A-WEAR PROJECT

A network for dynamic WEarable Applications with pRivacy constraints

Project no. 813278

H2020-MSCA-ITN-2018 - Marie Skłodowska-Curie Innovative Training Networks

---

Short Report

“Comparative performance of sub-m positioning technologies in wearables”

Editor/Lead beneficiary (name/partner):	Tampere University / University “Politehnica” of Bucharest
Internal reviewed by (name/partner):	Simona Lohan / TAU Aleksandr Ometov / TAU

Version	Date	Author(s)	Notes
1.0	01.06.2020	Viktoriia Shubina (ESR03) Laura Fluerătoru (ESR08)	Initial version
1.1	17.06.2020	Aleksandr Ometov	Revision

Abstract

This document provides a comparative performance of sub-m positioning technologies in wearables in order to support the Milestone ML4.1.

Disclaimer

This deliverable contains original unpublished work except where clearly indicated otherwise. Acknowledgement of previously published material and of the work of others has been made through appropriate citation, quotation or both.

A-WEAR is funded by the European Union's Horizon2020 research and innovation programme under the Marie Skłodowska Curie grant agreement No. 813278. The content in this deliverable do not represent the opinion of the European Union, and the European Union is not responsible for any use that might be made of its content.

"Comparative performance of sub-m positioning technologies in wearables"

In a vast majority of positioning scenarios, the goal is to achieve seamless positioning with sub-m accuracy. In this deliverable, Viktoriia Shubina (ESR03) and Laura Fluerătoru (ESR08) provide a review and comparison of the accuracy levels for positioning technologies.

Commonly, positioning is widely used on mobile phones, yet with the advancements in the Internet of Things (IoT), miniature sensors as wearable devices acquired the same functionality. Nowadays, these devices can sustain different wireless connectivity ranges: from ultra-short and short to long ranges. Therefore, the literature review in [1] compiles novel challenges with respect to the characteristics of mobile phones and wearables.

1.1. Positioning Accuracy Metrics

It is essential to define a proper error for the performance evaluation of the positioning method. There are two main approaches [2] to estimate the localization error of any system:

- *Error Probability* refers to the probability of the measurement error to not exceed a specific value.
- *Cramer-Rao Lower Bound (CRLB)* which is a lower limit for the variance of estimation.

Erroneous data should be considered especially in situations with a massive number of IoT sensors to perform data processing in the IoT environment. This example highlights the need to estimate errors and allow data evaluation and data fusion at the second stage.
Additional error-related metrics such as *Positioning Error Bounds (PEB), Barankin bound,* or *Ziv-Zakai bound* have also been used in some of the literature.

1.2. Positioning Privacy Metrics

As stated in [3], with the advancements of wearable technology and built-in sensors, accuracy confronts privacy, and vice versa. To balance efficiently the accuracy and anonymity, such metrics as *entropy* [4], *k-anonymity* [4], *l-diversity* [5] and successors are used to evaluate the level of privacy of the positioning method in considered circumstances. Moreover, these metrics assist in creating and improving privacy-aware approaches used for localization to preserve users' privacy.

1.3. Localization techniques

Localization systems typically employ techniques based on one or a combination of the following measurements: *received signal strength* (RSS), *channel state information* (CSI), *angle of arrival* (AoA), *phase of arrival* (PoA), and *time of flight* (ToF) of the signal (along with its multiple variants).

RSS is relatively easy and cheap to acquire, but it can heavily fluctuate in multipath environments [6]. As a result, the signal strength can vary over time and frequency without being correlated with a particular location. CSI provides a more granular look at the RSS fluctuations. Fingerprinting methods commonly rely on RSS and CSI measurements associated with a particular location.

AoA techniques measure the angle impinged by a signal on an antenna array and, based on information from multiple reference nodes with known locations, the position of a target can be computed [7]. This technique is hindered by multipath and non-line of sight propagation and requires more sophisticated equipment (antenna arrays) and signal processing algorithms. Similarly, measuring the PoA at a *single* antenna can be used to compute the distance traveled by the signal between two devices [8].

