Indoor Localisation with Intelligent Luminaires for Home Monitoring

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Abstract: This paper presents the initial results of our experiments regarding accurate indoor localisation. The research was carried out in the context of a European Union funded project targeting the development of a configurable, cost-effective cyber-physical system for monitoring older adults in their homes. The system comprises a number of hardware nodes deployed as intelligent luminaires that replace light bulbs present in the monitored location. By measuring the strength of a Bluetooth Low Energy signal generated by a device on the monitored person, a rough estimation of the person's location is obtained. We show that the presence of walls, furniture and other objects in typical indoor settings precludes accurate localisation. In order to improve accuracy, we employ several software-based approaches, including Kalman filtering and neural networks. We carry out an initial experiment showing that additional software processing significantly improves localisation accuracy.

1 INTRODUCTION

In the context of demographic and social changes nowadays (World Health Organization, 2015) care for older adults can be transformed according to their own desires and necessities. Recent years have seen a shift towards technology-driven, personalised solutions designed to assist and monitor older adults living in their own homes, with the support of their families, friends and trained caregivers.

The work reported in this paper is part of a European Union-funded research project during which a technological platform for home monitoring and assisted living was developed. This cyber-physical system (Marin et al., 2018) is based on the use of energy-efficient intelligent luminaires equipped with embedded sensing, indoor localisation and communication systems. They enable a pervasive, seamless, and inexpensive home monitoring scheme. These newly developed luminaires can replace existing light bulbs, ensuring simple and straightforward deployment. The platform removes some of the adoption barriers faced by such systems by reducing costs and simplifying installation. Furthermore, it conforms to standards, and using it does not require specially trained staff.

The main system components, together with proposed innovations were described in previous papers (Marin et al., 2018; Bocicor et al., 2017). One of the important components is the one for indoor localisation. Existing satellite-based technologies such as GPS perform very poorly indoors due to the presence of walls and furniture, which have a detrimental effect on signal strength, thus requiring alternative approaches. Our system employs trilateration based on the received strength of a Bluetooth Low Energy (BLE) signal. Other approaches include visible light communication (Haigh et al., 2014), acoustic background fingerprinting (Tarzia et al., 2011) and user movements (Tarrio et al., 2011). The main advantages of BLE technology is the low cost of hardware and its ubiquity in mobile devices and wearables. In addition, Bluetooth signal is omni-directional and it permeates walls, albeit imperfectly. We carry out an experiment where we replace one light bulb in every room with an intelligent luminaire incorporating Bluetooth technology used both for localisation and communication. This leads to a deployment that does not require additional wires or devices and with no components that look out of place. In addition, as most lights are ceiling-mounted, there is less interference from furniture or other equipment.

2 STATE OF THE ART

The last years we have witnessed a dramatic rise in the number and diversity of intelligent devices deployed within homes. Location-based applications play an important role in identifying and studying user behaviours and their interests by analysing activities and interactions with other people or objects.

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In outdoor environments, accurate location information can be easily obtained using the Global Positioning System (GPS). While GPS positioning is reliable outdoors, it cannot be used for accurate indoor localisation due to poor signal strength (Ozsoy et al., 2013). As such, efforts have been put into designing accurate indoor positioning systems based on acoustics, optics, Wi-Fi, Bluetooth, GSM and Radio Frequency Identification (Ta, 2017; Lymberopoulos et al., 2015; Xiao and Zhou, 2016). Some of these systems employ Received Signal Strength Index (RSSI) (Luo et al., 2011; Sadowski and Spachos, 2018; Maduskar and Tapaswi, 2017), due to the existence of the inverse-square law between the strength of the received signal and the distance from the source of the electromagnetic wave (Dong and Dargie, 2012). This relation allows determining the distance starting from signal strength. Unfortunately, the RSSI varies over time due to multipath fading, with the level of fluctuation being higher in indoor environments (Pu et al., 2011). This instability degrades localisation accuracy, keeping indoor localisation and object detection an area of ongoing research.

