Design and Implementation of an RSSI-Based Bluetooth Low Energy Indoor Localization System

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Abstract—**Indoor Positioning System (IPS) is a crucial technology that enables medical staff and hospital managements to accurately locate and track persons or assets inside the medical buildings. Among other technologies, Bluetooth Low Energy (BLE) can be exploited for achieving an energy-efficient and low-cost solution. This work presents the design and implementation of an received signal strength indicator (RSSI)-based indoor localization system. The paper shows the implementation of a low complex weighted k-Nearest Neighbors algorithm that processes raw RSSI data from connection-less iBeacon's. The designed hardware and firmware are implemented around the low-power and low-cost nRF52832 from Nordic Semiconductor. Experimental evaluation with the real-time data processing has been evaluated and presented in a 7.2 m by 7.2 m room with furniture and 5 beacon nodes. The experimental results show an average error of only 0.72 m in realistic conditions. Finally, the overall power consumption of the fixed beacon with a periodic advertisement of 100 ms is only 50 µA at 3 V, which leads to a long-lasting solution of over one year with a 500 mAh coin battery.**

Index Terms—**Bluetooth Low Energy, Localization, Indoor Localization, Low Power Design, kNN, wkNN**

I. INTRODUCTION

The complexity of medical buildings such as hospitals, clinics and nursing facilities are increasing every day due to the increasing number of patients/hosts [1]. Moreover, the complexity increases due to new equipment and technologies offered to the staff, ranging from medical equipment to electronic medical data storage. In recent years, we are assisting with the introduction of information technology location aware devices and systems for healthcare environments that are exploiting different internet of things (IoT) technologies [1], [2]. The main goal of those emerging Indoor Positioning System (IPS) is enabling medical staff and hospital managements to accurately locate and track persons or assets inside the medical buildings [1]. Among other scenarios where IPS can be exploited, the promising hospital scenarios could become a reality for IPS in the near future: the vision is to have a next-generation nurse smart-calling system that is able to locate the nearest nurse in the medical building. This can make medical work more efficient [3], e.g. to locate and track medical equipment, which simultaneously helps identifying paths of infection [4]. Moreover, finding equipment and other medical devices inside a hospital or a building is often a complicated

and time-consuming task. In large hospitals time is crucial and having a fast and reliable way to identify the location of equipment could save lives [5]. Finally the IPS leads to more freedom for patients and helps medical staff to track patients inside the hospital or large indoor areas. This can especially be helpful when patients with a critical disease such as dementia get lost in the medical building. These are only a few examples of how an IPS can improve the internal functionalities inside a hospital.

Advances in electronics, computer sciences, miniaturization, and wireless communication enable energy-efficient communication among battery-operated smart devices inside the IoT paradigm [6] [7]. The presence of a smart device allowing the discovery, communication, and data analysis, is the key enabling factor for the real development and deployment of IoT applications such as IPS [1]. Wireless communication technologies are enabling IPS with a precision of a few meters [8]. The development of a functional localization system accurate to one or two meters could be applied to many application scenarios, especially within the medical section. In addition to the highest possible precision, this should also be cost-effective and easy to set up as possible which guarantees a large application area. Global Positioning System (GPS) is a well-known and established technology to precisely identify the location – however, it is well-known that it cannot be used indoors [8] [9]. Different systems and technologies have been investigated and proposed in the recent literature, and few of them are available on the market to address the need for indoor localization, including systems that are using cameras or other combinations of sensors [10]. However, emerging research is investigating new ways using wireless communication to enable accurate indoor localization [8] [11].

