A Wireless Low-power System for Digital Identification of Examinees (Including Covid-19 Checks)

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Keywords: Indoor Navigation, Indoor Localisation, Low-power Devices, Internet of Things, RSSI, BLE Beacons.

Abstract: Indoor localization has been, for the past decade, a subject under intense development. There is, however, no currently available solution that covers all possible scenarios. Received Signal Strength Indicator (RSSI) based methods, although the most widely researched, still suffer from problems due to environment noise. In this paper, we present a system using Bluetooth Low Energy (BLE) beacons attached to the desks to localize students in exam rooms and, at the same time, automatically register them for the given exam. By using Kalman Filters (KFs) and discretizing the location task, the presented solution is capable of achieving 100% accuracy within a distance of 45cm from the center of the desk. As the pandemic gets more controlled, with our lives slowly transitioning back to normal, there are still sanitary measures being applied. An example being the necessity to show a certification of vaccination or previous disease. Those certifications need to be manually checked for everyone entering the university's building, which requires time and staff. With that in mind, the automatic check for Covid certificates feature is also built into our system.

1 INTRODUCTION

Industry projections estimate that nearly 75 billion Internet-of-Things (IoT) devices will be online by 2025 (Ikpehai et al., 2019). A common IoT application is to provide location services in indoor environments. The indoor localization and navigation involving the use of Received Signal Strength Indicator (RSSI) information of radio signals is an area in active development (Spachos et al., 2018). As Global Navigation Satellite Systems (GNSS) systems are not suitable for the indoor application (Laoudias et al., 2018), most attempts used RSSI information from WiFi or Bluetooth signals, emitted by routers and Bluetooth Low Energy (BLE) beacons, respectively (Zafari et al., 2019).

In order to perform localization, signal fingerprinting is commonly applied and performed in a two phase process (He and Chan, 2016). First, the RSSI fingerprint of each emitter in the room/building has to be collected, this phase is denominated the "offline" one. During the "online" phase, the collected signals used to build a signal map of the scanned environment enables the location by means of trilateration, when 3 beacons are detected, or by multilateration, in case more beacons are detected (Spachos et al., 2018).

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In 2020, the whole world was hit by surprise by the outbreak caused by the Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2). It forced governments for actions inhibiting the spread of the deadly disease. Lockdowns and curfews were imposed, masks were made mandatory and places where social gatherings used to take place, like restaurants, had to be closed and offices and universities had to move to an online format (Ciotti et al., 2020).

At the OTH Regensburg, all lectures were converted to the online format. However, the exams were still held in presence. This required some adaptations. The room should allow the placement of the desks up to 2 meters apart, and all students obligatory should wear a mask during the period of the exam. Each student was assigned to a table, before leaving the room he/she should inform this to the examiner.

In parallel, contact tracing measurements for positive tested persons were adopted. At first, manually by health vigilance professionals, but, as far as the number of infected individuals increased exponentially, it quickly turned out unfeasible. Thus, governmental and private companies developed mobile applications for the tracking of infected individuals and their contacts, detecting the Bluetooth signals of the nearby devices (Li and Guo, 2020). However, this approach had some pitfalls. As the determination of the

Nunes, D. and Volbert, K.
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DOI: 10.5220/0010912800003118
In *Proceedings of the 11th International Conference on Sensor Networks (SENSORNETS 2022)*, pages 51-59
ISBN: 978-989-758-551-7; ISSN: 2184-4380

distance between 2 phones is based on the RSSI, this information can be affected by multiple factors as the multipath signal propagation, interference, or simply different power levels of the Bluetooth signal of the different smartphones, resulting in imprecise and inconsistent measurements (Ahmed et al., 2020).

In this study, we present a different approach to indoor location that solves the problems involving RSSI based distance estimation for both contact tracing as well as for indoor localization. For this, BLE beacons were attached to each desk and used as anchors, therefore, with no need to rely on trilateration / multilateration methods using the RSSI information from multiple beacons to locate. By filtering the environmental noise with Kalman Filters (KFs) and discretizing the location task, it allows to achieve better metrics, as well as more efficient contact tracing, all comprised in a single phase with no need for calibration, saving a considerable amount of time.

