Sensor Platform for Counting Users in Public Transport

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Abstract

There is a current trend towards the concentration of populations in large urban centres, thus overloading public transport systems which, because they are not always able to handle high demand, end up having a negative impact on mobility and consequently on the environment. For transport operators to be able to improve the service provided, it is essential that they know the needs of users through passenger counting systems.

To solve this problem, a platform was developed using sensor technologies, infrared and ultrasonic sensors, wireless networks, Wi-Fi, as well as location, to acquire data related to the entry and exit of people, the permanence through the identification of mobile devices and the location of the vehicle through a GPS receiver. It was also implemented an estimation system on a central server with the purpose of calculating the affluence of a vehicle using the data collected.

Although the system tests were performed in a simulated environment, due to the limitations adjacent to the desiase COVID-19, it was verified that the ultrasounds correctly identified the passage of people, showing an F-Measure value above 0.97 for slow and normal speeds. Meanwhile, the identification of mobile devices was not successful due to the fact that the system could not always detect the presence of them. With regard to the geographical location of the vehicle, the system showed a difference of less than 1 meter to the previously defined point, with a standard deviation between 2 to 4 meters. **Keywords:** People Counting; Public Transport; Sensors; Wireless Networks

1. Introduction

Nowadays, it is increasingly common for the population to concentrate in large urban centres, causing enormous pressure on public transport systems, which are not always able to respond effectively to demand. As a result, there is an increase in the number of cars on the road, which despite deteriorating the mobility condition, has a negative impact on the environmental [14, 5].

Reinforcing the transport services has been one of the alternatives to reduce urban traffic [9], however, it is crucial that mobility operators are able to identify the mobility patterns of users in order to match the supply of the service with demand. On the other hand, the entities responsible for managing public areas do not have enough mobility information to plan properly the evolution of the urban areas [7], which reflects in poor service management, causing dissatisfaction among the citizens and degradation of traffic conditions. In addition, and given the current state of the world with regard to the SARS-CoV2 pandemic, new rules had to be adopted in order to minimise the transmission rate. namely to limit the number of people in enclosed spaces, such as public transport [6].

These problems can be addressed by counting the number of users in public transport, however, the current methods are not very effective, essentially for two reasons: first, because there is a significant percentage of passengers who do not validate their ticket on entry, or who do it late; second, because it is not always possible to identify the passenger's exit [4]. For this reason, it is essential to have an automatic and effective passenger counting system in public transports to enable all stakeholders - transport operators and municipalities - to better manage their mobility resources as well as ensure the safety and satisfaction of citizens.

This paper aims to present a solution to these problems, using data from infrared and ultrasonic sensors, mobile devices scanning and a GPS receiver. The data collected is later analysed on a central server in order to estimate the passenger flows and also to identify the mobility pattern on the public transports.

2. Background

2.1. Technologies

The detection of people using wireless networks can be performed by identifying devices in the surroundings, or by verifying those associated with the network. In Wi-Fi and Bluetooth, the identification of the devices is carried out through the MAC address, unique identifier associated with the Network Interface Controller of the device, while in RFID and NFC, the identification of the devices is carried out based on the information that they provide.

The scanning technique is only used in Wi-Fi and Bluetooth technologies. This consists of detecting terminal systems that have the network interface active, even if they are not connected to a network. The identification process consists of capturing and analysing the packets circulating in the access medium. On the other hand, when a device is connected to a wireless network, or to another device, it leaves a record of its identity which, even if provisional, can be consulted in the competent authority. It is possible to identify this record in Wi-Fi, RFID and NFC technologies, however in Bluetooth it is not achievable because the network is usually private, i.e. the association is usually made between users' devices.

