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Channel Diversity for Indoor Localization Using Bluetooth Low Energy and Extended Advertisements

MACIEJ NIKODEM AND PRZEMYSŁAW SZELIŃSKI
Department of Computer Engineering, Wrocław University of Science and Technology, 50-370 Wrocław, Poland
Corresponding author: Maciej Nikodem (maciej.nikodem@pwr.edu.pl)

ABSTRACT Bluetooth Low Energy (BLE) is a ubiquitous low-power communication technology used in many applications including location-based services. Typically, in BLE localization, the beacons transmit advertisement messages while moving devices infer their location from radio signal strength measurements. Previous work has noted that three radio channels used for advertisement transmission exhibit different propagation conditions including frequency dependent shadowing and multipath. Because most of the consumer electronic devices report only the measured signal strength value without the number of a channel in which it was measured, the variance of the measurements increases and adversely affects the accuracy of localization. Information on the channel used can improve the localization accuracy, however, the existing approaches are limited to three advertisement channels, ignoring the remaining 37 channels available in BLE communication. This article analyses the impact of channel diversity on the accuracy of BLE-based indoor localization. In contrast to previous work, we use signal strength measurements from all 40 channels and show that channel diversity can significantly improve the localization accuracy. Experiments conducted in $100\,\mathrm{m}^2$ office area show that using signal strength measurements in 40 channels improves the average localization accuracy by approximately 50 % and 20 % compared to the use of 3 channels without and with information on the channel used, respectively. Overhead of the proposed method can be reduced through careful selection of the radio channels used in measurements. We propose a channel selection method which allows to significantly improve the localization accuracy using measurements collected from between 10 and 15 channels.

INDEX TERMS Bluetooth low energy, extended advertising, communication channels, indoor radio communication, localization.

I. INTRODUCTION

Bluetooth Low Energy (BLE) is a widespread communication technology available in many consumer electronic devices including smart watches, mobile phones, laptops, and tablets. Due to its prevalence, use in IoT applications, and the need for location-based services (LBS), BLE is not only considered a communication technology but also a localisation technology. Unfortunately, when designed, the BLE was not meant to provide reliable location information and the existing BLE-based LBS mostly relay on received signal strength measurements. These approaches use the received signal strength indicator (RSSI), reported by every BLE device receiving the radio message. Unknown position of the device is estimated based on the transmitted advertisement messages. Anchors measure RSSI of the received advertisements and use a multilateration or fingerprinting procedure to estimate the unknown position of the device. This is possible because the signal strength drops with the distance from the transmitter. Unfortunately, contemporary devices measure the RSSI with low accuracy, and the value of the signal strength at the receiver depends on various other factors including antenna type, device orientation, as well as environmental and propagation conditions, some of which are frequency dependent [1]. Because the typical BLE-based localization system uses three advertisement channels but does not use channel information (i.e. does not recognize the

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channel number for which RSSI was measured), the resulting accuracy of the localization is even lower [2].

Several authors (e.g., [3]–[5]) have already observed that measuring RSSI and analysing it together with channel information[1] leads to improved accuracy. Previous work in this area only focused on the three primary advertisement channels because it was impossible to transmit advertisement messages on the remaining channels, which were historically reserved for connection-based communications and dedicated for the exchange of data between a pair of BLE devices. However, the introduction of the BLE standard version 5.x [6] brought in a new type of radio event called extended advertisement. When configured, the BLE 5.x device transmits the advertisement packets on three primary channels and a single auxiliary packet on one of the data channels. Devices receiving the extended advertisement report RSSI for auxiliary packets, allowing to measure RSSI on this data channel. Because the transmitter randomly chooses the data channels, transmitting a number of extended advertisements allows to measure RSSI on all 37 data channels. Switching the transmitter between legacy and extended advertising modes allows the receiver to collect RSSI from all 40 BLE channels and use it to improve the localization.

This article proposes a general approach that can be used to improve the accuracy of all localization methods that are based on signal strength measurements and BLE. We analyse the effect of channel diversity and show that the use of appropriately selected communication channels improves the accuracy significantly even for simple localization methods. The main contributions are the following:

- we show that extended advertisements and RSSI measurements in multiple communication channels improve the localization accuracy,
- we present that the use of multiple channels allows to reduce the number of measurements required to derive the path loss model parameters and simplifies the calibration in new environments,
- we show that the localization accuracy can be improved when channel information is exploited for both distance and location estimation. Consequently, the channel information should be maintained until the final stages of the localization procedure.

This paper is structured as follows. Section II presents the most important work on channel diversity in BLE, emphasises on the progress beyond the state-of-the-art, and argues the benefits of the proposed approach. Section III describes the concept of extended advertisement, presents the experimental setup, structures of the localization procedure, and details the implementation of the localization algorithms. Section IV discusses results of the experiments and the impact of the number of channels used, structure of the localization procedure, and the callibration data set on the localization accuracy. Final conclusions are presented in section V.

II. BACKGROUND AND MOTIVATION

Until now, a number of researchers have investigated the effect of RSSI measurement variability in three advertisement channels (37, 38, 39), and their impact on signal strength-based localization.

