IET Research Journals

H4LO: Automation Platform for Efficient RF Fingerprinting using SLAM-derived Map and Poses

ISSN 1751-8644
doi: 0000000000
www.ietdl.org

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Abstract: One of the main shortcomings of Received Signal Strength based indoor localisation techniques is the labour and time cost involved in acquiring labelled 'ground-truth' training data. This training data is often obtained through fingerprinting, which involves the user visiting all prescribed locations to capture sensor observations throughout the environment. These prescribed sites must be annotated with reference coordinates which correspond to a known floor plan. In this work, we present 'H4LO' (Helmet for Localisation Optimisation): a low-cost robotic system designed to cut down on the labour by utilising an off-the-shelf Light Detection and Ranging device. This system allows for Simultaneous Localisation and Mapping, providing the human user with an accurate pose estimation and a corresponding map of the environment. The high resolution location estimation can then be used to train a positioning model, where Received Signal Strength data is acquired from a human-worn wearable device. The method is evaluated using live measurements, recorded within a residential property in Bristol. We compare the ground-truth location labels generated automatically by the H4LO system with a camera-based fingerprinting technique from previous work. We find that the system remains comparable in performance to the less-efficient camera-based method, whilst removing the need for time-consuming labour associated with registering the user's location.

1 Introduction

Fingerprinting is a well established family of model training methods in wireless indoor localisation literature [1, 2]. The usual pipeline of 2-dimensional fingerprint training follows the discretisation of evaluation space into x and y locations, or reference points [1]. A transmitting device must visit each reference point and a number of receivers will capture RF information at that time, typically in the form of Received Signal Strength (RSS) [3]. This process is then repeated for each pre-defined location until a labelled fingerprint for the space is obtained [1, 4].

The labelling of each reference point in the fingerprint is an arduous task which takes a significant amount of time. A floor plan is often necessary, in order to derive a list of training reference locations which have to be manually annotated in space. Then, depending on the use case, a tailored method is devised to accurately denote when the participant visits these predefined locations [4, 5].

Another major shortcoming of this technique is that it suffers from performance deterioration over time and requires periodical re-training [6]. This can happen due to changes in the layout of the space [7], or through deliberate hostile action [8]. It is therefore in the best interest of the system for the fingerprinting method to be as simple and efficient as possible, in order to be easily performed when required.

In addition to the above issues, it is also important to consider each user's propagation characteristics. A model trained on a specific user is unlikely to perform well when generalised for other users [5]. This further complicates the problem, especially for cases when training with non-technical participants who are unfamiliar with the technologies involved [9, 10]. A chosen fingerprinting paradigm has to therefore be easy to understand and utilise by users of various technical experience.

The aim of the proposed system is to address all of the above concerns, by utilising a Light Detection and Ranging (LiDAR) device to obtain the human user's pose in space. This will generate ground-truth coordinate labels without requiring any *a-priori* knowledge of the environment. These labels will then be directly related to RSS signatures captured during fingerprint training. We utilise Simultaneous Localisation and Mapping (SLAM) and pervasive indoor localisation techniques, and propose a novel method of associating the two through the help of a robotic platform designed for efficiency.

In this paper we present the hardware used, recent experimental findings, and show the viability of this method as compared to previous work. The proposed H4LO fingerprinting training method is evaluated using measured RSS data that was obtained from a wrist-worn wearable device where participants occupied a residential two story property in Bristol. This domicile was fully furnished, photographs are shown in Figure 1. The dataset used is available to the community. The main contributions of this paper therefore are:

1. We outline the proposed hardware for 'on-the-cheap' LiDAR scan acquisition, utilising popular 'off-the-shelf' devices.
2. We then present the exhaustive 'free-living' and fingerprinting experiments gathered to prove its viability and upon publication, the dataset used will be released for public access.
3. Finally, we compare the performance of this method to our previous work where floor tags were used to provide location labels [4].

We first provide the current overview of the literature in Section 2. In Section 3 we outline all of the methods which are utilised by our system. Section 4 will detail the pipeline of the system, from the hardware setup to map generation and localisation. In Section 5

Fig. 1: The experimental environment included all typical amenities of a residential house. This photo shows the kitchen area.