Sensors can also be used to identify and count people on public transport. In wireless network detection it is necessary for people to have a mobile device, unlike in sensor technologies, which use only sensor readings. Infrared sensors are best suited for vehicles where the entrance and exit of passengers is done in an orderly manner, since the interruption of the beam or the variation in temperature only gives an indication of movement. Detection by ultrasonic sensors is based on the propagation time of the wave transmitted by the emitter. Initially, the average wave propagation time is calculated under normal conditions, i.e. without any object between the sensors and the surface opposite them. When a person passes in front of the sensors, the wave propagation time decreases or increases substantially because it is reflected at a shorter distance. Thus, whenever the wave propagation time is shorter or much higher than the normal, the passenger can be considered to be entering or exiting the vehicle. Load cells are another technology that can be used, however they are not able to distinguish two or more people simultaneously, since they are only sensitive to the force exerted on the ground and not to the point of contact. Finally, the detection of passengers using video cameras is carried out by using specific algorithms, which first identify the objects and their limits, for locating and tracking purposes, followed by classification methods, to identify people.

For the purposes of counting people, video cameras perform this role most effectively, however, the implementation cost is substantially higher compared to the other technologies studied. In addition to this disadvantage, there are legal issues associated with the General Regulation on Data Protection. If a technology without additional implementation costs is desired, Wi-Fi is the most suitable. In this technology, the detection of devices connected to the Access Point may be carried out through the analysis of MIB but, if the intention is to detect any devices, even if they are not connected to the AP, the scanning technique is the most indicated. Other technologies for identifying people with a relatively low cost are infrared and ultrasound, which are advantageous because they do not require additional devices. On the other hand, they may suffer from environmental interference or occlusion problems. In addition, this type of sensor system requires a physical infrastructure capable of properly protecting the sensors from any type of damage or vandalism. This infrastructure, as well as its installation, is totally dependent on the vehicle's structure, however, it is advisable to hide the wiring inside the vehicle in order to minimise possible cuts or disconnections, and to create boxes and fixing brackets using 3D printing, an economical and easily customisable technology.

2.2. State of the art

There are several systems and articles describing how to use technology to count people, however a relatively small sample was described, since most of the work studied presented common points, namely in the technologies and techniques used to identify and consequently count users in a public space.

The most relevant article in this thesis, RGB-D Video System for Bus Passenger Counting [8], describes an effective system for counting passengers on public transport, using video cameras, however, and as stated in the article RFID-based System for School Children Transportation [2], this type of system has a high implementation cost, as well as may violate some privacy policies.

Regarding the solution presented in the Bluesound system [10], the counting of people passing through a door is done through two types of low cost sensors, ultrasound and passive infrared sensors. Although were only used the ultrasound sensors to count the passages under the door, infrared sensors have also proved to be effective in identifying them, an essential condition for the solution presented in this dissertation. Another relevant aspect in the Bluesound system is the use of the infrared module to determine the direction taken by people. In this way, and by adapting to a public transport, it is possible to determine the number of entrances and exits made in both front and rear doors of the vehicles.

Finally, the Estimating Pedestrian Flows Using

Wi-Fi and Bluetooth system [13] has proven capable of counting users via wireless networks, taking advantage of the Wi-Fi and Bluetooth technologies present in mobile devices. In this way, and using a computational device capable of supporting these technologies in monitoring mode, it is possible to identify the affluence of terminal devices in public transport, particularly in the identification of the time of permanence.

3. Implementation

The system was designed with two main components, bus and central. The first is designed for each vehicle and comprises the data acquisition and preparation, storage in a local database and transfer to the central system. The second aims at storing, processing and presenting the information gathered from all vehicles.

3.1. Bus component

This component consists of a computer device, Raspberry Pi, and infrared and ultrasonic sensors as well as a smartphone to emulate a GPS receiver. Due to the limitations imposed by the COVID-19 disease, it was only possible to develop the user detection system based on the Wi-Fi scanning and ultrasonic sensors.

What regards to the Wi-Fi scanning, the process consists of analysing the packets roaming in the access medium, recording an hash of the MAC address of the devices, the first and last moment in which it became visible, the signal strength as well as the MAC address of the BSSID to which the device is connected. With this information it is possible to find how long a particular device has been kept inside the vehicle, supporting this way other sensor modules. On the other hand, the signal strength gives an indication of the user's proximity to the vehicle's AP, thus indicating its relative position. In order to secure the data throughout the vehicle's itinerary in case of device failure or any other disruption cause, it was defined periods for data acquisition, which proceed a first level of analysis and to gathered and the most important fields.