Nikoukar *et al.* [1] have analysed and modeled the advertisement channels in four different environments. Their work shows the variance of noise floor, the effect of WiFi interference on advertisement channels, and differences in signal propagation for those channels. They derive log-normal shadowing models for each advertisement channel and recommend to use it for localization. Presented results also show that for a given transmission distance, both the RSSI values and their variance differ significantly for various channels, especially in complex indoor environments. This is also presented in [2] where the composite variance (calculated across advertisement channels) may exceed a single channel variance by more than 4 dB. As presented, this corresponds to 3 m difference in localization accuracy for the analysed scenario.

Localization performance for advertisement channels, different device orientations, and protocols (Eddystone and iBeacon) was analysed by De Blasio *et al.* [3]. They showed that RSSI measurements vary significantly between channels and protocols used, and searched for the best combination of protocol and channel that yield the highest values of accuracy and precision. Conducted experiments show that the best results are achieved for channels 38 and 39 depending on the device orientation. However, when all measurements are considered regardless of orientation, the best average results are achieved for channel 37. This shows that choosing a single radio channel for accurate localization in various situations is challenging and the use of multiple channels is recommended.

Several authors have so far attempted to benefit from multi-channel RSSI measurements and channel information to improve the accuracy of localization. Zanella *et al.* [7] argued that the accuracy of signal strength-based ranging and localization can be increased by averaging the RSSIs measured at different channels. Simplicity and applicability to all BLE devices, even those that do not report channel information together with the RSSI measurement, is an advantage of the proposed approach. Paterna *et al.* [8] used three different methods to combine channel-wise RSSI measurements: max, average, and maximum ratio combining. In their test scenarios, the max method gives the best results and allows to significantly improve the resulting localization accuracy.

Zhe *et al.* [4], on the other hand, argue that a simple mean of RSSI measurements from advertisement channels is not a good approach and increases localization errors. As presented, the characterization of the advertisement channels and inter-channel bias allows to effectively combine RSSI measurements from different channels, improving the resulting

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[1] In this article *channel information* denotes an integer number between 0 and 39 identifying the BLE channel used for radio transmission and RSSI measurement.

localization accuracy. Consequently, instead of a simple mean, they recommend to use parametric multi-channel calibration models for measurement combination. Estimation of the models requires additional measurements before localization can be used, but allow to improve the positioning performance.

Slightly different approach is presented by Huang *et al.* [5]. Instead of aggregating the RSSI measurements from different channels, they propose to use RSSI and channel information to build separate propagation models for each channel. During localization, the RSSI measurements and models are used to estimate the channel-wise distances (separate distance estimate for each channel). Distances are then combined to output a single distance estimate which is then used in multilateration. Their approach requires offline training, but together with a dedicated distance decision method, and weighted multilateration, allows to significantly reduce the localization error. Improvements were also reported for localization methods based on fingerprinting when RSSI fingerprints were created individually for each advertisement channel [9].

Previous works have already presented that using channel diversity improves signal strength-based indoor localization. Some results also suggest that the improvement depends on the spacing between the channels, while the impact of the number of channels used is less important. For example, for 802.15.4 radios, the use of 6 and 16 channels equally spaced in the 2.4 GHz frequency band, yields similar results when using multichannel RSSI information [7]. Although BLE channels 37 and 39 are maximally spaced apart and the use of three advertisement channels improves RSSI-based localization, the impact of using additional channels is not presented in the literature.

This article complements previous results and is the first to analyse the application of extended advertisements to localization, and the impact of RSSI information from all 40 BLE radio channels on the localization accuracy. Benefiting from the new features of BLE 5 standard, we show that the use of extended advertisements and communication in multiple radio channels improves the accuracy of signal strength-based localization. We present how channel information can be exploited in localization algorithms, the impact of the number of channels on localization accuracy, and a method to choose channels for location estimation. The proposed approach can easily scale and generalize as a range of tools and methods, which improve signal strength-based localization, could be directly applied to our approach. The proposed approach is agnostic to such improvements.

III. EVALUATION METHOD

BLE devices transmit radio messages using 40 radio channels within 2.4 GHz frequency spectrum. Three radio channels, numbered 37, 38, and 39, are dedicated to connection-less communication and referred to as primary advertisement channels. These channels are used by peripheral devices to transmit advertisement messages, which are used to inform neighbouring central devices about the device presence and its basic capabilities, e.g., if the peripheral device accepts connections or allows scanning. Upon advertisement reception, the central device can initiate and establish connection with the peripheral device. After the connection is established, the devices use the remaining 37 channels (numbered 0 to 36) for connection-based communication. With the growth of IoT applications and due to the limited number of BLE devices that can be simultaneously connected [10], researchers started to investigate other possibilities. Because advertisement messages allow the peripheral device to transmit a small chunk of application-specific data and the number of simultaneously communicating devices can be large [11], [12], they were adopted to various applications including opportunistic sensing, and localization [13], [14].