The developed solution also allows automatic checkup of Covid vaccination or previous infection certificates, user identification and exam registration with no need of the user's interaction.

Section 2 shows the related work; Section 3 presents the motivations and the goals of this study; Section 4 reports the description of the hardware; Section 5 presents the architecture of the system and the software stack. Section 6 shows the accuracy of the system, section 7 the conclusion and further studies.

2 RELATED WORK

In recent years, wireless systems especially so-called low-power or even ultra-low-power wireless systems become more and more popular. In the theoretical area (Schindelhauer et al., 2007; Lukovszki et al., 2006; Meyer auf der Heide et al., 2004) as well as in practice, with applications like smart metering, smart submetering, and/or smart grid (Kenner et al., 2017).

Concerning indoor localization, recent studies have shown that it is possible to achieve sub-meter precision in indoor scenarios using various techniques and technologies.

Klipp et al. reported that it is possible to achieve sub-meter precision localization by using magnetic signatures in combination with Inertial Measurement Unit (IMU) data. The results, however, depend on an unambiguous magnetic disturbance pattern and a known initial position (Klipp et al., 2018).

Neges et al. have presented a solution combining IMU information with natural visual markers, not requiring investments in additional infrastructure (Neges et al., 2017). Gong et al., presented a similar method, using Convolutional Neural Networks (CNNs) to perform image recognition and enable localization, achieving an error rate of 2.3 meters (Gong et al., 2021). These methods still require a calibration phase to collect the natural markers and a high degree of user interaction to work.

Despite early claims of the unreliability of RSSI-based methods (Dong and Dargie, 2012), many developed solutions are based on these methods due to its ease of use and implementation and the wide hardware availability (El-Sheimy and Li, 2021).

The RSSI value, measured in *dBm*, is given by the following equation (Dong and Dargie, 2012):

$$\mathrm{RSSI} = -10 \cdot n \cdot \log_{10}(d) - A \tag{1}$$

In Equation 1, n is the signal propagation constant in the environment, d is the distance between the student's smartphone and the BLE beacon attached to the desk and A is a reference received signal strength in *dBm*. It represents the value measured when the distance between the smartphone and the BLE beacon is one meter. RSSI Values closer to zero indicate a stronger signal.

RSSI-based methods are highly subjected to instabilities (Xiao et al., 2013) which may alter the signal map collected before an exam. This is due to errors such as multipath signal propagation, Non-Line-of-Sight (NLoS) conditions, and signal interference.

To mitigate the signal instabilities, KFs can be applied to reduce the impact of noise in the environment (Bulten et al., 2016). Mackey et al. has shown an improvement in the localization accuracy of up to 78.9% in a four beacon setup (Mackey et al., 2018).

Many works apply a fingerprinting approach to perform indoor localization using the RSSI and channel state information (CSI) based information (Alhomayani and Mahoor, 2020). Luo and Gao have shown improved localization accuracy when employing Deep Belief Networks for fingerprinting on Ultra Wide Band (UWB) signals (Luo and Gao, 2016) and Ayyalasomayajula et al. introduced a two-step process applying CNNs on WiFi CSI data (Ayyalasomayajula et al., 2020). These methods, however, lack of support in consumer devices and require a higher energy consumption (on the client-side) when compared to BLE, respectively. Another problem involving fingerprinting approaches emerges by the fact that it is subjected to inconsistencies between the data collected during the "offline" phase and the data being presented during the "online" phase. Fingerprinting in an empty room would generate a different signal map than when done in a room full of students.

This paper describes a simple approach to indoor localization that uses BLE beacons as anchors, therefore, avoiding weaknesses and extra complexity involving signal trilateration or fingerprinting. The task consists of finding the closest beacon instead of calculating the distance itself.

