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A Hybrid Indoor Localization Framework in an IoT Ecosystem

Marc Junior Pierre Nkengue, Ivan Madjarov, Jean Luc Damoiseaux,
and Rabah Iguernaissi

Abstract The Global Position System (GPS) does not work in the indoor environment because of the satellite signal attenuation. To overcome this lack, we propose a Hybrid Indoor Positioning and Navigation System (HIPNS), based on Li-Fi (Light-Fidelity) localization and optical camera positioning analyses deployed in an indoor environment. The localization approach is based on the fuse of two positioning strategies where the camera-based part is responsible for localizing individuals and recovering their trajectories in zones with low coverage of Li-Fi LEDs. A third-party element is planned to operate in the event of loss of contact. So, the step detection technique and heading estimation are applied in a smartphone-based indoor localization context between two referenced points. The main contribution of this paper focuses on the use of techniques, algorithms, and methods from different spheres of application that generate heterogeneous data. We apply a data integration approach based on REST Web service architecture to allow localization operations in this hybrid indoor positioning system (HIPS). In this work-in-progress paper, we also present a state-of-the-art survey of techniques and algorithms for indoor positioning with the help of smartphones, as well as the main concepts and challenges related to this emergent area.

Keywords Indoor navigation · Li-Fi-based localization · Scene analysis · Smartphone-based positioning · IoT ecosystem

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1 Introduction

Devices providing sensing, actuation, control, and monitoring (positioning) activities are defined in [1] as the Internet of Things (IoT) ecosystem. The Indoor Positioning Systems (IPS) has been developed using a wide variety of technologies and sensors, or even combining several of them in hybrid systems. Our work is part of this approach as our indoor guidance system combines low-cost technologies that are simple to implement and operate: Li-Fi lamps and video cameras. Besides, we have chosen to process the positioning data from these sensors via a Web service platform, thus ensuring dynamic contact with the user and considering guidance constraints in real-time. Among all indoor positioning technologies, we will focus on those most often used with a mobile phone, namely Wi-Fi, low-energy Bluetooth (BLE), and inertial sensors. We will also present solutions based on the use of light and computer vision.

After a reminder of the possible technologies and the existing hybrid systems, we will then detail the architecture of our guidance system, and the tests carried out, to finally conclude with the follow-up envisaged to our work.

2 Related Work

As multiple published surveys attest [2–6], a wide variety of IPS have been proposed, for performances that are not always satisfactory in dynamic environments and often require costly investments for a significant improvement of the latter. Usually, in IPS, the position of the object or person is estimated using either the measurement of its angle of arrival (AOA), time of arrival (TOA), the difference between arrival times (TDOA), or received signal strength (RSS) [2, 4–6]. If several measurements of the same type are used to determine the position more precisely, the term lateration and angulation is used [4]. The measurement-based systems are complex to implement and expensive in terms of material.

A WLAN is a high-speed wireless network that uses high-frequency radio waves to connect and communicate between nodes and devices within the coverage area. To correctly perform indoor geolocation from a WLAN, it is necessary to densify the network infrastructure to counteract the effect of environmental and human disturbances [4, 5], and also to be able to combine several position measurements or used propagation model within the same algorithm [4, 5].

Very similar to Wi-Fi, the Bluetooth has recently seen a resurgence of interest with the development of Bluetooth Low Energy (BLE) [3, 4]. The low cost of BLE equipment and its long energy autonomy is often cited advantages as they make it easier than Wi-Fi to obtain better radio coverage also necessary for good performance [2, 4]. For geolocation systems, based on WLAN or BLE, many studies propose to improve their performance either by mapping beforehand (fingerprinting) the environment in which the object or person evolves [3–5] or by combining these technologies [2, 4, 5].

59 The use of the smartphone’s sensors (i.e., accelerometer, gyroscope, etc.) is also
60 a research topic tested in the context of IPS [2–4]. Most of the time, they estimate
61 walking parameters (number of steps, length of steps, direction) or determine the
62 nature of the movement. The performances obtained were not convincing, notably
63 because of the difficulty of taking into account the relative position of the smartphone
64 in motion or of integrating physiological parameters (weight, age, etc.) of the person
65 and the nature of the surface of the movement. The current trend is, therefore, to
66 integrate these sensors into WLAN/BLE geolocation systems [2, 3].