The most promising wireless technologies for meters-precision indoor localization are the Wireless Local Area Network (WLAN) [12], Ultra-Wideband (UWB) [13]- [14], radio-frequency identification (RFID) [15], Long Range (LoRa) [16] including the combination with GPS [17], and Bluetooth Low Energy (BLE). Many researchers have been investigating the possibility of using WLAN for the fact that it is pervasive in all buildings, and it has a long-range – however, the high energy consumption for a battery-powered system and the not excellent accuracy in the detection are the main

weaknesses. Due to the ultra-wideband and the nature of the technology [13], the solutions based on UWB allow very high accuracy of less than 30 cm in a radius of hundreds of meters - however current UWB modules have still a too high power consumption in the range of hundreds of mW [14] that reduces its use in a real-application scenario where the IoT device needs to last months with a coin battery. RFID allows to achieve very low energy consumption as many tags can even work without any supply. Moreover, the passive tags achieve the most accurate cm accuracy. The operative range is only to the small range of less than 1m while the active tags for extending the ranges are affected by larger energy consumption and bigger antennas. Long Range sub-giga wireless communication such as LoRa [18] have been investigated to provide localization information, however, the range achieved is in the order of several hundred meters, which makes them not suitable for high-precision indoor localization. Some researchers combined LoRa with GPS to achieve below-meter accuracy with real-time Kinematics, however, this solution works only outdoor [17]. Bluetooth Low Energy (BLE) 5.x offers an optimal trade-off of accuracy, range, energy consumption, and availability in all modern phones that has been exploited by many recent works, including the novel features of estimation of angle of arrival enabled from the 5.2 version of BLE [19]. Fig. 1 gives an overview of the most exploited wireless technologies for indoor localization with some key parameters such as range, accuracy and energy efficiency when supplied by batteries.

Fig. 1. The most common wireless technologies exploited for localization in buildings, LoRa and GPS are excluded since unsuitable accuracy in indoor application scenarios.

Although technology is advancing wireless communications, indoor localization systems are still prone to errors - attenuated by software algorithms. Many previous works focusing on the use of convolutional neural networks (CNNs) have been proposed as a competitive solution, especially for WLAN [20] and BLE [21]. CNNs are improving the precision performance on one hand and on the other hand, CNN models are designed to be executed on a CPU or GPU, requiring data to be transmitted from the mobile sensor node to an external compute engine through wired or wireless communication. Recently, a new generation of mobile smart IoT are attracting academic and industrial researchers, using microcontroller units (MCUs), supposed to bring computing capabilities towards the "edge" to perform real-time computation [22]. Edge computing offers the following advantages: 1) lower

energy consumption for the data transmission between IoT devices and remote processing; 2) longer battery lifetime; 3) significantly shorter latency compared to remote computation; 4) user comfort; 5) security and privacy improvements, as the data are processed locally [22].

This paper focuses on the design and implementation of a hardware-software low-cost and battery-operated system for indoor localization. In particular, the system is based on BLE 5.0 using the low-power general-purpose multi-protocol system on a chip (SoC) nRF52832 from Nordic Semiconductor. We hereby present the following contributions:

- On the software side, the paper proposes a system which is able to work with packets received via BLE and an algorithm based on (w)k-Nearest Neighbors (kNN).
- The design of the anchors and the mobile nodes are presented and evaluated with experimental results showing an overall accuracy of the implemented algorithm below 1 m on average for a $7.2\,\mathrm{m} \times 7.2\,\mathrm{m}$ room.

II. BACKGROUND ON RSSI-BASED BLE LOCALIZATION

Localization with BLE based on received signal strength indicator (RSSI) can be implemented in two ways. One corresponds to the variant in which a mobile device receives packets from the fixed anchors and records the signal strength. The other method would be to have multiple fixed receivers and a mobile device as a transmitter of the packets. Fig. 2 illustrates the two options where the yellow circle in the middle identifies the mobile tag. The 4 circles in the corners are the BLE anchors that are fixed.
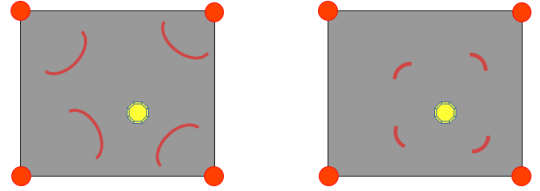
Fig. 2. Two possible constellations for localization based on RSSI using BLE.

