [32]–[34]). The Coronavirus Resource Center, Johns Hopkins University (JHU), developed a very accurate map visualization presenting aggregated data from multiple credible sources to track the spread of COVID-19, updated in near real-time throughout the day [34]. To present another example, [32] is a web interface that visualizes the globe and the related COVID-19 data for each country, developed by two students at Carnegie Mellon University. The web site is constantly fed by data provided by *worldometers*[1], just one of the numerous available data sources that make possible the implementation of variegated data visualizations.

Besides the location-based visualization, several data visualization have been created to explain the COVID-19 diffusion and infection trajectory (see, for instance, [35]). In some cases, interactive systems are also providing simulations to explain different scenarios based on the variables kept into account (e.g., [36]).

The authors of [37] investigated data visualization to analyze the epidemiological outbreak of COVID-19 in a scientific publication. Adding more details, the study presents an effort to compile and analyze epidemiological outbreak information on COVID-19 based on the several open datasets on COVID-19 provided by the Johns Hopkins University, World Health Organization, Chinese Center for Disease Control and Prevention, and National Health Commission. In [38], the authors presented a study focusing on the possibility to use GIS with

[1] https://www.worldometers.info/coronavirus/

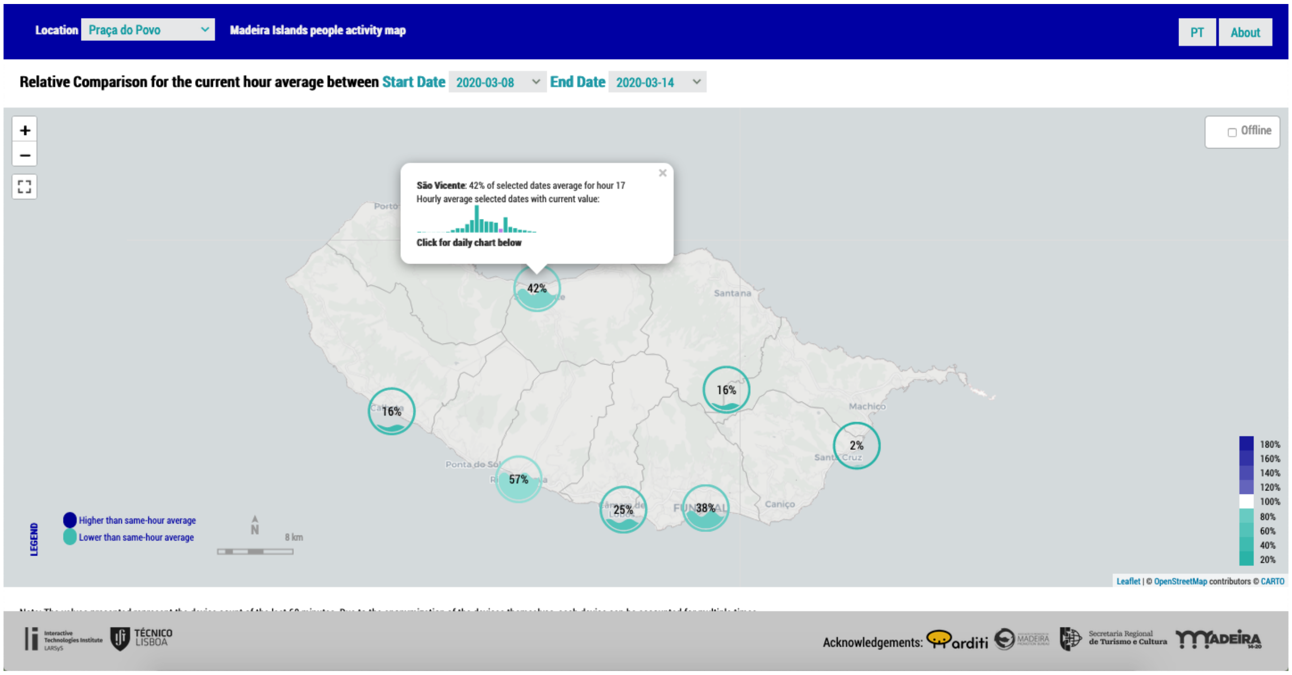

Fig. 1. The interactive data visualization system: on overview of the island data

big data to provide geospatial information to fight COVID-19. In particular, the authors analyzed the spatial representation of the disease, material, population, and social psychology at three scales: individual, group, and regional. Despite the interesting findings, the study concludes pointing out that several challenges concerning data aggregation, knowledge discovery, and dynamic expression remain to be studied.

