This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/JSEN.2018.2888862, IEEE Sensors Journal

Device-free Localization Systems Utilizing Wireless RSSI: A Comparative Practical Investigation

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***Abstract*—Device-free localization (DFL) systems that rely on the wireless received signal strength indicator (RSSI) metric to localize targets with no device attached to them have been reported in the literature for almost a decade. Approaches using RSSI can be split into three main categories. Link-based approaches utilize weighted summation or probabilistic methods to infer location. Location-based approaches create a fingerprint map of an area. Radio Tomographic Imaging treat DFL as an imaging problem solved with a linear inverse. In this article, we implement and investigate the performance of all three major RSSI approaches in two test environments. We demonstrate how different environments and walking trajectories can have significant effects on the localization accuracy. The experimental results lead us to the conclusion that without implementing and testing within the same environment for the same target trajectories, the performance of various classes of DFL systems cannot be reliably evaluated. Relying on the stated accuracy from the literature for comparison is a flawed premise.**

***Index Terms*—Device-free Localization (DFL), Indoor Positioning Systems (IPS).**

I. Introduction

THE widespread adoption of wireless technology and growing popularity of the Internet of Things (IoT) have led to increased interest in indoor localization technologies. Indoor Positioning Systems (IPS) have potential application in a diverse range of fields, including assisted living [1], office monitoring [3], multi-subject counting/tracking [5], [6], hostage negotiation [7], human-robot interaction [8] and smart homes [9]. Indoor localization implementations can either be Device-based or Device-free. Device-based systems work by localizing a tag that is attached to the tracked entity. Device-free localization (DFL) does not require the tracked entity to carry any form of tag. Wireless DFL systems work by measuring the changes a tracked entity causes on wireless links within an environment, and use those to infer the location of the target. While DFL systems can be implemented using Radio Frequency (RF) [1]–[7], [9]–[12], or other approaches, such as visible light [13], in this paper we only focus on RF based implementations using the Received Signal Strength Indicator (RSSI).

This work was supported in part by the Massey University Research Fund (MURF) and the Massey University Doctoral Scholarships.

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Manuscript received April XX, 2018; revised August XX, 2018.

RSSI is the most popular metric for localization as it is implemented in many mainstream wireless technologies (Wi-Fi, Zigbee, Bluetooth) and is commonly available in commercial-off-the-shelf (COTS) equipment. This is very important as implementations within a standard built environment would likely require multiple devices, which makes cost and the ability to integrate with and/or utilize existing infrastructure extremely important. The RSSI metric is also immune to the effects of interference, though the networks packet reception ratio (PRR) may be affected [14]. Since the PRR would only effect system latency and not overall system accuracy, Wi-Fi interference is not a major concern in this paper. However, a major limitation of RSSI is its vulnerability to multipath. Since the RSSI is a non-coherent metric with no phase information, it is unable to resolve multipath components. This limits its suitability for indoor ranging approaches as multiple locations may share the same RSSI value over a LOS link path [15]. Other limitations include large variance between successive RSSI values and varying receiver sensitivity [16]. Variations between different chipsets have also been observed [17]. Channel State Information (CSI) values have a significantly higher resolution than RSSI values and are more immune to the adverse effects of multipath [15], [18], [19]. However among COTS devices, CSI is only available on a few Atheros [20] and Intel [21] devices using modified drivers. Another problem with wireless based localization is the issue of secure localization. Both RSSI and CSI approaches assume that the senders MAC address reported by a packet is authentic. This makes it possible for a malicious entity to cause the system to report incorrect position estimates. This can also be exploited to attain location-based information from users. Recent literature suggests these may be mitigated through utilizing new network architectures [22], or utilizing cloaking areas [23]. However, wireless technologies are inherently vulnerable due to the broadcast nature of propagation and thus localization systems based on them are vulnerable to privacy exploitation. Recently, anonymous authentication protocols have been developed to resolve this problem for RFID systems [24], which may lead to breakthroughs for COTS equipment.

Device-free wireless positioning systems utilizing RSSI can be implemented on any platform that uses that (RSSI) metric. We chose to use Zigbee radios as they are prevalent within smart home applications and hence justify device-free localization as a secondary service. Wi-Fi nodes could also be utilized provided there was sufficient node density. In order to be commercially attractive, device-free localization should be a secondary service, where the primary service of the network

TABLE I
RTI IMPLEMENTATIONS

Features	Through-wall	Online Calibration	Stationary Target	Channel Diversity	Antenna Selection	Major Contribution
RTI	No	No	Yes	No	No	Formulated DFL as a regularized linear equation, with the output as an image [12].
VRTI	Yes	No	No	No	No	Enabled better tracking of moving targets and through wall imaging [36].
SubVRT	Yes	No	No	No	No	Reduce localization errors occurring due to intrinsic motion which cannot be removed from the environment [37].
CDRTI	Yes	No	Yes	Yes	Yes	Accuracy of through wall attenuation based DFL improved by switching the channel of measurement based on either the packet reception ratio (PRR) or the channels fade level [38].
dRTI	Yes	Optional	Yes	No	Yes	Directional antennas provide better localization accuracy in both attenuation based and variance based RTI schemes [39].
ARTI	Yes	Yes	Yes	Optional	No	Presented a spatial model that can retrain itself using live unlabeled data [40].
KRTI	Yes	Yes	Yes	Optional	No	Can localize moving and stationary targets, works through walls and requires less nodes than previous RTI efforts [7], [41].

would be to provide data communication, sensing etc. While other technologies can potentially provide a higher level of accuracy, they are often prohibitively expensive for consumer smart homes.

DFL implementations using RSSI can be divided into three categories: region-based approaches, link-based approaches and Radio Tomographic Imaging (RTI). In region-based approaches, RSSI information is collected from multiple links and associated with a specific location within the target area. These algorithms are often defined as fingerprinting approaches as they collect offline data before localization begins, and attempt to compare it with live data during the localization process [2], [6], [25], [26]. In link-based approaches, the system attempts to either model a tracked entity's effect on specific links which can be used to infer location [9], or use a probabilistic method to maximize the expected region of interest, for a given entity [3], [27]. RTI [12] approaches assume that the magnitude of change caused by a person near a link can be modelled by an ellipsoid formed along the line-of-sight (LOS) link path, and that location can be estimated by solving the inverse of a linear equation.