The former configuration achieves a higher energy efficiency of the mobile device, as it can wake up autonomously and decide when to receive messages and must not be connected to the anchors. In addition, all calculations can be carried out on the receiver – thus the beacon themselves can be passive without further communication. The fixed beacons, also called anchors, broadcast their unique identifier number. Moreover the mobile device receives these packets with their RSSI and processes the data. To recognize the position correctly, training data must be collected at certain locations before usage. This training data is then like a footprint, which can be compared with the measured data and thus indicates the respective position.

A. BLE and iBeacon Protocol

As protocol for the beacon, the decision has been made on the proprietary standard for indoor localization using BLE

iBeacon [23] from Apple because this protocol is commonly used in many applications and commercial systems, and it is fully supported by the Nordic software development kit (SDK) [24] and other commercial SDKs of BLE modules. To understand how the beacons work, the principle of BLE should be clear first. In BLE, there are two different operating modes [25]: Generic Access Profile (GAP) and Generic Attribute Profile (GATT). The GAP is responsible for ensuring that the device is visible from the outside.

GAP: In GAP, the involved devices are not connected to each other. There are different roles and the most frequently used are central and peripheral. Simply put, peripherals behave like servers and centrals like clients. This means peripherals are devices that provide data. These can be beacons, heart-rate monitors, or other devices. Centrals are usually smartphones, tablets, or computers. In GAP, data can be transferred in two ways. First, there is the so-called Advertising Data payload, which is sent by the peripheral in constant time intervals to all clients (broadcasting). Then there is the Scan Response payload, which the central can request from the peripheral if it wants to learn more about the peripheral. Both packets are 31 B in size, but only the Advertising Data payload must be implemented. The time between two advertisements can be freely chosen (of course, in compliance with the MCU limits). Mostly the GAP mode is only used so that other centrals can recognize the peripheral, and they can connect (which allows a faster and bidirectional transmission and enables specific services). Another use is to broadcast the same message to different devices. Once a connection has been established between a peripheral and a central, they switch to the GATT mode.

GATT: The GATT defines the way of how two connected devices exchange their data. Typically, the systems look at the peripheral as a GATT server, while the central one provides the GATT client, making requests to the server. In the GATT, only the central can initialize a transaction. The GATT transactions are based on Profiles, Services, and Characteristics.

iBeacon Protocol: Since beacons do not want to be connected to a specific device but send their packets to all possible devices, they are in GAP mode. This means that their packets can have a maximum size of 31 B and they advertise their packets at constant intervals. The iBeacon's structure is presented in Fig. 3 and reported in [26]. BLE hardware module can identify the RSSI of each received iBeacon, and this is the key information used in RSSI-based localization systems, as the RSSI can estimate the transmitter's distance.

B. Fading of received signal strength indicator

To enable RSSI-based location, the decrease in signal strength has to be clarified with the increase in distance in a medium such as air. This information can then be used in a trilateration algorithm (or to increase robustness of the kNN further) to estimate a distance based on signal strength. A well-known mathematical model is the logarithmic distance loss model. In this model, the decrease in signal strength is assumed to be logarithmic decreasing with the increasing
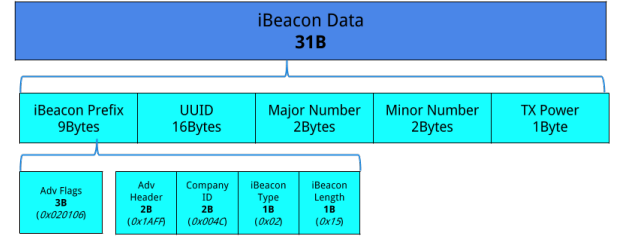
Fig. 3. Structure of iBeacon [26]

distance [27]. Equation (1) illustrates the model used for the RSSI value to approximate the distance.

$$RSSI(d) = RSSI(d_0) - 10n \cdot \log_{10}\left(\frac{d}{d_0}\right) \qquad (1)$$

Where d is the estimated distance, d_0 describes a self-defined reference distance, $RSSI()$ the function that assigns the expected signal strength to each distance and n the path loss parameter given by the properties of the environment.