3 MOTIVATION AND GOALS

While the pandemic is getting more controlled, our lives are slowly transitioning back to normal social activities, but there will still be a need for sanitary vigilance in all spheres of the society, as safety distance, the wear of face masks, vaccination/previous infection certification, and the further integration of contact tracing apps.

Actually in Germany, for any subject to enter the university building it is necessary to present a certification of vaccination or previous disease, or a negative Covid test (not older than 24 hours). In scenarios with more intense social gathering as restaurants or bars, in addition to the previously mentioned measurements, a manual registration step, which one has to share his/her contact information through a QR code or through the Luca App[1], is required. All these steps need to done repetitively by each customer.

As all certifications and registrations on the app have to be checked by the staff before entering the venue. Although all these checks and measurements are necessary, they will slow down a previously fluid process, creating unnecessary waiting queues, beside increasing the human error.

Another problem which emerges from this process is the necessity of the precise registration of the check-out time, to avoid false warning of contact with a positive infected person, due to a false timeline overlap of the presence. The Luca App offers an "auto-check out" function, however, it requires, however, access to GPS, rising privacy concerns.

At the OTH Regensburg, all these difficulties would be seen during the exams in presence, with additional steps as the proof of identity and the examinee's signature of the list confirming that he/she had taken the exam. In order to reduce the manual actions required for the registration and consequently, the waiting time for the students enrolled in the exam, and the work load of the examiner, normally the professor, we developed an app integrated to the system of the faculty, which enables the automatic registration for the exam, the check in/out time, as well as the precise localization of each user in the room. The system also reduced the need of repetitive checks of Covid certificate by staff. The user needs minimal interaction with the app, just being required a one time user account setup step, similar to the Luca App. The integration of our app with the system of the faculty facilitates the students' identification, and automatically inserts his/her presence into the faculty system.

With these problems in mind, we developed a system that enables the automatic check in/out step and the registration into an exam as well as the precise location of the user in the room. It also completely eliminates the need from repetitive Covid certificate checks by the staff, all that, at the same time, requiring no user interaction with the app. The only interaction required with the App is a one time user account setup step, similar to what is done in the Luca App, but with integration with the faculty's system.

This system also facilitates and improves contact tracing. The automatic registration for check- in and check- out also facilitates and improves the correct contact tracing, minimizing false positives. The more precise desk localization of each examinee based on discrete and not on distance inferred from RSSI data, also allows the identification of at risk neighbours (within a distance of 4 desks) to an infected person, limiting the necessary notification.

As we discuss in section 7, this system could be adapted and applied to other contexts like restaurants and other events.

4 HARDWARE

For this work, ten iBKS105 BLE beacons from the Spanish manufacturer Accent Systems were used.

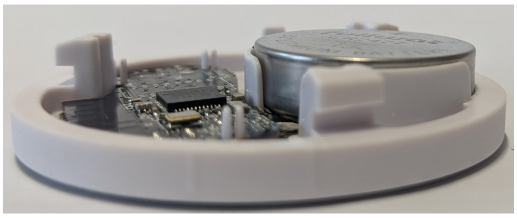
The use of ultra-low power solutions was considered, as they would require less power and, therefore, have easier maintenance regarding the batteries. The use of BLE beacons was chosen, however, due to the ease of development, compatibility with technologies currently present in smartphones, thus with no requirement for special gateways (Kenner and Volbert, 2016; Altmann et al., 2017).

The beacons have a diameter of 52.6 mm and a thickness of 11.3 mm (closed case). Figure 1 show a view of it inserted in its acrylonitrile butadiene styrene (ABS) case.

