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RasPos: Subsurface People Detection and Localization using Wi-Fi Probe Requests

Alexandros EVANGELATOS (Montanuniversität Leoben)*

Robert WENIGHOFER (Montanuniversität Leoben)

Abstract:

Wi-Fi probe requests are defined in the Institute of Electrical and Electronics Engineers (IEEE) 802.11 standard as an active mechanism accelerating the connection process and being repeatedly sent to some devices once per minute on average. They contain the unique MAC address of the device as well as other information, e.g., its type and manufacturer. This paper further pays special attention to the received signal strength indicator (RSSI) value, from which an estimation of the distance can be derived. Locating and positioning people in underground structures is important as complex structures make it difficult for rescue and security forces to direct operations and, in the event of an accident or fire, to evacuate people out of the danger zone as safely and efficiently as possible. Existing systems are being tested for the positioning of the task force as well as for civilian detection via surveillance cameras at the Zentrum am Berg (ZaB). To counteract their limitations, RasPos was developed and tested based on the worldwide increase of smartphone users, which could allow the detection of close to 90% of people. First, the behaviour of the RSSI was investigated, then a modified software was implemented that produced two estimates of the number of people in the vicinity. The first estimate includes only the explicit identified mobile devices, while the second estimate represents the number of all Wi-Fi-enabled devices.

Key Words: Subsurface, Indoor Positioning, Wireless Localization, People Detection, Mobile Wi-Fi

1. Introduction

The aim of this approach is to expand and improve the existing people detection and localization systems under development at the ZaB in Eisenerz. These include the research project NIKE BLUETRACK and a people detection and tracking software applied to the live surveillance camera feeds of the ZaB.

a. Existing Systems

NIKE BLUETRACK was developed primarily for military use in subsurface structures, as underground navigation cannot rely on signals of Global Navigation Satellite Systems (GNSSs)(Mascher et al. 2022; Hofer 2019). Therefore, systems based on short-range communication technologies, such as ultra-wideband (UWB), Wi-Fi and Bluetooth, as well as inertial navigation systems (INSs) are suitable (Kim Geok et al. 2021; Mascher et al. 2022). An INS is based on the inertial measurement unit (IMU), which is mostly built on multiple micro-electro-mechanical systems (MEMSs) due to their robust, low cost, small and lightweight characteristics (Woodman 2007). The requirements of the system were to enable the localization of forces in subsurface structures, which also requires a vertical component, to integrate and visualize this information into 3D models for a field of view in complex structures and furthermore to detect changing body postures such as walking, running, jumping and crawling. These were fulfilled through the use of UWB modules, tags, mounted on each person's helmet, and anchors, placed on premeasured locations, as well as two IMUs per person attached to each shoe. The Fast Tunnel Modelling Tool (FTMT) and the Subsurface Operation Mission Tool (SOMT) are software components for the 3D visualization and mission coordination (Mascher et al. 2022).

*(corresponding author) alexandros.evangelatos@stud.unileoben.ac.at

For the detection and tracking of people in subsurface structures who are not members of the emergency or military forces, i.e., civilians who are not pre-equipped with the devices used in NIKE BLUETRACK, other approaches are required. Therefore, an additional image-processing-based tracking system was installed, which uses the live stream of the surveillance camera system in the optical and thermal spectrum available at the ZaB in combination with a computer vision system based on artificial intelligence. With the known positions of the pre-installed cameras at ZaB, their orientation, the measured size or pixel height of the detected persons and an assumed average size of the actual persons, the position of each can be determined and projected onto a map or into a 3D model in real time. Besides the ability to classify a person as stationary or moving, an algorithm is used for human pose estimation, which can distinguish between standing, sitting and lying (Perko et al. 2021). In addition to the high quantity of previously installed cameras required, this approach also has the disadvantage of being inoperable in conditions of poor visibility such as smoke, for instance, in the event of a fire (Mascher et al. 2022).