Over time, the need for connection-less communication in BLE caused the Bluetooth SIG consortium to define new functionalities. Among others, BLE version 5 compatible devices support not only the transmission of advertisement messages (legacy advertisements which are used to ensure backward compatibility with BLE version 4) but also extended advertisements. The extended advertisements [6] include auxiliary radio packets that are transmitted after the transmission of advertisement packets on channels 37, 38, and 39. To avoid congestion on primary advertisement channels, auxiliary packets are transmitted using channels 0-36, which are referred to as secondary advertising channels. Because the peripheral device decides which secondary channel to use and when to transmit the auxiliary packet, the number of the secondary channel and the time offset from the advertisement are included in the advertisement. This informs the observer device on which channel and when the auxiliary packet should be received.

Although the extended advertisements were introduced to offload primary advertisement channels from data transmission and increase the amount of transmitted application-specific data, they can be also used for localization. Because the peripheral device changes secondary advertising channels, and the observer device reports RSSI measurement for the auxiliary packet, the localization procedure can benefit from multi-channel RSSI measurements and use channel information to improve the accuracy of localization.

To assess the effect of channel diversity, we have conducted localization experiments in real-life conditions, analysed RSSI measurements, and the localization accuracy when using two localization algorithms and different number of channels.

A. EXPERIMENTAL SETUP

We used nRF DK 52840 development boards from Nordic Semiconductor that are compatible with BLE 5 which allow to transmit extended advertisements and collect RSSI measurements for legacy and extended advertisement together with channel information. One device was a mobile node that was configured to periodically transmit legacy and extended advertisements with an advertisement interval of 20ms and

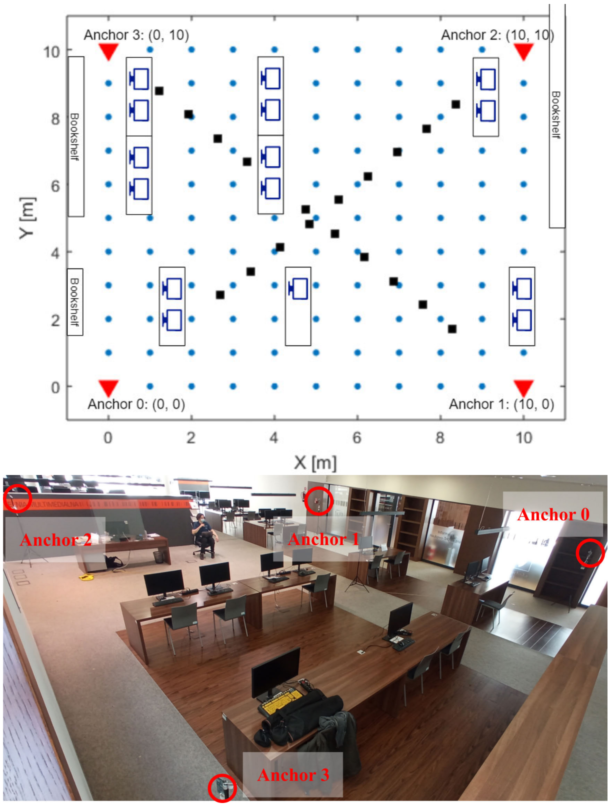

FIGURE 1. (Top) Localization area, location of anchors (red triangles), 105 test points along a square grid (blue dots) and 19 test points along the diagonals of the area (black squares). (bottom) Photography of the localization area with location of the anchors.

a transmission power of +8 dBm. For extended advertisements a mobile node transmits an advertisement in a primary channel and a single auxiliary packet in a randomly chosen secondary advertisement channel. Four devices (anchors) were deployed in the corners of the evaluation area and configured as passive scanners in continuous scanning mode (scan interval and scan window set to 10 s). Anchors were responsible for receiving advertisements from the mobile node and recording RSSI and channel information. When the extended advertisement is received, the anchor reports RSSI only for the auxiliary packet and not for the preceding legacy advertisement. Consequently, using extended advertisements, we were able to collect RSSI measurements only for the secondary advertisement channels (0-36). To collect RSSI measurements from both primary and secondary channels, we periodically switched the mobile node between the legacy and extended advertisement modes. The node spent 100 ms transmitting legacy non-connectable and non-scannable undirected advertisements and 900 ms transmitting extended advertisements with a fixed advertisement interval of 20 ms. In this configuration, the anchors were able to collect at least 44 RSSI measurements in every radio channel during 60 seconds.

The experiment was conducted in office space, 10 m by 10 m area free of large obstacles (Fig. 1). Devices were mounted on tripods approximately 1.6 m above the ground. The anchors were deployed in corners of the area while the mobile device was moved between test points. There were 105 test points located approximately 1 m apart in a square grid – due to the obstacles in the area, some test points were skipped. Additional 19 calibration points were located along the diagonal of the area, spaced approximately 1 m apart. Measurements were collected in each test point for 2-3 minutes, allowing to collect approximately 100 RSSI values for each channel.

