

Indoor Localization Services for Hearing Aids using Bluetooth Low Energy

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Abstract

BACKGROUND: Hearing loss is a common disorder which is usually treated with hearing aids. The context of use, whether being outside, inside of large or small rooms, in a quiet or noisy environment, or talking with someone near or at a distance, often requires the hearing aid user to adjust the settings of the hearing aids manually in order to reach an optimal or even acceptable hearing experience. Knowing the context of a hearing aid user in the home setting, including the position within the home, could likely automate and optimize relevant hearing aid settings as needed. Several modern hearing aids are already equipped with Bluetooth Low Energy (BLE) antennas enabling their connectivity with smartphones and other compatible devices. This allows for the development of positioning and localization services using BLE. **OBJECTIVES:** The aim of this study was to investigate the potential of using the BLE radio signal of hearing aids to provide indoor localization and positioning support when used in combination with fixed radio access points in a home setting. **METHODS:** A research platform based on a single Oticon hearing aid and three embedded Raspberry Pi computers placed at three strategic locations in a home setting was developed. The Raspberry Pis used the two statistical learning methods K-Nearest Neighbors and Decision Trees for non-obtrusive detection, classification, and determination of the location of the hearing aid. The efficacy of the research platform was evaluated during two hearing experience relevant efficacy studies: 1) room classification and 2) proximity detection of hearing aid users to their conversation partners. **RESULTS:** Room classification results provided an accuracy of 88.79% and it was found feasible and reliable to differentiate whether the hearing aid user was within a comfortable conversation distance or not. **CONCLUSION:** These results open up for a wide range of audiological applications in indoor environments for supporting new context-aware services for improving the hearing experience of the users.

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Keywords: Indoor Localization Services, Bluetooth Low Energy, Hearing Impairment, Hearing Aids

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1. Introduction

The auditory system is responsible for the sense of hearing. It is divided into two subsystems: the peripheral auditory system which includes the outer ear, middle ear and inner ear, and the central auditory system starting from the cochlear nucleus up to the primary auditory cortex. If any part of the auditory system does not function as expected, it leads to a hearing loss, which can be understood as a total or partial inability to hear [22]. The World Health Organization (WHO) defines a normal hearing threshold at 25 dB or better in both ears. Anything outside of this boundary is considered a hearing loss. However, only a hearing loss greater than 40 dB in the

better hearing ear in adults, and a hearing loss greater than 30 dB in the better hearing ear in children, is defined as a disabling hearing loss [39]. According to the WHO over 5% of the world's global population has some level of a disabling hearing loss. WHO also estimates that around one third of people over 65 years old are affected by hearing impairment, and anticipates that by the year 2050 over 900 million people, or one in every ten, will have some level of a disabling hearing loss [39].

In general, hearing aids are the most common remedy to hearing loss [4]. However, the hearing experience resulting from the usage of hearing aids is highly dependent on the auditory characteristics of the environment [9, 15]. For that reason, modern hearing aid devices use additional sensors, and multiple settings specialized for different hearing

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situations [23, 28, 31, 33, 38]. Multiple studies suggest that the user experience of the hearing aid devices could benefit from enabling those devices to automatically adapt their settings according to available context information [14, 16, 37]. One type of relevant context information is indoor localization. According to Eurostat [21], people in Europe spend between 60% and 78% of their time at home and people aged over 65 can spend daily up to 20 hours at home. Therefore, it has been suggested that the information about the hearing aid's user's current position at home could likely be used to enhance the user experience [35].

Indoor localization has been addressed from several perspectives, and diverse solutions have been proposed and evaluated. A 2019 survey of indoor localization systems and technologies, with a focus on the positioning of humans and their devices, identified a range of technologies being used by indoor localization systems, including WiFi, Bluetooth, ZigBee, radio frequency identification (RFID), ultra wide band (UWB), visible light, acoustic signals, and ultrasound. Also, the review found that several techniques for calculating the distance and angle were used including received signal strength (RSSI), channel state information (CSI), angle of arrival (AoA), time of flight (ToF), time difference of arrival (TDoA), return time of flight (RTof), and phase of arrival (PoA), which are often combined with the use of probabilistic methods including neural networks (NN), k-nearest neighbors (kNN), and support vector machines (SVM) as well as the fingerprinting method [40]. A 2019 study using Wifi fingerprinting using the local feature-based deep long short-term-memory (LSTM) method found this approach to perform better than traditional fingerprinting methods for a wifi based approach [7]. While both ultrasound [26] and [20] vision and several other methods have been successfully demonstrated for indoor localization [40], the most widespread localization approach is to utilize radio-frequencies used in communication standards such as Bluetooth or wifi [10, 40].