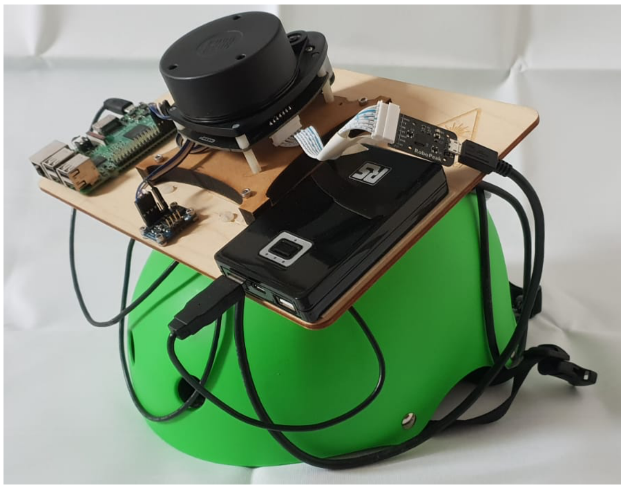

Fig. 2: The 'H4LO'.

we present the dataset, and reflect on the experiments performed and present the results, comparing our approach to fingerprinting method used in previous work. We discuss their viability and shortcomings in Section 6. We conclude and provide points for future work in Section 7.

2 Related Work

The literature relating laser range finders and RSS fingerprinting is sparse [11–13] and not entirely comparable. The presented literature indeed collects the RSS fingerprints and LiDAR data, but through the use of trolleys and rigs, specifically designed to be traversed through the environment by a technician or on its own. The trolleys remain stationary while the relevant LiDAR data is collected. In our implementation, we use a human user which collects their own unique fingerprints in a residential environment.

The use of human participants performing the fingerprinting can be motivated by considering the uniqueness of each person's walking gait and radio propagation characteristics. It was shown that the performance of indoor localisation algorithms differ, depending upon the training which was received from the participants [5]. This is especially true in the case of residential indoor localisation, where the environment is small but saturated with various obstacles [4]. It is therefore likely, that trolley-based fingerprinting methods are unable to capture each user's unique propagation characteristics.

Some applications of LiDARs use human handlers [14, 15]. These implementations assume that the LiDAR device is not used as part of a robot's perception sensor, but rather as a mapping tool [14, 15]. We aim to exercise a similar operation of the LiDAR in this paper, by attaching the device on the participants themselves. However, our implementation uses the entirety of SLAM pipeline, as in order to be effective, the fingerprinting method must acquire reliable ground-truth locations and generate the corresponding map.

The use of LiDARs for SLAM is well established in the community [16, 17]. LiDAR-based SLAM follows the pipeline of matching consecutive scans in order to recover the map and locations. Pure scan matching however, suffers from accumulating error, due to imperfections in measuring equipment and the environment [18]. There exist methods of error minimisation, such as loop closure from graphs [18].

There exist implementations which utilise SLAM for sensor signal-based localisation through Gaussian Process (GP) regression [19, 20]. For example, WiFi-SLAM appropriates the SLAM pipeline of localisation and mapping in a setting of RSS modelling, as opposed to spatial features. Work in [19] used various ambient background sensor traces to perform PDR which was subsequently optimised through SLAM techniques.

As is evident, there exist a need for reliable, automated indoor localisation ground-truthing platform. This platform would be worn by the users themselves as they perform RSS fingerprinting of the environment. Furthermore, it has to be robust enough as to capture each user's unique gait and propagation characteristics, and at the same time flexible enough to be able to deal with various environmental obstacles which the users can encounter, such as stairs and doorways. The presented system was designed to address the lessons learnt from previous work [4] and to the authors' best knowledge, this is the first system and dataset of its kind.

3 Background

3.1 *Map Generation and Pose Estimation*

The map, along with the approximate location is provided by 2-dimensional SLAM. It can be formalised by considering the LiDAR returns as scan point clouds $\boldsymbol{S} = \{\boldsymbol{s}_t\}_{t=1,\dots,T} \in \mathbb{R}^2$. Each scan is recorded as a set of polar coordinates in a corresponding location, given by $\boldsymbol{X} = \{\boldsymbol{x}_t\}_{t=1,\dots,T}$, such that each $\boldsymbol{x}_t$ specifies a pose estimate in SE2:

$$\boldsymbol{x}_t = \{x, y, \theta\} \tag{1}$$

The locations are constrained within the boundaries of a map M. SLAM aims to extract $p(\boldsymbol{x}_t, M|\boldsymbol{S}_{0:t-1})$, or the location $\boldsymbol{x}_t$ and the map M simultaneously by matching consecutive scans $\boldsymbol{S}_{0:t-1}$ together. The procedure of scan matching attempts to find a rigid transformation of the scan at $t-1$ into the frame of scan at t, given by [16, 21, 22]:

$$\boldsymbol{S}_t(\xi) = \begin{bmatrix} p_x \\ p_y \end{bmatrix} + \begin{bmatrix} \cos\phi & -\sin\phi \\ \sin\phi & \cos\phi \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} \tag{2}$$

where $\xi = (p_x, p_y, \phi)$ is the transformation vector. In terms of a global map, this transformation aims to minimise the non-linear least squares error between the current map and the transformation of the most recent scan [21]:

$$\arg\min_{\xi} \sum_{t=1}^{T} (1 - M(\boldsymbol{S}_t(\xi))^2 \tag{3}$$

The mapping of our environment is done through an occupancy grid. We will omit its clarification here, directing the reader instead to [23] for an in-depth explanation.

Due to the unpredictability in data collection and the environment, the scans, even if collected at the same location, might not be precisely the same. A method relying purely on scan matching will therefore accumulate error and make the location and the map drift over time. To rectify this, the accumulated error is minimised when visiting previously unveiled locations, as in GraphSLAM [18]

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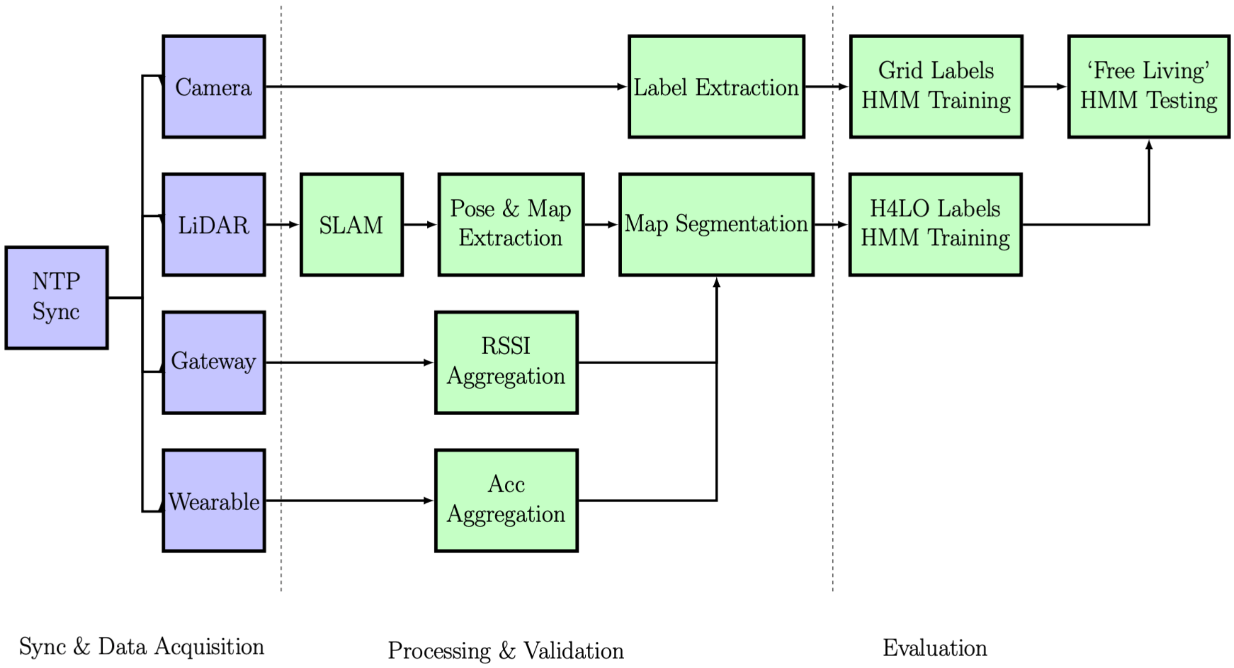


Fig. 3: High level representation of the processes used to evaluate H4LO. The blue nodes describe hardware implementations and the green software algorithms. The two unique HMM models are shown to highlight that the algorithms used different labelling techniques.

and Google's Cartographer [21]. This aims to minimise the squared error between the expected and relative measurements of a scan and an underlying sub-map [21]. The algorithm used in this paper utilises the MATLAB Robotics Toolbox, based on [21].