67 Other systems use LED-light for geolocation purposes [2, 4]. Because LEDs are
68 capable of flashing very quickly without impairing human vision, they can substitute
69 for conventional lighting while transmitting information to a smartphone. All posi-
70 tioning algorithms (RSS, TDOA, lateration, angulation, fingerprinting, etc.) can then
71 be used. However, to overcome certain inherent defects of light, it’s short-range or it’s
72 possible obscuring, couplings with other technologies have already been proposed
73 (e.g., Li-Fi & Wi-Fi) [6].

74 Finally, there are IPS based on computer vision [2, 4]. In the simplest cases, the
75 phone to determine its position identifies with its camera markers type QR-Codes.
76 But there are also more complex solutions where the mobile device uses video scene
77 analysis to estimate its location by comparing a snapshot of a scene generated by
78 itself with several pre-observed simplified images of the scene taken from different
79 positions and perspectives.

80 3 A Hybrid System Model for IPS

81 The localization methods in an IPS are classified into two groups as noted in [7]: (1)
82 based on distance estimation; and (2) mapping-based localization. In the first group,
83 the distance estimation process employs techniques based on the signal strength
84 and/or the elapsed time between two signals. In our work, we opt for the second
85 group where the mapping-based localization works with pre-stored signals (tags)
86 values in a database.

87 We apply the mapping localization approach in a Li-Fi based positioning system
88 that uses a signal emitted from a LED (light source) to determine the position of the
89 user’s device (receiving device). The user’s device, which is equipped with a recep-
90 tacle (e.g., photodiode-dongle), receives the signal from the LED i.e., its identifier.
91 So, we use the ID as a positioning tag associated with a LED lamp installed in a
92 known location, both data prior stored in a database.

93 We also use a vision-based positioning system to estimate the position and the
94 orientation of a person indoor by identifying an image that is within a view. In [8]
95 authors note that the commonly used methods for image-based indoor positioning
96 are focused on calculating the Euclidean distance between the feature points of an
97 image.

98 For smartphone-based indoor localization as a compliment, we opt for a Pedestrian
99 Dead Reckoning (PDR) technique to give the position of a mobile user relative to a

100 reference, as presented in [9]. PDR approach relies on IMU (Inertial Measurements
101 Unit) based techniques, which typically comprise an accelerometer, gyroscope, and
102 compass. We use the step detection technique (accelerometer) and heading estimation
103 (gyroscope) to reassure the guided person between two identified positions in case
104 of contact losses from other technics.

105 In this research and development project, we opt for a hybrid IPS system based on
106 Li-Fi technology with path positioning from optical cameras placed in shadow zones
107 to compensate for each other's shortcomings and take advantage of each other's
108 strengths.

109 *3.1 Positions Data from Camera*

110 The camera-based positioning strategies is responsible for localizing individuals and
111 recovering their trajectories in zones with low coverage with Li-Fi LEDs. Thus, we
112 proposed a mono-camera tracking system that is designed in three main phases. The
113 first ones consist of the detection of individuals and the initialization of trackers
114 which is done in two parts the motion detection and motion segmentation. Then,
115 the second phase consists of the tracking of detected individuals from the first phase
116 to recover their trajectories within the camera's field of view. The last part of our
117 strategy consists of the association of image positioning of individuals with their
118 ground plane positioning. The system design is illustrated on Fig. 1.

119 The first part of our positioning system is the detection of individuals within the
120 camera's field of view. This is done in two main parts, which are motion detection
121 and motion segmentation. We started by using a background subtraction algorithm,
122 which is based on the use of the Gaussian mixture model as proposed in [10], to
123 detect the foreground of the studied scene. This model is applied to all pixels gives a
124 binary image representing the moving objects within the current frame of the video
125 (Fig. 2).