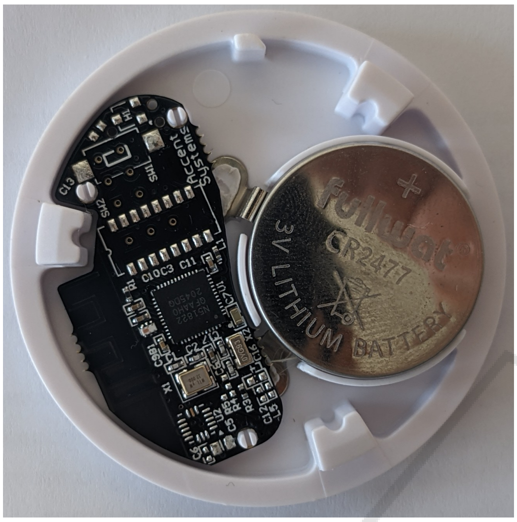
Each beacon is powered by a nRF51822 Bluetooth Low Energy System-on-a-Chip (SoC) from Nordic Semiconductor and a CR2477 coin cell 3V battery. It has a programmable output power from +4 dBm to -30 dBm, 4 available Eddystone slots, with 4 possible frames (UID, URL, TLM and EID) and 2 available iBeacon slots.

The selection of the beacons was based on their high quality, the ease of their configuration, and their affordable price, with each unit costing 13€. The con-

[1] See https://www.luca-app.de/system-2/



(a) View from the side.



(b) View from the top.

Figure 1: Example of beacon used. It has 52.6 mm of diameter and 11.3 mm of thickness.

figuration of the beacons was performed by the app provided by the manufacturer, iBKS Configure.

The app also allows for Over-The-Air (OTA) updates, so there is also no need to develop update protocols (Schwindl et al., 2019).

The beacons were configured to transmit only one Eddystone frame containing the beacon's UID. This is performed 3 times a second with a transmission power set to -30 dBm. This low transmission power was set to assure that nearby beacons would not interfere with each other, as well as to extend the life of the battery, estimating the consumption to about 97.78 μA, with an expected battery life of 14 months. All other slots were disabled with the same intention.

5 SOFTWARE

In the following Section we present the software used to build the presented system. An overview of the architecture of the system can be seen in Figure 2. The data flow diagrams from the students' and examiner's perspective is presented in figures 3 and 4, respectively. The localization algorithm is shown in Figure 5. The communication between the mobile Apps and the server is done through a REST API (Masse, 2011).

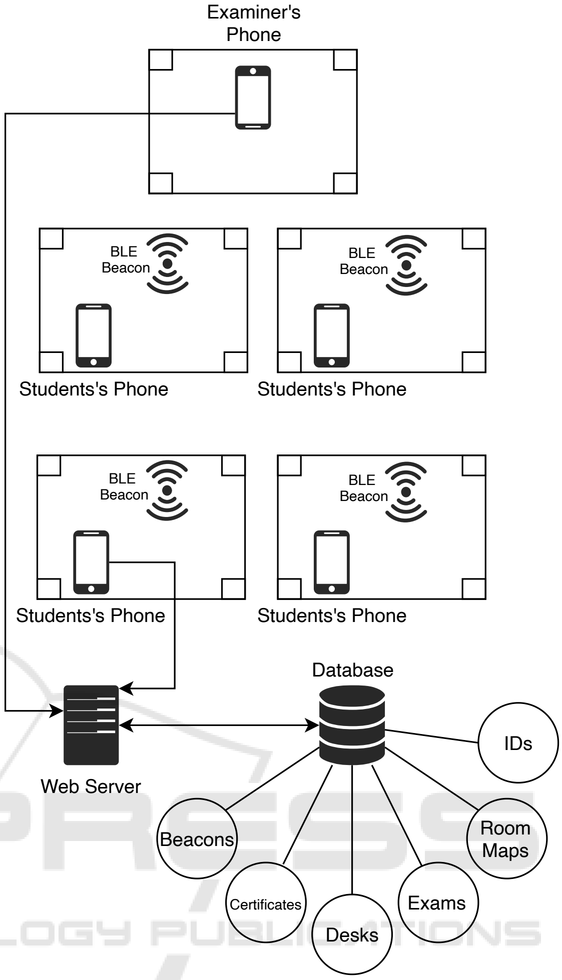


Figure 2: System's Architecture.

5.1 Mobile Apps

The mobile Apps are the central part of this system, having one app to be used by the students, and a second one by the examiner.