Fig. 4 shows the decay evaluated with the equation (1) based on approximations done in a room with the received RSSI values of the nRF52832 for both beacon and receiver and transmission power of 0 dBm.
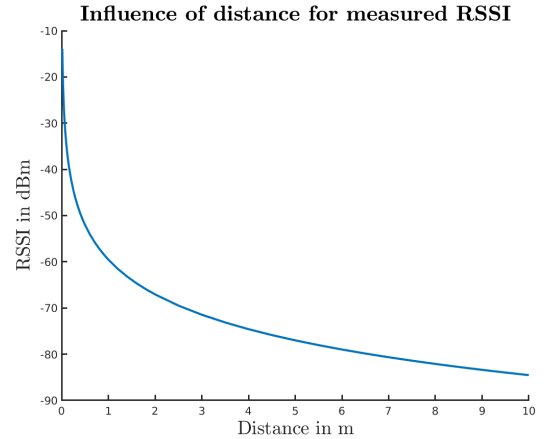
Fig. 4. Theoretical path-loss decay calculated for the Nordic nRF52832 used in this work.

III. System Architecture

This paper presents both the beacons and the receiver that were developed based on the Bluetooth Low Energy 5.0 SoC nRF52832 from Nordic Semiconductor. This was the most advanced BLE chip at the beginning of the design, as it had the lowest power consumption among all available chips. This module contained an ARM Cortex-M4F microcontroller for the user firmware.

A. Beacon nodes

Fig. 5 shows the prototype and block diagram of the beacon developed and implemented in this work. The beacon is designed to operate from a 3 V button battery, which is used

directly to power the nRF52832, represented by the MCU block in the figure. The beacon is designed for low power consumption and a small footprint (limited by the battery holder, the diameter is now $3\,\mathrm{cm}$). Power consumption averages $50\,\mu\mathrm{A}$, resulting in over a year of runtime on a $500\,\mathrm{mAh}$ battery, even taking into account battery self-discharge. Due to the low power consumption, the beacon node could easily be powered only by photovoltaic energy harvesting allowing an unlimited runtime. The average current is calculated with an advertising interval of $100\,\mathrm{ms}$ implemented in the on-board firmware. The implemented chip antenna allows a smaller device with a range of several meters at $0\,\mathrm{dB}$ transmit power.

Fig. 6. Prototype of the receiver including the antenna and WLAN module.

Fig. 5. Prototype of the beacon and block diagram.

B. Receiver nodes

In our system, messages from the fixed beacon nodes are received by a mobile receiver. The receiver (Fig. 6) was designed using the same architecture of the beacon node and therefore has the same components as the beacon. The only differences are the elimination of the battery compartment and its replacement with a USB-to-UART bridge that also serves as an interface to an external device. To obtain results that are le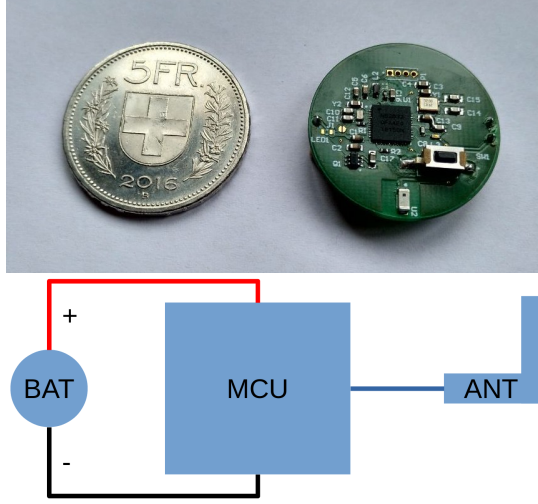ss dependent on the orientation of the antenna, the chip antenna was replaced with an external antenna and the π-network was adjusted accordingly. To obtain the best possible results from the RSSI measurements, a holding device was made for the receiver. This consists of a small piece of wood on which the receiver is fixed with screws made of plastic and not steel, as these could potentially cause inaccuracies. With the help of a WLAN module that sends information to an access point, the receiver can be used on its own equipped with a power bank.