A. Contribution

The literature lacks an apple-to-apple comparison of DFL schemes across the three major techniques. Most works test their algorithm within their own test environment, benchmarking it against previous works of a similar type. For example, a reported work on RTI compares the developed system against an RTI based system. It also holds true for a fingerprint-based work. As far as the authors are aware of, no work compares the performances of DFL systems across all three major approaches based on a common physical implementation with multiple trajectories. Cassara et al performed a good comparison in [1]. However, out of the three algorithms tested, two were from RTI and they did not provide a comparison between all three major approaches. They also did not consider varying human trajectories, which we show have a significant impact on tracking accuracy.

Survey papers have compared the *stated* accuracy of DFL techniques [10], [28]–[30]. They try to compare tests by stating the size of the test area, protocol and number of nodes used. However, they incorrectly assume that algorithms from different works are environment agnostic, and do not implement the DFL systems themselves. Thus, they are unable to provide a true comparison of existing work. We demonstrate that the environment has significant impact on the performance of the localization algorithms by providing experimental results from multiple algorithms in contrasting indoor environments which show significant inconsistencies in localization and tracking accuracy.

Another area that has been overlooked is the potential for real-world implementation. If DFL technology is to become a standard part of a built environment installation, it must be incorporated into and operate alongside existing smart devices, in real-time and with a low node density. Commercial DFL solutions are not readily available at present. A standard 2 story home with a ground floor area of approximately 140m2 would require more than 30 nodes for reasonable performance using the commercial solution from [31]. This also assumes that the home has that many available power sockets with spatial separation around the home, which is unrealistic for many smart homes. Fair algorithm comparisons have also been hindered by the lack of a standardized performance metric. The EvAAL framework has been proposed to ensure fair comparison of multiple algorithms within a physical test environment [32]. However, the EvAAL framework was primarily designed for use in active tracking solutions. EvAAL uses the 75^{th} percentile Euclidean error as their accuracy score. This does not provide enough information about the difference between the average errors and maximum errors to choose an appropriate implementation candidate. The first known formal attempt to standardize IPS systems is the ISO/IEC 18305:2016 International Standard [33], which defines a framework for testing and evaluating IPS systems. It proposes several accuracy score metrics based on the Root-Mean-Square-Error (RMSE), median 2D error (termed as Circular Error Probable),

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TABLE II
FINGERPRINT IMPLEMENTATIONS

Features	Through-wall	Stationary Target	Multiple Targets	Calibration Required	Cycle Duration	Major Contribution
Nuzzer	Yes	Yes	Yes	High	Low	Defines the DFL problem in terms of a discrete space estimator followed by a continuous space estimator [4].
SCPL	Yes	Yes	Yes	Medium	High	Adopts a novel sequential counting strategy followed by classification (LDA), a conditional random field (CRF) as a geometric filter and Viterbi tracking for probabilistic pathing [6].
ACE	Yes	Yes	Yes	High	Low	Incorporates a novel fingerprinting approach which is followed by an energy minimization framework for localization, and a second order Hidden Markov Model to track multiple targets [5].
GL-FDFL	Yes	Yes	No	Medium	Unknown	Uses a probabilistic localization approach coupled with an improvement strategy which limits the number of cell estimates based on the significance and location of shadowed links [2]

and the 95^{th} percentile 2D error (termed as Circular Error 95%). There are two fundamental issues with the ISO/IEC 18305 standard when applying it to DFL. Firstly, it provides no explicit provisions for DFL techniques. Secondly, Circular Error Probable (CEP) and Circular Error 95% (CE95) are insufficient in describing the whole behavior of each individual approach.

The best-known localization comparison testing is provided by the annual Microsoft Indoor Localization Competition [34], or the Indoor Positioning and Indoor Navigation (IPIN) competition [32]. However they are not ISO/IEC 18305 compliant [35], and are primarily focused on active tracking, and therefore are not useful for benchmarking DFL efforts, or addressing problems that arise in DFL approaches. In commenting on the deficiencies of ISO/IEC 18305, Potortì et al proposes the use of the 50^{th} (CEP), 75^{th}, 90^{th}, and 95^{th} (CE95) percentile errors to allow for easier comparison of two approaches [35]. We believe that this should be extended further and that using empirical Cumulative Distribution Function (CDF) error plots should be standardized, as it allows for algorithm comparison at any percentile level. ISO/IEC 18305 also does not include any accuracy metrics related to the overall trajectory traveled. This is flawed as the subject's trajectory can have a significant impact on the localization error.

This paper seeks to address these gaps by implementing algorithms from multiple DFL approaches and comparing them within a common environment. One representative algorithm from each of the three major approaches were selected based on their accuracy, and likelihood of implementation into existing built environments. This enables us to make credible and fair performance comparisons, appropriately comment on their strengths and limitations, and demonstrate the deficiencies of current evaluation regime and findings of the literature. By testing the implemented DFL's in two indoor environments, this paper contributes the following novel aspects:

1) A true comparison of leading Device free localization schemes from the three major localization approaches.
2) A comparison of multiple walking trajectories within each indoor environment to compare the accuracies and limitations of tracking. This also shows the impact of walking trajectory on the performance of DFL algorithms which has not been considered by others.
3) Propose empirical CDF error plots to be used as an information rich accuracy score in place single statistic like median or percentile errors and support this through experimental findings.
4) A critical analysis on the limitations of current DFL schemes and their suitability for real world implementation.

II. DEVICE-FREE LOCALIZATION

A. Fingerprinting

Fingerprinting schemes assume that the influence of an entity on the RSSI values remains relatively constant and time invariant. The system localizes the target based on the best match with the live RSSI values and the ones previously stored. They have the advantage of not requiring knowledge of where the nodes are located. However, they require significant calibration since RSSI values from every possible location of interest must be obtained in advance. Also, the assumption of RSSI remaining time invariant is flawed in practical environments. Any substantial changes to the physical environment, such as moved furniture, significantly changes the global RSSI values, and therefore degrades the systems accuracy.

Fingerprinting approaches typically take two sets of measurements during an offline phase, which are then compared to live values in the online phase for localization purposes. The first offline measurement set typically consists of RSSI values from all links when the environment is empty of entities. The second set typically consists of K batches of N RSSI values from L links; where K is the number of possible locations (cells) an entity can be present within; N is the number of samples per location, and L is the number of recorded TX-RX link pairs. Fingerprinting approaches have the benefit of allowing for fewer nodes, at the cost of a significant calibration effort , as it needs to be recalibrated regularly. As such, they are not applicable to emergency situations, where a system cannot be calibrated beforehand and their usefulness in Smart Homes may be limited as the calibration effort required exceeds the ability of typical consumers. These systems may be ideal for factory installations with fixed physical layouts where the calibration effort can be justified. A summary of the comparable features of fingerprinting based DFL systems can be seen in Table II.

