Distributed Opportunistic Wireless Mapplicationing System towards Smart City Service Provision

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Abstract—**The knowledge of wireless signal distribution within an urban scenario can provide useful information to users as well as to enhance connectivity and device operation or to perform municipal logistics based on crowd density and user mobility patterns. In this work, a distributed wireless mapplicationing system, based on a combination of opportunistic nodes such as smartphones which map geolocated WiFi access point connection and received power levels, and a cloud-based information gathering architecture is described. The proposed system and the developed tool has been tested in the framework of the Smart City platform of the city of Pamplona, providing signal distribution heat maps, which can be used for multiple municipal services.**

Keywords—Distributed Wireless Monitoring; Smart City Platforms; Digital Twins; Sensor Network

I. INTRODUCTION

Digital twins are a very interesting applicationroach to define and construct a smart city. The simulations that are made from these digital twins need physical models, sensors and all types of mapplicationings to become a practical and vital tool. One of these mapplicationings that feed these models is the distributed systems of wireless networks that operate in the city. The European Commission is encouraging all these technological solutions to improve the management and efficiency of the urban environment. One of these initiatives is the one covered by EU Horizon 2020 Smart Cities project. Under the umbrella of this project, various cities are providing solutions from different applicationroaches and with the aim of improving the quality of life of citizens. One of these works framed in the Stardust project [1] is the one presented in this paper aimed at contributing ideas and data with which to nurture the initiatives of digital models that may arise in the different partner and follower cities, as well as the rest of the cities of the world that may be interested.

Within the framework of Smart Cities, mapplicationing wireless signals is gaining relevance, owing to multiple aspects related with user information, device handling, context awareness and connectivity enhancement, among others. One of the goals is to monitor interference sources, which can impact the operation of electronic devices and systems, such as massive transceiver IoT deployments [2]. In this line, wireless signal mapplicationing is also being explored in order to provide information to users in relation to human exposure to non-ionizing radiation, usually based in the use of purpose specific personal dosimeters, operating as point receivers or as a set of distributed body receivers [3-5].

Knowledge of wireless signal distribution provides also relevant information in relation with potential security vulnerabilities, which can lead to fairly straightforward attacks, such as denial of service attacks owing to undesired message flooding, interference jamming or man in the middle attacks leading to identity theft or impersonation, among others [6-7].

The massive deployment of WiFi hotspots and public/private WiFi networks in urban scenarios with relatively high radiated power densities has led to the unintentional creation of a wireless power grid. Such grid can be employed in an opportunistic way to power wireless devices using electromagnetic energy harvesting techniques. In dense urban scenarios, hundreds of WiFi access points can be detected from a single location, which potentially can lead to harvest a non-negligible amount of energy depending on the location and transmitted power of such access points. This applicationroach has also been exploited with other wireless technologies [8-10], where high efficiency rectennas are proposed in order to maximize the electromagnetic energy collected. However, in order optimize the use of the WiFi infrastructure deployed to this aim, it is required to have prior knowledge about the expected power densities available in the different locations within a certain urban area. In this sense, the availability of the average energy heatmaps resulting from this work may become a very useful tool.

Another applicationlication that derives from the knowledge of wireless signal distribution is related with crowd sensing, based on the study of signal variations as a function of the number of users, their density and their movement patterns, providing potentially useful information in relation with person heat maps or user mobility analysis, following different mobile network signal capture analysis [11-14].

In this work, a distributed wireless signal mapplicationing system is proposed, based on the use of opportunistic measurement sensors, such as smartphones. The geolocated data of WiFi access points and there received signal level is collected and processed by the monitoring system, capable of interoperating with the Smart City platform in the city of Pamplona, Spain, thanks to a cloud-based scalable architecture. The proposed system gives information which can be employed in multiple applicationlications, such as to inform users in relation with EM signal levels related with human exposure, enhance WiFi based connectivity, crowd sensing processing and potential EM based energy harvesting deployments. On the other hand, the construction of a wireless map with the help of artificial intelligence technology will help to infer useful knowledge and data not only to feed the models of digital twins of smart cities and for the rest of the applicationlications mentioned above, but also to learn in a dynamic way on the behavior of citizens from a different perspective.

II. Distributed Wireless Signal Monitoring System Design

A. *Mobile distributed sensors architecture*

In this case, our sensor network is composed by a set of mobile devices running an application to gather data from the environment when the mobile is operating. In this case, mobile devices collect information about the Service Set Identifier (SSIDs), and the measured Received Signal Strength Indication (RSSI) for each one at a given location in a particular timestamp (data = (timestamp, GPS, {(SSID, RSSI)}). Gathered data is transferred to the cloud, where data is stored, filtered, and analyzed.

Each mobile device operates as a sensor, building all together a distributed sensor network (MASK – Mobile Application Sensor networK). Such sensor network has two main properties: redundancy, and wide coverage. On one side, as mobile devices can be close to each other, and they are capturing information continuously (sampling time can be configured), we could have a lot of redundant information. Filtering algorithms based on device location, SSID names, and timestamp are used to consolidate gathered data in order to get quality data. On the other side, as mobile devices can operate at any place, we are sensing practically every point of the city, granularity of the measures decreases as time increases.