Several studies have used BLE-fingerprinting following a similar approach to our study, while no one, to the best of our knowledge, have used BLE-equipped hearing aids for positioning of the user. However, BLE can to a certain extent be considered a generic technology, and even though there may be other potential issues with BLE data originating from hearing aids as compared to BLE data originating from smart phones or beacons, it is relevant to survey related work based on other BLE approaches. For instance, a study described in [17], investigated the accuracy of a room classification algorithm based on the BLE RSSI signal with use of a single receiver mounted in every room together with the application of a smoothing procedure (i.e., simple moving average). The approach proposed in the paper did not use any of the well-established machine learning classifiers, but instead utilized a custom, probabilistic propagation model. The accuracy achieved in the study for a three room setting was equal to 94.5%. However, it has to be noted that the reported result was determined by running the classification

on the same set of data, which was used for the construction of the propagation model. Therefore, the reported accuracy is considered to be a training accuracy, which is likely biased as an overestimation of the test accuracy [29]. A related study [3] proposed a system utilizing Bluetooth enabled devices, distributed at least one per room and in large areas with one for every 20 meters, and a mobile device carried by the user to be tracked. The algorithm described in the paper was based on fingerprinting, and used a Multiple Neural Networks model for a determination of the user's position. The test setup consisted of a total of five BLE receivers deployed in an apartment composed of a long corridor and five rooms. The study investigated a precision of position determination in 8 different locations throughout the corridor. The reported results indicated 90% of precision and 0.5 meter of accuracy. Although the resulting precision of the algorithm is considered impressive, it would be interesting to see the performance of the system in a multi-room scenario, similar to the one investigated in this paper. Another study, focusing on the performance analysis of multiple indoor positioning systems in a healthcare environment [12] investigated three localization algorithms: fingerprinting, Time of Arrival (ToA), and an approach based on the linear relationship between the RSSI value of the signal and the distance between the sender and the receiver (MLAT), with use of three different technologies: WiFi, ZigBee and BLE. The results from this study indicated that fingerprinting provides the best localization performance with a 79% accuracy for a BLE room classification. The interesting finding presented in the paper is the superiority of WiFi over BLE technology. However, a lack of detail in the description of the used classification techniques makes it difficult to replicate. A study from 2019 [19] suggests that the Bluetooth RSSI signal can be used for indoor localization detection for visually impaired people. It investigates RSSI combined with the trilateration geometric technique and concludes that the RSSI signal is more reliable than other signal parameters (TOA, TDOA) but also that the measurement estimations depend heavily on the environmental interferences. Another study from 2019 on Indoor Localization using Wireless Fidelity (WiFi) and Bluetooth Low Energy (BLE) signals [36] investigated an indoor localization technique similar to the one proposed in this paper. The authors considered a set of WiFi and BLE devices deployed in a home environment consisting of 3 bedrooms, 2 bathrooms, a living room, and a kitchen to locate an elderly resident. They used 6 receivers placed in different locations in the apartment and utilized RSSI based fingerprinting method as a position estimation technique. They managed to achieve a less than 2 meter precision in localizing the user in 10 predefined locations in the apartment and concluded that both WiFi and BLE provide promising and acceptable results sufficient for locating elderlies inside a home environment. Another related 2019 study also used BLE-based fingerprinting relying on the analysis of the signal strength of adjacent reference points in a fingerprint database using the "eight-neighborhood template

matching method" resulting in a locating error of 1.0 m in their laboratory evaluation study consisting of a single room of size 8 x 8 meters and with 4 iBeacon access points [18].

Most modern commercial hearing aids available in the market are equipped with BLE antennas to enable smartphone connectivity [23, 28, 31, 33, 38]. This connectivity is mainly used to enable remote control of the hearing aids, but also to utilize the sensors available in the smartphone to provide a better hearing experience. This study proposes to extend the functionality of the BLE antenna in the hearing devices by using it for indoor location services. More specifically, this study investigates indoor localization based on the BLE RSSI signal parameter, which characterizes low cost and complexity. The fingerprinting method is proposed for indoor position estimation because of its superior accuracy compared to geometric approaches, lower receiver devices deployment density requirement in comparison to proximity methods, and the fact that the in-house environment is considered relatively stable, meaning that the model constructed during the training phase should reliably represent the in-house environment throughout the period of system operation [11].

The aim of this study was to investigate the potential of using the BLE radio signal of hearing aids to provide indoor localization and positioning support when used in combination with fixed radio access points in a home setting.

The novelty of this contribution lies in the analysis of the feasibility and accuracy of using of BLE equipped hearing aid devices for BLE indoor room and proximity localization with the main purpose of supporting the application of the indoor localization services in the hearing aid sector. To the best of our knowledge, this has not been investigated in previous work.