We have chosen to implement SCPL for our fingerprinting localization benchmark. SCPL is well documented and easy to implement while also attaining a very similar CDF error plot when compared to multi-entity ACE [5]. GL-FDFL was not implemented as it did not include a tracking approach.

B. Link-based

Link-based schemes work by using models to analyse link behaviour and trigger the detection of anomalous activity based on predefined thresholds. To simplify localization and tracking, particle filters (also termed as Sequential Monte Carlo) are commonly used as they allow for location estimate to be defined as the centroid of multiple weighted particles within a region of multiple triggered links. A summary of the comparable features of link-based DFL systems can be seen in Table III.

All three link-based methods presented share similarities. Guo et al uses an Exponential-Rayleigh model for a link model [3], in contrast to an exponential model used by Zheng and Men [27]. All three methods implement particle filters, with Ichnaea defining a movement vector for state updates while Zheng and Men model movement as a zero-mean gaussian white noise. We chose to implement Ichnaea's method as it contains a novel way of updating its state orientation motion vector, by referencing the midpoints of changing dominant links, and we wish to investigate its tracking consistency in different environments [9].

C. Radio Tomographic Imaging

Radio Tomographic Imaging (RTI) creates an image of the attenuation caused by physical objects within wireless networks. While RTI analyses the behavior an entity causes on overlapping links, RTI divides up the environment into an image of fixed pixel locations. By solving the inverse of a linear equation, location of the entity can be estimated as the brightest pixel of the output image. RTI has the benefit of not requiring extensive calibration efforts, however it does require knowledge of where the nodes have been positioned. Patwari and Wilson first implemented RTI using the RSSI attenuation as the contributing feature [12]. This worked in wide open spaces, but performs significantly worse in typical indoor environments due to the undue influence of multipath components. RTI has gained wide acceptance in the literature and there have been subsequent improvements. A summary of the features provided by various RTI implementations and the improvement provided can be seen in Table I.

RTI systems can track moving or stationary targets and require minimum offline calibration to operate which makes them ideal for deploying in unknown environments in emergency situations. A major drawback to RTI approaches is that they typically require a large amount of nodes to operate, for relatively small deployment areas, which makes them hard to justify for incorporating into Smart Home equipment. For this paper we chose to implement Kernel RTI (KRTI). RTI does not work well in through wall environments and in complex environments with many multipath components; whereas, KRTI has also been shown to have higher performance than

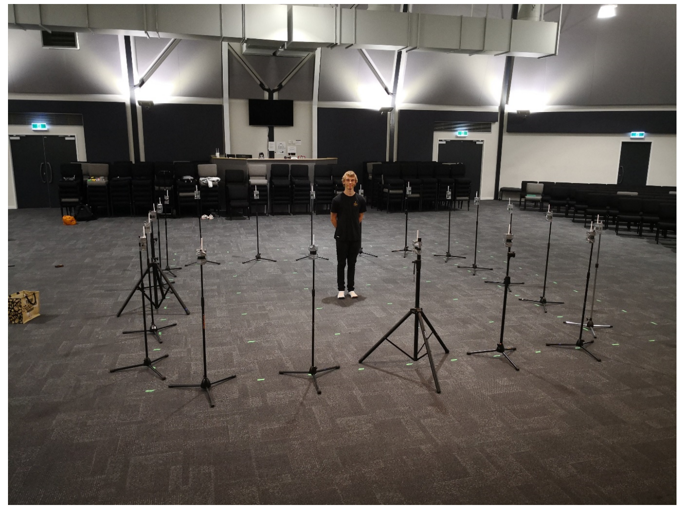

Fig. 1. Auditorium Test Environment.

Varience RTI (VRTI) and Subspace RTI (SubVRT). Channel Diversity RTI (CDRTI) requires more bandwidth than normal RTI as it searches for channels not under deep fade. With the ubiquitous use of wireless technology, and the density of network deployment in urban areas, it is unreasonable to expect that multiple bands can be dedicated to an IPS, especially within commonly used ISM bands. The use of direction antennas makes directional RTI (dRTI) unrealistic for utilization in Smart Homes as it would complicate its incorporation into existing Smart Home devices, and would require a dedicated calibration / placement procedure that may be difficult to follow for an end user. Adaptive RTI (ARTI), which seems very promising, has not been implemented in this paper for several reasons. ARTI's online calibration approach assumes that most affected links will exhibit an attenuation effect from a targets presence. This is problematic as even though most links typically do exhibit an attenuating effect, this cannot be guaranteed in a complex indoor environment.

III. Implementation

The network used for testing was implemented using Texas Instruments CC2530 Zigbee radios on channel 26. A token ring protocol was used where each node would broadcast a packet while all other nodes recorded the RSSI value from it. The broadcast packet from each node contained a list of the last received RSSI value from every other node. This allowed for a Master node to listen in on all network traffic, and to send the RSSI values from all links to a processing computer. The system was set up to run at 5Hz, allowing for 5 RSSI values from all links to be recorded each second. For both experiments, Wi-Fi was disabled to avoid interference [14]. Tests were performed in two contrasting indoor environments. The first environment was an open auditorium where there were no walls or structural pillars within 5m of the test setup as seen in Fig. 1. The second environment consisted of a cluttered university laboratory where there were many objects (e.g. walls, computer monitors, desks and chairs) that could contribute to multipath. A Rohde & Schwarz Spectrum Rider