Both apps were written using the React Native framework (Eisenman, 2015), as it enables rapid development and testing, with support for hot-reloading. It also eases multi-platform development, allowing the sharing of most of the code base between both iOS and Android apps.

The student's app was designed to require the less amount of user interaction as possible to work.

For the first use, the student will register with his/her university credentials, thus, allowing access to their examination schedules. The app will ask for the upload of the certification of vaccination or recovery.

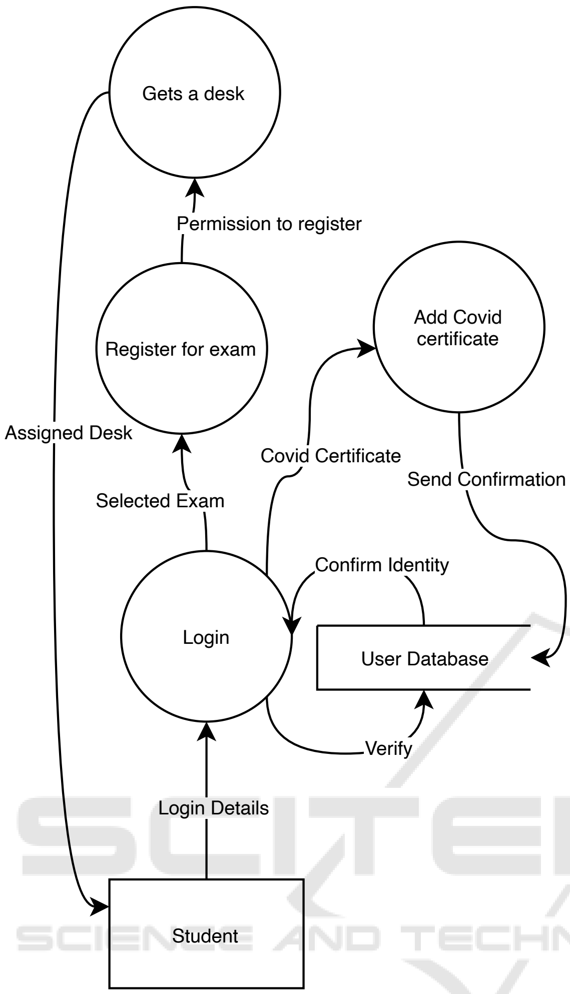


Figure 3: System's Data flow Diagram from the user's perspective.

It will then scan the uploaded pdf or picture and extract the QR code that it holds. This QR code will then be decoded, extracting the Base45 encoded CBOR Web Token (CWT). The Base45 encoded CWT will then be sent to a self-hosted instance of the Open Covid Certificate Validator API[2]. The API response will contain, between other pieces of information, a Boolean value indicating if the uploaded certificate is valid or not. Except for this information, no other information is stored neither in the student's smartphone nor in the servers.

The student will receive the confirmation of the registration with an assigned desk and a map of the room, which are then stored by the app, facilitating the localization of his/her desk.