2. Methods

2.1. Research Platform

As a part of this study, a research platform allowing for evaluating the feasibility of using hearing aids for localization services in the home setting was developed. It consisted of three components: BLE receivers (home nodes), a hearing aid and a smartphone. It was decided to choose a Peer-to-Peer architecture with one home node device mounted in every room. The home nodes were implemented with use of the Raspberry Pi 3 Model B hardware platform, together with an external Logilink Bluetooth radio. The second component of the research platform was the Oticon hearing aid, which was used as a BLE transmitter. Furthermore, the system included an android application with two modes: System Calibration and Beacon mode. The System Calibration mode was used to gather data, about the RSSI signal distribution in the test environment, used for the training of the classification models utilized by the system in the operation mode. The Beacon android application was used as a BLE receiver for the proximity detection study. The application was able to read the hearing aid's BLE signal, which was further used to determine the proximity to the hearing aid user. The

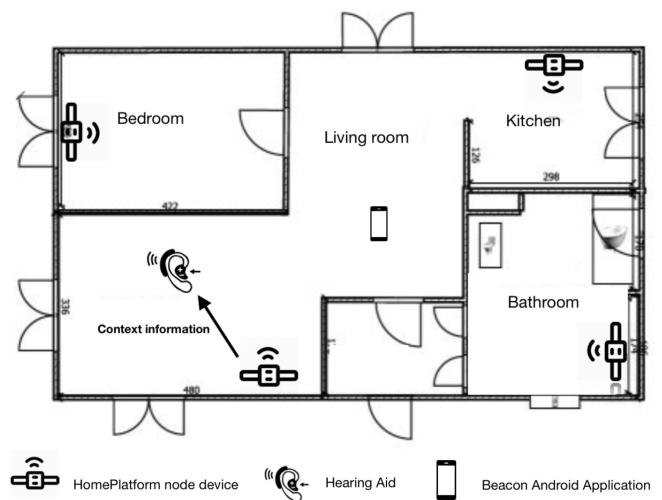


Figure 1. Conceptual diagram showing the home setup of the research platform, presents exemplary placement of the home devices in the house, together with the hearing aid and beacon android application.

conceptual diagram showing the home setup of the research platform can be seen on the figure 1.

2.2. Indoor Localization Studies - Data Preprocessing

In two experimental studies we investigated different aspects of BLE technology and the usability of the hearing aids for indoor localization services. In both studies, two data preprocessing methods were applied. Firstly, it was recognized that a predefined sampling ratio may result in missing data points. Therefore, inspired by [24], who showed that the imputation of the missing data can improve the performance of the prediction models, it was decided to replace all missing values with the last recorded RSSI reading before the missing time slot. Secondly, it was decided to apply a data smoothing procedure in order to tone down the fluctuations in the data so that the distortions were reduced to a minimum. Two common approaches were considered: simple moving average (SMA), and exponential moving average (EMA). Simple moving average approach for every sample calculates the average by taking into account this sample and N samples closest to it. The closeness of the samples can be defined by different measures and include preceding samples, following or both. The main characteristic of this approach is the fact that the method assigns the same weights to all the samples taken into average, therefore all samples have the same impact on the resulting value. The problem with SMA is that it introduces delays in the signal equal to the span of the moving average window. An alternative approach is the exponential moving average, which is a modification of SMA which instead of giving equal significance to the neighbor data points, assigns to them exponentially decreasing weights. This results in a model

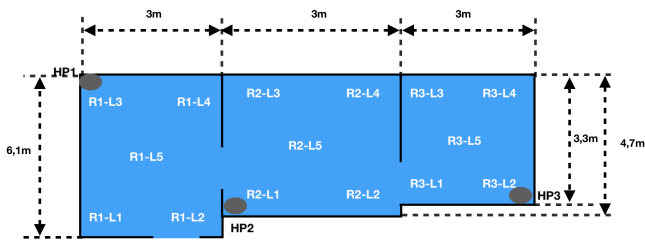


Figure 2. The setup of study 1 showing three home nodes (HP1, HP2, HP3) mounted in each room (R1, R2, R3) with additional indication of five locations (L1, L2, L3, L4, L5) in every room from where the measurements were gathered

which is more sensitive than an SMA, and tackles an issue of delay in the signal [25]. Due to this considerations, it was decided to apply the EMA smoothing procedure throughout the studies.

2.3. Study 1: Room Classification Study

This study evaluated room classification methods with the proposed research platform based on a BLE fingerprinting using two classification algorithms: K Nearest Neighbors and Random Forest. The main inducement for using KNN and RF classifiers was their simplicity, and straightforward tuning procedures. What is more, those methods provide high level of interpretability, while still achieving high classification accuracy. They were both proven to perform well in a range of classification problems, especially when the decision boundary is very irregular. Hence, they require little assumptions about the data [11]. The study setup is presented on the figure 2. The setup consisted of three home node devices located in the corners of three different rooms, and one hearing aid. The data acquisition process consisted of two phases: training and testing data acquisition. For the training data phase, the hearing aid was placed in 15 different locations - four corners and the center of every of the three rooms. Each measurement lasted five minutes, and throughout this time the home nodes recorded a median RSSI value of received advertisement packets for every second together with a timestamp and information about the current room, and location in the room. In contrast, the process of gathering the test data was deliberately less structured to better resemble real life operation. In this setup, for each room, the user was wearing the hearing aid on the ear, and moved randomly throughout the room for five minutes, trying to visit all the possible areas in the room.