B. LOCALIZATION PROCEDURE

When BLE receivers record RSSI separately for each transmission channel, the localization procedure can use the RSSI separately for each channel or jointly, i.e., irrespectively of the channel. The localization procedure can use channel information in distance estimation and localization algorithm execution. However, at some point of the procedure, the channel-wise results have to be aggregated (channel information is lost) to produce a final location estimate. The localization procedure utilizing channel information can therefore have two basic structures (Fig. 2):

- structure A uses the channel information for distance estimation only – each anchor calculates a single distance estimation as an aggregate of channel-wise distances estimated from RSSI and channel information. Single distance and location for each anchor is used in the localization algorithm to find the unknown location. Structure A is a typical method to utilize channel diversity for localization (e.g., [5], [9]).
- structure B uses the channel information for both distance and location estimation – anchors estimate channel-wise distances and feed them to a localization algorithm that calculates the estimated location based on all distances and corresponding channel information. Details of this calculation depend on the actual localization algorithm used and are discussed in section III-E.

Structure A requires the aggregation of channel-wise distances to a single distance estimate, and this can be implemented in various ways (e.g., [4], [8]). In the experiments, the channel-wise distances are aggregated using a weighted average:

$$d^{(j)} = \frac{\sum_{i=0}^{39} w_i \cdot d_i^{(j)}}{\sum_{i=0}^{39} w_i}, \tag{1}$$

where $d_i^{(j)}$ is an estimated distance to j-th anchor based on the RSSI measurements in the i-th channel. Weight w_i is distant dependent and defined as:

$$w_i = \frac{d_i^{-p}}{\sum_{i=1}^{N} d_i^{-p}}, \tag{2}$$

where $p = 0, 1, 2, \ldots$ controls the preference to smaller distances compared to large ones. In particular, when $p = 0$ then all weights are equal. As p increases, the weights for larger distances quickly drop to zero. Small weight for a large distance effectively minimizes its impact on the estimated

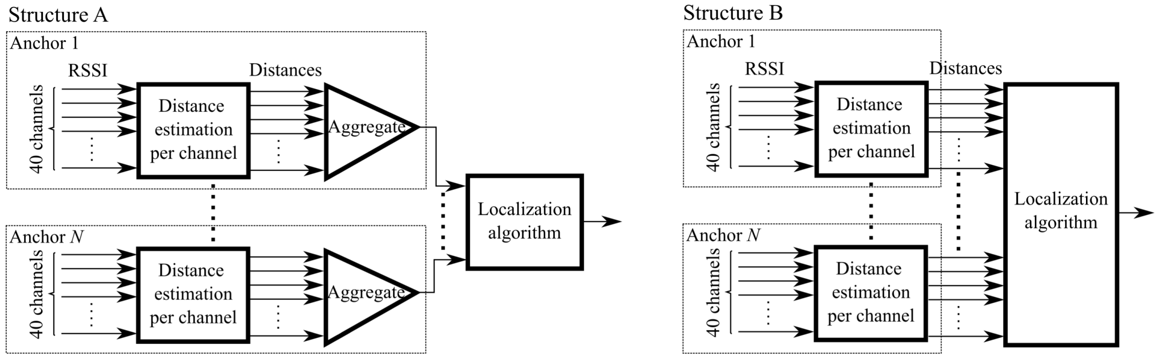

FIGURE 2. **Structures of the localization procedures using channel information. (left) In Structure A the channel information is used in distance estimation only – each anchor finds channel-wise distances and aggregates them to a single distance estimate. Localization algorithm uses *N* distances and corresponding anchor locations to estimate the unknown position. (right) In Structure B the channel information is used both in distance and location estimation – each anchor finds channel-wise distances all of which are forwarded to localization algorithm. Localization algorithm takes 40 · *N* inputs to estimate the unknown position.**

location. In the experiments, we have set $p = 4$ which effectively promotes shorter distances.

In the experiments, the log distance path loss model is used for distance estimation, weighed multilateration [8], [15] and GeoN [16] as localization algorithms. These are described in the following subsections. The resulting localization is not corrected in any way, even when it falls outside the localization area.

C. PATH LOSS MODEL

The localization algorithms used in the evaluation are range-based, which means the signal strength measurements need to be transformed to distances from the anchors. According to the BLE specification, the reported RSSI is an absolute receiver signal strength value in dBm [6]. Using log distance path loss model, the received signal strength at distance d equals:

$$\mathrm{RSSI}(d) = P_{\mathrm{TX}} - \left(\mathrm{PL}(\mathrm{d}_0) + 10 \cdot \alpha \cdot \log \frac{d}{d_0} + \chi\right), \quad (3)$$

where P_{TX} is a transmission power, $\mathrm{PL}(d_0)$ is a path loss at reference distance d_0 (usually 1 m), α is a path loss coefficient that depends on the environment and propagation conditions, and χ is a noise modelled as a random variable with zero mean and bounded variance. Assuming $d_0 = 1$ and setting $P_{\mathrm{RX}}(d_0) = P_{\mathrm{TX}} - \mathrm{PL}(d_0)$ the (3) simplifies to

$$\mathrm{RSSI}(d) = P_{\mathrm{RX}}(d_0) - 10 \cdot \alpha \cdot \log d - \chi, \quad (4)$$

where the unknown parameters can be estimated from the calibration measurements collected in selected locations of the localization area. In the experiments, we have used two sets of calibration points (Fig. 1): the first set includes 25% of randomly selected measurements collected in 105 locations along the square grid; the second set contains data from 19 calibration points located along the diagonals of the area.