With this study, we intend to provide a first investigation of how to exploit human mobility data collected by an already existing infrastructure [19], to interactively present phenomena related to COVID-19, with the future aim to use such information to predict and contrast the disease diffusion in Madeira Island.

III. The passive Wi-Fi infrastructure

The deployed infrastructure is a community-based system that uses passive Wi-Fi tracking to understand the mobility and flows of people at scale [19]. The community-based aspect of the system consists in letting community stakeholders gather information about the flow of people near their businesses (i.e., number of clients per hour) by installing a Wi-Fi passive node, and accessing the data visualization dashboard of the system. In doing so the community stakeholders adopt and take care of a node, in exchange for information while helping to augment the numbers of passive nodes in the network and contribute to the large-scale analytics. Moreover, the community can voluntarily contribute and enrich the mobility data with additional information, providing crowdsourced ground truth and helping fellow stakeholders make sense of automatically collected sensor information when an unusual condition is detected, through commenting on the dashboard.

The system was developed and tested in the wild in a medium-sized European Island, Madeira. During a period of four years, 82 Wi-Fi routers have been deployed in 81 points of interest (POIs) to collect more than 572 million (anonymous) data points. The POIs include a medium-sized urban center (Funchal) and several touristic hot spots as well as very rural and isolated locations, and terminals of the transport system as the main entrance and exit points of the island (port and airport). It is interesting to notice that the number of POIs can be easily enlarged thanks to the voluntary contribution of interested parties, that just need to provide a stable internet connection and electricity.

The infrastructure was built making use of off the shelves inexpensive commercial Wi-Fi routers (40$ each) flashed to run an open-source GNU/Linux based firmware program for embedded devices (openWRT). The routers operate in monitoring mode and the probe request information is stored in a central MySQL database (for more details see [19]). The MAC addresses detected in the probe requests were locally transformed into device IDs using a SHA-256 cryptographic hash function. This was done to prevent access to the original identifiers that could be used to compromise the privacy of users [39]. The system is in this way anonymous, respecting the privacy of people by avoiding to identify citizens or owners of the detected mobile devices. At the same time, this infrastructure allows us to know the actual number of devices preset at any specific POI, and to track their movement across the different POIs deployed within the island.

The server side components (developed using apache[2] and

[2]https://httpd.apache.org/

node.js[3]) perform the calculations and optimizations required for analyzing the captured data and provide the results through a web server to the clients. The Wi-Fi routers are connected to a VPN located on the server to allow remote management, as well as the scripts (processing the data) to interact with several external services and APIs. Unlike previous work, our infrastructure was deployed and maintained by the community itself for four years, spanning different generations of devices and operating systems and conditions.

IV. The Interactive Data Visualization System

Thanks to the data provided by the server-side web APIs, we designed and implemented web-based interactive data visualizations, focusing on specific needs and social issues [14], [15], [19]. In this paper, we focus on an interactive web-based application designed considering the new needs the COVID-19 outbreak brought about. The interactive system was built using Web Technologies, such as HTML5, CSS3, JavaScript, and frameworks and libraries, such a bootstrap[4], jquery[5], highcharts[6], and leaflet[7]. The interface provides a multilingual feature, with the possibility to choose between Portuguese or English.

The data visualizations provided in the web application have been designed to present the human mobility data in Madeira Island, considering the new reality we are living due to the COVID-19 pandemic. In particular, the system can provide relevant information to: i) stakeholders, to control and predict the COVID-19 diffusion, monitoring the situation in real-time, ii) citizens, who can be assisted by the tool in planning their daily activities based on the crowding level of a specific POI, also considering the new regulations and restrictions. At the same time, users can also contribute to the data collection and/or validation task, providing numerical information about the number of people in a specific POI.