3.2 *Discrete State Space Localisation*

To combine these labels with the recorded RSS data to track the user, a state space localisation method is used [4, 24, 25]. The floor plan is parametrised as approximately equal size states. The models of states contain the signals arriving from N Access Points (APs). To simplify the model assumption, we choose for these signals to be normally distributed. Following the notation for a Bayesian filter, the probability of observing signal $\boldsymbol{z}_t$ given location $\boldsymbol{x}_j$ across all APs N is:

$$p(\boldsymbol{z}_t|\boldsymbol{x}_t) = \sum_{k=1}^{N} \mathcal{N}(\boldsymbol{z}_t|\mu_{jk}, \sigma_{jk}) \tag{4}$$

where $1 \leq j \leq L$ is the location state, and $1 \leq k \leq N$ is the index of AP sensor. Observations are given by a vector $\boldsymbol{z}_t(j) = \{z_1, ..., z_N\}$, and the location is specified as a point in Cartesian space $\boldsymbol{x}_t(j) = \{x, y, z\}$. Equation 4 follows the Hidden Markov Model (HMM), where $\lambda = \{\pi, \boldsymbol{A}, \boldsymbol{B}\}$ specify the prior, transition and emission parameters [26]. These parameters are estimated deterministically in this work [24, 25]. The joint distribution over all states and observations is given by:

$$p(\boldsymbol{x}_{1:t}, \boldsymbol{z}_{1:t}) = p(\boldsymbol{x}_0) \prod_{i=1}^{t} p(\boldsymbol{z}_t|\boldsymbol{x}_t) p(\boldsymbol{x}_t|\boldsymbol{x}_{t-1}) \tag{5}$$

where $p(\boldsymbol{x}_t|\boldsymbol{x}_{t-1})$ specifies the system transitions, or stochastic dynamics. The estimate of the posterior probability of each location state is then computed recursively by the forward-backward algorithm, which we will omit in this paper and refer the reader to [27].

4 The 'H4LO' System

4.1 *RSS Acquisition*

The system makes use of the SPHERE-in-the-box infrastructure, described in [9]. This infrastructure uses numerous Raspberry Pi-based Access Points (APs) which act as a signal 'anchor' for a SPHERE wrist-worn wearable [28], transmitting over Bluetooth Low Energy (BLE) at 5Hz. The BLE RSS is recorded as the user moves through the environment. This infrastructure does not provide labels.

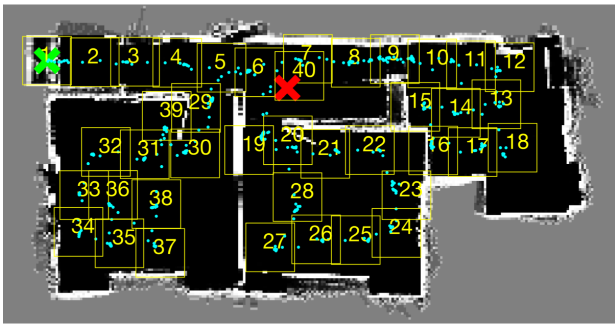
4.2 *Ground-truth Acquisition*

The ground-truth labelling method which we will use as a reference baseline in this study is exactly the same as the method from previous work, detailed in [4]. This method is based on a abdomen-mounted camera, and relies on floor-mounted fiducial tags, specifying empirically created state space. The synchronisation between the labels and the RSS is done through the extraction of floor tag labels [29] from the camera video.

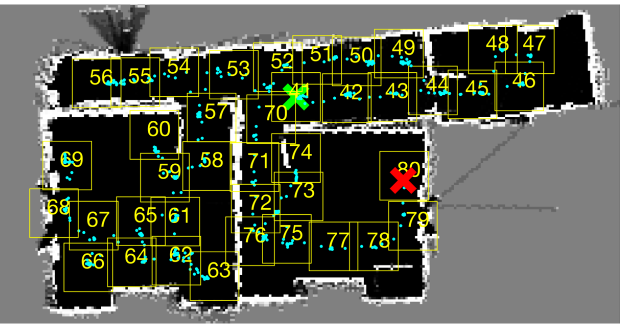
'H4LO' relies on the LiDAR scan collection from head-worn helmet, shown in Fig. 2. During data collection, the user performs fingerprinting much like before, by walking through the environment and collecting the RSS measurements. In our system however, the helmet also provides the corresponding LiDAR point clouds, representing different areas in the environment. This ensures that the data from both RSS and LiDAR collected is user-centric and unique across all participants.