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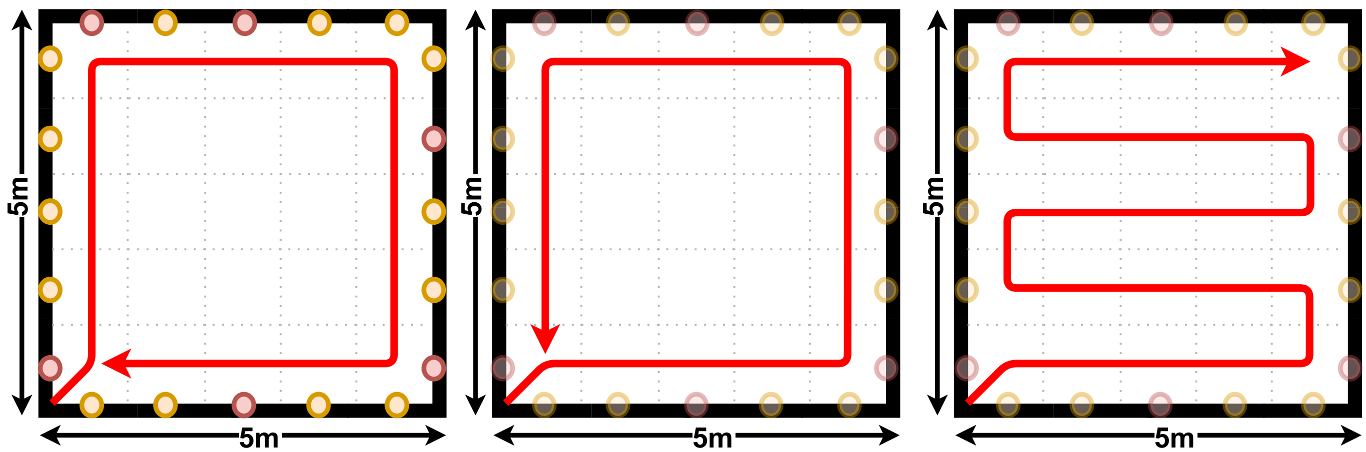
TABLE III
LINK-BASED IMPLEMENTATIONS

Features	Through-wall	Stationary Target	Multiple Targets	Computational Complexity	Major Contribution
Ichnaea	Yes	Yes	No	High	Monitors a global link score to detect movement within the environment, updates the offline silence profile with online links that do not show considerable variation, then uses a particle filter to track an entity where the motion vector is defined by the current/previously most affected links [9].
Zheng and Men	Yes	Yes	No	High	Models the link behaviour as a Gaussian mixture, use a particle filter to track an entity and update the parameters of the Gaussian mixture model online to ensure the algorithm is robust to environmental changes [27].
Guo et al	Yes	Yes	Yes	High	Introduces an Exponential-Rayleigh model for classifying the effect entities have on TX-RX RSSI links to achieve superior accuracy to traditional magnitude or exponential models. Localization is done through Bayesian inference, with a particle filter used for tracking purposes [3].



(a) (b) (c)

Fig. 2. Auditorium Walking Trajectories - (a) Clockwise, (b) Anticlockwise; and (c) Zigzag.

FPH spectrum analyser was used in both environments when the experiments were undertaken to ensure that no measurable 2.4GHz interference was present.The nodes were mounted at 1.2m above the ground on stands in the auditorium, and were wall mounted at 1.4m above the ground in the laboratory. The minimum Euclidean distance between deployed nodes was 0.7m in the auditorium and 1.0m in the laboratory. The maximum Euclidean distances were 6.4m and 10.1m respectively. In both environments the subject's were asked to walk following a clockwise, anticlockwise or zigzag trajectory as outlined in Fig. 2 and Fig. 3. Subjects walked in a heel-toe fashion while using a metronome. This ensured that all step sizes remained consistent between tests with the same subject, the walking speed remained constant, and a ground truth could be captured over the course of the trajectory, at any given time. Since homes are not likely to have 20 devices available to cover a small area, for the second sets of tests we reduced the number of nodes to the lowest number of nodes (6) that resulted in consistent performance with the algorithms. The node placement are represented by the small circles in Fig. 2 and Fig. 3. The node placement used for the 6 node tests is marked with red circles. Each set of experiments was repeated three times with at least 30 minutes between each test.

IV. ALGORITHMS

In this section, implementations of KRTI, SCPL and Ichnaea are described [6], [7], [9]. Each algorithms parameters were fine-tuned empirically. For a more in-depth explanation of the algorithms used the reader is urged to read the respective original works.

A. KRTI

A histogram based RTI implementations calculates the difference between histograms calculated for each link to determine whether a specific link is currently affected by the presence of an entity. Assuming RSSI values have the range $1-N$, each histogram is constructed with N bins, where the N-*th* bin value increases as the frequency of recorded RSSI value N increases. A scheme based on an exponentially weighted moving average (EWMA) calculates the histograms as:

$$h^{l,t} = (1-\beta)h^{l,t-1} + \beta\zeta(R^{l,t}) \quad (1)$$

where $h^{l,t}$ is the histogram of length N for link l at time t where each value is between $0-1$; $\beta$is the forgetting factor between $0-1$, which determines the weight put on recent measurements; ζ is an indication vector; and $R^{l,t}$ is the RSSI

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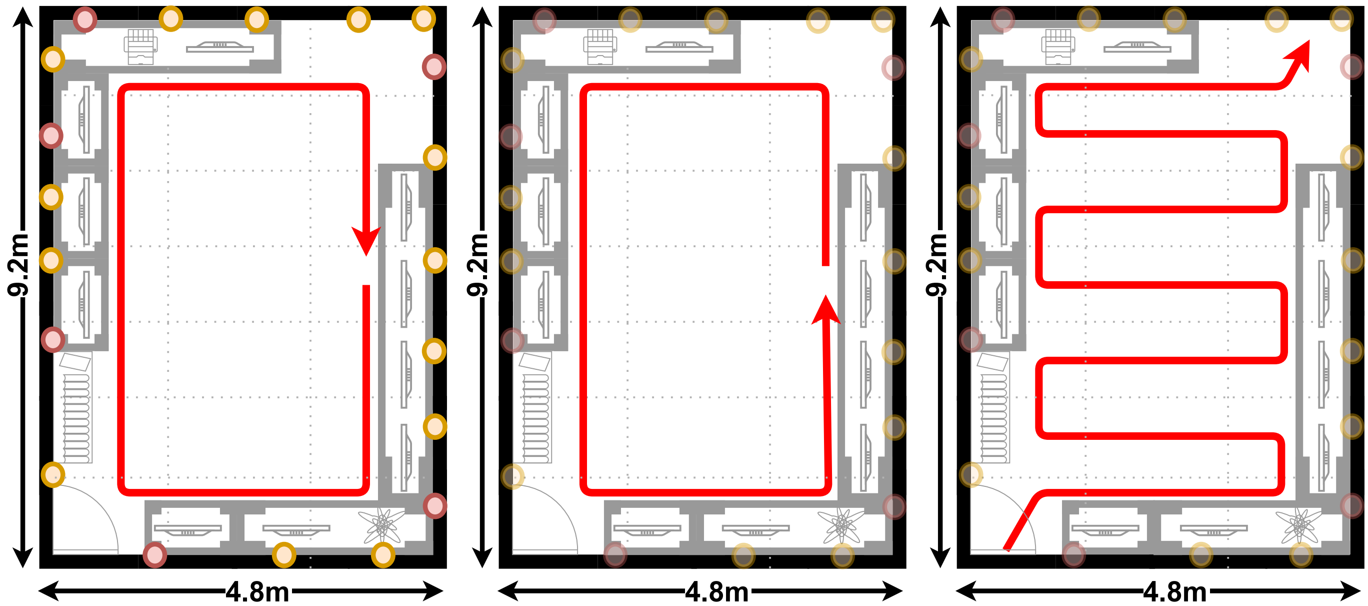