In the detection of people through ultrasound sensors, the wave propagation time of the ultrasound wave is measured in order to calculate the distance from the sensor to the user at the time of their passage. In this process, and as in the scanning module as well as with the same purposes, a set of measurements are taken over a period of time, being then processed and stored in the local database to be sent to the central system whenever possible.

For the GPS module, the same principle as the scanning and ultrasound module is applied. It was defined periods for data acquisition, which

consisted in acquiring the geodetic coordinates of the vehicle, to calculate the Cartesian coordinates through the formulas 1, 2, 3 and 4, and the correspondent speed, in order to correlate all data acquired from the other modules with the geographical location of the stops, thus provide an overview of the affluence of the bus along its route. Since it was not possible to use a GPS receiver, an Android smartphone and a mobile application were used to acquire all data and to send to the computer device via Bluetooth.

$$R_n = \frac{a}{\sqrt{1 - f(2 - f)(\sin \phi)^2}}$$
(1)

$$x_axis = (R_n + h)\cos\phi\cos\lambda \tag{2}$$

$$y_axis = (R_n + h)\cos\phi\sin\lambda$$
 (3)

$$z_axis = ((1-f)^2 R_n + h) \cos \phi \tag{4}$$

All data acquired from the sensor modules, and after being analysed so that the system could retrieve the most important fields, are stored in a local *sqlite3* database in order to persistently store all the necessary information until they can be sent to the central system. To minimise the impact on the vehicle network associated with the transfer of data to the central system, the connection with the central database is established only when the bus approaches the parking lot, namely when it is less than 100 metres away from it. To calculate the distance between this two points, bus and garage, it is used the formula 5.

$$d = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2 + (z_1 - z_2)^2}$$
 (5)

The connection to with the central database is established through TCP/IP sockets via a Python API named *pymongo*.

3.2. Central component

In order to centralise the core system, for data storage, estimation and reporting purposes, a network attached storage and docker containers were used. This device was deployed in a home environment, and it was reachable through the public IP address of the Internet Service Provider router, through port forwarding rules. Each constituent module runs in a container, separating this way the different workloads.

For the design of the central database, it has been taken into account the characteristics of the non-relational databases, namely the fact that they focus mainly on the availability and consistency of the data after writing operations, as well as on the constant change in the state of the system. From the perspective of IoT, as well as of this dissertation, it is important that the central database is horizontally scalable as also flexible and heterogeneous, making it possible to add data from new sensors without having to change its structure [12]. In addition, it has to provide concurrent capabilities, both for writing and reading, in order to minimise performance issues in case of an increase in the number of accesses. For these reasons, the non-relational database, also called NoSQL, MongoDB, which stores the data in Binary JSON format, was chosen. Each BSON document contains key-value pairs, simplifying the process of analysing and managing the data gathered from the sensor modules [3].

With regard to the estimation module, only the data whose instant of time is coincident with the moments when the vehicle is close to a stop and in the immobile state are considered. For the data acquired from the scanning module, all instants are considered, since the counting of mobile devices is performed by identifying the same device in at least two stops. The estimation process is triggered by a MongoDB feature named change streams, that allows to perform tasks when changes occur in the central database, namely the addition of new data. In the analysis process, the periods of time during which the bus was stationary and close to a stop intended for passenger entry and exit are first identified within a maximum radius of 15 metres. With this information, it is possible to restrict the amount of sensory data and consequently identify the passage of people under the doors. The estimation using Wi-Fi scanning is carried out with the data obtained along the entire route of the vehicle, so it is necessary to identify the first and last instant of time in which a certain mobile device was identified, as well as the registered signal strength.