One proposed solution to address RSSI measurement variance is to filter RSSI values. The Simultaneous Localisation and Configuration algorithm proposed by Bulten et al. (Bulten et al., 2016) is based on a factored solution to the simultaneous localisation and mapping problem (FastSLAM) for localisation based on RSSI values. Everything is done locally on the user's device. Another approach is the Kalman filter (Welch and Bishop, 1995), which can be used to smooth noisy data, i.e. RSSI value estimations. This technique is amenable for use in many contexts given its low computational requirements. The Kalman filter is an efficient recursive filter that factually evaluates the internal state of a system from a series of measurements which are subject to noise. When a new measurement occurs, the filter uses a weighted average for prediction, with the goal of reducing uncertainty. The weights are computed based on the covariance. The weighted average is a state estimate which is between the predicted and measured states. This process is repeated at a certain period of time, computing the new average and covariance for every iteration. The Kalman filter aims to remove signal noise when multiple measurements are taken.

In (Robesaat et al., 2017), the authors showed that Kalman filtering increased the accuracy of the indoor localisation of the monitored person. The Kalman filter reduced accumulated errors by reducing noise (Sung, 2016). It also diminished the energy consumption and enhanced the stability of RSSI values.

Similar to GPS technology, indoor localisation requires the use of several signal emitters. Each signal emitter is placed at a known location, and RSSI values for each are determined to calculate the distance between each signal emitter and the target of monitoring. Using at least three signal emitters results in the creation of three circles, the radii of which are determined by the RSSI values. The target of monitoring is found at the point where these circles intersect. This technique is called trilateration. Due to the issues detailed above, RSSI values require post-processing and filtering in order to achieve accurate localisation.

The system we proposed uses custom developed BLE-enabled devices, which are physically deployed in the form of intelligent luminaires that replace existing light bulbs (Marin et al., 2018). While the physical design of the intelligent bulbs is beyond the scope of this paper, care was taken to ensure luminaire design does not affect signal strength or directionality. The light bulbs are typically ceiling mounted and thus the signal is less prone to physical and electromagnetic obstructions.

Our experiments employ a mobile phone to emit a BLE signal that is received by intelligent luminaires and transformed into localisation information. Any smartwatch or smart life saving button can act as a signal emitter, as long as it supports the BLE standard. The main advantage of our setup is cost, both regarding the design of the intelligent luminaires, as well as the possibility of using a wide range of existing BLE-enabled wearable devices

3 INDOOR LOCALISATION COMPONENT

3.1 Intelligent Luminaires

Figure 1 presents a high-level view of the system's deployment architecture. The hardware side of the cyber-physical system is represented by two types of hardware devices, dubbed as *dummy* and *smart* nodes. Both are implemented in the form of luminaires.

Dummy nodes are designed for small size and low cost. They also work as luminaires, but lack the advanced processing and communication functions of the smart nodes. Their main role, besides lighting, is to perform BLE scans for other devices and report the RSSI values to the smart node they are connected to. As such, dummy nodes are employed to detect the presence of monitored persons. This design reduces the overall system cost and improves its accuracy, by allowing several inexpensive nodes to be deployed and connected to the same smart node. Smart nodes provide several wireless interfaces and higher computation power than is available to dummy nodes. Smart nodes are both Bluetooth and Wi-Fi enabled. They also include a sensor module with a suite of sensors used to monitor the indoor environment. They receive dummy node readings via Bluetooth, process them and transmit them to the software server using a permanent Wi-Fi connection. In order to achieve this, every monitored room typically includes between 1 and 3 luminaires, depending on its size and shape. By replacing ceiling mounted light bulbs with intelligent devices, homes and buildings can be monitored with minimal installation and maintenance costs. In addition, when deploying the system in more personal spaces, such as hospital wards, or in the homes of older adults with the purpose of monitoring, they have the advantage of being inconspicuous.