2.4. Study 2: Nearby Person Detection Study

The study aimed to determine the feasibility of detecting the relative change of the distance in range of "the arc of comfortable conversation", which inspired by [30, 32], was assessed to be equal to 2 meters. The setup of the

study consisted of one Xiaomi Redmi 4x smartphone, and one hearing aid. The smartphone had a Beacon Android application, able to read the BLE signal of the hearing aid, installed. Both the hearing aid and the smartphone were placed on a chair and the distance between the devices was changed. The data acquisition procedure was designed so that it resembled a situation of two people getting close to each other, and then walking away from each other. Each recording lasted three minutes: first minute at a three meters distance, second minute at a two meters distance and the last minute at a three meters distance.

3. Results

3.1. Study 1: Room Classification Study

In total, 134,738 measurements for 15 different locations in three rooms were gathered. After merging the measurements with use of a timestamp, room, and room location as common properties, the number of data samples was 44,920. The scatterplot showing the data is presented on the figure 3.

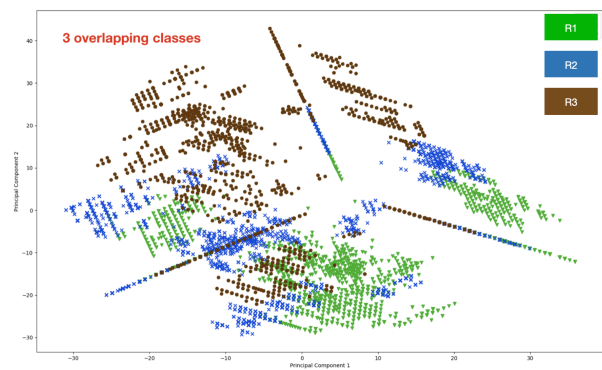


Figure 3. Scatter plot showing RSSI measurements with no data preprocessing divided into three classes corresponding to three rooms (R1, R2 and R3).

The number of samples for which RSSI measurements corresponding to all three rooms were missing for a given time slot was equal to 8,194, meaning that 18.24% of all the samples had no readings. Applying missing data imputation method tackled this issue, and resulted in all 44,920 samples having a RSSI value. The data after missing data imputation procedure can be seen on the figure 4.

The next step was smoothing the data, with use of the exponential moving average (EMA) method with a value of the span parameter determined empirically equal to 5. The original data, without missing data imputation but after the smoothing procedure was visualized on the figure 5.

Combining the missing data imputation with moving average smoothing operation resulted in the structure of the data presented on the figure 6.

The preprocessed training data recordings were fitted into two classification algorithms: K Nearest Neighbors and Random Forest. 3-fold cross validation was used to train the

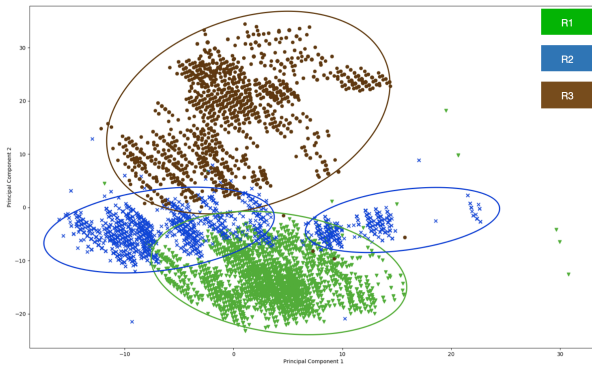


Figure 4. Scatter plot showing RSSI measurements after missing data imputation procedure divided into three classes corresponding to three rooms (R1, R2 and R3).

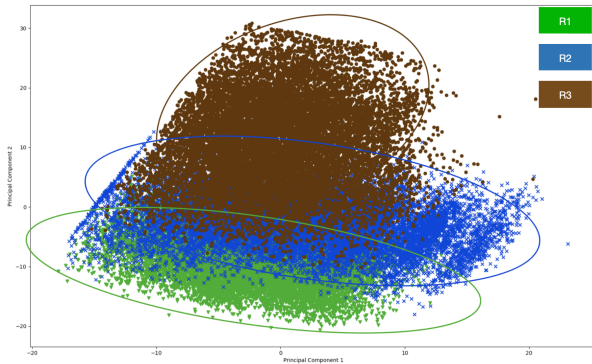


Figure 5. Scatter plot showing RSSI measurements after smoothing procedure divided into three classes corresponding to three rooms (R1, R2 and R3).

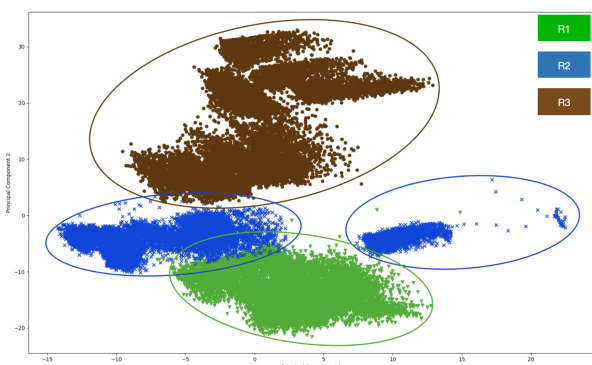


Figure 6. Scatter plot showing RSSI measurements with both missing data imputation and smoothing procedure divided into three classes corresponding to three rooms (R1, R2 and R3).

algorithms and the algorithm accuracy was evaluated against the testing data set.