B. *Gathering algorithm*

Each mobile device operates a service in background collecting RSSI information. Figure 1 describes the algorithm followed by this service. The algorithm waits for a parametrized time before looking for active wireless networks in the surrounding area. In case the mobile device can reach any network, it collects the received SSIDs, and RSSI values. Once collected, the mobile device builds JSON packet (see figure 2) and transfers it to the cloud.

```
SensorGatheringData(long delay)
Precondition: GPS is ACTIVE and (WiFi is
  ACTIVE or Bluetooth is ACTIVE)
while (1)
  wait(delay);
  listSSIDs = collectWirelessNetworksSSIDs();
  if (listSSIDs.contains() != emptySet) then
        location = readGPS();
        sendMessageToTheCloud(gettimeofday(),
  location,
              listSSIDs);
```

Fig. 1. Pseudocode of sensor node.

{"timestamp": "2021-06-10 12:31:43.064000", "location": "lat=XXXX; lon= XXXX; altitude=440.4", "listSSID": [{ "ssid": "Vodafone1453", "rssi": -76}, {"ssid": "MiHouse", "rssi": -54}]}

Fig. 2. JSON packet format.

The cloud platform consists of an Apache Kafka component devoted to collect sensor data (data feeds), an Apache NiFi devoted to transform the JSON messages received to SQL sentences, a MySQL database management system where data is properly stored, and, finally, the visualization component in charge of data plotting with the aid of Google Maps. Figure 3 depicts the cloud platform, a simple cascading architecture based on reliable and well-known components.

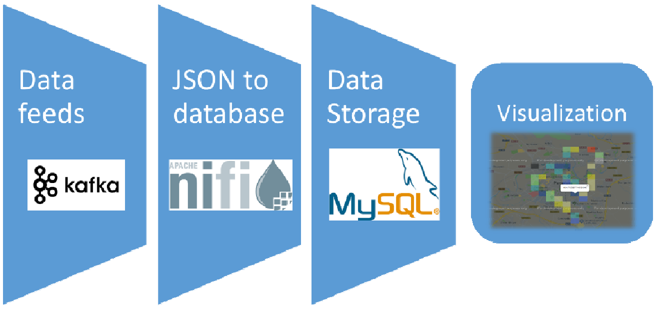


Fig. 3. Schematic description of the employed Cloud platform architecture.

Figure 4 shows the insertion of the JSON file described in Figure 2 into the Kafka's topic, while Figure 5 illustrates the creation process of the NiFi stream that will allow to store the data in the MySQL database.

```
[redacted]@[redacted]:~/Descargas/kafka_2.13-2.8.0$ bin/kafka-console-con
sumer.sh --topic quickstart-events --from-beginning --bootstrap-server loc
alhost:9092
{"timestamp": "2021-06-10 12:31:43.064000", "location": "lat=XXXX; lon= XX
XX; altitude=440.4", "listSSID": [{ "ssid": "Vodafone1453", "rssi": -76},
{"ssid": "MiHouse", "rssi": -54}]}
```

Fig. 4. JSON message submitted to the Kafka component.

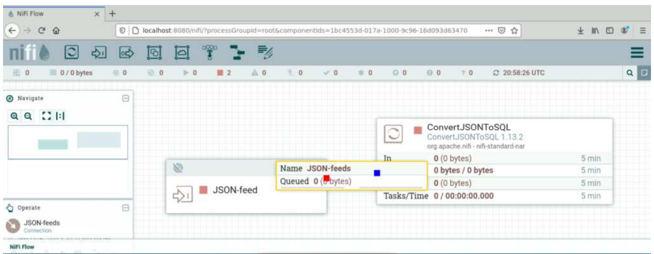
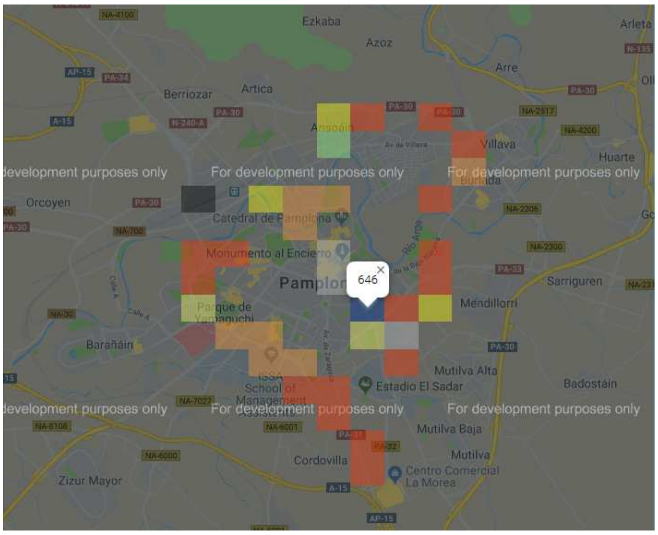
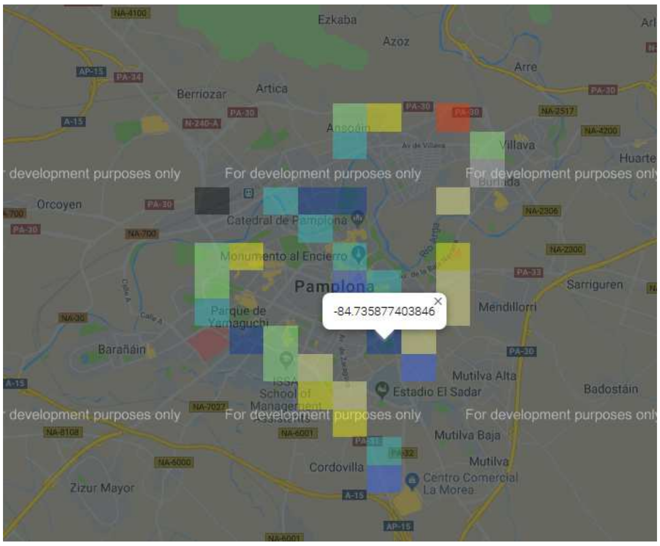