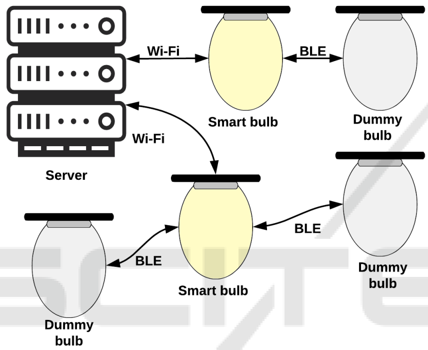


Figure 1: High-level architecture of the system.

Communication between smart and dummy bulbs is achieved via BLE technology. To establish a BLE connection, the smart bulb acts as a master, performing a scan to detect dummy bulbs in its proximity, while the dummy acts as a slave, advertising itself. On the other hand, the dummy must also be able to scan the environment and detect additional devices, such as those employed for localisation. As such, it must also act as a master. As a result of these constraints, smart and dummy bulbs switch between roles with regularity. For a certain period of time, each node acts as a slave, emitting advertisement packets detected by bulbs in a master role, and then switches to slave mode, in order to detect and maintain information about other devices.

The localisation algorithms based on the RSSI values are run on the system's server several times every minute, and the retrieved indoor coordinates are recorded in a database. Considering current and recent positions of the monitored person, the system is able to detect possibly dangerous situations and emit real time alerts, which are sent to designated caregivers. As an example, assuming that the monitored person has been in the bathroom for too long, using a custom period defined at system configuration, the platform will generate and send an alert to their caregiver.

3.2 Methodology

In this section we present the direct and hybrid methods that we use to accurately identify the indoor position of the monitored person. Direct trilateration and prediction of coordinates via an artificial neural network are the two major techniques we are using. Furthermore, we employ Kalman filtering (Welch and Bishop, 1995) to account for the inherent noise of RSSI measurements.

3.2.1 Direct Trilateration

To convert RSSI values into distance measurements we use the RSSI lognormal model described in (Dong and Dargie, 2012), in which the distance can be computed as shown in Formula 1:

$$d = \frac{10^{A-RSSI}}{10 * n} \tag{1}$$

In Formula 1 the significance of variables is as follows:

- n represents the path-loss exponent and it ranges between 2 to 6 for indoor environments.
- A is the signal strength expressed in dBm, measured from a distance of one meter. This parameter is experimentally computed once for each type of luminaire.
- $RSSI$ is the received signal strength index. This is the measure the system uses for trilateration.
- d is the computed distance. It is the distance between the luminaire that makes the measurement and the person being monitored, or more specifically the Bluetooth device that the person has on them, such as a smartphone or smartwatch.

The distance is calculated relative to minimum 3 intelligent luminaires in order to achieve trilateration. Following the calculations, at least three values are deduced, for the three distances which represent the three circles' radii. The person's location is computed as the point of intersection of these circles. Because of various environment interference caused by objects blocking the signal, RSSI values are subject to noise. We evaluate three different techniques to reduce noise and improve the accuracy of localisation.

First, location at each recorded timestamp is not computed using the RSSI value at that particular timestamp, but considering an average of RSSI values. Let us consider n RSSI values for each moment in time when signal strength was recorded, for each of the considered luminaires $(l_i^1, l_i^2, \cdots, l_i^n)$, where $i \geq 3$. To compute the location at time t $(1 \leq t \leq n)$ an option would be to use all RSSI values recorded at time t (l_1^t, l_2^t, l_3^t), compute the distances according to Formula 1 and identify the intersection point of the three circles having as radii the computed distances at each moment t. However, the noise present in RSSI measurements precludes us from doing this. We use a different approach, one that involves the last 10 recorded RSSI values, for each luminaire $(l_i^{t-10}, l_i^{t-9}, \cdots, l_i^{t-1})$. The reasoning is that single-reading RSSI errors will be attenuated when taking multiple readings over a longer time interval. Thus, for each intelligent bulb, out of these ten values possible outliers are eliminated and then the average avg_t and standard deviation $stdev_t$ are computed. Out of all ten values, we retain only those that are within the interval $[avg_t - stdev_t, avg_t + stdev_t]$ and use their average to compute the distance.