With his/her user setup complete, there is no more

[2]https://github.com/merlinschumacher/Open-Covid-Certificate-Validator

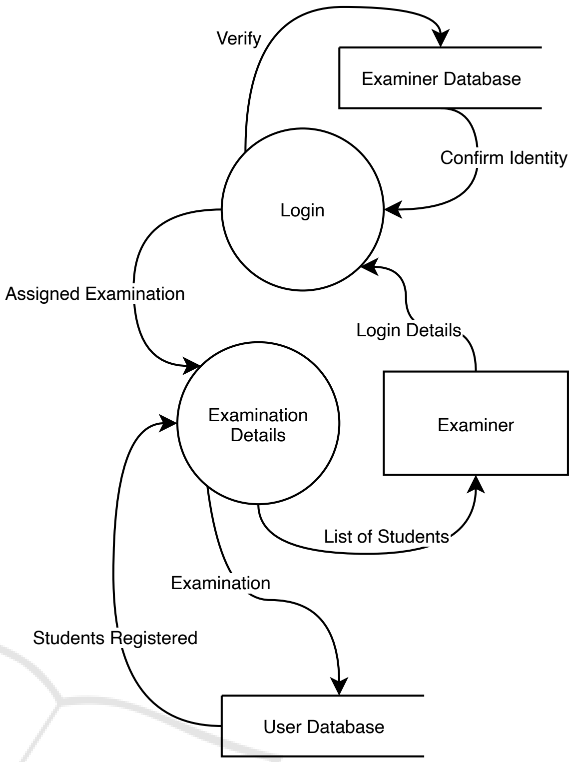


Figure 4: System's Data flow Diagram from the examiner's perspective.

required interaction of the user with the app. The app will run as a background process, shortly scanning for nearby beacons every fifteen minutes.

When the app detects a known beacon (one that match the set UID), it will start a foreground service (Android) for the app to increase the rate of signals being collected. Due to the already mentioned unstable nature of BLE signals, KFs were used to stabilise the signals of the beacons.

KFs are recursive stochastic filters and will be used to process and smooth the noisy RSSI information received by the smartphone. For that, one-dimensional KFs were used.

A KF is divided in two stages, prediction and update. In the prediction stage, the current state of system and the next state estimate uncertainty are predicted through the Equations 2 and 3, respectively.

In the update stage, a new Kalman gain is calculated using Equation 4 and the state estimate uncertainty is updated following Equation 5.

The filtered signal is obtained by the following equation:

$$\hat{x}_{n,n} = \hat{x}_{n,n-1} + K_n(z_n - \hat{x}_{n,n-1}) \qquad (2)$$

Where $\hat{x}_{n,n-1}$ is the previous system state estimate, K_n the Kalman gain, obtained by Equation 4, and z_n the measured system state.

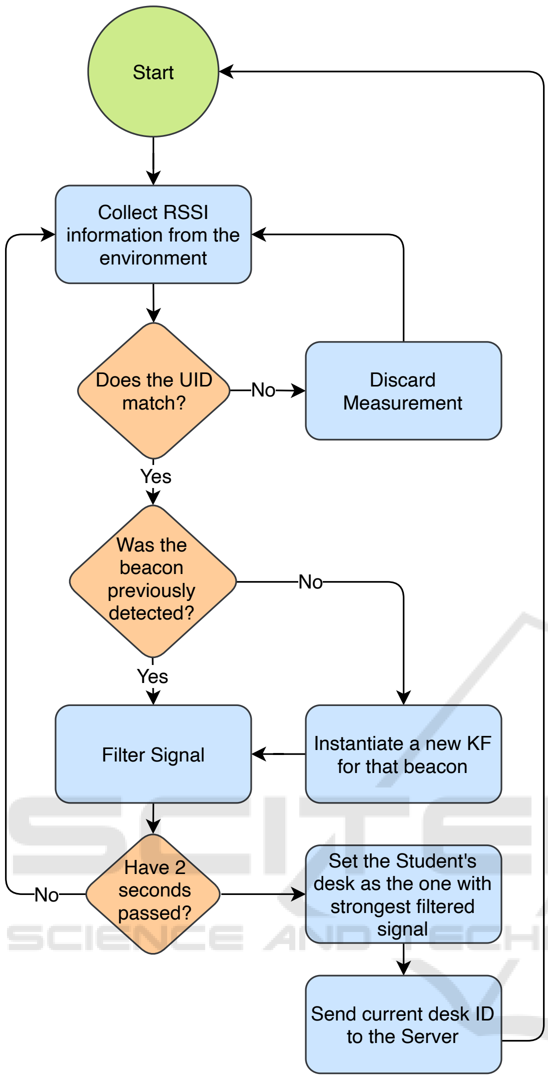


Figure 5: Flowchart of the localization algorithm.

The prediction of the next state estimate uncertainty is performed as follows:

$$p_{n+1,n} = p_{n,n} + q_n \tag{3}$$

Where $p_{n,n}$ is the current state estimate uncertainty and q_n the process noise variance, which is the variance of the uncertainty of our dynamic model.