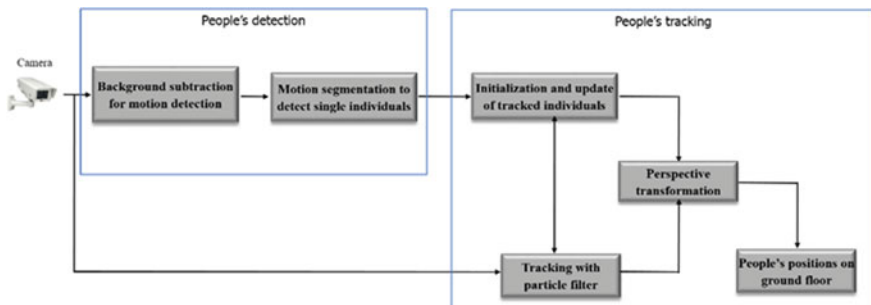


Fig. 1 Ground floor positions from a camera

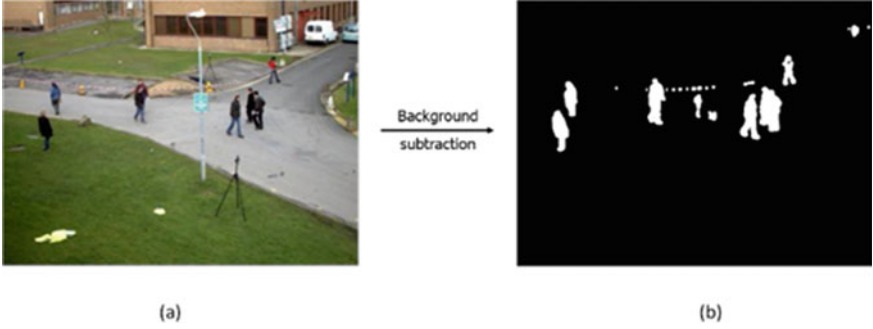


Fig. 2 Motion detection: **a** original image and **b** moving parts

126 The used strategy for motion detection enables the detection of blobs representing
 127 the moving objects within the studied scene at a given time t . The detected blobs
 128 may represent either a single individual or a group of individuals. Thus, we used
 129 a method based on connected components analysis, which is associated with some
 130 restrictions on the width and height of blobs, to separate the detected blobs into blobs
 131 each representing a single individual. We represented each blob with a rectangle of
 132 width w and height h . The properties of this rectangle are estimated based on Eq. (1).

$$133 \quad \begin{cases} (x_0, y_0) = \left(\frac{x_{min} + x_{max}}{2}, \frac{y_{min} + y_{max}}{2} \right) \\ w = x_{max} - x_{min} \\ h = y_{max} - y_{min} \end{cases} \quad (1)$$

135 Then, we used a restriction on the ratio between the width and the height of
 136 each blob to estimate the number of individuals within the blob. This is done by the
 137 assumption of Eq. (2).

$$138 \quad N_{ind} = \begin{cases} 1 & \text{if } Th_{min} < \frac{w}{h} < Th_{max} \\ \text{round} \left(\frac{w}{h * \left(\frac{Th_{min} + Th_{max}}{2} \right)} \right) & \text{if } \frac{w}{h} > Th_{max} \\ \text{round} \left(\frac{h * \left(\frac{Th_{min} + Th_{max}}{2} \right)}{w} \right) & \text{if } \frac{w}{h} < Th_{min} \end{cases} \quad (2)$$

140 The estimated number of individuals is used to perform new segmentation of
 141 blobs based on Eq. (3) for an example of a blob with a ratio $\frac{w}{h} > Th_{max}$ and an
 142 estimated number of individuals $N_{ind} = 2$ (illustration of results is shown in Fig. 3).

$$143 \quad \begin{cases} (x_{01}, y_{01}) = \left(\frac{x_{min} + x_{max}}{4}, \frac{y_{min} + y_{max}}{2} \right) \\ (x_{01}, y_{01}) = \left(\frac{3 * (x_{min} + x_{max})}{4}, \frac{y_{min} + y_{max}}{2} \right) \\ w = \frac{x_{max} - x_{min}}{2} \\ h = y_{max} - y_{min} \end{cases} \quad (3)$$

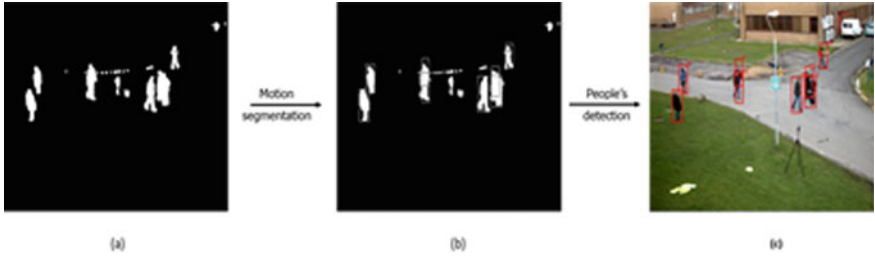


Fig. 3 Motion segmentation and people's detection: **a** moving parts, **b** segmented blobs and **c** detected individuals