IV. WEIGHTED k-NEAREST NEIGHBORS INDOOR LOCALIZATION ALGORITHM

The main contribution of this paper is the design and implementation of the weighted k-Nearest Neighbors (wkNN)

algorithm with RSSI information using the nRF52832 for training and evaluation. The wkNN algorithm is one of the most widely used algorithms to improve the performance of indoor localization based on RSSI [28]. Moreover, the algorithm runs on the ARM Cortex-M4F microcontroller in the nRF52832 because it does not require large memory and computational resources. This algorithm requires that the position of the beacons and the positions of the training points are known. Fig. 7 shows the setup used to acquire the data set for training. Through a previous training (fingerprint), the RSSI values at each position are determined (vector with one RSSI value per beacon). Due to the nature of wkNN, only positions within the trained positions can be estimated.
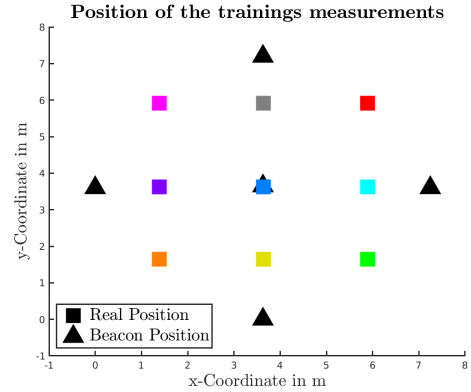
Fig. 7. Experimental setup used to acquire training data. The setup consists of 5 beacons and 9 positions where the mobile receiver can be placed to get data from known position.

wkNN is a complement to kNN. kNN attempts to match the measured RSSI values with the previously trained positions by finding the distance between all measured RSSI values of the training position using the Chebyshev or Euclidean norm.

Then k smallest differences are taken to form an arithmetic mean, which then corresponds to the estimated position. In wkNN, the k closest training data with their positions are considered. The difference with kNN is that in wkNN, the arithmetic mean is formed by weighting the position of the k nearest neighbors by the reciprocal of the estimated distance
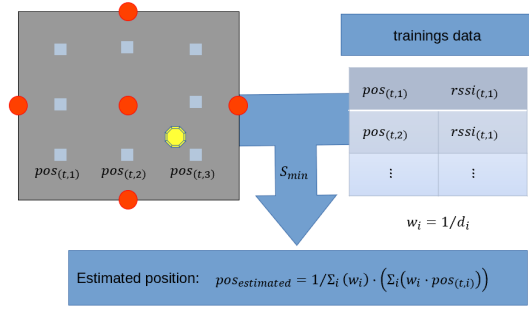
Fig. 8. The overview of the wkNN with the used application scenario (left).

to the receiver. This assigns a very high value to the training position with a difference close to zero, while the others split the remainder, promoting a convergence to the nearest positions. According to this value, the averaging is now done in favor of the correct position. It is important to note that only positions within the area spanned by the positions of the training data can be correctly detected by averaging.

V. Experimental Evaluation

To evaluate the designed prototypes and algorithm, we distributed four beacons with the setup shown in Fig. 7. Fig. 9 shows the classroom used for the experimental evaluation with an area of $7.2\,\text{m} \times 7.2\,\text{m}$. The beacons were placed at a height of $1.8\,\text{m}$. Obstacles in the room were the chairs and desks, which were about 1m high, as shown in the figure.


Fig. 9. The classroom used for experimental evaluation had an area of $7.2\,\text{m}\times 7.2\,\text{m}$, with the beacons at a height of 1.8m. Obstacles in the room were the chairs and tables, which were approximately 1m high.