K-Nearest Neighbors. Table 1 presents hyperparameters used in the study, selected with use of the randomized search method, and the table 2 shows the classification results evaluated on both training and testing data.

Parameter	NI-NS	I-NS	NI-S	I-S
n_neighbors	22	85	90	22
weights	distance	uniform	uniform	uniform
metric	chebyshev	chebyshev	chebyshev	manhattan

Table 1. Results of the randomized search for optimal values of the hyperparameters of the K Nearest Neighbors Classifier. NI-NS: No Imputation - No Smoothing, I-NS: With Imputation - No Smoothing, NI-S: No Imputation - With Smoothing, I-S: With Imputation - With Smoothing

Further empirical investigation showed that the setting with only smoothing, without missing data imputation performed on the training set, and both operations carried out for the testing set provided the best accuracy result equal to 0.8879. The hyperparameters for this setting found through randomized search were $k = 90$, chebyshev distance, and uniform metric. The corresponding confusion matrix can be seen on the figure 7.

	KNN training	KNN test	RF training	RF test
NI-NS	0.8957	0.5393	0.9022	0.5566
I-NS	0.9933	0.7213	0.9976	0.7688
NI-S	0.8177	0.6185	0.8205	0.6161
I-S	0.9995	0.8468	0.9996	0.8093

Table 2. Results of 3-fold cross validation for K Nearest Neighbors and Random Forest classifiers run against training and test data set. NI-NS: No Imputation - No Smoothing, I-NS: With Imputation - No Smoothing, NI-S: No Imputation - With Smoothing, I-S: With Imputation - With Smoothing

Random Forest. The table 3 presents hyperparameters for Random Forest algorithm, selected with use of the randomized search method. The classification results can be viewed in the table 2.

The confusion matrix for the Random Forest classifier for the setting with best prediction performance can be seen on the figure 8.

3.2. Study 2: Nearby Person Detection Study

The study measurements were sampled with a one second sampling ration, and a mean value for every second was calculated. The measurements, showing the RSSI signal in consecutively 3 meter, 2 meter, and again 3 meter distances with and without missing data imputation procedure, are visualized on the linear plot shown on the 9. The box plot, showing the relationship between the RSSI and the distance, can be seen on the figure 10.

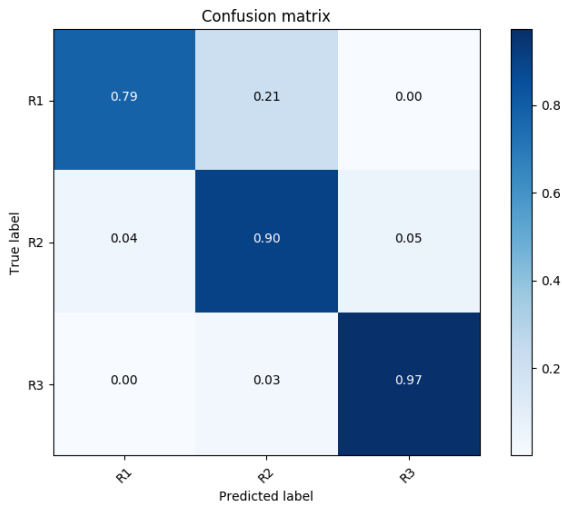


Figure 7. Confusion Matrix for the KNN algorithm trained on the training data, with optimized parameters for the training data subject only to smoothing operation, and validated with the test data subject to both imputation and smoothing procedures.

Parameter	NI-NS	I-NS	NI-S	I-S
n_estimators	1115	452	1557	1115
min_samples_split	10	2	5	10
min_samples_leaf	4	4	1	4
max_features	auto	auto	auto	auto
max_depth	10	40	10	80
bootstrap	False	True	True	False

Table 3. Results of the randomized search for optimal values of the hyperparameters of the Random Forest Classifier. NI-NS: No Imputation - No Smoothing, I-NS: With Imputation - No Smoothing, NI-S: No Imputation - With Smoothing, I-S: With Imputation - With Smoothing

4. Discussion

4.1. Study 1: Room Classification Study

First finding of the study was that with a one second sampling ratio for the RSSI measurements more than 18% of the measurements had no readings. This is considered an important issue because as it can be seen on the figure 3 the raw RSSI measurements with missing values gathered from the experiment do not provide a clear distinction between the rooms, hence posing a difficulty for the room classification algorithms. This indicates that the measurement sampling ratio should be increased, which can be limited by the energy consumption and processing power of the hearing aid, or other mechanisms such as proposed missing data imputation procedure should be implemented. Missing data imputation greatly improves the separation between the three classes corresponding to the rooms in the research setup, which is in

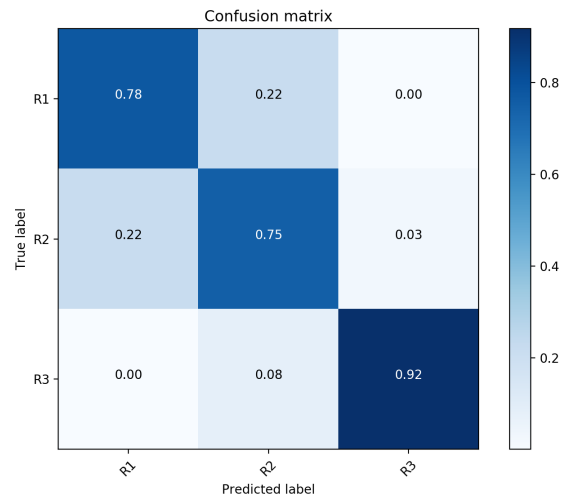


Figure 8. Confusion Matrix for the Random Forest algorithm trained on the training data, with optimized parameters for both imputation and smoothing operations, and validated with the test data.