D. RSSI AND DISTANCE PREPROCESSING

BLE devices measure signal strength with a low accuracy of ±6 dBm [6] and the measured values are affected by varying propagation conditions. This leads to fluctuations in RSSI measurements which should be filtered before the measurements are used for path loss model (4) calibration. In the calibration phase, a two-stage RSSI filtering is implemented. In the first stage, the frequency and distribution of RSSI measurements for a radio channel are analysed. Measurements that are infrequent (below 10% of the number of all measurements for that point and channel) are dropped. The second stage removes low RSSI values measured at short distances from the anchor. Experimentally, we have decided to drop all measurements with RSSI smaller than $-1.5 \cdot d - 56\,\mathrm{dBm}$. Both methods filtered out less than 17% of the calibration measurements.

Although filtered, the RSSI values may still lead to large inaccuracies in distance estimation. This is a consequence of the logarithmic dependency on the distance (4) and becomes clearly visible for large distances and small RSSI values where small variations in measurements yield large differences in the estimated distance. Consequently, the estimated distances may exceed the dimension of the localisation area and adversely affect the resulting localization accuracy. In the evaluation, all estimated distances are saturated at 15 m, which is slightly larger than the maximal distance between any anchor and a test point in the evaluation area.

E. LOCALIZATION ALGORITHMS

Two localization algorithms were selected to assess the effect of channel diversity on localization.

Multilateration is one of the most common methods used for signal strength-based localization in indoor environments. Because of its popularity, it has different variants that use different path loss models, methods to select distance information when redundant information is available, and algorithms to calculate the location based on selected distances. Despite the differences, every multilateration variant uses distance estimates to define rings around the corresponding anchor and calculates the estimated location as an intersection point of the rings. We use weighted multilateration which takes all distance estimates and assigns weights based on the distance value. In the implemented approach, higher weights are assigned to smaller distances and the estimated location is found through optimization of a cost function

$$F(x, y) = \sum_{i=1}^{N} w_i \cdot \left((x - x_i)^2 + (y - y_i)^2 - d_i\right)^2, \qquad (5)$$

where (x, y) is the unknown location, N is the number of anchors, (x_i, y_i) is the location of i-th anchor, d_i is the estimated distance to the anchor, and w_i are weights (2).

The second localization algorithm is Geo-N [16]. This is a geometrical algorithm that attempts to eliminate distance estimates that contribute significantly to the localization error. Due to the large complexity, we run Geo-N separately for each channel and calculate the resulting locations as a centroid

$$(x, y) = \left(\frac{\sum_{i=0}^{39} x_i}{40}, \frac{\sum_{i=0}^{39} y_i}{40}\right), \qquad (6)$$

where (x_i, y_i) is an estimated location in the i-th channel. The Geo-N algorithm takes into account both the real intersection points between a pair of circles (defined by a pair of anchors and the corresponding distances) and the approximated intersection points, when the two circles do not intersect due to inaccurate distance estimates. The algorithm uses two-stage filtering to obtain representative intersection points and remove those that do not improve the accuracy. Finally, the estimated location is calculated as a weighted centroid of the selected intersection points with different weights assigned to real and approximated intersection points. In the evaluation, these weights were experimentally sset to 0.1 and 0.9 for real and approximated intersection points, respectively.

IV. RESULTS AND DISCUSSION

The following subsections present results of the experiments and the impact of various parameters on the localization accuracy. The first subsection presents the results varying the number of channels used, using structure B of the localization procedure and calibrating the path loss model on 25 % of randomly selected RSSI measurements. The impact of the localization procedure structure and the choice of calibration measurements are presented in the second and third subsections, respectively.

A. THE NUMBER OF CHANNELS

Figure 3 presents a cumulative distribution of localization error for four scenarios: using legacy advertisements (transmitted on channels 37, 38 and 39) with and without channel information, and using extended advertisements transmitted on all 40 channels with and without channel information. The plot shows that the channel information improves accuracy for localization using both legacy and extended advertisements irrespective of the localization algorithm used. The improvement in mean localization error, compared to the use of legacy advertisements without channel information, exceeds 35 % when using 3 primary advertisement channels, and achieves 53 % for extended advertisements with 40 channels, when the channel information is available (Tab. 1). This confirms the results presented in previous work on the use of primary advertisement channels for improved localization, and shows that further improvement is possible when extended advertisements and secondary advertisement channels are used. Results also show that using extended advertisements with 40 channels without channel information achieves better localization accuracy compared to using only 3 primary channels with no channel information. This means that even consumer electronic devices, which do not report channel information together with RSSI measurements, may improve localization accuracy when they switch to extended advertisements.

