ISSN 1816-6075 (Print), 1818-0523 (Online)
Journal of System and Management Sciences
Vol. 12 (2022) No. 3, pp. 117-134
DOI:10.33168/JSMS.2022.0307

Indoor Localization in Wireless Networks Using Received Signal Strength: A Model using Bregman Distance to Increase Public Utility Benefits

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Abstract. This study explores and evaluates cost-effective indoor localization systems that utilize where possible existing technology and infrastructure, whereby making services available to meet broad public utility needs. As a relatively new market, indoor localization is growing rapidly through the interconnection of businesses and consumers using smartphone and other position-location technologies. This paper explores and evaluates the most affordable indoor location offerings using available technology and the model of Bregman distance to maximise public utility benefits at an affordable price for vulnerable communities. We incorporate a review of the findings from technical literature associated with indoor location technology coupled with our experiments using the Bregman distance model, which maximises the properties of received signals, to find and evaluate affordable solutions using available technology. We used the Bregman model in conjunction with selected machine-learning algorithms, including the relatively new lightGBM process to test over our experimental indoor localisation wireless network using Zigbee and RF channels. The lightGBM algorithm tested on our wireless network using Zigbee and RF wireless channels presented the best performance in F1-scores, followed closely by two other more standard processes. The three algorithms were equivalent in their AUC measure. Notably, the simpler algorithm KNN demonstrated excellent results for both AUC and F1-scores. Our findings from both the literature overview and experiments indicate effective, energy-efficient, cost-effective indoor localisation wireless networks can be established using available technology that does not require additional signal generation. Specifically, existing buildings do not require costly modifications or to incorporate energy inefficient methods to make use of effective indoor localization systems for the benefit of customers and broader community. Using alternative measuring metrics, public utility objectives such as affordability for vulnerable communities and environmental sustainability due to reduced energy consumption can be addressed and quantified.

Keywords: accessible networks, indoor positioning systems, legislated welfare, KNN algorithm, zigbee wireless network services, human rights, law, policy.

1. Introduction

As everyday appliances and activities are increasingly interconnected through the internet of things, greater demands for accuracy and reliability are placed on a variety of location-based services, which are able to leverage location data shared among users (Sadowski & Spachos, 2018). All Location-based systems, whether indoor or outdoor (Cho & chun, 2022; Jung et al., 2022) require the expertise of multiple providers, including developers who create relevant technologies consisting of mobile devices, a communication network, and positioning components. In addition, service application and data content providers enabling basic services are also involved in the process of developing a functional location system (Uradzinski et al., 2017). Consequently, location-based systems employ different technologies, phases of development and deployment of new and established systems, as well as engagement with a variety of technical experts. Certain compromises among developers and providers, and other decision makers associated with positioning system design metrics are required to enhance the accessibility and interoperability of these technologies. The scope of this paper is confined to exploring cost-effective indoor positioning systems. An indoor positioning system identifies the position of an object within an enclosed setting and continuously updates itself in real-time (Cheng & Yan, 2018). Using the appropriate digital technology enables indoor positioning systems to serve both market and broader public utility functions.

According to some analysts, at USD $7.0 billion in 2021 projected to reach $19.7 billion by 2026, the global Indoor localization market is not only growing but set to expand rapidly across the next five years (Markets and Markets 2021) A proliferation of consumer and business applications around beacons, integration of beacons in cameras, Point of Sale devices, digital signage are some of the uses driving the market growth. With their ability to link to personal communication devices, indoor localization systems can interconnect and position consumers and businesses within a wide array of interior public spaces such as shopping malls, museums, and administrative buildings.