(a) (b) (c)

Fig. 3. Laboratory Walking Trajectories - (a) Clockwise, (b) Anticlockwise; and (c) Zigzag.

of link l at time t. ζ is a vector of length N where the index given by $R^{l,t}$ is 1 and every other position is 0.

If we define the long term histogram as L and the short term histogram as S, where $\beta_L < \beta_S$, then the kernel distance between them can be defined by:

$$D(S,L) = S^T KS + L^T KL - 2S^T KL \tag{2}$$

where K in a N by N kernel matrix and T represents a transpose operation. The Epanechnikov kernel was utilised for this paper [42]. KRTI assumes that the location of a person can be given by the maximum value of the image x, where x can be defined by the vector $x = [x_0, , x_{P-1}]$ and P is the number of pixels. KRTI also assumes that d, the set histograms differences for each link, can be expressed as a linear combination of x:

$$d = Wx + n \tag{3}$$

where n is a noise vector; and W is a weighting model, where $W_{l,p}$ for pixel P is zero unless it is located within an 2D ellipse defined with foci at link l's transmitter and receiver nodes. Since RTI is by nature an ill-posed inverse problem, regularization is used. By utilizing a least squares formulation the image x can be defined by:

$$x = (W^T W + \sigma_n^2 C_x^{-1})^{-1} W^T d \tag{4}$$

where σ_n^2 is the noise variance and C_x is the covariance matrix of x. For tracking, KRTI uses a Kalman filter where the state transition model includes the persons location and velocity, and the observation inputs are provided by the location estimate from x. All the parameter values used for implementing KRTI in both environments are contained in Table IV.

TABLE IV
KRTI PARAMETERS

Parameter	Value	Description
β_S	0.9	Forgetting factor S
β_L	0.05	Forgetting factor L
σ_E^2	30	Epanechnikov kernel width*
σ^2	0.01	Regularization parameter*
δ	1.3	Space parameter*

*Following the process outlined in [7], K in (2) is formulated using σ_E^2, while C_x^{-1} in (4) is formulated using σ^2 and δ.

B. SCPL

Since this paper only focusses on single target tracking, SCPL can be simplified to a classification problem using Linear Discriminant Analysis (LDA), a conditional random field (CRF) and Viterbi tracking [6]. SCPL splits the environment into cells and uses offline RSSI measurement vectors from all links while a person is standing within a cell as a class. By assuming the density of each class c is a multivariate Guassian with mean μ_c and a shared covariance matrix Σ, given an RSSI vector R:

$$f_c(R) = \frac{1}{(2\pi)^{0.5L}|\Sigma|^{0.5}} e^{(-0.5(R-\mu_c)^T \Sigma^{-1}(R-\mu_c)} \tag{5}$$

By applying Bayes rule, the objective function is defined as:

$$y = \underset{c}{\operatorname{argmax}}\, f_c(R)\pi_c \tag{6}$$

The discriminant function in log scale is defined as:

$$\delta_c(R) = R^T \Sigma^{-1}\mu_c - \frac{1}{2}\mu_c^T \Sigma^{-1}\mu_c + \log \pi_c \tag{7}$$

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where T represents a transpose operation; and the final cell estimate model is:

$$\begin{aligned} V_c(1) &= \delta_c(R^{t=1}) \\ V_c(t) &= \operatorname*{argmax}_c V_c(t-1)\delta_c(R^t)M_{c_0,c} \end{aligned} \tag{8}$$

where R^t is a RSSI vector of all links at time t, M is a transition model based on a a 1^{st} order trajectory ring and $M_{c_0,c}$ defines the probability of a transition from state c_0 at $t-1$ to state c at time t. For SCPL the auditorium was split into 25 cells (states), and the laboratory into 21 cells as shown in Fig. 2 and Fig. 3. SCPL was set up to use a 1st order trajectory ring.

C. Ichnaea

Ichnaea works in two phases. The offline phase creates a normal profile for each stream, followed by the monitoring phase where each link is iteratively checked for anomalous behaviour. Links flagged as anomalous are passed to a particle filter which tracks the subject and defines the location estimate as the centroid of the weighted particles.

Ichnaea represents each stream as a density function where:

$$f_j(x) = \frac{1}{h_j}\sum_{i=1}^{n} w_i V\left(\frac{x - x_{j,i}}{h_j}\right) \tag{9}$$

where j, represents a link, n is a set of sliding windows each of length l samples, $x_{j,i}$ is the variance of the RSSI values within a window of length $n+l-1$, h_j is the bandwidth, w is a weight, and V is the kernel function. The motion tracking module is activated if sufficient global activity is detected over a threshold, defined by:

$$G_t = (1-\beta)G_{t-1} + \beta\alpha_t \tag{10}$$

where β is a smoothing coefficient and α_t is a global anomaly score defined by $\alpha_t = \Sigma\alpha_{j,t}$, where:

$$\alpha_{j,t} = \frac{x_{j,t}}{F_j^{-1}(\gamma)} \tag{11}$$

where: $F_j^{-1}(\gamma)$ is the γth percentile of the CDF, of the distribution shown in Equation [9]. The final location of the entity is tracked using a particle filter and can be defined as the centroid of the particles by:

$$p_t = \sum_{i=1}^{N}\left[p_{i,t}\max_j\left(a_{j,t}\frac{d_j}{dAP_{j,i} + dMP_{j,i}}\right)\right] \tag{12}$$

where N is the total number of particles; d_j is the length of stream j; $dAP_{j,i}$ is the length between the particle and the AP, and $dMP_{j,i}$ the length between the particle and the MP. The parameter values for the smoothing coefficient and particle filter implementation were kept the same as in [9].