b. New Approach

The limitations of the first two methods, the need for special portable equipment on the one hand and the required high density of cameras with the additional drawback of poor viewing conditions on the other, gave the impetus to the idea for RasPos. The abbreviation comes from the use of Raspberry Pis for positioning. The number of adult smartphone users worldwide is increasing and was above 80% in 2021, reaching higher percentages in the USA (85%), Germany (89%) and Austria (87%)(Statista 2022c; Pew Research Center 2021; Statista 2022b, 2022a). Therefore, the ability to scan and detect individual smartphones in a certain area could help to locate almost 90% of people. There are already numerous scientific papers dealing with indoor localization, even with positioning in underground mine tunnels, but many of them use a specific transmitter, require the transmission of explicit signals, or try to achieve a significantly higher positioning precision by means of complex antenna arrays, which would not be necessary in this case (Cypriani et al. 2013; Sadowski and Spachos 2018; Hou et al. 2018; Huang et al. 2021). A requirement of the system to use only information that is already exposed, for instance, by smartphone Wi-Fi chips, and does not necessitate any changes to the hardware or firmware. Nevertheless, the system allows for many different approaches to localizing the origin of the signal. The different methods rely on direction-based parameters, such as angle of arrival (AOA), which requires antenna arrays, or distance-based parameters for signal measurement, such as time of arrival (TOA), which requires time synchronisation, and signal-based systems, such as received signal strength (RSS)(Kim Geok et al. 2021). The simplicity of RSS systems along with the abundance of literature and publicly available software were decisive for their selection.

The RSSI is used to describe the total signal power received in milliwatts, usually expressed in the logarithmic scale of decibel-milliwatts (dBm), where typical values would be above -60 dBm for a very strong and below -100 dBm for a low signal level (Sauter 2014). Localization systems using RSSI are based on the decrease of signal strength with increasing distance between transmitter and receiver, which however strongly depends on the output signal strength, in this case on the individual Wi-Fi enabled device, as well as its orientation and environment (Hou et al. 2018). The signals considered in this paper are so-called probe requests, which can be obtained with wireless sniffers and contain the unique MAC address of the device along with other information, e.g., its type and manufacturer (Vattapparamban et al. 2016). Probe requests are defined in the IEEE 802.11 standard as an active mechanism accelerating the Wi-Fi connection process and being repeatedly sent to some devices once per minute on average, but intervals strongly depend on the manufacturer, model, operating system (OS) and settings (Freudiger 2015).

2. Design

The software used in this paper is a slightly modified python script of a contribution on GitHub, running on Linux and installed on a Raspberry Pi with an additional USB Wi-Fi adapter that supports monitor mode, which allows to monitor all traffic received on a wireless channel (Schollz 2017). The Raspberry Pi is an affordable, uncased and credit-card sized computer developed in 2012 at the University of Cambridge's Computer Laboratory, that can run from a portable battery and was therefore suitable for the use in this paper (Brock et al. 2013). Trials were held on the authors Raspberry Pi model 3B+ as well as on the authors laptop using a virtual machine for the Linux based software, both with a USB Wi-Fi adapter.

To observe the effect of increasing distance between the transmitter and receiver on the RSSI, attention was paid only to the RSSI values measured in the initial tests with the monitor mode-enabled USB Wi-Fi adapter and using the authors two mobile phones, i.e., a Realme GT Master Edition and a Xiaomi Redmi Note 3, as probe request transmitters. The test was carried out indoors avoiding disruptive interactions with the surroundings. After five measurements, at a distance from very close to four meters, an additional measurement was taken with the authors body placed in between close to the transmitter, to simulate maximum effect on signal strength of a person carrying the mobile phone on the body. To detect effects of different orientations of the transmitter in relation to the receiver, the mobile phones were placed in a subsequent test at a distance of one meter from the receiver in six different orientations, whereby, for instance, in the case of "Face" in Figure 2, the surface normal of the display was directed towards the receiver. The results of both tests can be viewed in Section 3.a.