However, if the supply of indoor localization software and infrastructure is influenced only by market profitability, there is a risk the technology may fall short of fulfilling broader social objectives such as functioning effectively as a public utility for vulnerable populations where markets may be less lucrative and able to meet the high prices paid for premium services. Some researchers have identified historical errors in telecommunication infrastructure design when system developers and service providers have minimized attention to broader societal concerns Furthermore, arguably the transformative quality of life opportunities in the form of greater independence, mobility and confidence, deserve at least equal consideration to less profitable markets indoor positioning systems offer other consumers. Specific examples of broader public benefit include assisting people with disabilities and the elderly to locate goods and services, enhanced medical monitoring, and effective delivery of emergency services (Bianchi et al., 2018), all of which can be accessed in health-care facilities, shopping centers, recreational facilities, and other industries (Al-Ammar et al., 2014). Therefore, it makes sense for citizen-consumers to be widely represented in the design and discussion around provision of such services. Others have already argued an ideal indoor localization using Wi-Fi should be deployable, universal, accurate, and reliable (Kotaru et al, 2015) and (Zafari et al, 2019). To this taxonomy, in consideration of the public utility benefits that are often ignored due to prohibitive costs, we add affordability.

This paper proposes a machine learning method to model indoor positioning using a universal and deployable system that leverages the pre-existing Wi-Fi infrastructure, without having to modify the hardware of the pre-existing Wi-Fi Access Points, thus keeping the cost low.

The remainder of this paper is organized as follows: Section 2.0 provides a literature overview of existing technologies. Section 3.0 presents the proposed methodology. Sections 4 & 5 presents the findings and discusses the results. Finally, Section 6 concludes the paper.

2. Literature Review

2.1. A taxonomy of technologies: Pre-existing wi-fi infrastructure

The development of an indoor localization system can leverage a number of factors associated with the pre-existing Wi-Fi infrastructure. The inherent factors include: not having to modify the hardware of the pre-existing Wi-Fi Access Points (AP) or calibrating the environment; exploiting only the angle of arrival (AoA) of multipath signals; time of flight (ToF); and, received signal strength indicator (RSSI) measurements (Kotaru et al, 2015). Recent advances in both device-based localization and free based localization modes are based on different wireless modalities, localization principles, data fusion techniques (Zafari et al., 2019; Xiao et al., 2016), indoor fusion-based positioning systems (Ferreira et al, 2017) and protocols (especially for ad-hoc networks) (Ridolfi, 2016). Each localization technique has its advantages and disadvantages with respect to versatility and suitability for universal deployment. In addition, some indoor localization environments may require a combination of different positioning techniques (Uradzinski et al., 2017; Cheng & Yan, 2018; Lukianto & Sternberg, 2011). With this in mind, the indoor positioning technologies can be broadly categorized into two groups: building-dependent and building-independent.

Building-dependent technologies rely on the internal infrastructure of the buildings in which they operate (Bianchi et al., 2018) as shown in Figure 1.

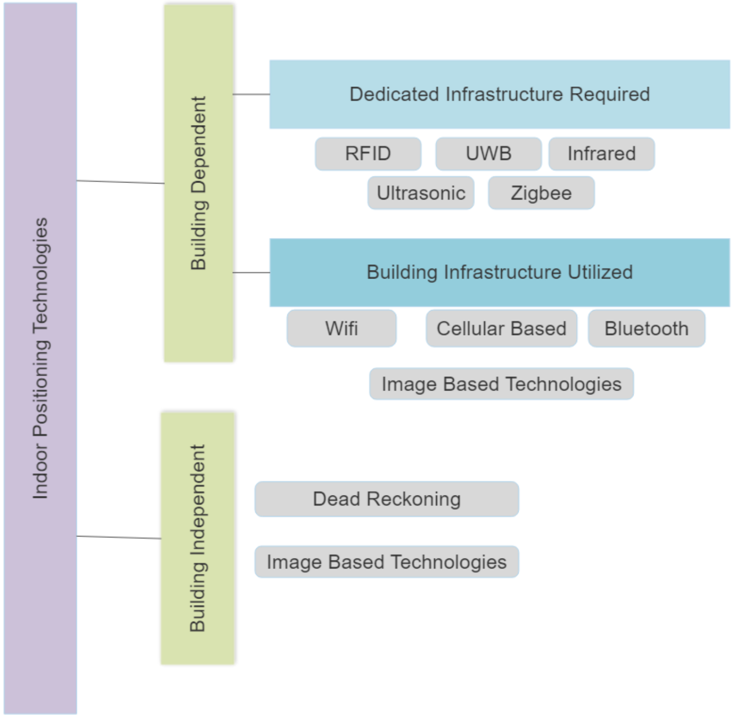

Fig. 1: Building-dependent and building independent indoor positioning technologies

This grouping is affected by the presence of technology within the building and the internal structure of the building. These technologies can be further grouped into those requiring new, dedicated building infrastructure and those employing existing infrastructure.