The second technique used to account for noise is Kalman filtering. Starting from observed noisy measurements and assuming a Gaussian distributed noise, this algorithm infers the parameters of interest, taking into account the history of measurements. For this specific case the Kalman filter will be used to make estimations of noise-free signal strength values. The process is based on two equations that describe the system's state: one defines the observed measurement in relation to the real measurement and noise and the other defines the current estimate recursively, using the previous estimate. There are two main steps to be performed: a *prediction* about what the state should be and an *update* to this prediction, based on the measurement data and the old estimate. For each moment in time we compute the RSSI estimates, using Kalman filtering. Then the trilateration is performed using the distances obtained starting from these estimates.

The final technique is a combination of the previously presented methods: initially, a Kalman filter is applied on the raw RSSI values and the RSSI estimations are obtained. Then, we apply the heuristic described previously, that we proposed as the first technique for noise reduction. We compute the location at a certain moment by considering the RSSIs associated with the past 10 measurements. The difference is that instead of employing the measured RSSI values, we use the estimates. Given that calculations are carried out on the server, further software-based improvements can be integrated without affecting already deployed devices.

3.2.2 Using an Artificial Neural Network

In addition to the previous methods that employ direct trilateration to obtain location, we also use an artificial neural network to predict the position of the monitored person, starting from tuples of RSSI values. Such machine learning models have successfully been employed in recent years for indoor positioning (Zhanga et al., 2016; Lukito and Chrismanto, 2017; Mittal et al., 2018). The network's architecture is not fixed, as a suitable architecture is dependant on the problem space and specific data. Therefore, we experimented with various architectures. Still, certain aspects are established: the input layer contains three neurons, one for each RSSI measurement, corresponding to the three intelligent luminaires used in our experiment. The output layer contains two outputs, representing the resulting indoor coordinates in a two-dimensional space. We experimented with a variable number of hidden layers and report the obtained results. The used activation function for all hidden layers is rectified linear unit (ReLU) (Nair and Hinton, 2010). Optimisation is achieved via stochastic gradient descent enhanced with the *adam* optimiser (Kingma and Ba, 2014). Training was performed during a variable number of epochs and the network is evaluated using k-fold cross validation.

4 EXPERIMENTS AND RESULTS

The experiments were carried out in a three-room dwelling in which the system was installed. The room dimensions are: 2.50m x 3.29m (bedroom), 2.50m x 1.00m (study room), 2.34m x 2.21m (hallway). The apartment also includes a kitchen and a bathroom, but these were not considered in the evaluation. Each room was fitted with a ceiling-mounted smart node connected to the software server over Wi-Fi. The two-dimensional plan of the dwelling is represented in Figure 2, in which the smart bulbs are illustrated using yellow circles with black borders.

Both interior and exterior walls are made of brick and cement. Exterior walls have a thickness of 35cm, while the interior walls are 17cm thick. This is important to note because these materials strongly influence obtained RSSI values.

Formula 1 uses two parameters that need calibration: A - the signal strength at 1 meter from the luminaire and n - the path loss exponent. The value of A depends on the luminaire, and is computed once for each type. In our case, we obtained a value of $A = -67$. To obtain the most suitable value for n we used a grid-search procedure and kept the value that

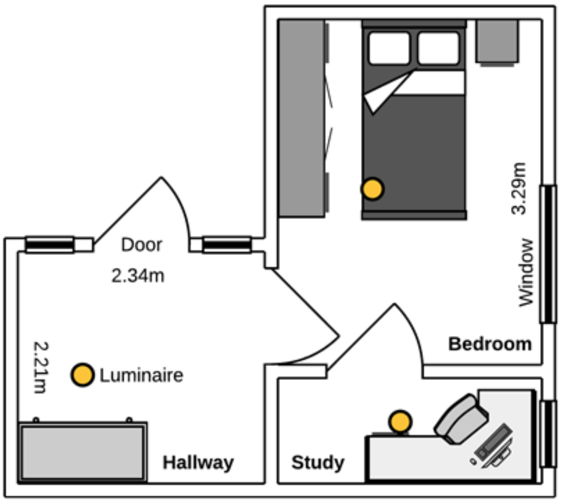


Figure 2: Plan of the dwelling used for experimentation (icons from https://www.vecteezy.com).