145 The previous steps end up with the list of detected individuals at a given instant
 146 t_0 . This list is used to initialize the list of tracked individuals, which are then tracked,
 147 and their trajectories recovered. For this, we used a strategy based on the use of a
 148 particle filter similar to the one proposed in [9] to estimate the position of the tracked
 149 individual at instant t based on his position at the instant $t - 1$ (Eq. 4).

$$150 \quad \begin{cases} (x, y)_t = (x, y)_{t-1} + (u, v)_{t-1} * \Delta t \\ (u, v)_t = (u, v)_{t-1} \end{cases} \quad (4)$$

152 With $(x, y)_t$ and $(u, v)_t$ the position and velocity of the individual at instant t .

153 Then a set of N particles are propagated around this position and weighted based
 154 on the difference between their color histograms and the color histogram of the
 155 individual in the HSV color space.

156 The positions of these weighted particles are then used to refine the position of
 157 the tracked individual at the instant t . The new position of the individual within the
 158 current frame is estimated by Eq. (5).

$$160 \quad \begin{bmatrix} x \\ y \end{bmatrix} = \sum_{n=0}^N w_t^{(n)} \begin{bmatrix} x \\ y \end{bmatrix}^{(n)} \quad (5)$$

161 The last step of our localization algorithm consists of the association of the image
 162 positioning of individuals with their ground plane positioning. In fact, the previous
 163 steps are used to recover the trajectories of the individuals on the video. These
 164 trajectories are represented by a set of detections representing the individual while
 165 moving on the camera's field of view. These detections are then used, first, to localize
 166 the individual within the image and, second, to localize the individual on the ground
 167 plane. The first part consists of the association with the bounding box of a tracked
 168 person with a single point representing his position on the ground plane on the image
 169 (u_0, v_0) . This is done by considering the point of intersection between the central
 170 vertical axes of the detection with the bottom limit of the bounding box.

171 Then to get the positions of individuals on the ground plane, we use a perspective
 172 transformation, similar to the one used in [11], which maps the locations of indi-
 173 viduals in the image with their corresponding positions in a plane representing the
 174 ground floor of the studied scene. This method is based on the use of four initials
 175 points, located by the user in both the image and the plane, that are used to calcu-
 176 late the transformation that will be used later on to map the points from the image
 177 to their corresponding positions on the plane. This perspective matrix is estimated
 178 using the Eq. (6) and the selected points. Then this perspective matrix is used to get
 179 the correspondence between any point on the image and its position on the viewing
 180 plane.

$$182 \quad [x' \ y' \ z'] = [u \ v \ w] \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \quad (6)$$

183 With: x, y the coordinates of pixels on the viewing plane (ground floor), u, v the
 184 coordinates of pixels on the image. At the end of this part, we map the trajectories
 185 obtained previously to the estimated trajectories on the ground floor of the studied
 186 scene. These trajectories on the ground floor are then sent to the server as camera
 187 data that will be combined with the Li-Fi data to localize individuals.

188 **3.2 Data from Li-Fi Lamp**

189 The Li-Fi indoor data model is part of infrastructure-based positioning, non-GPS
 190 technologies, where fixed beacon nodes are used for location estimates. The posi-
 191 tioning algorithms are associated with Proximity Based Localization (PBL) as clas-
 192 sified in [7]. Proximity sensing techniques are used to determine when a user is near a
 193 known location. The provided location is the area in which the user is detected. In our
 194 case of using, a Li-Fi lamp emits tag to be detected by a mobile target when passes
 195 within the covered area. The most common manufacturers' technical parameters for
 196 a Li-Fi LED mounted in a standard ceiling height indicate a luminous flux dispersion
 197 in a range of 30°–40°. So, to calculate the detector's area, a simple cone-diameter
 198 equation can be used, as presented in (7).

$$200 \quad D = 2 \times h \times \text{tg}(\alpha), S = \pi \times \left(\frac{D}{2}\right)^2 \quad (7)$$

201 where: D expresses the LED covered area, h indicates the ceiling height, α the angle
 202 of light dispersion, and S expressed the surface covered by the detector. In a general
 203 case, we can count on a detector area with 3 m of diameter i.e., approximatively
 204 7 m². This is quite reassuring for the installation of Li-Fi lamps on points of interest

205 in a building. So, the detection infrastructure can be developed as a mesh of Li-Fi
206 lamps, which can be presented as nodes in a graph-path.