The existing structure of buildings likely determines the need for, or viability of, dedicated infrastructure. For example, most current buildings lack radio frequency (RF) identification and therefore might make use of Wi-Fi support. However, selected indoor localization technologies, such as Zigbee, infrared, RF identification, and ultra-wideband, typically require dedicated infrastructure (Al-Ammar et al., 2014). As well as Wi-Fi, cellular and Bluetooth are also compatible with existing infrastructure in typical buildings.

Building Independent indoor technologies have several advantages because specialized hardware is not required within a building. This category includes dead reckoning and image-based technologies. Dead reckoning localizes an object based on its past position in relation to its speed and direction of movement(Bianchi et al., 2018), while image-based technologies rely on cameras and image processing. In addition to physical infrastructure considerations, indoor positioning systems employ one or more techniques to locate objects or nodes within a physical domain. A list of advantages and disadvantages of indoor positioning technologies is provided in in Table 1.

Table 1: Advantages and disadvantages of the various indoor positioning technologies

Technology	Advantages	Disadvantages
Radio frequency identification	– Penetrates solids – Penetrates non-metals or insulators – Maintains high level of compatibility	– Lacks communication capabilities – Determines radio frequency by antenna – Provides limited positioning coverage – Provides insecure radio frequency communication – more power
Ultra-wideband	– Provides high localization accuracy – Penetrates obstacles effectively – Provides compatibility with existing RF system	– Lacks compatibility with liquid and metallic materials – Requires very high investment
Infrared	– Provides basis for sensitive communication	– Lacks ability to penetrate obstacles – Lacks multi-room capability – Lacks compatibility with fluorescent lighting and sunlight
Ultrasonic	– Provides compatibility with electromagnetic waves	– Lacks capability of penetrating obstacles – Creates false signals – Lacks compatibility with high-frequency sounds (Xiao et al, 2016)
Zigbee	– Requires very little energy for the sensors – Requires less investment	– Vulnerable to various signal sources using the same signal – Requires fast (millisecond) communications - Could easily cause transceiver to go to sleep
Wireless local area	– Covers more than one building readily available	– Potentially requires the recalculation of a predefined signal strength map for each slight adjustment
Network	– Provides high compatibility with devices (Bianchi et al., 2018)	
Cellular based	– Provides compatibility with hardware for customary mobile phones – Provides compatibility with devices operating at the same frequency	– Reduces reliability because the signal propagation varies depending on conditions
Bluetooth	– Provides a lighter standard – Highly ubiquitous – Built into or embedded within most devices	– Relies on relatively expensive receiving cells – Requires inbuilt host computer – Prone to RF interference
Dead reckoning	– Works without additional hardware (e.g., sensors)	– Only calculates approximate positions
Image-based	– Relatively inexpensive	– Provides limited coverage

2.2. A taxonomy of technologies: Positioning techniques

Indoor positioning techniques fall into four major classes: fingerprinting, triangulation, proximity, and vision analysis. Triangulation applies the properties of geometric triangles when computing the object positions. Fingerprinting refers to the characterization of unique identifying attributes, typically, location-dependent signals (received signal strength indicators). The proximity localization technique considers the positions of target objects with respect to a previously established location; the location of the transmitting access point (AP) is used to approximate the position of an object within a limited range. Vision analysis techniques rely on images obtained from cameras for localization. Table 2 summarizes the available techniques used for indoor positioning.