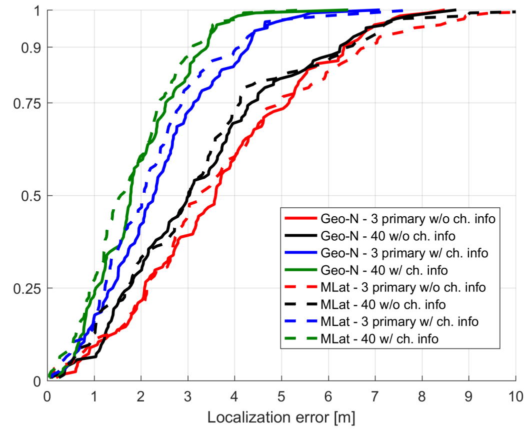

FIGURE 3. Cumulative distribution of localization error when using 3 primary and 40 advertisement channels with and without channel information. Using channel information and 40 channels improves the accuracy of localization irrespective of the localization algorithm.

TABLE 1. Statistics of the localization error for various test scenarios - using different number of channels, with and without channel information, and both localization algorithms.

Alg.	Channel		mean	Localization error [m] Percentile				
	No.	Info		25th	50th	75th	90th	95th
Geo-N	3	no	3.67	2.08	3.60	5.16	6.34	6.93
	40	no	3.32	1.75	3.02	4.36	6.26	6.81
	3	yes	2.39	1.40	2.27	3.13	4.30	4.70
	40	yes	1.92	1.04	1.78	2.53	3.43	3.6
MLat	3	no	3.75	2.12	3.23	4.96	6.88	7.84
	40	no	3.28	1.72	3.03	4.12	6.52	7.13
	3	yes	2.21	1.23	2.07	2.86	4.16	4.64
	40	yes	1.77	0.93	1.57	2.39	3.12	3.53

Figure 3 and Tab. 1 also show that the improvements in the localization accuracy are not linear with the number of channels used. For example, while the channel information for 3 primary channels improves accuracy by 35 %, the difference between using 3 and 40 channels is slightly below 20 %. Therefore, it might be desirable to reduce the number of channels used for localization, reducing the number and time of RSSI measurements while not affecting the accuracy significantly. To decide which channels to use, we analysed the variability of RSSI measurements for all test points and each channel-anchor pair. Figure 4 presents the average value

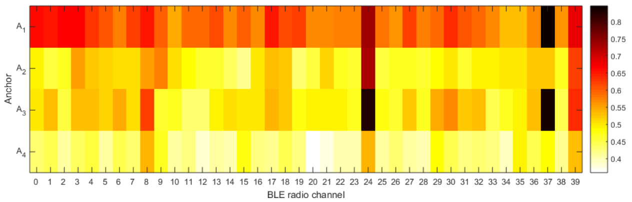

FIGURE 4. **Average standard deviation of RSSI measurements for each anchor-channel pair. Smaller values denote lower variance in RSSI measurements and thus channels and anchors preferred for localization.**

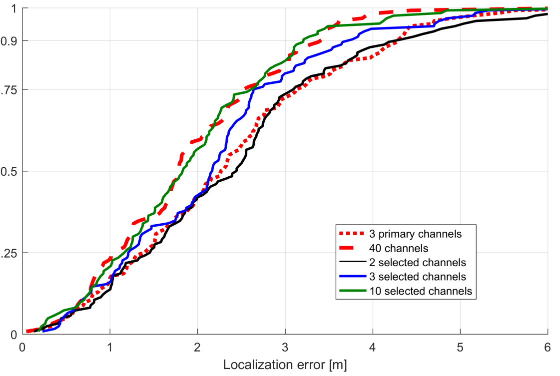

FIGURE 5. **Cumulative distribution function of localization error for different number of channels and Geo-N algorithm. The error distribution for 2 and 10 selected channels is similar to the distribution for 3 primary and 40 channels, respectively.**

of standard deviation for each anchor and radio channel calculated across all localization points in the area. The figure shows that the variations in RSSI measurements are different for different channels as well as for different anchors. For example, the primary advertisement channels (37, 38, 39) yield relatively large variations which suggest that the distances estimated from measurements in these channels will be biased with larger errors. Similarly, the RSSI values measured by anchor A_1 vary more compared to the remaining anchors. This may suggest that the measurements taken by this anchor are less reliable and should be assigned lower weights.

While the differences in the RSSI variations may result from various reasons, the channels with smaller variations are preferred. Therefore, selecting the advertisement channels for localization, we choose k channels with the smallest average values of RSSI's standard deviation $\bar{\sigma}$. Precisely, we choose channels with indices $i_1, i_2, \ldots, i_k$ such that

$$\max_j \bar{\sigma}_{i_1,j} \leq \ldots \leq \max_j \bar{\sigma}_{i_k,j} \leq \max_j \bar{\sigma}_{i_{\text{other}},j}, \tag{7}$$

where $\bar{\sigma}_{i_c,j}$ denotes mean standard deviation of RSSI measured by j-th anchor on channel with index i_c, and i_{other} denotes channel indices other then $i_1, \ldots, i_k$.