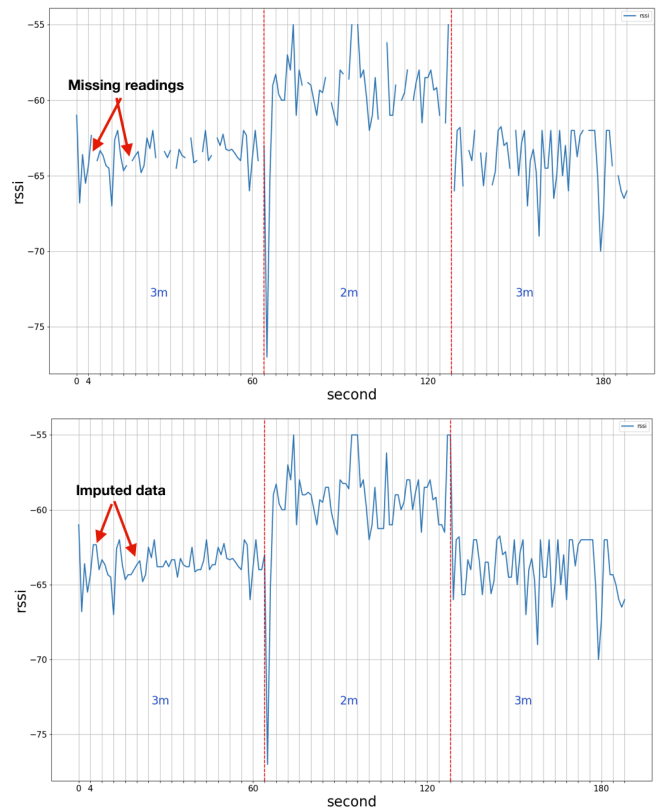


Figure 9. Rssi signal distribution with (top) and without (bottom) missing data imputation.

compliance with [24], who showed that the imputation of the missing data can improve the performance of the prediction models. Furthermore, the results of the application of the exponential moving average smoothing procedure proved to

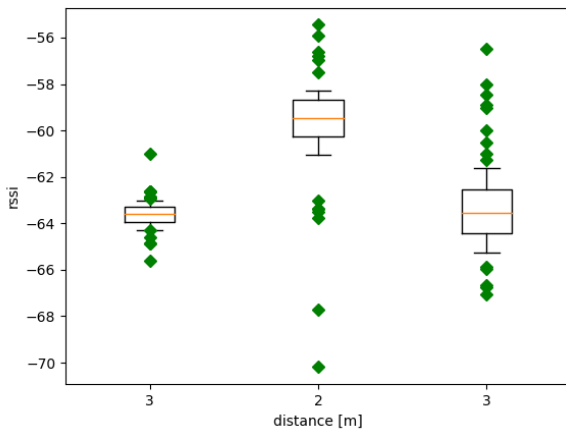


Figure 10. The box plot showing the readings from three phases of the study corresponding to different distances between the devices, 3m, 2m and 3m consecutively after application of the data smoothing procedure.

decrease the noise in the data, resulting in the data points from the same classes being less distributed across the plot space, as compared with the original data set. However, it is not clear from the scatter plots if the smoothing operation provides improvements in separation between the clusters. Nevertheless, the combination of both operations resulted in three distinguishable clusters, with reduced noise. However, it is recognized that those operations introduce delay into the signal, and therefore an appropriate trade-off between the system responsiveness, and accuracy needs to be determined.

The results of the 3-fold cross validation performed on the algorithms showed that the missing data imputation improved the classification performance from 89% to 99%. This is in accordance with the presented scatter plots showing a clear distinction between the classes. On the other hand, the smoothing procedure resulted in a decreased classification accuracy (81%), meaning that reduction of the noise without missing data imputation resulted in more overlapping classes. The combination of both techniques lead to 99% accuracy. However, it is important to note that the 99% accuracy achieved with a 3-Fold Cross Validation can be misleading as the K-Fold Cross validation provides only an estimation of the test error, based on the training data, which is usually an underestimation of the real test error rate [29]. Therefore, the results of the test set validation were further examined.