Table 2: Indoor positioning techniques

Technique	**Divisions**
Triangulation	Literation and angulation
Fingerprinting	Online and offline
Proximity	Physical contact, wireless cellular access points, and automatic ID systems
Vision analysis	No Division

2.3. A taxonomy of technologies: Algorithms

This section provides an analytical study to identify the most effective indoor positioning algorithm for our work (Sadowski & Spachos, 2018). The four major indoor localization algorithms are characterized by the following parameters: signal strength indicator, time difference of arrival, time of arrival, and angle of arrival (Obeidat et al., 2021). The RSSI is frequently used with fingerprinting or propagation model algorithms (Uradzinski et al., 2017) and approximates the distances of unknown nodes from a common established reference node. When the AP is near, the received signal and strength indicator values will be higher. The time-of-arrival allows us to accurately synchronize the arrival of the transmitted signal at the mobile device to determine the signal transmission period between the transmitter and the receiver. In contrast, the time-difference-of-arrival allows us to measure the propagation time variation among the base stations and multiple target nodes. The angle-of-arrival algorithm is vital for measuring the angle of signal reception between the transmitter sources in unknown locations. To facilitate the adoption of received signal strength for localization by the Zigbee wireless network system, the designers embedded a Zigbee chip into the sensor nodes to facilitate, in a linear format, the transformation of the power value into the RSSI values (Sadowski & Spachos, 2018).

Thus, Zigbee systems facilitate the offline path loss survey, real-time RSSI collection, and online position calculation. Significantly, Zigbee requires less investment and requires very little energy for the sensors which makes it more equitable providing more social value and sustainability benefits for the environment through reduced energy consumption.

3. Methodology

3.1. Bregman distance-based model of the indoor localization system

In this study, we consider an indoor localization system installed in a dedicated square shaped floor, where we have four Xbee Access points distributed equally across the floor emitting RSSIs. The square floor plan is defined as a grid space where any location M is limited inside the grid dimensions. Any position will be represented in 2-D (x,y) coordinates on the grid. At each point of the grid, we have collected a set of RSSI readings and stored the data in a dedicated RSSI Database. Each entry in the database includes a mapping of the grid coordinate (x, y) to the vector of corresponding RSS values from all access points in the area.

Because of the very high variation and interference that RSS suffers from, the accuracy of finding the exact location indoor is a challenge. Calculating and measuring the distance between different components is conducted using the Euclidean Distance or Mahalanobis distance. However, Bregman distance can be a suitable alternative for distance calculation and measurement since it measures the distance by merging the relative entropy and the geometric Euclidean distance. A Bregman distance measures the distortion between classes that is defined by a Jensen convexity gap that is induced by a strictly convex function as in the following equation:

$$D_{\varphi}(p,q) = \varphi(p) - \varphi(q) - < \nabla\varphi(\mathrm{p}), \mathrm{p} - \mathrm{q} >$$

Where <p, q> represent the inner product of p a d q and <p, q> is computed as follows:

$$< p, q > = \sum_{i=1}^{d} p^{(i)} q^{(i)} = p^T q$$

and where ∇φ(p) is the gradient operator of φ at point p.

$$\nabla\varphi(p) = [\frac{\partial\varphi}{dp_1} \ldots\ldots \frac{\partial\varphi}{dp_d}]^T$$

3.2. Indoor setup

Hence, our hardware and software-based solution for indoor localization includes a wireless network over Xbee and RF channels. Four access points are localized to communicate with a receiver terminal and the RSSI is measured as the main indicator for system input and distance calculation. The study area represents a single floor with a simple square structure including 3 rooms and a walking area. The localization process is implemented to determine whether the user is localized in a room or a walking area. The hardware is designed around Arduino MCU, Xbee modules, and RF 433 MHz modules to finalize the entire system requirements.

Xbee is selected for its ability to work as a completely independent wireless communication module in closed areas with an acceptable communication distance. On the other hand, the RF 433 MHz is selected for its simple prototype specifications and properties.