It is important to note that the implemented algorithm is evaluated as a regression problem and not as a classification problem of the 9 known positions. This is done to obtain a more realistic and useful system that can be used in an indoor localization system for medical applications. However, to obtain an evaluation of the accuracy of the estimation, the reference positions were created identical to the trained positions. The finally used value for k resulted from previous experiments with different parameter choices. Fig. 10 shows the average error obtained over all 9 positions using the Chebyshev norm, $k = 3$ and only 4 of the five beacons. The average error is only $0.704\,\text{m}$ over 1000 samples. In the experimental setup, the accuracy was found to be $2.5\,\text{m}$ in

the worst case and $0.27\,\text{m}$ in the best case. Fig. 11 shows instead that the Euclidean norm performs slightly worse in terms of average error, at $0.746\,\text{m}$. On the other hand, the reported maximum error was lower than $2.37\,\text{m}$. To evaluate the influence of the fifth beacon we re-evaluated the best configuration with Chebyshev norm, $k = 3$ and 5 beacons. As Fig. 12 shows, the performance deteriorates with increasing number of beacons, which is due to the asymmetric RSSI of the central beacon.

Fig. 10. Training positions compared to real-time measurements calculated with the implemented wkNN with $k = 3$, Chebyshev norm.

Fig. 11. Training positions compared to real-time measurements calculated with the implemented wkNN with $k = 3$, Euclidian norm.
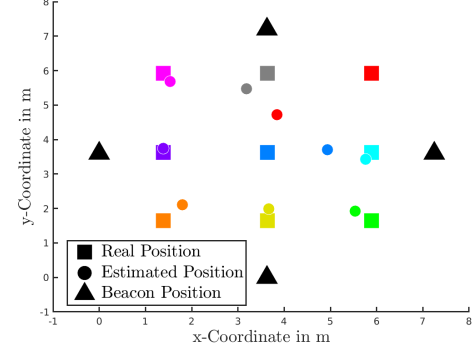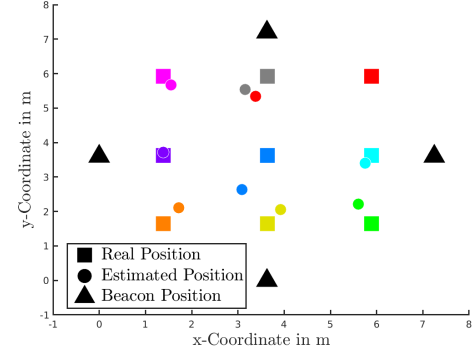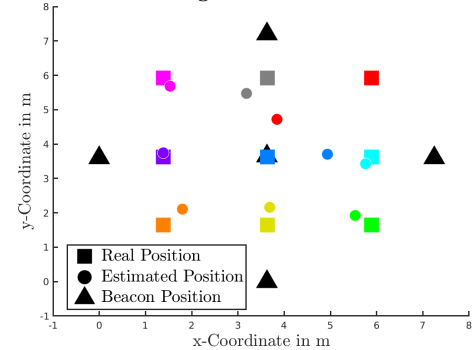

Fig. 12. Training positions compared to real-time measurements calculated with the implemented wkNN with $k = 3$, Chebyshev norm and 5 beacons.

VI. Conclusion

This paper presents the design and implementation of an indoor localization hardware-software system that enables lo-

calization and tracking in medical applications. The algorithms use a low-complexity algorithm based on RSSI and weighted k-Nearest Neighbors that can run on an ARM Cortex-M4F microcontroller. Experimental results have shown high accuracy of the solution with an average error of only $0.7\,\text{m}$ in a $7.2\,\text{m} \times 7.2\,\text{m}$ scene. The average power consumption of the mobile tag is only $50\,\mu\text{A}$ at $3\,\text{V}$, resulting in a long lifetime when powered by a coin battery. The advantages of the presented system are the availability of BLE on many conventional devices, the high energy efficiency and the reliable use for rough localization at least room by room. Future work will improve the experimental evaluation and find the optimal parameters of the algorithm.

REFERENCES

[1] T. V. Haute, E. D. Poorter, P. Crombez, F. Lemic, V. Handziski, N. Wirström, A. Wolisz, T. Voigt, and I. Moerman, "Performance analysis of multiple indoor positioning systems in a healthcare environment," *International Journal of Health Geographics*, vol. 15, no. 1, p. 7, 2016. [Online]. Available: https://doi.org/10.1186/s12942-016-0034-z

[2] M. N. K. Boulos and G. Berry, "Real-time locating systems (rtls) in healthcare: a condensed primer," *International Journal of Health Geographics*, vol. 11, no. 1, p. 25, 2012. [Online]. Available: https://doi.org/10.1186/1476-072x-11-25