The test set validation approach, as expected, provided worse results than a 3-Fold Cross Validation. The accuracy of both classifiers, without any data preprocessing, was around 55%, which is below the accuracy required for the correct operation of the system. The missing data imputation increased the prediction accuracy to 72% for the KNN, and 76.88% for the Random Forest. The smoothing procedure in this case also provided improvement resulting in the accuracy

equal to 61%. The application of both operations lead to 84.68% accuracy for the KNN, and 80.93% for the Random Forest. The comparison between the accuracy scores for both classifiers can be seen in the table 4. The test set validation approach clearly demonstrates the benefits, and necessity of the missing data imputation, and exponential moving average smoothing operations, emphasizing the positive impact of the missing data imputation procedure. What is interesting, further empirical investigation found that in case of the KNN classifier the setting with only smoothing, without missing data imputation performed on the training set, and both operations carried out for the test set provided better accuracy equal to 88.79%. This is attributed to the overfitting phenomenon, where too well separated classes in the training data set, do not correspond well to the test data points. The same was not registered for the Random Forest classifier, which is considered to be attributed to a better resilience to overfitting of the algorithm [11].

	Accuracy KNN	Accuracy RF
No Imputation - No Smoothing	0.5393	0.5566
With Imputation - No Smoothing	0.7213	0.7688
No Imputation - With Smoothing	0.6185	0.6161
With Imputation - With Smoothing	0.8468	0.8093

Table 4. The comparison of the accuracy scores, achieved from the test data validation for the KNN and Random Forest classifiers.

The results from this study can be compared to the results from other studies. For instance, a study described in the paper [17] achieved an accuracy for a three room setting on the level of 94.5%. However, it has to be noted that the reported result was determined by running the classification on the same set of data, which was used for the construction of the propagation model. Therefore, the reported accuracy is considered to be a training accuracy, which is likely biased as an overestimation of the test accuracy [29], and in the case of the technique proposed in this research was equal to 99%. Another study [3] investigated a setup consisting of a total of five BLE receivers deployed in an apartment composed of a long corridor and five rooms. The study investigated a precision of position determination in eight different locations throughout the corridor. The reported results indicated 90% of precision and 0.5 meter of accuracy. Although the resulting precision of the algorithm is considered impressive, it would be interesting to see the performance of the system in a multi-room scenario, similar to the one investigated in this paper. The study on performance analysis of multiple indoor positioning systems in a healthcare environment [12] achieved results of fingerprinting equal to 79% accuracy for

a BLE room classification, which is 9.79% worse than the best accuracy achieved in this study. One recent study [36] used a technique similar to the one proposed in this paper and achieved a less than 2 meter precision in determination of user's position in the 8 room apartment with use of 6 BLE receivers. This shows that the number of the receivers does not necessarily need to match the number of the rooms in the apartment, and that the proposed system can also work for more complex environments. However, the results of both studies cannot be reliably compared as a precision in closeness to predefined locations in the apartment and a room classification accuracy are different metrics of measurement. All things considered, comparison of results from this study, and the results presented in referenced articles proves that the accuracy achieved by the technique proposed in this research is comparable to related studies in the field and can be considered a viable technique for an indoor localization.

An important aspect to note is that the approach investigated in this research used 15 calibration points for a three room setting. In comparison, the study [17] gathered data from 27 different locations in the apartment (nine for every room), which is 12 locations more than in the approach proposed in this study (five locations for every room). The number of five calibration points for every room was decided based on considerations regarding user experience, as more points could be argued to result in a more time-consuming system calibration phase. Moreover, the study [17] placed the BLE receivers in the center of every room, while the research setup used in this study had devices placed in the corners of every room. This can also have an impact on the performance of the system, and should be further examined.

Another important aspect of indoor localization, which was discovered during the study is the dimensions and structure of the apartment. The confusion matrix for the K Nearest Neighbors method, presented on the figure 7 shows a prediction performance discrepancy between the rooms. The discrepancy seems to correlate with the dimensions of the rooms, presented on the figure 2. The classification accuracy was the highest 97% for the smallest room, decreasing to 90% for the second biggest room, and to 79% for the largest room. The results, as can be seen on the figure 8, differ for the Random Forest classifier, where the smallest room R3 still provides the best accuracy equal to 92%. However, the classifier performs on a similar level for both rooms R1 and R2, with a 78% accuracy for room R1 and 75% accuracy for room R2. This indicates, that the characteristics of the apartment, such as dimensions and relative positions of the rooms have influence on the room classification performance. This is in accordance with the previously mentioned study [17], which found a discrepancy in classification error rates between rooms of different dimensions, as well as the study [19] which showed that many variables such as atmospheric conditions, environmental noise, multipath fading, and ground reflection affect the actual BLE signal being received by the receiver. Hence, it would be

recommended to perform further investigation of the impact of this features.

All in all, the results proved that the research setup with three home devices, mounted in three rooms, and the hearing aid used as a BLE transmitter can be used to classify, with the room granularity, user's location in the apartment. The classification accuracy achieved in the study is considered satisfactory compared to the results from other studies in the field, and it is believed that further improvements of the proposed classification method could be made resulting in an even better system performance. An exemplary improvement could be the usage of Multiple Neural Networks as proposed by [3], or an investigation of the combination of approaches proposed in this study, and the probabilistic RSSI signal propagation model described in the paper [17].