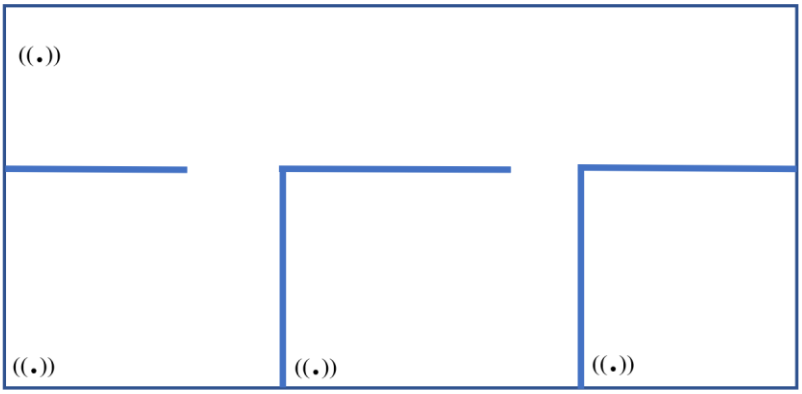

Fig. 2: Setup of the test environment

Mainly we need to understand also the relation between the number of access points distributed in the floor and Standard Deviation of the RSSs with the probability of having a correct localization result. So we need to simulate the probability of the correct location calculation processes on different Access Points number as well as on different Standard Deviation values. Below we can notice the effect of having a large number of Access Points on the probability calculation among 4 different small Standard Deviations.

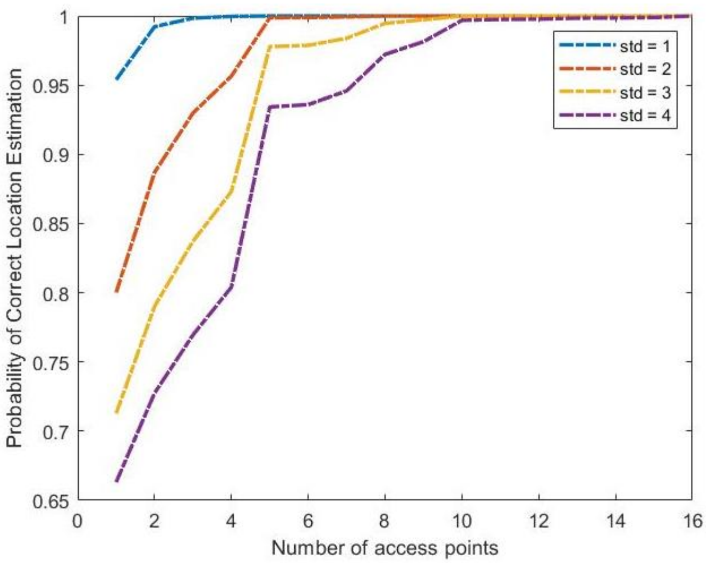

Fig. 3: The relation between the number of access points and probability of current location estimation

Clearly, we can see the large effect in terms of correctness with the reference to the Access Points number raises with the smallest standard deviation value. Therefore with σ=1 and almost 5 Access Points, we can estimate the location correctly with a probability of 1. On the other hand, we needed almost 10 Access points to reach the highest probability with σ=4. Below we present a figure showing the negative impact of high σ on the probability calculation:

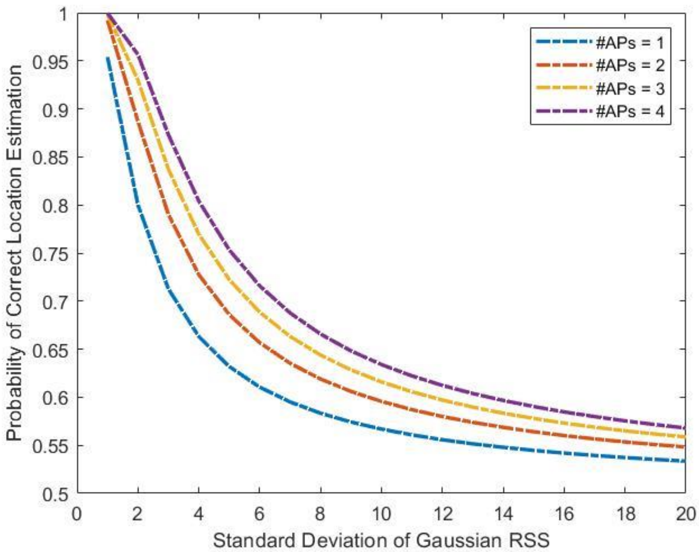

Fig. 4: The relation between the standard deviation of Gaussian and probability of current location estimation

The probability dropped in half with a high σ=20 despite the number of access points found in very good range of 4.