V. Results

The results were averaged over three iterations of each route taken.

A. Auditorium

This was an ideal open indoor environment, with minimal objects that could cause multipath within the immediate vicinity. However, there were still small dead spots within the test area where all DFL solutions struggled to localize a person correctly. This was surprising, as this experiment had a high node density (one node per 1.25m^2) and there was no interference. The experiments were repeated with the same subjects three times, with a time separation to minimize the risk of radio links remaining in a deep fade for the entire duration of the experiment. If the algorithms cannot correctly track through the dead spots, it takes a while for the tracking to catch up once the subject can be localized correctly again. This behaviour results in strong transient errors getting extended over a longer period than which they occurred within, leading to further degradation to the overall accuracy. The most interesting effect this has on the DFL solutions presented, is that the accuracy of walking clockwise around the environment is not always the same as walking anticlockwise.

Fig. 4 and Fig. 5 show the CDF error plots from the clockwise and anticlockwise routes. KRTI significantly outperforms the other two algorithms when walking clockwise, while Ichnaea performed better on the anticlockwise route. KRTI outperformed both Ichnaea and SCPL in the zigzag route which was the longest and covered the entire test area. Though some of the maximum errors experienced by KRTI exceeded those of Ichnaea.

Reducing the nodes from 20 to 6 in the second set of tests resulted in a significant decrease in performance with the worst median error of 2.49m, in contrast to a worst median error of 1.7m for 20 nodes. Whilst KRTI still functioned and had the most consistent performance across all routes with 6 nodes, the lack of node density resulted in a significant increase in error with the mean error almost doubling. Ichnaea's unique tracking strategy has a significant effect on the results achieved in the 6 Node tests. Since Ichnaea creates a motion vector from the midpoint of the last dominant link to the midpoint of the current one, it performs well in some situations even with sparse links. If the subject crossed links that were approximately parallel, Ichnaea's tracking would perform well. For the anticlockwise route, these characteristics helped Ichnaea perform as expected. The contrast was seen in the clockwise test when the successive dominant triggered links were near perpendicular in several cases. This resulted in a motion vector being used that did not accurately follow the motion of the subject and resulted in large errors.

B. Cluttered Laboratory

In the cluttered laboratory environment with 20 nodes both KRTI and SCPL had consistent performance across all 3 routes and attained overall median errors of under 1m as shown in Table V. Both KRTI and SCPL suffered significant performance degradation when only 6 nodes were used. KRTI maintained a more consistent performance across multiple routes while SCPL's performance was largely route dependant as the algorithm failed to reliably track through dead spots when approached from certain directions. Ichnaea performed

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TABLE V
OVERALL LOCALIZATION ERRORS (M) FOR COMBINED TRAJECTORIES IN EACH ENVIRONMENT

Auditorium 20 Nodes	**Mean**	**Median**	**RMSE**	**90^{th} percentile**	**Max**
Ichnaea	1.21	1.14	1.34	2.01	**2.65**
KRTI	**1.09**	**0.97**	**1.29**	**1.99**	3.48
SCPL	1.33	1.24	1.55	2.23	4.68
Auditorium 6 Nodes					
Ichnaea	**1.37**	**1.25**	**1.52**	**2.29**	**3.03**
KRTI	2.08	2.06	2.18	3.02	4.02
SCPL	1.82	1.55	2.20	3.81	4.90
Laboratory 20 Nodes					
Ichnaea	1.72	1.70	1.88	2.62	4.37
KRTI	**0.99**	**0.75**	**1.23**	**2.06**	3.79
SCPL	1.05	0.94	1.27	2.13	**3.46**
Laboratory 6 Nodes					
Ichnaea	2.15	2.06	2.35	**3.40**	**4.74**
KRTI	**2.00**	**1.85**	**2.33**	3.80	6.70
SCPL	2.45	2.49	2.70	3.65	5.37

considerably worse in the 20 node route tests, though the results were more consistent with the other approaches when only 6 nodes were utilized.

C. Overall Comparison

Table V was created by combining the route data, to give overall errors for each environment and associated node deployment density. KRTI outperformed Ichnaea and SCPL in both environments when 20 nodes were present, and in the cluttered laboratory when only 6 nodes were available. SCPL performed poorly in comparison to the other approaches in all trials except for the cluttered laboratory, utilizing 20 nodes. This is understandable as when 6 nodes were used, the system struggled to clearly classify neighbouring cells. The effect of this was exacerbated as both the auditorium and cluttered laboratory were open environments with minimal movement constraints which can improve SCPL's accuracy. Since the cluttered laboratory had better spatial separation across the whole room, SCPL performed better than in the auditorium when 20 nodes were present. It should be worth noting that we attempted to use both zero order trajectory rings and second order trajectory rings, but they resulted in degraded performance. A problem with the utilized first order ring was that occasionally SCPL would report a constant unchanging location when the subject walked through a blind spot. Even with correct cell responses after leaving the blind spot, the trajectory ring would not allow for the tracking system to catch up, resulting in large errors. This was partially improved by allowing for diagonal cell transitions in the movement model in the first order ring, but the problem still occurred occasionally. Ichnaea performed adequately in the auditorium, and poorly within the cluttered laboratory. It was discovered that the accuracy of Ichnaea, both in localization and tracking, is strongly dependant on node positioning. As previously mentioned, Ichnaea works well when a subject traversing an environment passes through links that are approximately parallel to each other. It also performs better when crossing shorter links than longer ones as the estimated motion vector is more likely to be accurate.

The ambiguity resulting from using a single valued statistic, (CEP and CE95 accuracy scores), can be clearly observed in Fig. 5 and Fig. 7. Figure 5 (b) and (c) show that while SCPL has a better median (CEP) error, KRTI has better CE95 performance. Depending on which of the two metrics is used, either of these algorithms can be presented as the more accurate one. The 75^{th} percentile accuracy score used by EvAAL also suffers from the same issue. Figure 7 (a) and (b) show similar ambiguity where the CEP and CE95 errors do not adequately identify the best localization candidate.