A-WEAR is funded by the European Union's Horizon2020 research and innovation programme under the Marie Skłodowska Curie grant agreement No. 813278. The content in this deliverable do not represent the opinion of the European Union, and the European Union is not responsible for any use that might be made of its content.

Time-based methods use the propagation time of the signal to compute the distance between the tracked object and several reference devices. This class of techniques has tight synchronization constraints, since even small timing errors can lead to large errors in the computed distance. As a result, the equipment and processing are typically more sophisticated in the case of devices which use time-based methods.

1.4. Comparison of Positioning Technologies

Out of the existent localization technologies, WiFi, Ultra-Wideband (UWB), Bluetooth and Bluetooth Low Energy (BLE), ultrasound, visible and non-visible light, LoRa, and RFID are usually considered the most important enablers of localization in the IoT [9]. Table 1 presents a comparison between these technologies in terms of the maximum accuracy obtained by systems employing these technologies, their range, current consumption, localization techniques typically used with them, and their advantages and disadvantages.

Table 1: Comparison of Positioning Technologies

Technology	Maximum accuracy*	Range	Current consumption	Localization Techniques Used	Advantages	Disadvantages
Wi-Fi	Decimeter-level [10], [11]	250m outdoor 50 m indoor	Hundreds of mA	Fingerprinting [12], AOA [10], TOF [11]	Widely-available, low-cost, often does not need dedicated infrastructure.	High-accuracy localization methods based on fingerprinting require extensive training and are prone to changes in the environment, relatively low accuracy.
UWB	Up to 10 cm [13], [14], [15]	80 m – 300 m	30 – 150 mA	TOF [13], [14], [15], AOA [16]	High accuracy and precision, moderate cost.	Not widely-available (yet), needs dedicated infrastructure.
Bluetooth	85 cm [17]	100 m	<30 mA	Fingerprinting [18], AOA [17]	Widely-available, low-power.	Relatively low accuracy, fingerprinting localization methods require extensive training.
Bluetooth Low Energy	2.5 m [19], [20]	100 m	<15 mA	Fingerprinting [19], TOF [20]	Widely-available, ultra-low power, protocol stack suitable for IoT.	Low accuracy.
Ultrasound	Centimeter-level [21], [22]	20 m	Low-Moderate	TOF [21], [22]	High accuracy.	Requires LOS, accuracy highly depends on the node placement.
Non-visible light	Sub-millimeter [23]	10 m	N/A	TOF [23]	Very high accuracy.	Requires LOS, sub-millimeter accuracy technologies used in gaming are very expensive.
Visible light	Centimeter-or	1.4 km	N/A	TOF [24], [25]	Can use ambient light sensors	Requires LOS, high-accuracy solution

A-WEAR is funded by the European Union's Horizon2020 research and innovation programme under the Marie Skłodowska Curie grant agreement No. 813278. The content in this deliverable do not represent the opinion of the European Union, and the European Union is not responsible for any use that might be made of its content.

	decimeter-level [24], [25]				commonly available in smartphones. [25]	requires dedicated hardware. [24]
LoRa	Meter-level [26], [27]	15 – 20 km	7 µA - 30 mA	TOF [26], RSSI [27]	Ultra-low power, low-cost, long range, designed for the IoT and sensor networks.	Relatively low accuracy.
RFID	Centimeter- and decimeter-level [28], [29], [30], [31]	Couple of meters	Hundreds of nA – mA	AOA [28], POA [29], RSSI [30], [31]	Can consume ultra-low power, low-cost, high accuracy.	Passive RFIDs that achieve centimeter-level accuracy require expensive infrastructure and cover small areas; active RFIDs support higher ranges but have only decimeter-level accuracy.

*Note: We refer to obtained, not achievable accuracy.

3.1 List of repositories with positioning data

Some examples of open-access datasets with location estimates can be found in Table 2. A particular choice of the right repository depends on the research interest and data format.