3.3. Machine learning models of choice

Several challenges must be addressed when selecting an effective indoor positioning system. Indoor environments are typically dynamic and element characteristics can interfere with signal integrity; in particular, they contain many reflective objects, leading to multipath signals and delays (Mahafzah & Abusaimeh, 2018). The positioning of these objects in the environment also affects signal scattering and attenuation. For indoor positioning, the reliance on non-line-of-sight signal propagation produces inconsistency at the receiver (Uradzinski et al., 2017). Other challenges include small-area coverage, slow air circulation, small humidity gradients, and low temperatures. Hence, high-precision indoor positioning applications are required to enhance the accuracy of localization mapping (Al-Ammar et al., 2014). The specific dynamics and needs of varying indoor environments determine the specific type of wireless network services and algorithms to adopt. When designing an indoor localization system, performance metrics such as accuracy, availability, area of coverage, scalability, cost, and privacy should be considered (Sadowski & Spachos, 2018).

In machine learning, regression algorithms attempt to predict a number (e.g., the physical locations of objects in an area), while classification algorithms try to predict the class to which an input instance belongs (e.g., sitting room, kitchen, office) (El Morr & Ali-Hassan, 2019). Our algorithm used for indoor localisation attempts to predict in which area an object exists, (i.e., room1, room2, room3, or hallway) not the exact geographic position of the object. Hence, our problem can be defined as a machine learning classification problem not a regression one.

An overview of research studies that used machine learning based indoor localization using Wi-Fi RSSI fingerprints published between 2011 and 2021 reveals the most common algorithms were K-nearest neighbours (KNN), Random Forest (RF), Decision Tree (DT), and Support Vector Machine(SVM) (Singh et al, 2021). For our study, we chose KNN and RF instead of the traditional DT. We also opted to test lightGBM, one of the more recently introduced algorithms closely related to DTs but more efficient. In addition, incorporated usually high performing algorithms in other indoor localisation studies: logistic regression (Abadi et al, 2014), Naïve Bayes (Wu et al, 2017), and the AdaBoost ensemble technique (Feng et al., 2014).

3.4. Evaluation of classifier performance

Since we would like to correctly localise an indoor object, we are interested in models that provide as low as possible false positive and false negative occurrences; that is models with high precision ($\frac{TP}{TP+FP}$) and high recall ($\frac{TP}{TP+FN}$). Therefore, we chose F1-score ($2\,\frac{Precision*Recall}{Precision+Recall}$) as a performance measurement criterion.

The Receiver Operating Characteristic (ROC) curve can also be helpful. The area under the curve (AUC) of the ROC represents the recall or true positive rate (TPR) in the y-axis and the false positive rate ($FPR = \frac{FP}{FP+TN}$) in the x-axis, at different classification thresholds. A high AUC value represents a model with high TPR and low FPR. A value of 0.5 represents a random guess; the larger than 0.5 the AUC value is, the better performance of the model.

4. Results

We have collected 5642 instances for training and 1672 instances for testing. The instances represent the RSSI values/vectors that are generated by each access point. The dataset is formed of three features representing the RSS reading that are all numeric type; the class is numeric the expected room (coded 1 to 4).

We have used (Ali, 2020) in Python to run the machine learning algorithms. Using 10-fold cross validation, we run the following algorithms: K Nearest Neighbors, Logistic Regression, Naive Bayes, Random Forest, LightGBM, and Ada Boost.

Table 3: Result of the cross-validation learning

Model	F1-Sore	AUC
Light Gradient Boosting Machine (LightGBM)	0.95	0.99
Random Forest (RF)	0.95	0.99
K Nearest Neighbors (KNN)	0.94	0.99
Naive Bayes	0.62	0.86
Logistic Regression	0.56	0.82
AdaBoost	0.51	0.67

The lightGBM algorithm presented the best performance in the F1-score, followed closely by RF and KNN. The three algorithms were equivalent in their AUC measure. Nayve Bayes, the logistic regression and Adaboost performance performed poorly in F1-scores. Their AUC was good for Naïve Bayes and logistic regression, and only satisfactory for Adaboost. It is notable that a simple algorithm such as KNN has shown excellent results for both AUC and F1-scores. 6