Experimental results show that existing RSSI approaches have an acceptable accuracy, with KRTI attaining sub-meter median error across both environments. However all have constraints that limit real world implementation. RTI approaches require the least calibration effort, but require a high

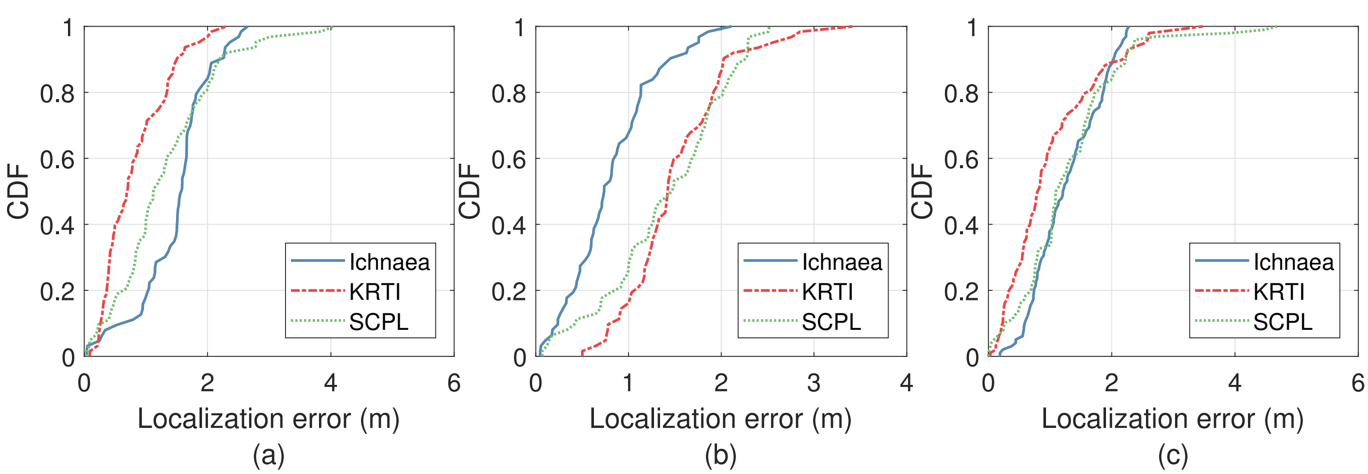

Fig. 4. Auditorium 20 Node CDF - (a) Clockwise, (b) Anticlockwise, (c) Zigzag.

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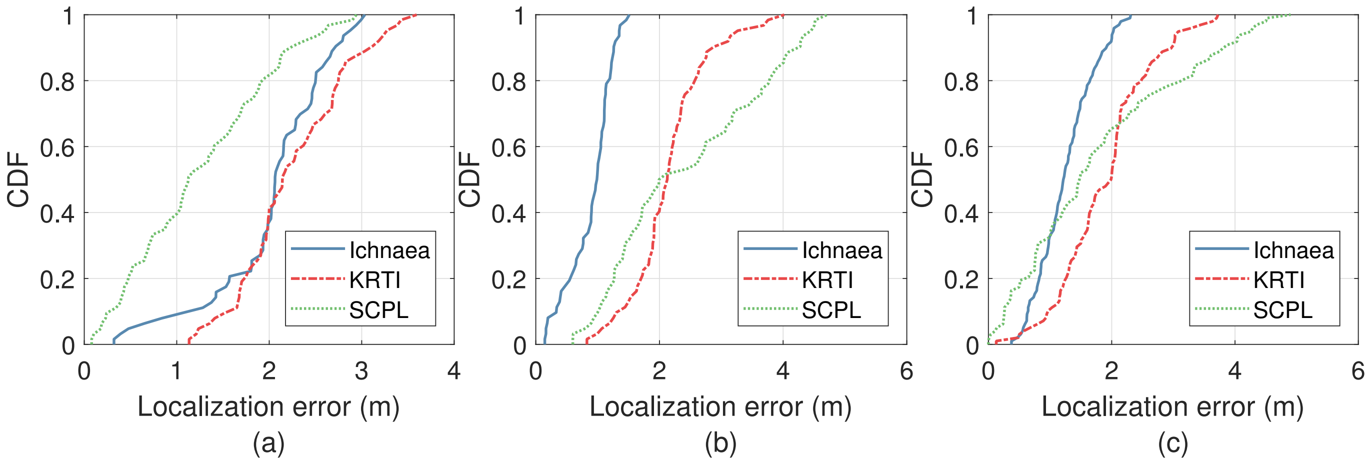

Fig. 5. Auditorium 6 Node CDF - (a) Clockwise, (b) Anticlockwise, (c) Zigzag.

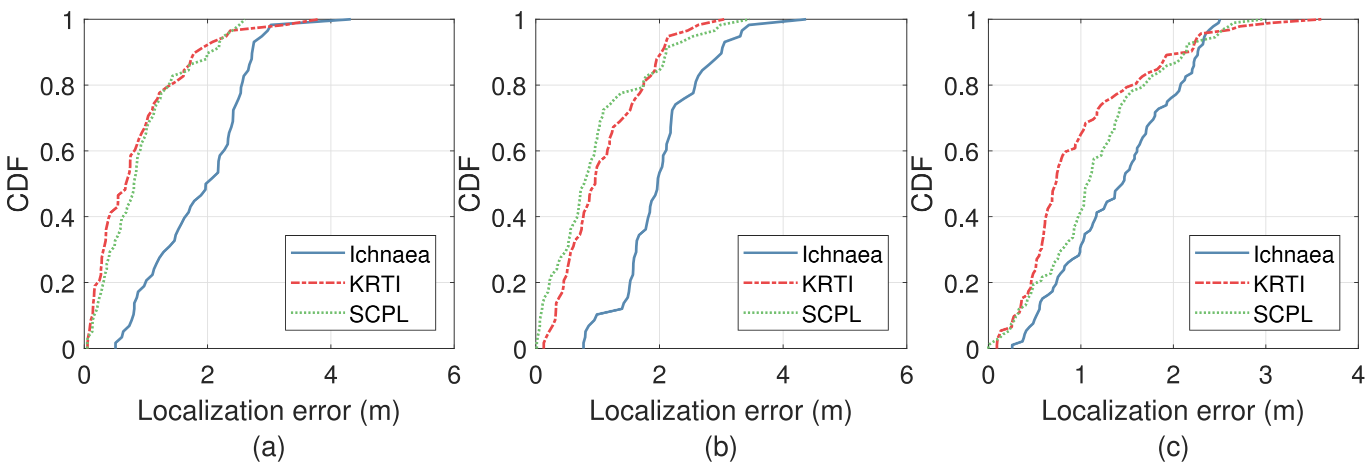

Fig. 6. Laboratory 20 Node CDF - (a) Clockwise, (b) Anticlockwise, (c) Zigzag.