207 3.3 Data Integration and Graph Path

208 **Hybrid System Model.** Li-Fi lamps and optical cameras (OC) are two promising
209 IPS technologies that can be implemented in all kinds of indoor environments using
210 existing infrastructures. However, both are subjected to data heterogeneity. In this
211 paper, we propose a hybrid IPS that integrates data from Li-Fi lamps and OC in
212 a RESTful architecture to improve the quality-of-service (QoS) of the user's posi-
213 tioning and navigation in order to provide better performance in terms of accuracy,
214 power consumption, and reduced costs of installation.

215 In the proposed system model, the source of data dissemination is a Li-Fi lamp and
216 a processed image from an OC, whereas the source data collection is a user device
217 with a photoreceptor. The collected data are analyzed and processed, and the local-
218 ization is performed via a Web service. In Fig. 4, a four layers system architecture is
219 presented: (1) data generation and image collection, (2) communication technology,
220 (3) data management and processing, and (4) application for data interpretation.

221 When the user passes under a LED his smartphone can receive the tag associated
222 with this LED lamp. Its path is followed by an optical camera to confirm the user's
223 position. An alert message will be sent in case of remoteness from the prescribed

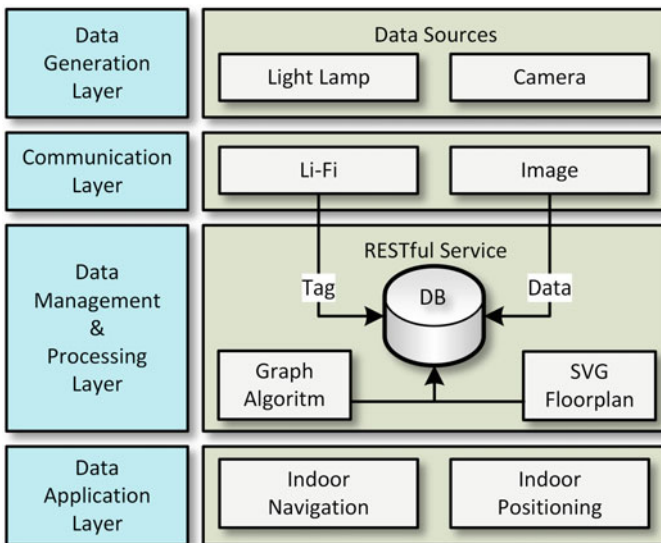


Fig. 4 System model for hybrid IPS

224 path or in case of unexpected barriers. A reconfigured path will be then sent to the
225 user.

226 **The graph-path algorithm.** The BFS-based graph-path algorithm resides on the
227 RESTful Web service side. This algorithm allows us to obtain the path to follow when
228 a destination is defined at the beginning (e.g., the entry point of a building). With
229 knowledge of the starting point and the endpoint, the algorithm determines all inter-
230 mediary points to be followed to guide the user to the destination. These intermediary
231 points represent the graph-vertices where the Li-Fi lamps are positioned.

232 The Graph algorithm is developed as a class with two methods. The first one
233 determines the vertices in the graph corresponding to the building's plan stored in
234 numerical format. Once the set of vertices is retrieved, the method locates for each
235 node the set of vertices that succeeds it in a unidirectional manner (i.e., for each
236 vertex, the edge to follow to the next vertex throughout the part of the suggested
237 path). The second one is essential to allow us to find the available path from the
238 starting point to the defined endpoint. Based on the graph-paths established by the
239 previously described method, this method allows the suggested path to be highlighted
240 on the user's screen.

241 **The vector floorplan.** The vector graphics format (SVG) used for the building's
242 plan representation allows us to manipulate the graph directly on the plan by asso-
243 ciating it to the user's path. Thus, the highlighting path can be displayed directly on
244 the graph with the points of reference (i.e., graph-vertices).