Figure 5 presents the cumulative distribution of the localization error for a Geo-N method and a different number of channels used by the localization algorithm. Using two channels, selected with the proposed procedure, and the three primary channels gives similar errors. The same is the case for 10 selected channels and all 40 channels. This suggests that careful selection of the channels allows to achieve expected accuracy while reducing the number of channels used and overhead of the localization procedure.

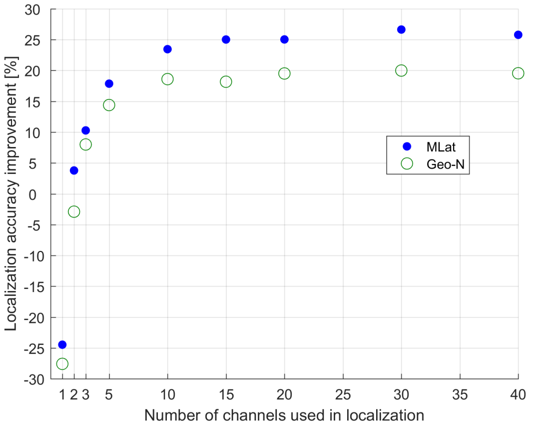

FIGURE 6. **Improvement of the average localization error using different number of channels. Results presented are relative to the localization error using legacy advertisements (3 primary channels) with channel information.**

This observation is also visible in Fig. 6 which shows the mean error for different number of selected channels, relative to the localization utilizing only three primary advertisement channels. As presented with the proposed channel selection method choosing the best 3 channels, the mean localization error can be reduced by approximately 8-11 % depending on the localization algorithm. Even using only two selected channels, the localization accuracy is almost the same as when 3 primary channels are used (lower by 3% for Geo-N and larger by 4% for multilateration). Using 10 channels, it is possible to improve the localization accuracy by 18-23 % compared to the use of 3 primary advertisement channels. Increasing the number of channels further does not provide significant improvement.

B. STRUCTURE OF LOCALIZATION PROCEDURE

As mentioned earlier, channel-wise RSSI measurements and distance estimates can be aggregated at different steps of the localization procedure (Fig. 2). Figure 7 compares the localization accuracy as a function of the localization method structure. Higher localization accuracy is achieved for structure B where the channel information is maintained through both distance and location estimation algorithms and lost in the final step of the localization procedure. Improved results are achieved at the cost of a larger computational overhead because the localization algorithm takes a larger number of inputs and requires more calculations. This is a shortcoming for algorithms with large computational complexity, including Geo-N.

Structure A trades off localization procedure complexity with accuracy. When channel information is lost before the localization algorithm, the mean localization errors are approximately 6-10 % larger. Consequently, structure A procedures should be avoided unless required by the needs and constrains of an application or localization algorithm.

TABLE 2. **Comparison of localization accuracy for various areas when using multilateration with and without channel diversity.**

Alg.	Description	Channel No	Channel Information	Area m^2	mean	Localization error [m] Percentile 25th	50th	75th	90th	95th
Our	40 separate channels, experiments	40	yes	100	1.77	0.93	1.57	2.39	3.12	3.53
[8]	3 primary adv. channels, experiments, small area, no Kalman filtering	3	yes	40	–	0.8	1.4	1.9	2.76	3.14
[8]	3 primary adv. channels, experiments, large area, no Kalman filtering	3	yes	290	–	3.4	4.6	5.6	7.08	7.78
[17]	no channel diversity, experiments, small area, multilateration w/o improvements	3	no	16	1.60	0.96	1.61	2.36	2.88	2.94
[17]	no channel diversity, experiments, large area, multilateration w/o improvements	3	no	204	4.35	2.64	4.02	6.64	7.66	8.03
[18]	3 primary adv. channels, experiments	3	yes	108	–	2.9	3.5	4.4	5.8	–
[19]	with Kalman filtering, simulation, no real measurements	N/A	no	100	–	1.6	1.8	2.1	2.5	2.7

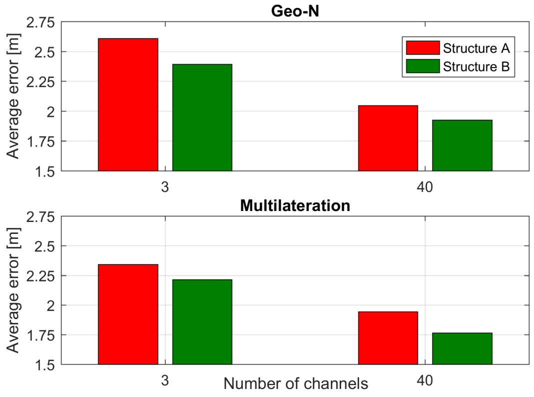

FIGURE 7. **Average localization error when using localization algorithms with channel information (using 3 primary and 40 advertisement channels) and different structures of localization procedure. For both localization algorithms (Geo-N, multilateration) maintaining channel information until location estimation improves the resulting accuracy.**