deployment density. Probabilistic link-based approaches, like Ichnaea, offer benefits over RTI and Fingerprinting approaches in that they require less nodes than RTI and do not require a site survey. However existing probabilistic approaches often require a floorplan of the environment with nodes placed in strategic positions to attain an acceptable accuracy. This is demonstrated in the 6 Node tests where Ichnaea had a significantly better accuracy in the auditorium than the laboratory. Even though SCPL performed poorly, this was partially due to both environments being open with few movement restrictions, which increases error in classification approaches. Since SCPL can track multiple targets with less complexity than a particle filter, it could be considered when constraints can be placed on valid movement, such as within small corridors and cubicle environments. Existing approaches are also presented in literature with simplistic human mobility expectations, which do not hold up well with realistic human movement. Overall for real world viability and widespread adoption to be achieved, a system needs to be developed that requires few nodes and minimalistic human involvement during the initial calibration process. Such a system must also maintain long term accuracy and not assume excessive mobility constraints for tracked targets.

VI. Conclusion and Future Works

Experimental results suggest that although significant work has been reported in the literature on indoor localization, the DFL problem has not yet been solved for realistic environments. Existing wireless DFL implementations in literature typically only use a single route for their measurement. We have shown that despite the infrastructure remaining constant, wireless DFL solutions cannot guarantee a consistent tracking accuracy across the whole environment. Experimental investigation is the only way to fairly compare differing DFL approaches. Review or survey papers are not able to do a true, apple-to-apple comparison of the different approaches. Results obtained using different platforms and hardware and conducted in different conditions can not be used for benchmarking and comparisons.

Our experimental results clearly show that walking trajectory has a significant impact on the precision of all algorithms. Therefore, even at identical test locations, the localization accuracy of an algorithm can be significantly different depending on the trajectory taken or the path navigated. This also suggests that localization error is not uniform across a test environment. Furthermore, since the shapes of the CDF

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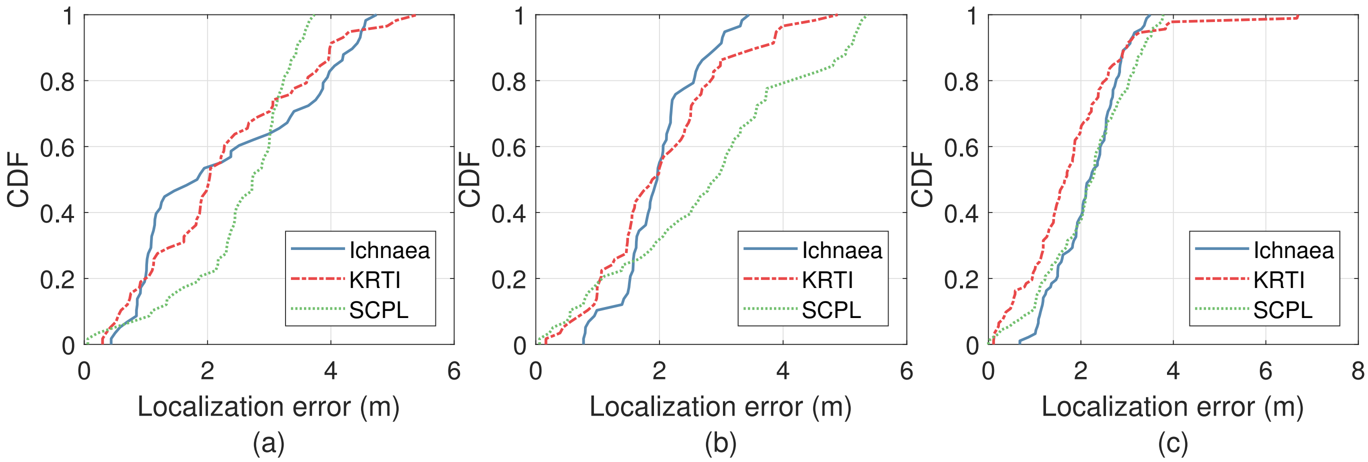

Fig. 7. Laboratory 6 Node CDF - (a) Clockwise, (b) Anticlockwise, (c) Zigzag.

curves are different across algorithms, spatial error variations affect each algorithm differently. As far as the authors are aware of, the significant impact of trajectories and the spatial error variation have not been shown in any published literature and are not appropriately addressed by the ISO/IEC 18305 standard. Further testing strategies need to be developed which appropriately include multiple trajectories within each test.

Both EvAAL and ISO/IEC 18305's accuracy score metrics are inferior to an empirical CDF plot which provides full percentile comparison. We believe that using graphical CDF error plots as an accuracy score should be standardized as it is more information rich than any singular percentile error.

While KRTI showed the best overall performance in both environments with a sub-meter median error when 20 nodes were used, it also had the worst overall median error in the 6 node auditorium test. Ichnaea showed the most consistent performance in the 6 node tests, but experienced severe accuracy issues caused by the orientation of sequential triggered links. This could potentially be fixed by modifying the motion model and how the direction of motion is determined. Overall the results show that no singular algorithm could surpass all others across all tests.

We noticed that several links did not show significant change even in the presence of movement, and others that triggered when no user was present. To be effective, localization schemes should aim to identify links that are either currently experiencing a deep fade, or spurious behaviour and reduce their weighting, for the duration of the measured abnormal behaviour. Existing approaches have used channel diversity to help partially mitigate this effect [38]. However, relying on multiple frequency channels being available may not be possible in urban environments. The system that achieved the best median error with a low node density (Ichnaea) was largely affected by node placement. Node placement was not a focus of this paper, but future works should explore how an installation methodology can be developed to optimize placement for unknown environments. All algorithms suffered from several incorrect position estimates, which occasionally caused KRTI and Ichnaea to head in the wrong direction, and SCPL to stop moving in any direction. Work needs to be done to predict human trajectories more accurately and enable reliable tracking on an entity through blind spots. While there are some reported works in this area using particle filters, more work needs to be done to ensure the tracking solution can function in real time on low cost COTS hardware. Also, significant work needs to be undertaken to allow for consistent performance in environments with sparse node deployment.

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