Fig. 5. Example of NiFi stream setup .Measuring scenario

We have measured a sector of the city of Pamplona (Spain). We have tested our mobile sensor network equipping a car with the application and driving through different streets of Pamplona. Gathered data have been used to create a heatmap to show the number of access points at a given location, and the average energy received at a given location. The heatmap is built considering the whole region divided in squares, where their side length is an analysis parameter. Depending on this parameter (square side length), we calculate the results and use a color code to represent graphically the obtained values (red squares means greater values than blue squares) being the reference the maximum value of the complete set of squares. Figure 6 shows two heatmaps, which represent the total amount of Wi-Fi access points detected (a), and the average RSSI measured (b).



a)



b)

Fig. 6. Heatmap with the number of access points (a), and with average RSSI (b).

The example described refers to Wi-Fi networks, but other technologies such as Bluetooth are also considered. The main relevant differences can be found, at the physical level where a Bluetooth receiver is used instead of the Wi-Fi receiver, and at the logical level, where a different channel is used in Kafka and where data is stored into a different database. Different statistical operators can be selected when drawing the heat maps: mean RSSI value, maximum and minimum values, standard deviation, mode, median...

Figure 7 shows the monitoring mobile applicationlication developed. Note that GPS coordinates are null since the capture corresponds to an indoor measurement.

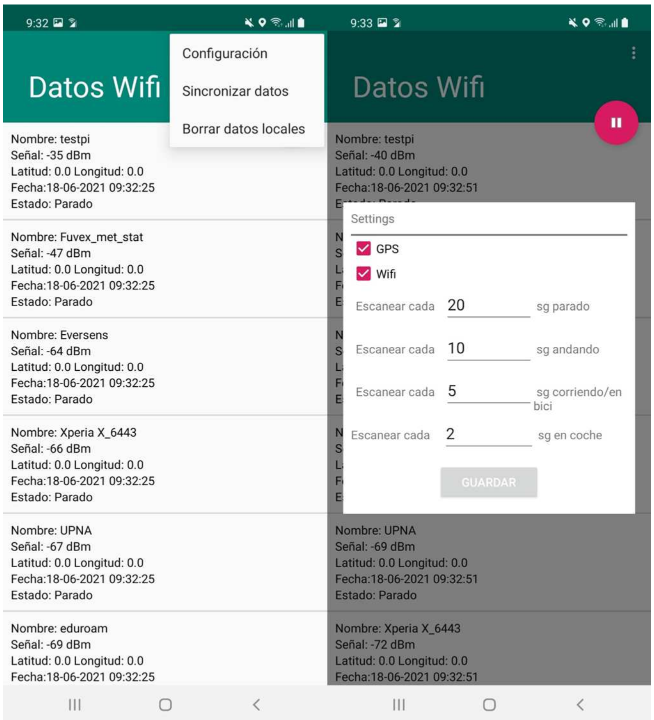


Fig. 7. Monitoring APPLICATION developed (in Spanish) to enable opportunistic signal detection and mapplicationing.

III. CONCLUSIONS

In this work, a distributed wireless mapplicationing system has been described, taking full advantage of opportunistic sensing capabilities. The system employs an ad-hoc implemented applicationlication which obtains geolocated information of Wi-Fi hot-spot SSID as well as RSSI, by taking advantage of smartphones acting as opportunistic sensors. The information is collected and transmitted to a cloud-based architecture, in order to be processed by different applicationlication modules, providing different services, such as human exposure distribution maps, municipal connectivity optimization, crowd sensing processing or EM based energy harvesting signal availability when employing RF rectennas. The proposed system has been deployed and tested within the city of Pamplona, providing comprehensive wireless signal heat maps. Future developments consider the use of alternative wireless systems, the integration of static measurement nodes or further data processing towards enhanced inference and data visualization.

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