[3] F. Furfari, A. Crivello, P. Baronti, P. Barsocchi, M. Girolami, F. Palumbo, D. Quezada-Gaibor, G. M. M. Silva, and J. Torres-Sospedra, "Discovering location based services: a unified approach for heterogeneous indoor localization systems," *Internet of Things*, vol. 13, no. nil, p. 100334, 2021. [Online]. Available: https://doi.org/10.1016/j.iot.2020.100334

[4] Y. A. Kim, H. Lee, and K. Lee, "Contamination of the hospital environmental by pathogenic bacteria and infection control," *Korean Journal of Nosocomial Infection Control*, vol. 20, no. 1, p. 1, 2015. [Online]. Available: https://doi.org/10.14192/kjnic.2015.20.1.1

[5] H. Chabbar and M. Chami, "Indoor localization using wi-fi method based on fingerprinting technique," in *2017 International Conference on Wireless Technologies, Embedded and Intelligent Systems (WITS)*, 4 2017, p. nil. [Online]. Available: https://doi.org/10.1109/wits.2017.7934613

[6] D. Macagnano, G. Destino, and G. Abreu, "Indoor positioning: A key enabling technology for iot applications," in *2014 IEEE World Forum on Internet of Things (WF-IoT)*, 3 2014, p. nil. [Online]. Available: https://doi.org/10.1109/wf-iot.2014.6803131

[7] V. Jelicic, M. Magno, D. Brunelli, V. Bilas, and L. Benini, "An energy efficient multimodal wireless video sensor network with ez430-rf2500 modules," in *5th International Conference on Pervasive Computing and Applications*, 12 2010, p. nil. [Online]. Available: https://doi.org/10.1109/icpca.2010.5704091

[8] J. Liu and R. Jain, "Survey of wireless based indoor localization technologies," in *Washington University in St. Louis*, 2014. [Online]. Available: http://www.cse.wustl.edu/~jain/cse574-14/ftp/indoor.pdf

[9] M. Magno, S. Rickli, J. Quack, O. Brunecker, and L. Benini, "Poster abstract: Combining lora and rtk to achieve a high precision self-sustaining geo-localization system," in *2018 17th ACM/IEEE International Conference on Information Processing in Sensor Networks (IPSN)*, 4 2018, p. nil. [Online]. Available: https://doi.org/10.1109/ipsn.2018.00043

[10] P. Fonseka and K. Sandrasegaran, "Indoor localization for iot applications using fingerprinting," in *2018 IEEE 4th World Forum on Internet of Things (WF-IoT)*, 2 2018, p. nil. [Online]. Available: https://doi.org/10.1109/wf-iot.2018.8355105

[11] J. Xiao, Z. Zhou, Y. Yi, and L. M. Ni, "A survey on wireless indoor localization from the device perspective," *ACM Computing Surveys*, vol. 49, no. 2, pp. 1–31, 2016. [Online]. Available: https://doi.org/10.1145/2933232

[12] X. Tian, W. Li, Y. Yang, Z. Zhang, and X. Wang, "Optimization of fingerprints reporting strategy for wlan indoor localization," *IEEE Transactions on Mobile Computing*, vol. 17, no. 2, pp. 390–403, 2018. [Online]. Available: https://doi.org/10.1109/tmc.2017.2715820

[13] L. Flueratoru, S. Wehrli, M. Magno, E. S. Lohan, and D. Niculescu, "High-accuracy ranging and localization with ultra-wideband communications for energy-constrained devices," *CoRR*, 2021. [Online]. Available: http://arxiv.org/abs/2104.11042v1

[14] V. Niculescu, M. Magno, D. Palossi, and L. Benini, "An energy-efficient localization system for imprecisely positioned sensor nodes with flying uavs," in *2020 IEEE 18th International Conference on Industrial Informatics (INDIN)*, 7 2020, p. nil. [Online]. Available: https://doi.org/10.1109/indin45582.2020.9442075