To count the passage of users through the ultrasound sensors, it is performed an initial data filtering, excluding all the values whose measurements are between the height of the door minus 120 cm (example: 200 cm - 120 cm = 80 cm), and 800 cm. The first measurement was chosen so that the system could account for the passage of children with more and less 12 years old, while the second threshold was defined as an indicative limit for the passage of people, since the wave can be reflected in an opposite direction of the sensors, due to the physiognomy of humans, leading to it not being detected and consequently a relative increase in the wave round trip time value. After the initial filtering, the time difference between two consecutive measurements is calculated and, to be considered a passage, the value has to be below 1 second. The number of entries or exits is then increased after the next value whose difference to the previous one is more than 1 second.

Once the users entrances and exits have been estimated, they are presented on a web page, using various illustrative elements such as graphs, cards and maps. The integration of the web page with the central database is performed through the web framework for Python, Flask [1], which allows the data stored in the database to be sent to the web page, in a JSON format, in order to build the illustrative elements through the parameters selected by the user, namely the career, route direction and departure time of the vehicle. Altering these parameters automatically triggers the acquisition of new data from the database and consequently the updating of these illustrative elements.

4. Results & discussion

In order to test the system, two types of tests were performed: (1) unit tests, to test each module of the system individually, namely the Wi-Fi scanning, ultrasound sensors and location modules, and (2) integration tests, in order to test the integration of at least two modules, which in this case, and mainly due to COVID-19 limitations, were the interconnection between both bus and central components.

4.1. Unit tests - Scanning Wi-Fi

The unit tests on the Wi-Fi scanning module were planned to verify the system's ability to identify the presence of a given mobile device along the vehicle's path, recording the first and last instant it was visible, as well as to verify the ability to recognise the proximity of the mobile device to the AP, through the recorded signal strength. For this purpose, 3 scenarios were considered: (1) device never associates to the network, (2) device is associated to the network, disassociating for a moment and then re-associating, and (3) device is always associated to the network.

In the first scenario, the system was unable to identify the device, since it generates a random MAC address frequently when it is not associated to an AP. This security measure, which is more common in recent smartphones, makes device identification and consequently tracking more difficult. However, it was possible to identify the proximity of the device to the AP, as the recorded signal strength was higher compared with the other devices.

For the second scenario, the system was able to recognise the presence of the mobile device even with periods of disassociation and association, however, it did not recognise the final association to the network, since no BSSID value appeared in the correspondent field. This behaviour showed some inconsistency in the results and consequently reduced the confidence in the tool used.

Finally, for the last scenario, it was possible to

prove that the system was capable to track mobile devices along the vehicle's path, as long as they remains connected to the wireless network.

4.2. Unit tests - Ultrasound sensors

In order to check the performance of the system using ultrasound sensors, a set of tests were defined, at three different speeds - slow, normal and fast, to simulate the passage of a person with reduced mobility, an adult or child under normal conditions, and a person coming at an accelerated pace, respectively. For each series, a total of 100 passages were performed, and at the end a binary evaluation was made to calculate the number of true positives, false positives and false negatives, in order to compute the accuracy and recall, through the formulas 6 and 7, respectively, and consequently the F-Measure of the system, through the formula 8 [11].

$$Precision = \frac{TP}{TP + FP} \tag{6}$$

$$Recall = \frac{TP}{TP + FN} \tag{7}$$

$$F_1 = 2 * \frac{Precision * Recall}{Precision + Recall}$$
(8)

The F-Measure is balanced metric between the accuracy of the system, i.e. the number of actual passages that the system has identified, and the recall, i.e. the number of actual passages that the system was able to identify.

Analysing the results presented in the table 1, it is possible to conclude that the system has an outstanding ability to identify when a person passes under the doors, showing F-Measure values above 0.97 for slow and normal passage speeds. It has, however, some difficult to identify persons when the speed is considerably faster than normal, which can be related with the estimation algorithm or with the measurement frequency of the ultrasound sensors.