The helmet comprises of a bike helmet, a power bank, Raspberry Pi 3 and RoboPeak RP1 LiDAR device mounted on top of plywood. The LiDAR collected scans at 10Hz, within a 6m range [30]. A 9-DOF BNO055 IMU [31] is present but was not used in this study. Timestamps are acquired through NTP from the SPHERE-in-the-box infrastructure [9] to match with the RSS data. This entire system was designed with cost in mind and comprises a total of £200 worth of hardware at the time of writing.

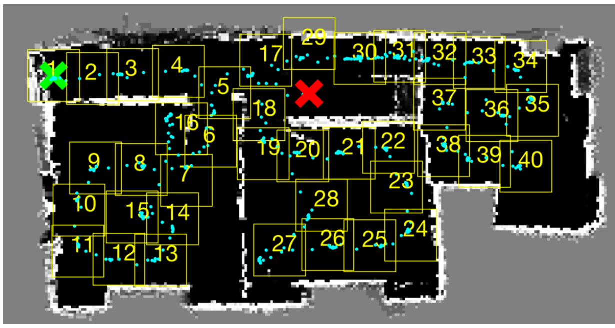
As described in Section 3, the sequential nature of the scans make it straight-forward to recover the map and the pose simultaneously. After obtaining both, the system recovers the RSS signals corresponding to the locations in the environment. By segmenting the



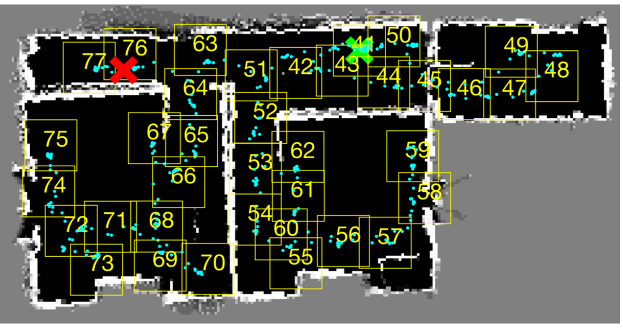
(a) Downstairs area map recovered from User 1.



(b) Upstairs area map recovered from User 1.



(c) Downstairs area map recovered from User 2.



(d) Upstairs area map recovered from User 2.

Fig. 4: Extracted SLAM maps 4a, 4b, 4c, 4d

space into states using spatial constraints, the system assigns the data to each state and learns the dynamics governing each state using an adjacency matrix, which is later used to acquire the state transitions.

4.3 House Plan Discretisation

The map was then stored locally on the Raspberry Pi. The pre-processing was minimal, in that the scans were only downsampled, as to help reduce the computational cost of the SLAM algorithm. After the pre-processing, the point clouds were fed to the MATLAB Robotics Toolbox for SLAM, where their locations and map were extracted. After extraction, the maps were rotated, as to face the same way, and the locations were used to parametrise the floor space into states. The algorithm used to parametrise can be found below:

The algorithm begins by establishing the initial state at the pose extracted at $t = 1$. The location of this pose will serve as the center point of the state, which is then assigned 'hard' boundary, visible as yellow squares in Figs. 4a, 4c, 5a and 4b, 4d, 5b and also 'soft' boundary, so called buffer, which acts as a decision border of whether or not to create a new state. If passed, new state is created. If not, the sensor readings are assigned to that state. At any time $t > 1$, the algorithm iteratively searches whether the given poses fall into an already assigned state. If so, the sensor readings are updated, as is the adjacency between states. If not, a new state is created.