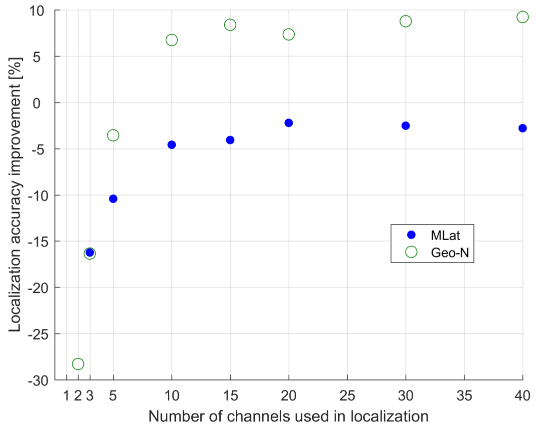

FIGURE 8. **Improvement of the average localization error when calibrating the path loss models using calibration measurements along the diagonals of the area. Results relative to the localization error using legacy advertisements (3 primary channels) with channel information when calibrated using measurements densely distributed in the area.**

C. CALIBRATION DATA

The localization procedure requires to derive path loss models to estimate the distance from the RSSI measurements. In previous experiments, these models were derived from 25 % randomly selected measurements from all test points evenly distributed over the area. While such an approach ensures a good diversity of calibration data and improves the results, it requires time-consuming measurements – although the experimental area is relatively small, there are 105 test points in which calibration measurements were collected. Reducing the number of calibration points shortens the preparation phase but adversely affects the resulting localization accuracy.

Figure 8 compares the localization accuracy when the log distance path loss model is derived using only 19 calibration points located along the diagonals of the area. Figure presents the average localization accuracy relative to the use of 3 primary advertisement channels and calibration using 25 % randomly selected measurements. As presented, when using 10 or more channels, the results of both approaches are similar – multilateration yields an accuracy lower by approximately 2-5 % while the Geo-N achieves results better by 6-9 %. This shows that the extended advertisements allow to lower the complexity of the preparation phase, reducing the number of calibration points by as much as 82 %. This simplifies the preparation phase while ensuring similar localization results as approaches that use extensive calibration and require a large number of measurements.

V. CONCLUSION

The use of extended advertisements and channel diversity can significantly improve the localization accuracy beyond what is possible using legacy advertisements. However, improved results are achieved at the cost of a larger number of measurements collected across different channels, and consequently an extended time for the localization to be calculated. Currently, the test devices do not allow to choose the secondary advertisement channel used for the transmission of an auxiliary packet of extended advertisements. Consequently, the devices have to use all 40 channels even if 10 carefully selected channels give the same localization accuracy as all 40. Although this limits the application to objects at rest and slowly moving, improvements are possible. The BLE 5 [6] standard already includes a channel mask mechanism that allows to choose the channels for auxiliary packet transmission. The localization procedure can thus adaptively select the channels depending both on the propagation conditions (e.g., interference) and the required localization accuracy, reducing the time needed for the localization procedure.

Because every device requires only a few channels for localization, devices may adjust the list of channels used so that mutual interference and collisions are minimised. This opens a new area of research in the optimization of channel selection in dense environments. This is important as the quality of RSSI measurements varies for different radio channels, transmitters, receivers (cf. Fig 4), as well as the location of the communicating nodes. Consequently, the best choice of the channels is likely to be device dependent, changing over time and as the device moves. Proposing efficient and low-overhead methods to update the list of channels used is an interesting topic for future work.

Table 2 compares the accuracy of the proposed approach with other results from the literature. The comparison is limited to approaches that use multilateration, four anchors, and similar evaluation areas to analyse the impact of RSSI measurements in multiple communication channels. As presented, the use of 40 communication channels allows to achieve better accuracy compared to other results in areas of similar size. Moreover, the results are almost as good as the ones reported in significantly smaller areas when using only three primary advertisement channels. The use of multiple communication channels improves the localization accuracy, can be generalized, and used together with a range of methods to improve signal strength-based localization (e.g., Kalman filtering, fingerprinting). Similarly to the results presented for 3 primary advertisement channels (e.g., [8]) this enables to further improve the localization algorithms and is an interesting investigation area for future work.

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MACIEJ NIKODEM received the M.Sc. degree in computer engineering (specialized in internet security) and the Ph.D. degree in computer engineering (specialized in cryptography) from the Wrocław University of Technology, Wrocław, Poland, in 2003 and 2008, respectively.

He is currently an Assistant Professor with the Department of Computer Engineering, Faculty of Information and Communication Technologies, Wrocław University of Science and Technology. His research interests include low-power wireless networks, dependable, reliable and secure communication protocols, and indoor localization.

PRZEMYSŁAW SZELIŃSKI received the B.Sc. and M.Sc. degrees in computer science from the Wrocław University of Science and Technology, Wrocław, Poland, in 2020 and 2021, respectively. Since 2018, he has been a Software Engineer at the Nokia RF Department, Wrocław. His research interests include software architecture and design, RF technologies, embedded systems, and indoor localization.

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