[15] Y. Ma, B. Wang, S. Pei, Y. Zhang, S. Zhang, and J. Yu, "An indoor localization method based on aoa and pdoa using virtual stations in multipath and nlos environments for passive uhf rfid," *IEEE Access*, vol. 6, no. nil, pp. 31772–31782, 2018. [Online]. Available: https://doi.org/10.1109/access.2018.2838590

[16] K.-H. Lam, C.-C. Cheung, and W.-C. Lee, "Rssi-based lora localization systems for large-scale indoor and outdoor environments," *IEEE Transactions on Vehicular Technology*, vol. 68, no. 12, pp. 11778–11791, 2019. [Online]. Available: https://doi.org/10.1109/tvt.2019.2940272

[17] P. Mayer, M. Magno, A. Berger, and L. Benini, "Rtk-lora: High-precision, long-range and energy-efficient localization for mobile iot devices," *IEEE Transactions on Instrumentation and Measurement*, vol. nil, no. nil, pp. 1–1, 2020. [Online]. Available: https://doi.org/10.1109/tim.2020.3042296

[18] P. Mayer, M. Magno, T. Brunner, and L. Benini, "Lora vs. lora: In-field evaluation and comparison for long-lifetime sensor nodes," in *2019 IEEE 8th International Workshop on Advances in Sensors and Interfaces (IWASI)*, 6 2019, p. nil. [Online]. Available: https://doi.org/10.1109/iwasi.2019.8791362

[19] Z. Hajiakhondi-Meybodi, M. Salimibeni, K. N. Plataniotis, and A. Mohammadi, "Bluetooth low energy-based angle of arrival estimation via switch antenna array for indoor localization," in *2020 IEEE 23rd International Conference on Information Fusion (FUSION)*, 7 2020, p. nil. [Online]. Available: https://doi.org/10.23919/fusion45008.2020.9190573

[20] X. Song, X. Fan, C. Xiang, Q. Ye, L. Liu, Z. Wang, X. He, N. Yang, and G. Fang, "A novel convolutional neural network based indoor localization framework with wifi fingerprinting," *IEEE Access*, vol. 7, no. nil, pp. 110698–110709, 2019. [Online]. Available: https://doi.org/10.1109/access.2019.2933921

[21] D. Sun, E. Wei, L. Yang, and S. Xu, "Improving fingerprint indoor localization using convolutional neural networks," *IEEE Access*, vol. 8, no. nil, pp. 193396–193411, 2020. [Online]. Available: https://doi.org/10.1109/access.2020.3033312

[22] X. Wang, M. Hersche, B. Tomekce, B. Kaya, M. Magno, and L. Benini, "An accurate eegnet-based motor-imagery brain-computer interface for low-power edge computing," in *2020 IEEE International Symposium on Medical Measurements and Applications (MeMeA)*, 6 2020, p. nil. [Online]. Available: https://doi.org/10.1109/memea49120.2020.9137134

[23] "Apple ibeacon." [Online]. Available: https://developer.apple.com/ibeacon/

[24] "nrf5 sdk." [Online]. Available: https://www.nordicsemi.com/Products/Development-software/nRF5-SDK

[25] K. Townsend, "Introduction to bluetooth low energy." [Online]. Available: https://learn.adafruit.com/introduction-to-bluetooth-low-energy/introduction

[26] A. Blackstone, "Understanding the different types of ble beacons," 3 2015. [Online]. Available: https://os.mbed.com/blog/entry/BLE-Beacons-URIBeacon-AltBeacons-iBeacon/

[27] Y.-C. Pu and P.-C. You, "Indoor positioning system based on ble location fingerprinting with classification approach," *Applied Mathematical Modelling*, vol. 62, no. nil, pp. 654–663, 2018. [Online]. Available: https://doi.org/10.1016/j.apm.2018.06.031

[28] X. Peng, R. Chen, K. Yu, F. Ye, and W. Xue, "An improved weighted k-nearest neighbor algorithm for indoor localization," *Electronics*, vol. 9, no. 12, p. 2117, 2020. [Online]. Available: https://doi.org/10.3390/electronics9122117