Input: $\{\boldsymbol{R}\}$ = Extracted poses, $\{\boldsymbol{L}\}$ = Location state vector, $\{b_l\}$ = Buffer distance of specific state l, $\{RSS\}$ = Sensor readings

while *t available* **do**
  if $\boldsymbol{L} == \emptyset$ **then**
    $l \leftarrow \{r_{t,x}, r_{t,y}\}$ // Input x and y from extracted poses at t.
    $l \leftarrow RSS_t$ // Assign sensor readings and store in the new state.
    $\boldsymbol{L} \leftarrow l$ // Create new location state in global state vector and store.
  else
    for *all available states in* $\boldsymbol{L}$ **do**
      if *r_t within b_l* **then**
        $l \leftarrow RSS_t$
      else
        $l \leftarrow \{r_{t,x}, r_{t,y}\}$
        $l \leftarrow RSS_t$
        $\boldsymbol{L} \leftarrow l$
      end
      for *all available states in* $\boldsymbol{L}$ **do**
        $l \leftarrow$ assign possible adjacent states from $\boldsymbol{L}$
      end
    end
  end
end

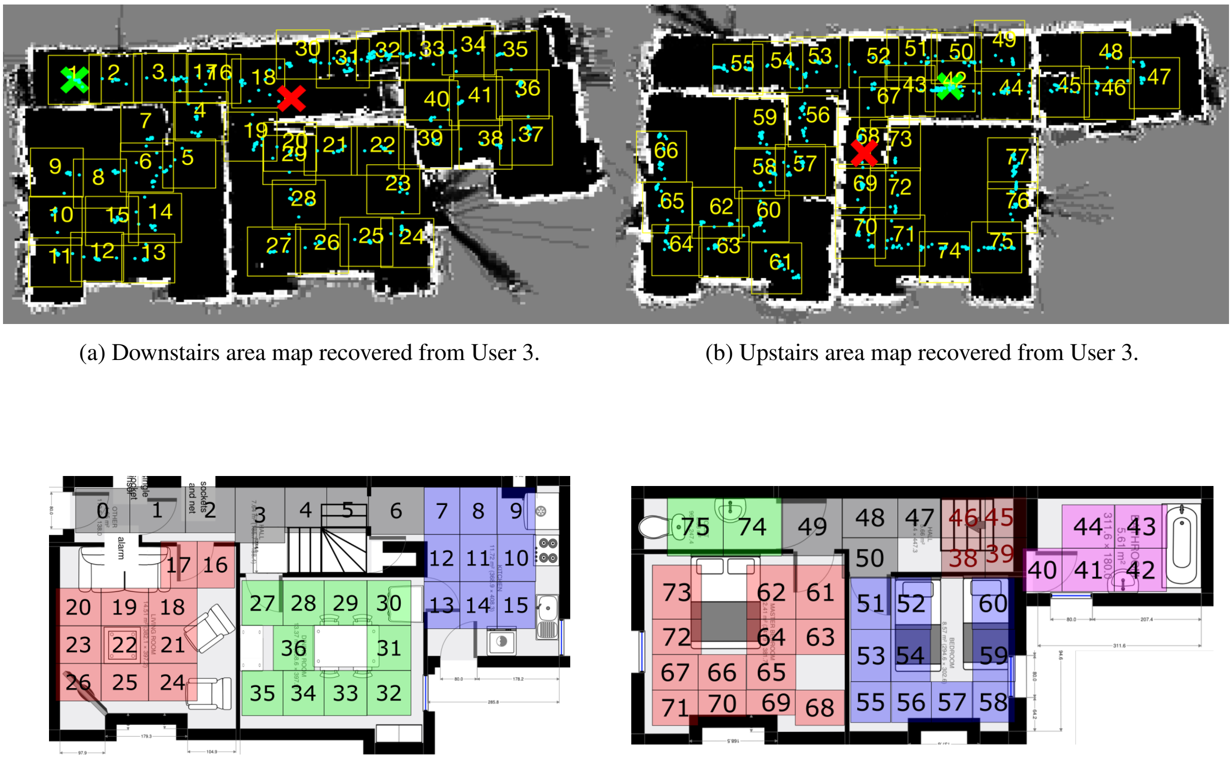
Algorithm 1: State creation algorithm

5 Experiments and Dataset

The experiments took place at a specially adapted test-bed house in Bristol [4, 32]. In order to compare the two methods fairly, the environment was parametrised into states at the same positions as in [4], shown in Figs. 5c and 5d. The underlying plan in those figures was obtained using 'magicplan' software* and is shown as a reference. Note, that the original state spaces in [4] do not include the house plan.

There were 3 unique users performing fingerprinting using the 'H4LO' and the camera based approach at the same time. Each user traversed the same environment at a different rate, taking different routes. The routes can be ascertained by the progression of the automatically generated states, whose index is monotonically increasing.

* *https://www.magicplan.app/*



(a) Downstairs area map recovered from User 3.