4.3. Unit tests - GPS

The third and last of the unit tests, oriented to the GPS module, had the purpose of evaluating the system not only in the recognition of the points for the entrance and exit of passengers, with the respective distance, but also in the duration that the vehicle was immobilised for this purpose. In this way, it was defined a route to be travelled by car with three stopping points to simulate a stop. In the first two stops it was established approximately 1 minute of permanence, while for the third it was defined about 30 seconds. To calculate the approximation of the vehicle to the stops, it was used the Google Maps to gather the exact coordinates of the previously defined points where the vehicle would

have to remain still to simulate the entrance and exit of the passengers.

The test consisted of performing the route five times, making stops in the previously defined locations, for the time referred to in the previous paragraph. Once the data had been acquired, the time spent at these points was calculated, as well as the minimum distance. In order to evaluate the influence of the external environment, such as trees or buildings, it was calculated the standard deviation of the measured distances.

From the analysis of the table 2 it can be concluded that the system was able to easily recognise the approach of the vehicle to the predefined stops, although the measurements showed a small variation. This variation could be related to several factors, such as the accuracy of the GPS receiver, weather conditions, or even the proximity to tall buildings. This last point, can be easily proven with the measurements from the second stop, where is standard deviation of approximately 3 metres. For the other stops the standard deviation is much smaller, due to the characteristics of the surrounding space.

4.4. Integration tests - Bus and central components interconnection

The purpose of the integration test was to verify the system's operation from the data acquisition, by the sensor modules, until their processing in the central component. For this purpose, in this test the system's operation was simulated, recording the first and last data at the time of their acquisition, as well as the total number of records, in order to subsequently confirm them at the time of their receipt in the central component. It was also used The MongoDB database logs as well as the tshark tool, in order to check the data transmission between both system components.

By analysing the events shown at figures 1, 2, 3 and 4, it can be concluded that after the acquisition of the ultrasound data, which occurred between 12:44:00 and 12:45:00, the bus component updated the local database, taking around 4 seconds to complete. After this step, and the data acquisition process was completed, the bus component started, at 12:45:05, transferring the data to the central component, taking in total approximately 7 to 8 seconds. In the central component, and after the process of authentication, which took approximately 2 seconds, the transfer of the information acquired was initiated, becoming then available in the central database for further analysis, which in this case consisted of checking not only the first and last record sent, but also the total number of measurements.

Table 1: Results of tests from the ultrasound module.

	ТР	FN	TN	FP	Precision	Recall	F-Measure
Test #1: Slow Passage	96	4	0	0	1.000	0.960	0.980
Test #2: Normal Passage	95	5	0	0	1.000	0.950	0.974
Test #3: Fast Passage	82	18	0	0	1.000	0.820	0.901

	Stop #1		Stop #2		Stop #3	
	Time interval (Δt)	Distance (m)	Time interval (Δt)	Distance (m)	Time interval (Δt)	Distance (m)
Test #1	16:45:41 -> 16:46:39 (58s)	2.594	16:47:33 -> 16:48:35 (62s)	3.144	16:49:18 -> 16:49:49 (31s)	3.929
Test #2	17:08:41 -> 17:09:45 (64s)	2.966	17:10:38 -> 17:11:42 (64s)	4.709	17:12:20 -> 17:12:51 (31s)	3.282
Test #3	17:13:56 -> 17:14:57 (61s)	1.270	17:15:43 -> 17:16:48 (65s)	8.711	17:17:29 -> 17:18:05 (36s)	3.808
Test #4	17:19:07 -> 17:20:11 (64s)	3.509	17:20:55 -> 17:21:59 (64s)	7.866	17:22:35 -> 17:23:11 (36s)	4.439
Test #5	17:33:27 -> 17:34:26 (59s)	2.132	17:35:10 -> 17:36:20 (70s)	11.378	17:36:55 -> 17:37:26 (31s)	3.742
Average		2.494		7.162		3.840
Std. Deviation		0.761		2.927		0.371