245 4 Implementation and Evaluation

246 **Implementation.** We have focused on server-side processing as a development
247 approach to reduce the user's client-server interactions. So, in this IoT schema,
248 the dedicated REST service, as shown in Fig. 4, can handle multiple requests at
249 once with correctly achieved data integration from heterogeneous sources like Li-Fi
250 lamp, optical camera, an accelerometer as shown in Fig. 5. On the other hand, this

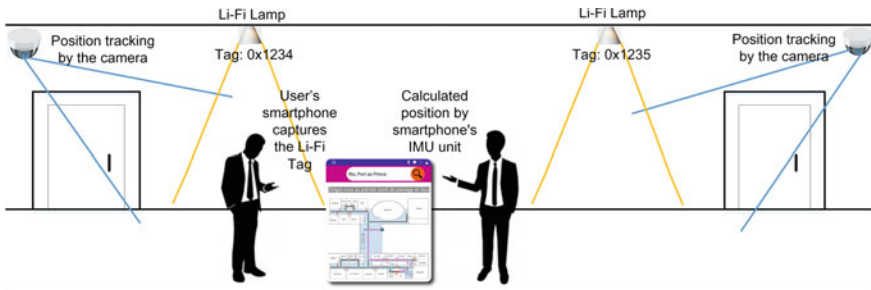


Fig. 5 Use case scenario for hybrid Li-Fi-camera-accelerometer IPS

251 centralization approach for indoor navigation process management allows server-
252 side service to track simultaneously different requested paths without interferences
253 between users.

254 A location-aware Android-based application for indoor navigation tracking is
255 developed. So, when a smartphone with a light sensor, is within the range of a Li-Fi
256 lamplight, it will compare the emitted from the lamp tag with the value recommended
257 in the building's path-list. The graph-path is highlighted on the building's plan,
258 already displayed on the smartphone's screen, with the highlighted intermediary point
259 of the detected position as shown in Fig. 5. The developed Android activity is based
260 on the Oledcomm GEOLiFi Kit [12], with GEOLiFi LED lamp, GEOLiFi Dongle
261 to be used with a smartphone, and GEOLiFi SDK Library for Android application
262 development.

263 The data integration of the camera and the Li-Fi lamps is done through the Web
264 service installed on a Node.js server running on a Raspberry pi 4. The reference points
265 identified by the camera for the guided person are stored in the database. When the
266 user passes through a Li-Fi point, the retrieved coordinates are compared with those
267 transmitted by the camera. In case of differences, the coordinates confirmed by the
268 position of the Li-Fi lamp are considered for the user's guidance.

269 To improve the accuracy of the localization system, we combine different tech-
270 nologies. To increase the quality of the data and to reassure the user in case of failure
271 of the main approach, an accelerometer, a gyroscope, embedded in a smartphone
272 are employed to develop a multi-sensor fusion approach. This results in the Android
273 application that integrates data from the IMU for the user's guidance between two
274 reference points. However, this data is not communicated to the server and its Web
275 service.

276 **Evaluation.** For this work-in-progress paper, the performance of each positioning
277 approach is partially analyzed due to objective reasons. Our project started at the
278 end of 2019. The containment imposed by the Covid-19 pandemic prevented us
279 from deploying the entire infrastructure, namely optical cameras, and Li-Fi lamps,
280 on a larger scale. We were planning to deploy four optical cameras and 32 Li-
281 Fi lamps. The pretests were carried out in an enclosed space with a minimum of
282 deployed equipment. The camera-based algorithms for localizing individuals and
283 recovering their trajectories were tested with an extern public database. Moreover,
284 this avoids some inconvenience in terms of image rights. The guidance activity with
285 an accelerometer and gyroscope was tested in extern associated to the main Android
286 application. The graph path algorithm, installed as RESTful service on Raspberry pi
287 4, was tested on a virtual floorplan with QR Codes in place of the Li-Fi lamps. The
288 developed Android application for user indoor guidance gave satisfaction.

289 To estimate the accuracy of the IMU unit associated with the user's activity, we
290 proceed by a test to count the number of steps over 10 m and then to compare with
291 real values. It appears that the accuracy of the IMU unit is quite good over the tested
292 distance. The observed error has a rate of up to 23%, which is a tolerable threshold.
293 A real difference begins to be created between the values of the IMU unit and the
294 real values beyond 9 m, so a distance lower than 10 m is recommended between two
295 Li-Fi lamps.

5 Conclusion

297 In this article, we present a hybrid IPS system based on the integration of data from
298 heterogeneous sources: i.e. Li-Fi tags to determine the positioning of a user on a
299 floorplan; trajectory tracking of the user by optical cameras; step counting by a
300 smartphone application supposed to guide the user between two reference points
301 and in case of loss of cameras tracking due to congestion, smoke or other disruptive
302 events.

303 Because it does not require any special infrastructure, the proposed solution is
304 easy to implement and low cost, and it would be easy to install it in most indoor
305 environments like hospitals, buildings, campuses, and malls.

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