5. Discussion

Our findings indicate that machine learning is a key tool for enhancing the indoor localization (Singh et al., 2021; Bharadwaj et al., 2022; Yan et al., 2021; Zhang et al., 2020; Xue et al., 2020; Li et al., 2020; Bhatti et al, 2020). The proposed model has shown high accuracy across the machine learning algorithms tested. The positive performance can be attributed partially to the consistency and stability of the environment parameters and conditions inside the testing/training area (indoor area), proving that the hardware selected can be considered stable for generating RSSI signals.

Although the analysis has shown that the LightGBM is the algorithm of choice, a case can be made for KNN owing to the simplicity of its implementation. This finding confirms findings that KNN is a good algorithm to perform indoor localisations (Huang & chan, 2011; Ni et al., 2003).

The low cost and relative high effectiveness of this system for effective indoor localization and positioning have both market and public utility relevance, as it supports equitable access for the most vulnerable and least affluent citizens. The gap between those who do have access to technology (e.g., broadband internet (Riddlesden & Singleton, 2014)) and those who do not, is commonly known as the digital divide (Van Dijk, 2006). Digital divide is a source of inequity in many domains of life, be it in education (Warschauer, 2004), economy (Bronson & Knezevic, 2019), or health (Chang et al., 2021). COVD-19 has stressed the need to access affordable technology, and to the imperative to close the digital divide to enhance equitable access to social educational, social and health needs. The United Nations expressed its conviction that narrowing the digital divide could contribute to more equitable access to social goods (UN, 2020). Indoor localisation is expected to play a social role as low cost technology is important for accessing healthcare (Pourhomayoun et al, 2012) and homecare (Pourhomayoun et al., 2012; Ballardini et al., 2015; Braun & Dutz, 2016; Stelios et al., 2008). Consequently, our study aligns with the concern to provide low-cost equitable access to technology to close the digital divide.

6. Conclusion

In this study, we presented a comparison of major indoor positioning technologies with respect to the available techniques and localization algorithms. Furthermore, we focused our research on exploring technologies and models that maximized public utility for vulnerable groups, which required adding affordability to the current taxonomy of universal access, reliability and …

Affordability has multiple stakeholders, including service providers, governments, and most importantly the vulnerable communities least able to afford new innovations that have major quality of life implications. For this reason, we incorporated into our evaluation of available indoor positioning approaches the Bregman distance of curvature model that values residue signal strength, and in the process reconceptualizes signal 'noise' as a valuable component of an effective and affordable system. In other words, the system we advocate is both effective and efficient. We tested other efficiencies of the model through applying AI algorithms that evaluate machine learning and found it scored highly on almost all performance measurements.

One limitation of this approach is its artificial setting. Future studies will add to the findings of this study by testing our approach in a live environment and natural setting. Additionally, it is essential to understand the parameters that contribute the most to enhancing the quality of the combined indoor localization technologies, positioning technique, and relevant positioning algorithms used in this study. The use of the proposed approaches can benefit developments that increase equitable access to innovations.

Another limitation of the current study is the lack of specified cost benefits between approaches using the properties of current received signals as opposed to technologies requiring the generation of new signals that are used for indoor positioning functions. Additionally, such a comparison should also account fort positive and negative externalities associated with power saving methods, environmental impact, as well as applications other than indoor localization that may emerge from incorporating technologies and techniques involving new signal generation. An economic analysis including direct costs and benefits as well as all economic externalities could be the focus of a broader study. These are considerations that also feed into policy discussions around carbon credits and financial recognition of energy-reducing initiatives. For governments and public bodies to invest and/or regulate networked systems, both costs and benefits need to be transparent and quantified to gain some degree of political acceptance.

From both public utility and environmental perspectives, it is evident our research is part of the larger research conversation that needs to take place when considering the nexus of innovations leading to the growth of the burgeoning indoor wireless global market industry and priorities in the broader society.

Acknowledgements

This study was funded by a seed grant offered by the Graduate Studies and Research Office at the Gulf University for Science and Technology.

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