Table 2: F	Results	of tests	from the	GPS module.
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pi@raspberrypi:~/Desktop \$ [12:43:40] Preparing ultra		main.py	
<pre>[12:43:42] Device ready to [12:44:00] Starting ultras [12:45:00] Stoping ultrass</pre>	start sound proc	ess	
[Info] Primeiro registo: 2 Último registo: 2 Total registos: 9	020-12-01		
[12:45:00] Updating local [12:45:04] Exiting ultrass [12:45:04] Clearing all sc [12:45:05] Updating remote [12:45:13] Closing local c [12:45:13] Closing remote [12:45:13] Exiting applica	ound modul heduled pr database latabase co database co	nnection	

Figure 1: Acquisition of ultrasound data.

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	8] Reading stream 7] Gathering data			
Ú	rimeiro registo: ltimo registo: otal registos:		12:44:00.288 12:45:00.278	
~/Deskto	р •100%			

Figure 2: Processing of the data received in the central system.

5. Conclusions

From the results presented, it was concluded that the system is capable of identifying with great precision and recall the passage of people under the doors using ultrasound sensors, mainly at slow and normal passage speeds, presenting F-Measure values above 0.97 (maximum of 1). It was also demonstrated that the system as high ability to identify the location, as well as the time that the vehicle was stationary, for the entry and exit of passengers, with a difference of less than 1 meter to the defined location point, showing a standard deviation of 2 to 4 meters.

On the other hand, the tests performed on the scanning module proved that the tool used did not correctly identify the presence of mobile devices without them being associated to the vehicle's network, thus not representing an added value compared to the analysis of the vehicle's MIB.

As for the general functioning of the system, it was possible to verify, with the integration test, that the system is capable of automatically starting the estimation process after sending the data to the central component, thus demonstrating the automation of the system from data acquisition to its availability to be presented on the web page.

However, it is important to note that the tests were not performed in an ideal scenario, due to the limitations imposed by the COVID-19 disease, so in order to prove the effectiveness and accuracy of the system in the estimation of people entering and leaving public transport, it is necessary to implement the system in a real vehicle and perform the appropriate tests.

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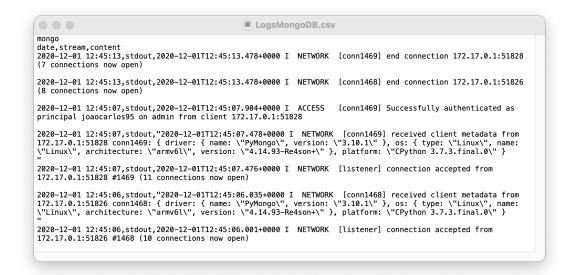


Figure 3: MongoDB database logs, concerning the integration test between the two system components.

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7	2020-12-	01	12:45	:06.	0424	20707	192.10	58.0.	99 →	89.	115.	187.X	(TCP	66	34414	→ 27	7017	[ACK]	Seq=254 Ack=674	
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0	2020-12-	01	12:45	:13.	3273	50673	89.11	5.187	.XX	→ 19	92.16	8.0.9	Э ТСР	66	27017	→ 34	1416	[ACK]	Seg=2414 Ack=2226	55
51	2020-12-	-01	12:45	:13.	3516	78372	89.11	5.187	.XX	→ 19	92.16	8.0.9	Э ТСР	296	2701	7 → 3	34416	[PSH	, ACK] Seq=2414 Ac	k=223476
																			Seq=223476 Ack=26	44
																			reassembled PDU]	
64	2020-12-	-01	12:45	:13.	4779	21812	89.11	5.187	.XX	→ 19	92.16	8.0.9	Э ТСР	229	2701	7 → 3	34416	[PSH	, ACK] Seq=2644 Ac	k=223719
55	2020-12-	-01	12:45	:13.	4780	63810	192.10	58.0.	99 →	89.	115.	187.X	< тср	66	34416	→ 27	7017	[ACK]	Seq=223719 Ack=28	07
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Figure 4: Packages intercepted by the Wireshark probe, running on the Raspberry Pi.

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