The Kalman gain is calculated by the equation:

$$K_n = \frac{p_{n,n-1}}{p_{n,n-1} + r_n} \tag{4}$$

Where r_n is the measurement error, calculated by Equation 5, and $p_{n,n-1}$ represents the estimate uncertainty calculated during the previous filter estimation. The Kalman gain the intensity of which the estimate will change given a measurement.

The update of the current state estimate uncertainty is done by:

$$p_{n,n} = (1 - K_n)p_{n,n-1} \tag{5}$$

The app will localize the student and the desk at every two seconds, avoiding false positioning due to loss of signal. An overview of the localization algorithm is shown in Figure 5.

If a student is not sitting on his/her correct desk, the app will vibrate, indicating the error. Simultaneously, the examiner will receive the information of the incorrect match between the student and the desk, to adjust the positioning promptly before the beginning of the exam. The student being recognized on the correct desk, automatically will be registered as ”taking the exam”, sending this information to the backend server, making it available for the examiner’s app.

The examiner’s app is designed as a more traditional app. The examiner will login with his/her university credentials, allowing to access the list of exams, the layout of the examination rooms, the list of student’s who registered for the exam and the desks they were assigned to. The examiner will receive a map of the occupied and free desks, at the end of the exam generating a list of the students who attended. If necessary, the examiner can replace a student to another desk on the app.

5.2 Backend Server

The backend server was implemented using the FastAPI Python framework (Voron, 2021). It was chosen due to its simplicity and development speed.

In the current state of the system, the backend is a simple component. It has to perform only two tasks: to query and store the data of both apps, and to assign each student a desk.

A PostgreSQL database (Obe and Hsu, 2017) was used to store the student’s and the examiner’s data. For the students, their credentials, registered exams and each assigned desk, and the confirmation of a Covid certificate are stored, and for the examiners, their credentials and assigned exams. The map of the examination room and the localization of each beacon are also stored in the database.

6 EVALUATION

As the localization through the beacons is the most critical part of the system, we performed a series of tests to analyse the reliability of the signal localization of each beacon and the limits of the system.

The tests were performed in the laboratory of Intelligent and Connected Systems in the computer science building at the OTH Regensburg. Ten beacons, numbered from 1 to 10, were placed in the room under the desks, right in the middle, within a distance of 1.5 meters apart from each other. A floor plan of the room is exposed in Figure 6.

To perform the measurement as realistically as possible, the phones were placed in a pocket of a trouser, and signals were collected while sitting at the desk for two minutes. Two examples of collected signals from two different desks are shown in Figure 7.

Figure 7a a shows the graph with the highest interference scenario from a nearby beacon. Even the signal of beacon n_8 being the strongest and the most stable, thus detecting the correct desk, it was clearly subjected to destructive interference from beacon n_9. Figure 7b shows the more common scenario, the signal of the desk being significantly stronger than the ones coming from nearby beacons.

Considering the challenging results at desk n_8, we tested the accuracy of the signal, changing the student's position from the center of the desk. Position was moved towards the desk n_9 in 15 cm steps, within a range from 15 to 75 cm. The samples were collected in these 5 different distances (15, 30, 45, 60 and 75 cm) during two minutes each. The results are exposed in Figure 8.

As we can observe, the strength of the signal of the beacon placed at desk n_8 is still the highest within the range of 45 cm away from the center of the desk. The signal strength drops significantly when increasing the distance to 60 and 75 cm, with a prominent increase of the signal of the neighbour desk n_9, as well as a smaller, but noticeable increase of the signal strength of desk n_{10}.

Figure 6: Experimental environment indicating the positions of the beacons from n_1 to n_{10}.

7 CONCLUSIONS AND FUTURE WORK

In this section we conclude our work and discuss some ideas for future work.

7.1 Conclusion

In this work, the authors present a feasible solution for the monitoring of examinee's localization in a room, as well as an automatic exam registration and Covid certification check app in an university environment.