Table 2: Open-access repositories with datasets for positioning

Name	Website
Zenodo	https://zenodo.org
GitHub	https://github.com
Kaggle	https://www.kaggle.com
CRAWDAD	https://crawdad.org
European Data portal	https://www.europeandataportal.eu/en
Microsoft Research Open Data	https://msropendata.com
EUDAT B2SHARE (B2DROP)	https://b2share.eudat.eu
Harvard Dataverse	https://dataverse.harvard.edu

A-WEAR is funded by the European Union's Horizon2020 research and innovation programme under the Marie Skłodowska Curie grant agreement No. 813278. The content in this deliverable do not represent the opinion of the European Union, and the European Union is not responsible for any use that might be made of its content.

Bibliography

[1] V. Shubina, A. Ometov, D. Niculescu and E. S. Lohan, "Challenges of Privacy-aware Localization on Wearable Devices," in *XXXV Finnish URSI Convention on Radio Science*, Tampere, 2019.

[2] R. Zekavat and R. Buehrer, "Handbook of position location: Theory, practice and advances", vol. 27, John Wiley & Sons., 2011.

[3] V. Shubina, A. Ometov, S. Andreev, D. Niculescu and E. S. Lohan, " Privacy versus Location Accuracy in Opportunistic Wearable Networks," in *ICL-GNSS*, Tampere, 2020.

[4] I. Wagner and D. Eckhoff, "Technical privacy metrics: a systematic survey.," *ACM Computing Surveys (CSUR),* vol. 51, no. 3, pp. 1-38, 2018.

[5] A. Machanavajjhala, D. Kifer, J. Gehrke and M. Venkitasubramaniam, "l-diversity: Privacy beyond k-anonymity," *ACM Transactions on Knowledge Discovery from Data (TKDD),* vol. 1, no. 1, 2007.

[6] H. Hashemi, "The indoor radio propagation channel," *Proceedings of the IEEE,* vol. vol. 81, no. 7, pp. 943–968, 1993..

[7] P. Kulakowski, J. Vales-Alonso, E. Egea-López, W. Ludwin and J. García-Haro, "Angle-of-arrival localization based on antenna arrays for wireless sensor networks," *Computers & Electrical Engineering,* vol. 36, no. 6, p. 1181–1186, 2010..

[8] M. Scherhäufl, M. Pichler, E. Schimbäck, D. J. Müller, A. Ziroff and A. Stelzer, "Indoor localization of passive uhf rfid tags based on phase-of-arrival evaluation," *IEEE Transactions on Microwave Theory and Techniques,* vol. 61, no. 12, p. 4724–4729, 2013.

[9] F. Zafari, A. Gkelias and K. Leung, "A survey of indoor localization systems and technologies.," *IEEE Communications Surveys & Tutorials,* vol. 21, no. 3, pp. 2568-2599, 2019.

[10] M. Kotaru, K. Joshi, D. Bharadia and S. Katti, "Spotfi: Decimeter level localization using WiFi," in *2015 ACM Conference on Special Interest Group on Data Communication*, 2015.

[11] D. Vasisht, S. Kumar and D. Katabi, "Decimeter-level localization with a single WiFi access point," in *13th Symposium on Networked Systems Design and Implementation*, 2016.

[12] P. Bahl and V. Padmanabhan, "RADAR: An in-building RF-based user location and tracking system," in *IEEE INFOCOM 2000. Conference on Computer Communications. Nineteenth Annual Joint Conference of the IEEE Computer and Communications Societies* , 2000.

[13] C. McElroy, D. Neirynck and M. McLaughlin, "Comparison of wireless clock synchronization algorithms for indoor location systems.," in *2014 IEEE International Conference on Communications Workshops (ICC)* , 2014.

[14] J. Tiemann, F. Eckermann and C. Wietfeld, "Atlas-an open-source tdoa-based ultra-wideband localization system.," in *In 2016 International Conference on Indoor Positioning and Indoor Navigation (IPIN)*, 2016.

[15] A. Ledergerber and R. D'Andrea, "Ultra-wideband range measurement model with Gaussian processes," in *2017 IEEE Conference on Control Technology and Applications (CCTA)*, 2017.