4.2. Study 2: Nearby Person Detection Study

The study 2 showed that the proposed research setup, using a hearing aid, and a smartphone with an Android application can be used for the proximity detection service. The RSSI signal response to the dynamic change of the distance in range of one meter is noticeable, and can therefore act as an indicator of two persons getting into "the arc of comfortable conversation" [30, 32].

Figure 9 shows that the missing data imputation procedure is required in order to avoid missing data points with one second sampling ratio. As mentioned before, the sampling ratio could also be increased. However, this would lead to the higher energy consumption, and processing power requirements for the hearing aids which as shown in the studies [2, 5, 27] shall be limited.

Figure 10 shows a clear distinction between the RSSI readings corresponding to the three meters, and two meters distances between the devices, which is in compliance with the RSSI propagation model proposed by [1]. What is more, based on the presented results, it is possible to establish RSSI threshold for determination of human proximity on the level of -61 dBm, which is somewhat compliant with the study on a Group Detection Based on Human Proximity for Human Relationship Extraction in Daily Life [13], which suggested two levels of good proximity thresholds: -69 dBm, and -75 dBm, indicating that greater values result in poor performance. Therefore, it is concluded that the RSSI signal between two devices can be used for the human proximity detection, which was also shown in [8, 34].

4.3. Research Platform

The proposed research platform consisting of the Android smartphone, three Raspberry Pi home devices and the Oticon hearing aid is an exemplary setup which could potentially be modified to include any type of smartphone, small computer platforms and any modern hearing aid providing support for the BLE. In case of platform components modification, an adjustment of the software and additional training of the algorithms would be required.

4.4. Audiological Applications

The presented studies proved the feasibility and identified important aspects of using BLE hearing aid devices in indoor localization applications. Those findings could lead to further clinical studies with possible clinical applications such as: adjusting the hearing aid's settings to the current room the user is in, adjusting the setting to the nearby persons, tracking the hearing aid in order to provide the user with useful notifications such as reminding to take off the hearing aid while entering the shower, or put it on while leaving the house, or helping with finding the hearing devices based on their last known location. The hearing aid's indoor localization information could also be used to provide further integration with smart home or ambient assisted living environments services.

4.5. Security and Privacy Issues

Location data and associated data, e.g. from hearing situation support situations based on the location data, as well as other data collected in the home setting are vulnerable to unauthorized access and misuse. Thus, a range of privacy and security issues exists that needs to be addressed before the research platform can be applied in a real world environment for a pilot study involving actual hearing aid users [6].

4.6. Future Work

The remaining functions, together with the experimental limitations identified throughout this study should be investigated in future work:

1. More relevant hearing situations should be investigated, and integrated into the platform providing hearing aid users with additional assistive technology support.
2. The characteristics of the hardware platforms should be further examined. For instance, the optimal sensitivity and gain of the Raspberry Pi nodes' BLE antenna, or the optimal power class and advertisement frequency of the hearing aid should be determined. They should be investigated keeping in mind the required accuracy and range of operation of the system, and the energy constraints of the hearing aids.
3. Clinical investigation of the hearing aid settings associated with specific hearing situations should be carried out. For instance, the optimal settings for rooms of different structures and dimensions (*Room classification*), or voices with different tones and frequencies (*Nearby person*) need to be investigated.
4. The proposed system should be extended in order to provide a direct feedback to the hearing aid. That means detecting the current hearing situation (context), and sending this information to the hearing aid, allowing it to adjust its settings. In order to complete this part, it is necessary to design and develop a communication API

between the hearing aid and the system, and close the loop by resolving the settings according to incoming context information.

5. The optimization and real world applicability of the algorithms proposed in this study should be tested outside of a controlled environment. Therefore, the algorithms should be tested on hearing aid users during daily activities in their homes, and the results from this tries should be used for tuning the algorithms.
6. The real life applicability and possible profits of context aware solutions in in-house environments in audiological applications should be tested in clinical studies. For instance, by using randomized controlled trials in which one group receives conventional hearing rehabilitation, while the other group of users is supported by the proposed Home Hearing Assistive Technology system.

5. Conclusion

This study investigated indoor localization services based on modern BLE hearing aid devices in order to provide additional context-aware support to hearing aid users in an in-house environment. A functional research prototype consisting of three home nodes mounted in three rooms, a hearing aid and a beacon Android app was implemented. The research prototype was used in two indoor efficacy localization studies. Study 1 showed that it is possible to achieve a room classification solution with a 88.79% accuracy using the proposed research platform. Study 2 showed that the BLE RSSI signal of a hearing aid allows for a clear distinction between the three meters, and two meters distances between the devices, thus being useful for proximity detection. Moreover, we found that it is feasible to determine a proximity threshold value of the RSSI signal equal to -61 dBm. Furthermore, we identified the relevance of using two data preprocessing methods namely missing data imputation and exponential moving average smoothing procedures in order to tackle data disruptions, together with energy and processing limitations of embedded devices such as the hearing aids. Finally, the need for addressing security and privacy issues was highlighted.

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