Our results reinforce the reliable use of BLE beacons, exposing also the limitations of such a system.

Considering the placement of the beacons on the desks and the fact that a person sitting at the assigned desk would absorb most of the signal coming from his/her desk's beacon, we believe that our results would even be better in a real life testing set (with a full room) as the interference between the beacons would be considerably reduced.

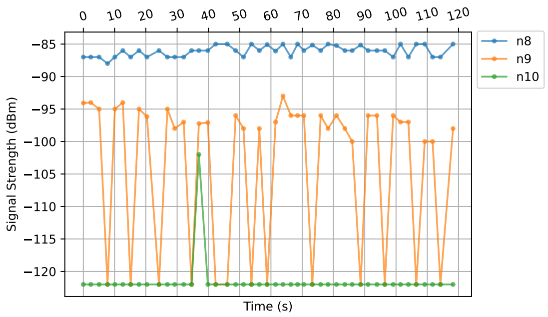
Taking into account the limitations of movement in an examination scenario and the imposed sanitary restrictions, in which the examinees are required to stay apart within a distance of 1.5 m, the situation of an examinee being 60 or 75 cm away from his/her desk's beacon (exposed in Figure 8) would hardly happen in a real life scenario.

Beside the accuracy of supervising the contact of possibly infected individuals, the system will also reduce the time to ingress in an examination room, facilitating the localization of the assigned desk. The integration to the university system also helps the examiner to generate the report of the exam.

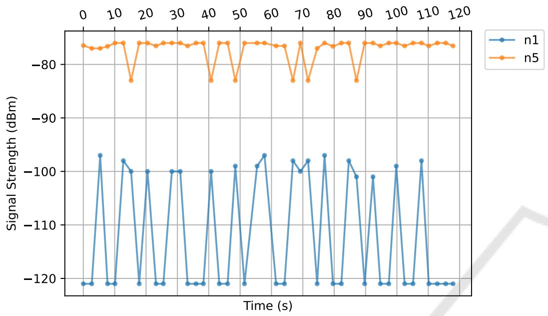
7.2 Further Work

As for future works, the reliability of the system might be improved, avoiding misplacement of an examinee as in the edge test. In addition to the Bluetooth based localization strategy, information of IMU sensor data can be combined, detecting the movement of an examinee, thus, avoiding situation in which the system would not be able to determine if the student changed the place or not.

As this app would be designed for the facilitation of registration and realization of exams, the functionality of the app can be enlarged, muting automatically the student's phones and restoring their original state



(a) Signals collected at desk n_8. This represents the worst scenario found in our test environment.



(b) Signals collected at desk n_5. This represents the most common scenario found in our test environment.

Figure 7: Graphs of signal strength from the beacons around each desk during 120 seconds.

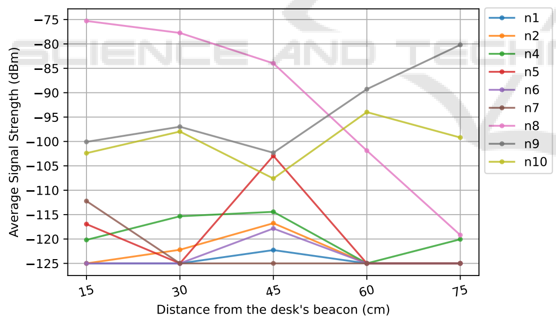


Figure 8: Average of the signal strengths during a 2 minute measuring period for each detected beacon when varying the phone's distance from the desk's beacon. Values equal to -125 dBm can be considerate as the nonexistence of signal.

after finishing the exam.

Taking into consideration the good results of our study, the benefits of this solution for an examination scenario could also be transported to a more social environment, like restaurants, bars, theaters, etc, with each table/seat having a beacon. This scenario will offer even more noticeable benefits for contact tracing and ease of registration.

ACKNOWLEDGEMENTS

This work was supported by the Regensburg Center of Energy and Resources (RCER) and the Technology- and Science Network Oberpfalz (TWO). Further information under www.rcer.de.

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