(b) Upstairs area map recovered from User 3.

(c) Corresponding ground-truth downstairs.

(d) Corresponding ground-truth upstairs.

Fig. 5: Extracted SLAM maps 5a, 5b with ground truth 5c and 5d

They performed two types of fingerprinting - one longer (16 minutes on average), staying at each state for a few seconds, and also a quicker 'fly-through' fingerprint (7 minutes on average).

In addition to the fingerprinting experiments, two of the users also performed 'free-living' experiments, performing everyday routines. These can be further separated into 'single free-living', where only one user took part and 'dual free-living' where both users, wearing wrist-worn sensors, participated at the same time. Note, that the 'free-living' experiments do not include the LiDAR data, and that the presented maps were extracted from the thorough 'longer' fingerprint data of each user. The use of 'free-living' experiments is motivated by the need of thorough validation of the system - in these experiments, the users were asked to behave naturally, traversing the environment as they saw fit, and did not conform to any script. This helps provide a good test bed for the robustness of this system.

Upon publication, the dataset used will be released for public access*. It comprises of the data from the wearable and the 'H4LO'. The wearable data includes the wrist-worn acceleration (sampled at 25Hz) and RSS (sampled at 5Hz). The 'H4LO' primarily provides data from the LiDAR device, with the scans arriving at an average rate of 10Hz. Additionally, the IMU attached to the 'H4LO' provides data for roll, pitch, accelerometer and gyroscope, sampled at 100Hz, and heading and magnetometer sampled at 50Hz.

The results of the SLAM run for a single user are shown in Figs. 4a, 4c, 5a and 4b, 4d, 5b. The green and red '$\times$' specify the beginning and end of the SLAM run. The states are given as yellow squares, and are enumerated as such. The cyan dots signify the locations extracted from the LiDAR scans. To make the comparison between the methods fair, when running SLAM, the data was manually segmented into downstairs and upstairs areas.

Each model was trained on the same fingerprint in two ways - one using the camera derived labels [4] and the other using the 'H4LO' system. Then, both of the models were tested against specific subsets of all the experiments. The results from these tests are separated into the fingerprinting, single and dual living results, seen in Figs. 6, 7, 8 respectively. They are averaged across all participating users. Note, that there were only four dual living experiments - results for both participants result in 8 test sets.

As described before, the metric used to test the performance of this system is the Euclidean error [33]. As is evident from the graphs, 'H4LO' has a comparable performance to the method used to gather data in [4], in some instances even outperforming the baseline. It is important to note here, that the expected results were not supposed to outperform the fingerprinting method outlined in [4]. These results, even if not entirely superior to the HRL, come at a fraction of the labour.

A possible reason for the results could also lie in the way the labels from both of the ground-truthing approaches are gathered and quantised. Camera-based approach has an inherent advantage, in that it is considered as the ground truth when gathering the data, considering only a single x, y position on the floor plan. The error for H4LO was calculated from the available extracted poses on the map. The error was therefore calculated between the quantised camera-based labels and much more resolute poses, extracted from the SLAM process. Inherently, this will yield more error, as the poses are spread across a larger area of the map, and thus would generate more uneven and unfair, discrepancy between the prediction and label.

6 Discussion

This paper has shown, that the efficient 'H4LO' system can be used to generate a fingerprint training dataset with comparable results to the time-consuming camera approach [4]. Through the utilisation of head-worn robotic rig, the 'H4LO' system performs mapping and localisation simultaneously. This solves a number of challenges which were set out in Sections 1 and 6, specifically regarding the labour cost of existing fingerprinting methods. In addition to providing automation to the location labelling process, the system also ensures a very reliable location estimation. Whilst the labelling system in [4] did provide similar localisation performance, it relied heavily on fiducial floor tags and their annotated coordinates within a

* *https://github.com/mkoz71/h4lo_fingerprint_automation_system*

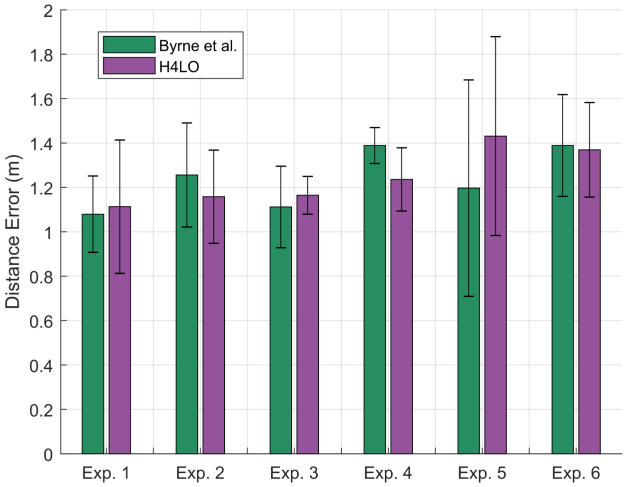


Fig. 6: Localisation Results of the fingerprint experiments.