[16] I. Dotlic, A. Connell, H. Ma, J. Clancy and M. McLaughlin, "Angle of arrival estimation using decawave DW1000 integrated circuits," in *2017 14th Workshop on Positioning, Navigation and Communications (WPNC)*, 2017.

[17] M. Cominelli, P. Patras and F. Gringoli, "Dead on Arrival: An Empirical Study of The Bluetooth 5.1 Positioning System," in *In Proceedings of the 13th International Workshop on Wireless Network Testbeds, Experimental Evaluation & Characterization*, 2019.

A-WEAR is funded by the European Union's Horizon2020 research and innovation programme under the Marie Skłodowska Curie grant agreement No. 813278. The content in this deliverable do not represent the opinion of the European Union, and the European Union is not responsible for any use that might be made of its content.

[18] F. Subhan, H. Hasbullah, A. Rozyyev and S. Bakhsh, "Indoor positioning in Bluetooth networks using fingerprinting and lateration approach," in *In 2011 International Conference on Information Science and Applications*, 2011.

[19] R. Faragher and R. Harle, "Location fingerprinting with bluetooth low energy beacons," *IEEE journal on Selected Areas in Communications,* vol. 33, no. 11, pp. 2418-2428, 2015.

[20] D. Giovanelli and E. Farella, "RSSI or time-of-flight for bluetooth low energy based localization? An experimental evaluation," in *2018 11th IFIP Wireless and Mobile Networking Conference (WMNC)*, 2018.

[21] M. Hazas and A. Hopper, "Broadband ultrasonic location systems for improved indoor positioning," *IEEE Transactions on mobile Computing,* vol. 5, no. 5, pp. 536-547, 2006.

[22] N. Priyantha, "The cricket indoor location system," Doctoral dissertation, Massachusetts Institute of Technology, 2005.

[23] A. Ng, L. Chan and H. Lau, "A low-cost lighthouse-based virtual reality head tracking system," in *2017 International Conference on 3D Immersion (IC3D)*, 2017.

[24] S. Shao, A. Khreishah and J. Paez, "PassiveRETRO: Enabling Completely Passive Visible Light Localization for IoT Applications," in *IEEE INFOCOM 2019-IEEE Conference on Computer Communications*, 2019.

[25] Z. Wang, Z. Yang, Q. Huang, L. Yang and Q. Zhang, "ALS-P: Light Weight Visible Light Positioning via Ambient Light Sensor," in *IEEE INFOCOM 2019-IEEE Conference on Computer Communications*, 2019.

[26] B. Fargas and M. Petersen, "GPS-free geolocation using LoRa in low-power WANs," in *2017 global internet of things summit (Giots)*, 2017.

[27] A. Mackey and P. Spachos, "LoRa-based localization system for emergency services in GPS-less environments," in *IEEE INFOCOM 2019-IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS)*, 2019.

[28] C. Duan, L. Yang, Q. Lin and Y. Liu, "Tagspin: High accuracy spatial calibration of RFID antennas via spinning tags," *IEEE Transactions on Mobile Computing,* vol. 17, no. 10, pp. 2438-2451, 2018.

[29] F. Xiao, Z. Wang, N. Ye, R. Wang and X. Li, "One more tag enables fine-grained RFID localization and tracking," *IEEE/ACM Transactions on Networking,* vol. 26, no. 1, pp. 161-174, 2017.

[30] L. Ni, Y. Liu, Y. Lau and A. Patil, "LANDMARC: indoor location sensing using active RFID," in *The First IEEE International Conference on Pervasive Computing and Communications*, 2003.

[31] Y. Zhao, Y. Liu and L. Ni, "VIRE: Active RFID-based localization using virtual reference elimination.," in *2007 International Conference on Parallel Processing (ICPP 2007)*, 2007.

A-WEAR is funded by the European Union's Horizon2020 research and innovation programme under the Marie Skłodowska Curie grant agreement No. 813278. The content in this deliverable do not represent the opinion of the European Union, and the European Union is not responsible for any use that might be made of its content.