To evaluate the approach of RasPos, the modified software mentioned above was carried out near a public building with the authors laptop as well as the Raspberry Pi, both systems showing similar results. Since the execution took place in an environment surrounded by a large number of different Wi-Fi devices, especially as they were not only smartphones but also network devices such as routers, the code had to be furthermore adapted. The observation duration setting already included in the programme was set to 120 seconds, as a more satisfactory number of nearby devices could be found. Other options included in the software, e.g., an adjustment of the person estimation based on the percentage of people with smartphones, were deactivated. Results and a terminal output can be viewed in Section 3.b.

3. Results and Evaluation

a. Testing RSSI

The effect of increasing distance, from very close to four meters, between the transmitter and receiver on the RSSI as well as the effect of a human body close to the transmitter and in between the one-meter distant receiver can be viewed in Figure 1. Figure 2 shows the effect of six different orientations of the transmitter relative to the receiver at a constant distance of 1 meter. Both Figures include the results of the Realme GT Master Edition and a Xiaomi Redmi Note 3.

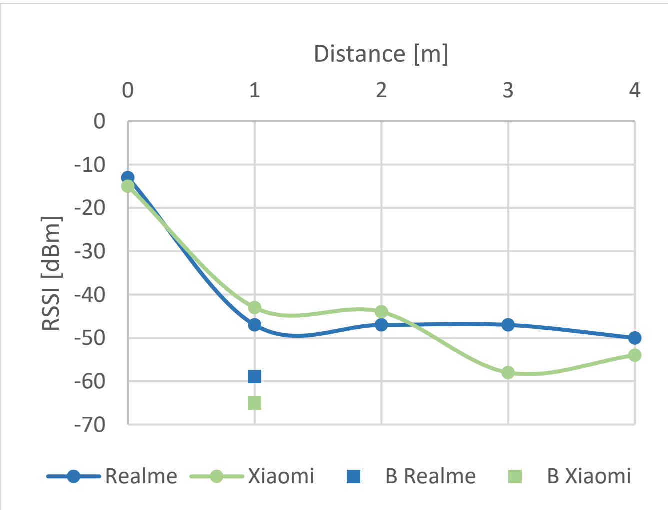

Figure 1: The effect of increasing distance between the transmitter and receiver on the RSSI and the effect of a human body close to the transmitter (B)

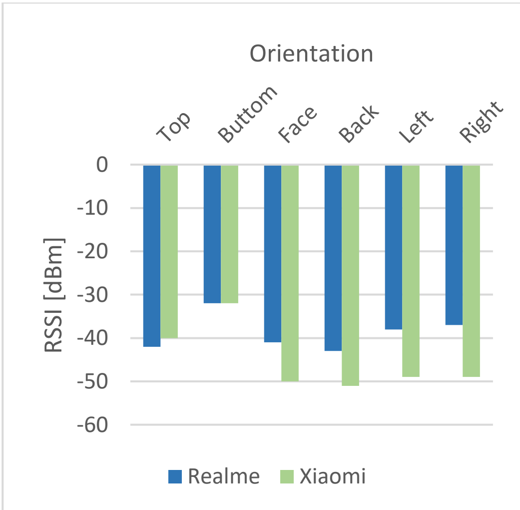

Figure 2: The effect of different orientations of the transmitter relative to the receiver at a constant distance of 1 meter

For a better significance, the measurements of the RSSI should be carried out over longer distances with a high number of repetitions as well as with several other mobile phones. Nonetheless, the tests show similarities to the reference (Hou et al. 2018), which runs the RSSI up to 50 metres.

b. Testing the Python Script

The python script from reference (Schollz 2017) was tested with slight modifications as described in Section 2 in a public building on the Raspberry Pi and laptop. A typical terminal output would be:

"There are about 8 people around (Phones with known OUI only).
But up to 23 people, including all devices."