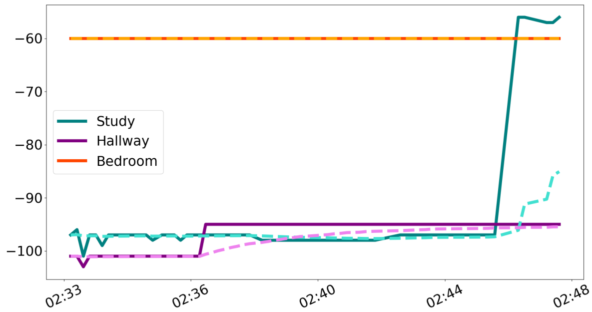
lead to the most accurate results for the considered indoor environment ($n = 2.5$). The result of the calibration step depends on deployment location, room shapes and sizes, as well as wall placement and materials. Calibration must be undertaken once per location, when the system is initially deployed.

The subsequent sections present the experiments that were carried out to test and improve indoor localisation, starting from RSSI values. *Mean squared error (MSE)* is the evaluation measure used and it is computed considering the real indoor two-dimensional coordinates as well as the coordinates obtained by the positioning algorithms.

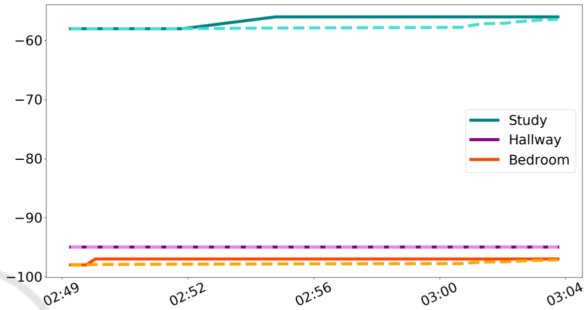
During the experiment the person is stationary in the middle of each room for 15 minutes: bedroom (02:33 - 02:48), study room (02:49 - 03:04) and hallway (03:07 - 03:22). Their mobile phone, which is used for recording measurements, is kept on them. RSSI value measurements are taken at an interval between 6 to 10 seconds. All doors between rooms are open.

Figure 3 illustrates the RSSI values for all 3 intervals of experimentation time, recorded by each of the three intelligent bulbs. The Kalman estimates computed starting from these RSSIs are also illustrated using dashed lines. During the last 2 time periods (3b, 3c) we observe that the RSSIs do not suffer significant changes. On the other hand, for the first time interval, there seems to be more noise attenuated by Kalman filtering.

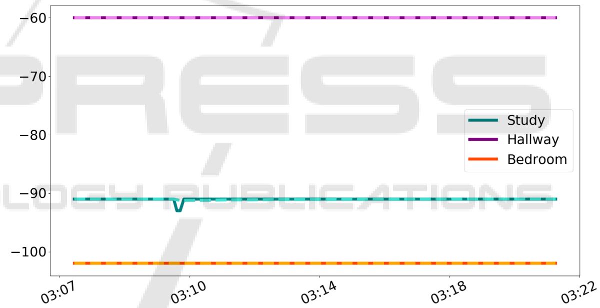
Table 1 shows the MSE for the three considered time periods, for each of the techniques. Original values refer to measured, unprocessed RSSI values. The second row presents the results for the heuristic proposed in Section 3.2: the values are calibrated according to the described technique and use the previous 10 measurements. The third row shows the obtained results when a Kalman filter is applied and the locations are computed using the obtained estimates. The bottom row presents the errors for the hybrid procedure - the heuristic is applied on the estimates obtained from running Kalman filters. It can be observed that when using trilateration applied directly on the original RSSIs the results are not as good as with the other techniques. On average, the proposed heuristic leads to the next better outputs, followed by Kalman filters, which result in even smaller errors. The hybrid combination described in Section 3.2 surpasses all previous ones. Another observation is that the results for the first time interval accurately reflect



(a) First interval - person is located in the bedroom.