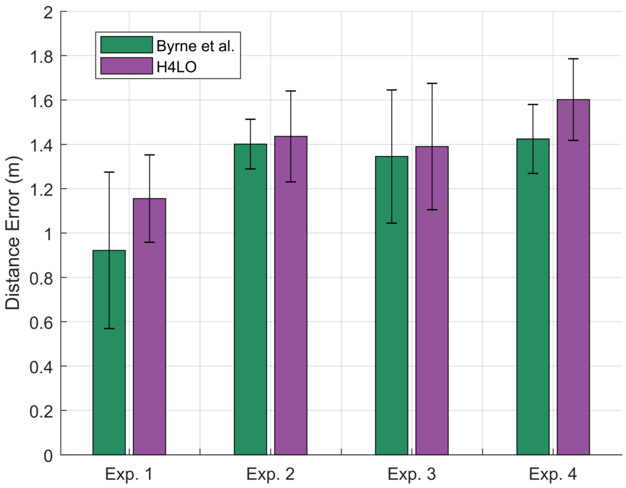


Fig. 7: Localisation Results of the single living experiments.

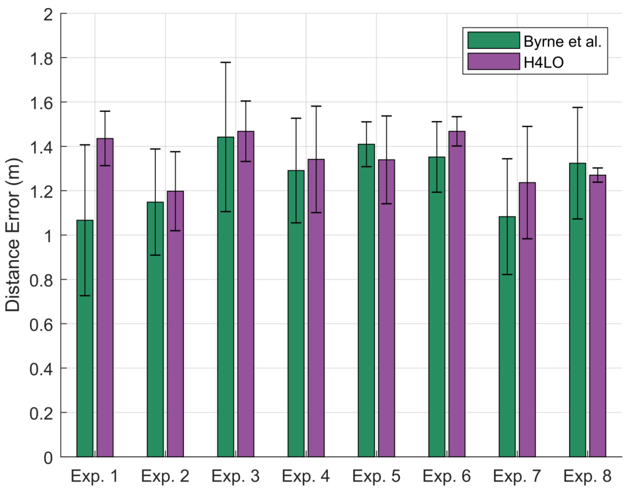


Fig. 8: Localisation Results of the dual living experiments.

house plan, both of which must be known *a-priori*. 'H4LO' removes the need for floor plans, tags, human coordinate measurements and costly processing of high dimensional camera data.

Since 2-dimensional SLAM is often sensitive to well-controlled topology and dynamics (e.g. the extraction plane is assumed to be at a constant height), the relative freedom of data capture in our setting is unusual and could be considered to be detrimental to the quality of the model's outputs. This includes each user's unique traits such as body build, gait, walking speed and having to negotiate various environmental challenges like stairs and door thresholds. Despite this, our system is capable of collecting good quality data which can be subsequently processed by existing state-of-the-art SLAM implementations.

7 Conclusion

This work proved the viability of the 'H4LO' in service of cheap and efficient fingerprinting technique. We have shown, that our system is able to match the performance of a much more arduous fingerprinting method with fraction of the required logistics. A comprehensive set of ground-truth location labels are generated from a sixteen minute data acquisition session. This helps reduce the human error associated with each fingerprint, and ensures a quick method of obtaining the map and the relative location. The future work will concentrate on improving the accuracy of the results using IMU data from a wrist-worn device. Also, the hardware system could be made to work in real-time. Additionally, this dataset can help with interpretability of RSS data with regard to spatial features, and vice versa.

ACKNOWLEDGEMENT

Supported by EPSRC and SPHERE IRC, grant number EP/K031910/1. NT is additionally supported by MRC Momentum award MC/PC/16029. The authors would like to thank all colleagues from EurValve and SPHERE.

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