Loading the main page, it is possible to see a map-based data visualization presenting liquid fill gauge charts, drawn in specific areas of the island (Figure 1). The number in the fill gauge chart represents the percentage value computed considering the devices count for the last 60 minutes in a specific area, against the aggregated average value, considering the same 60 minutes, during the selected period. Such a specific period can be manually defined using the two date pickers (*Start Date* and *End Date*), above the map. The default period is from 2020-08-03 to 2020-03-14, the last week before the day the state of emergency was declared in Portugal. Considering that period, in Figure 1, it is possible to see that people acted accordingly with the government recommendations and restrictions since the computed aggregate percentage values were really low, compared with pre COVID-19 values across the island. If pointing to one of the liquid fill gauge chart, it pops up a small information dialog including details about the specific area and value, and the preview of a chart presenting the average distribution frequency of the devices counts, hour by hour, in the selected period (*Start Date* and *End Date*), and with the current hour highlighted using a different color, i.e., purple (as presented in Figure 1). When selecting one liquid fill gauge chart, it is possible to zoom-in into the macro area and visualized the different POIs available in such an area. For example, Figure 2 focuses on the center of Funchal, the largest city and the capital of Madeira, where several POIs (actively monitored by our infrastructure) are available. Conversely, when selecting a specific POI, the focus goes to the char displaying (visualized under the map), that presents i) a bars char of the daily devices count for each day in the selected period and selected POI, ii) a line series presenting the effective and official number of people affected by COVID-19 (datasource: COVID-19 RAM[8]), considering the selected macro area and period. The period can be manually edited (top-right of the chart) or interactively selected using the timeline slider (bottom of the chart), as presented in Figure 3. By default, the period goes from the 1 March to the current date. It is also possible to visualize a narrow time-window, selecting the last week or the last month (starting from the current date - by default - or from the defined end-date). By selecting one specific day, it appears the hourly devices counts chart. Through such a chart, it is also possible to collect data via crowdsourcing. In fact, selecting a specific point on the line series, a dialogue window pop-ups enabling a user to include the estimated number of users in that specific POI, and a description (as shown in Figure 4). In both the charts (i.e., daily and hourly devices counts) the data are displayed in percentage, computed against the higher devices count value detected in the selected time-window (that corresponds to the 100%).

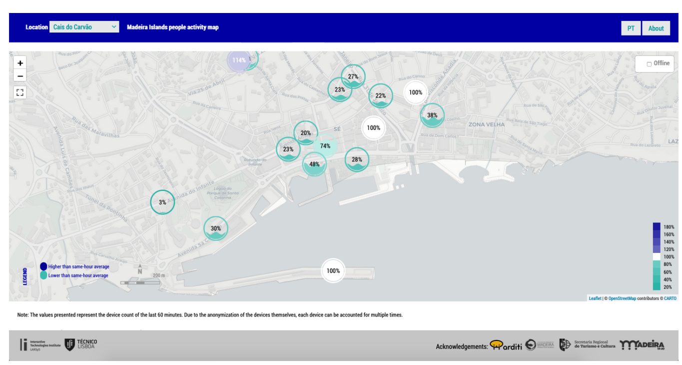

Fig. 2. The interactive data visualization system: detailed information related to Funchal city

V. Discussion and Future Work

The paper presents an interactive visualization of human mobility in Madeira island, data during the COVID-19 outbreak. The data is interpreted as compared with the mobility patterns of the previous weeks. The visualized data

[3]https://nodejs.org/en/
[4]https://getbootstrap.com/
[5]https://jquery.com/
[6]https://www.highcharts.com/
[7]https://leafletjs.com/
[8]https://covidmadeira.pt/dashboard/

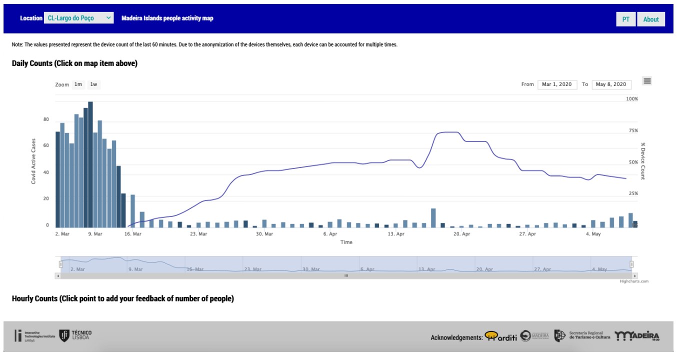

Fig. 3. The interactive data visualization system: daily counts

Fig. 4. The interactive data visualization system: hourly counts

are collected exploiting social sensing, and in particular, a community-based passive Wi-Fi tracking infrastructure. Over four years, the low-cost infrastructure collected more than 572 million data points from a total of 82 routers. The deployed infrastructure demonstrated to be suitable to provide relevant information related to the flow of people during the COVID-19 outbreak and illustrate the changes in the mobility patterns of the island. As future work, we will investigate if such a low-cost community-based system can act as a tool to contrast and prevent COVID-19 spreading.

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