(b) Second interval - person is located in the study room.



(c) Third interval - person is located in the hallway.

Figure 3: Recorded RSSIs (continuous lines) vs. Kalman estimates (dashed lines) for each time interval, corresponding to each location.

Table 1: Mean squared error using direct trilateration. Errors reported in centimetres.

	2:33-2:48	2:49-3:04	3:07-3:22	Avg. error
Original values	187.92	92.41	77.45	119.26
Heuristic	184.17	92.0377	77.69	117.97
Kalman filter	181.81	89.5987	77.50	116.30
Kalman filter + heuristic	178.11	88.87	77.47	114.81

the higher noise reduction achieved using Kalman filters, as shown in Figure 3a. The difference in error between the original values and Kalman filters (Table 1, column 2:33-2:48), first and third rows is significantly higher than that corresponding to the other two time periods.

The neural network described in Section 3.2 has been applied on the raw RSSI inputs measured during our experiment. These results are presented in Table 2. Note that generally the increase in the number of training epochs leads towards smaller errors, however this is not always the case, as over-fitting might arise. The number of hidden layers also has an essential impact on the network's performance. Generally, while our experiments show that the tendency of the output error is to diminish as the number of epochs increases, that was not always the case.

Table 2: Mean squared error obtained using the artificial neural network. Errors reported in centimetres.

	Number of hidden layers				
Epochs	1	2	3	4	5
500	48.14	47.67	26.18	47.39	16.45
1000	34.54	14.53	12.80	6.25	16.41
1500	40.12	6.32	7.58	5.20	4.18
2000	44.57	13.53	4.12	2.22	4.07
2500	9.31	14.24	4.94	6.02	2.83
3000	27.90	14.50	17.01	3.83	3.13

The highest average error obtained by the network (48.14 centimeters) is substantially lower than the best results reported in Table 1. In the best case, the network's error is less than 3 centimetres and on average it is less than 20 centimetres, for all undertaken tests. The 95% confidence interval for all runs is 16.87 ± 5.46 (centimetres). Thus, for the considered data, the network performs considerably better when compared to trilateration-based methods. However, a disadvantage of the network is that it has to be trained using a considerable amount of data collected in various settings and from various positions in order to be suitable for real-time localisation.

Figure 4 illustrates the positions obtained by the best performing trained neural network. This plot represents the two-dimensional floor plan of the dwelling, as seen in Figure 2. For more context, we mention that the left-most wall's x coordinate is 167 (left wall of the hallway) and the entrance door's y

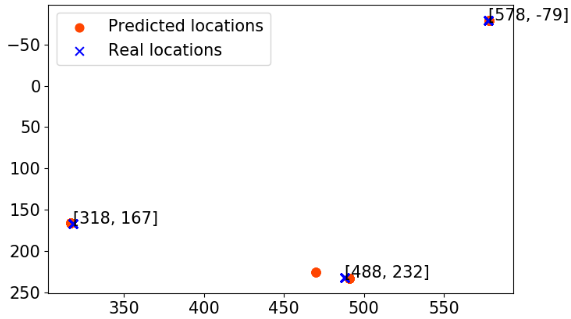


Figure 4: Indoor positions obtained by the neural network, represented in the two-dimensional floor plan of the dwelling (Figure 2). The units of measure in this plot are centimetres.

coordinate is 40; the measurements are in centimetres. For a certain location, many of the predicted positions are identical and thus, even though the number of predictions is the same with the number of recorded RSSI values, they are all superimposed in the image. We notice that the accuracy is very high, particularly for the first and the last periods of time (bedroom and hallway). In the case of the study (second period of time) the predicted locations are not all identical, however the error is low and the predictions are very close to reality.