There are two estimations for the number of nearby people in the terminal output, since the system first compares the received MAC addresses in the public database of the IEEE with the organisationally unique identifier (OUI) and initially only includes them if they are from smartphones. The second estimate considers all MAC addresses obtained. The high difference between the two assumptions can be explained by the dense network coverage in public areas but would be drastically reduced in a highly isolated environment, such as underground facilities, where there is usually no Wi-Fi network coverage.

c. Evaluation

In Section 3.a the drop in RSSI already shows strong fluctuations within a few metres distance in relation to different transmitters as well as the possible strong attenuation effect due to wearing the device close to the body. Also, the electromagnetic waves do not propagate evenly around the mobile phones, which is why their orientation can lead to fluctuations in the RSSI. Both effects do not prevent the localization of people but can cause a low positioning accuracy in case of crisis scenarios. The successful tests in Section 3.b confirm the possibility of detecting people via the transmitted probe request of their Wi-Fi-enabled devices but revealed additional limitations of the method described in Section 3.d. Therefore, from the author's point of view, this method should only be used as an additional support for the rescue and security forces to estimate the number of people in a certain area of the facility.

d. Limitations

Although increasing, the proportion of adults with a smartphone is below 90%. However, in an environment, for example, with many children, higher deviations between the number of identified smartphones and people are to be expected. Since all Wi-Fi enabled devices are detected, such as some smartwatches, laptops that are switched on, eBook readers, tablets and even cars, the second estimation of people can be significantly higher. In addition, smartphones may not be detected because they are not clearly listed as a mobile device in the OUI and would therefore not be included in the first estimation of nearby people. The frequency of the probe requests sent depends strongly on the respective manufacturer and operating system and can be much less frequent than about once per minute. Generally, in addition to the fluctuations of the RSSI, this leads to point positioning with large distances depending on the speed of movement and represents a drawback to the localization of people in crisis scenarios.

4. Conclusions and Future Work

The approach proposed in this paper demonstrates the ability to detect and locate people via the probe requests of their smartphones. For this purpose, tests were first carried out to observe the behaviour of the RSSI at increasing distances and for the case if the transmitter is carried close to a body. A further test showed the different signal strength propagation influenced by the orientation of the devices. Finally, a slightly modified python program based on the reference (Schollz 2017) was successfully tested, which gave two estimates of the number of people in a given area. In the first estimation, only MAC addresses are included that are listed as mobile devices in the manufacturer specific OUI and can therefore be identified as mobile phones. A second estimation was added as not all devices are listed in the OUI or are not clearly identifiable as a mobile device. Therefore, the second estimate represents the number of all Wi-Fi enabled devices in the area. Although, as described in the limitations of Section 3.d, no accurate continuous trajectories of people can be recorded due to the low frequency of probe requests sent, the system nevertheless could be used as an estimate of the number of people present in the facility to assist rescue and security forces, especially in areas with low camera density and where visibility is impaired in case of fire.

With the system presented, several detection devices connected and placed at specific locations, for example in case of a tunnel at the portals and in cross passages, could roughly record the movements of individual people. Further tests of the RSSI at greater distances as well as the effect of objects such as vehicles on the propagation in an underground facility are to be researched. In addition, experiments with similar public software from reference (Schollz 2016) and at least three devices, i.e., Raspberry Pis, using triangulation and machine learning could significantly increase the positioning accuracy of a RSSI approach. Based on this, there are more advanced systems from reference (Schollz 2018), which also include the detection of Bluetooth signals in the near environment, with which further tests could be implemented in subsurface structures.

Another approach could be realized in combination with the NIKE BLUETRACK system by loading the software presented in this paper and its possible extensions on their UWB modules. The dynamic localization and positioning of the UWB modules would additionally allow the detection of different devices near a particular task force member, which in turn could provide an estimate of the persons in the vicinity, e.g., even before they enter the field of view.

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