The location of the person during the second time interval is illustrated in Figure 5. The image is extracted from the cyber-physical system's software application, which allows displaying the computed indoor locations of the monitored person in real-time, both in a two- and and three-dimensional space. The image illustrates the positions of the smart bulbs as well as the person's estimated location. This application feature allows caregivers to supervise the monitored person's location in real time.

Figure 5: Illustration of the person's indoor location within the system's interface.

5 COMPARISON WITH RELATED WORK

We briefly compare relevant existing systems with ours. The RADAR system (Bahl and Padmanabhan, 2000) determines the person's current position by considering the signal strength of its k nearest neighbours. The signal is influenced by noise, building materials and other environment-dependant factors. The localisation error was between 2 and 3 meters. For the system where a neural network was used for determining the location of a person based on wireless LANs, the accuracy is of about 3 meters (Battiti et al., 2002). For the localisation based on trilateration and Kalman filters (Fariz et al., 2018), the error varied between 14.82 and 3.58 meters. The extended Kalman filter for indoor localisation based on fusing Wi-Fi (Deng et al., 2015) has a positioning error of 2.83 meters. Another paper targeting indoor positioning (Li et al., 2018) reported a maximum positioning error of 3.29 meters when using direct trilateration with Bluetooth and 1.61 meters when using a back propagation neural network. As opposed to these reports, our techniques lead to smaller errors for the considered experiment, having a maximum average error of 1.19 metres. However, a thorough comparison cannot be undertaken given differences in experiment setup, measurement devices and procedures.

Indoor localisation based on RSSI data gathered via Wi-Fi was tested within two environments and triggered lower positioning errors (Sadowski and Spachos, 2018). The first environment was one big room in which there were several BLE devices and multiple Wi-Fi networks causing interference. The second environment comprised a smaller room that only contained furniture with no other devices present, leading to a low level of noise. Inside the first environment the average error for positioning was 0.84 meters, while for the second environment it was 0.48 meters. The nodes which measured the RSSI values have been placed on tables of the same height for limiting the number of signal reflections. In our work, the nodes were ceiling-mounted and three rooms were considered, having eight Wi-Fi networks and seven BLE connections causing interference. The phone was placed at about 1 meter above the floor. The walls made of brick and cement caused reflections and due to the multiple path signal propagation, a higher than desired positioning error was obtained. Transmission signals are also blocked due to surrounding furniture and equipment, as well as persons who move inside the environment (Wang et al., 2012), including the monitored person itself.

6 CONCLUSION

During the past decades there has been a dramatic increase in the world's older population and this trend is expected to continue. Population ageing has a series of major effects in various sectors such as housing, local communities and healthcare. As a consequence, a variety of technology-based solutions have emerged, which aim to facilitate maintaining an independent lifestyle for older adults within their communities and to ensure their safety. This study presents the results of our experiments regarding the indoor localisation component of a cyber-physical system designed to aid in monitoring older adults.

The system is built around a network of intelligent luminaires equipped with embedded sensing for environment monitoring, indoor localisation and communication. The system measures received signal strength from nearby BLE devices and is able to compute their indoor location with actionable accuracy. Two techniques were used for indoor positioning: one using direct trilateration and one based on an artificial neural network. We proposed a heuristic for more accurate localisation that also incorporates a noise reduction technique. Our experiments show that the neural network is superior to direct trilateration. With regard to trilateration, results indicate that heuristics combined with Kalman filtering for noise reduction lead to smaller localisation errors.

Compared to other indoor positioning systems that require fingerprinting or additional wires or devices, our system has a significant advantage: no complex indoor measurements are needed. Furthermore, deployment is straightforward, as existing bulbs can be replaced by intelligent luminaires using the same electrical infrastructure.

Future work will be carried out towards further improving localisation accuracy. Further experimentation will be performed within the same setup, with both opened and closed doors and considering user movement to augment static localisation results. As a consequence of more tests, additional data will be collected, which will also enable a more thorough training process for the artificial neural network and enable other approaches.

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