

# Supporting Autonomous Navigation of Visually Impaired People for Experiencing Cultural Heritage



Daniele Croce, Giovanni Galioto, Natale Galioto, Domenico Garlisi,  
Laura Giarré, Federica Inderst, Federica Pascucci and Ilenia Tinnirello

**Abstract** In this chapter, we present a system for indoor and outdoor localization and navigation to allow the low vision users in experiencing cultural heritage in autonomy. The system is based on the joint utilization of dead-reckoning and computer vision techniques on a smartphone-centric tracking system. The system is explicitly designed for visually impaired people, but it can be easily generalized to other users, and it is built under the assumption that special reference signals, such as colored tapes, painted lines, or tactile paving, are deployed in the environment for guiding visually impaired users along pre-defined paths. Differently from previous works on localization, which are focused only on the utilization of inertial sensors integrated into the smartphones, we exploit the smartphone camera as an additional sensor that, on one side, can help the visually impaired user to identify the paths and, on the other side, can provide direction estimates to the tracking system. The users with the help of the navigation system may experience the museum or the cultural site in auton-

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D. Croce · G. Galioto · N. Galioto · I. Tinnirello (✉)  
DEIM, Università degli Studi di Palermo, Viale delle Scienze, 9, 90128 Palermo, Italy  
e-mail: [ilenia.tinnirello@unipa.it](mailto:ilenia.tinnirello@unipa.it)

D. Croce  
e-mail: [daniele.croce@unipa.it](mailto:daniele.croce@unipa.it)

G. Galioto  
e-mail: [giovanni.galioto@unipa.it](mailto:giovanni.galioto@unipa.it)

N. Galioto  
e-mail: [natale.galioto@unipa.it](mailto:natale.galioto@unipa.it)

D. Garlisi  
CNIT Consortium, Viale G.P. Usberti, 181/A, 43124 Parma, Italy  
e-mail: [domenico.garlisi@cnit.it](mailto:domenico.garlisi@cnit.it)

L. Giarré  
DIEF, Università degli Studi di Modena e Reggio Emilia, Via P. Vivarelli, 10,  
41125 Modena, Italy  
e-mail: [laura.giarre@unimore.it](mailto:laura.giarre@unimore.it)

F. Inderst · F. Pascucci  
DING, Università degli Studi Roma Tre, Via della Vasca Navale, 79, 00146 Rome, Italy  
e-mail: [federica.pascucci@uniroma3.it](mailto:federica.pascucci@uniroma3.it)

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14 omy, by following a path previously decided and by going from a location of interest  
15 to another, without any external personal assistant. We demonstrate the effectiveness  
16 of our approach, by means of experimental tests performed in a controlled indoor  
17 environment and in a real outdoor installation.

## 18 **1 Introduction**

19 In the last years we have assisted to many initiatives and experiments for strength-  
20 ening the social role of museums, from a place mostly dedicated to the storage  
21 and exposition of art crafts, to a space of social dialogue and cultural activities,  
22 where museum interpretations and representations are often co-created by visitors  
23 and museum staff. In such a context, participation of vulnerable groups can be one  
24 of the key aspects to promote and reinforce their social inclusion. In this chapter  
25 we focus on people affected by visual problems. Visual impairment affects approxi-  
26 mately 285 million people worldwide, of which 39 million are blind, and 246 million  
27 have moderate to severe visual impairment [1]. Estimates suggest that another per-  
28 son in the world goes blind every 5 s [2]. This is a large number of people who rely  
29 on a combination of their other senses—hearing, touch, and even smell—and tools  
30 like walking sticks and helpers. Improving museum accessibility for these groups  
31 of people is very relevant, especially taking into account that the impact of these  
32 disabilities is increasing with the aging of the world population.

33 Dealing with museum accessibility requires to face two different problems:  
34 extending the accessibility of the art experience, by finding innovative ways of per-  
35 ception beyond the sense of the sight; extending the physical accessibility of the  
36 spaces in which the art collections are placed. Most of the current research and  
37 experimentation efforts are focused on the first aspect. Indeed, people with visual  
38 impairment are excluded from directly experiencing the cultural heritage presented  
39 by museums in a traditional manner. A common approach for mitigating this problem  
40 is participating to the museum visits through audio descriptions and explanations of  
41 pieces, whether they are live (or recorded) commentaries provided by museums or  
42 provided from friends in real time. However, descriptions provided by others pre-  
43 vent one of the key aspect of art fruition, that is interpreting pieces of art by the  
44 users themselves. Innovative ways of perception are considering the exploitation of  
45 multimodal descriptions relying on multiple senses. Braille extensions and 3D recon-  
46 structions of paintings or building models, for example, have been proposed in many  
47 museums and exhibitions. Multimodal interaction allows visually impaired people  
48 to access cultural heritage involving large spatial information content, as described  
49 in [3] or [4], where the system makes it possible to interact with haptic/acoustic  
50 active objects and to select the information that must be shown on the basis of user  
51 requirements. But we really think this is only an aspect of the problem. As stated  
52 in a recent article appeared online [5]: *people are disabled more by inconsiderate*  
53 *design, inaccessible services, and other people's unaccommodating attitudes than by*  
54 *their own impairment*. Social inclusion of such large portion of population resides in

55 letting them enjoy culture by a personal and autonomous experience, i.e. by allowing  
56 a low vision or blind person to enter in a museum, walk, visit and stop in front an  
57 artwork without a personal assistant.

58 The focus of the present chapter is concerning navigation systems for blind users,  
59 devised to encourage autonomous visits and improve physical accessibility of muse-



Fig. 1 An exemplary installation of the ARIANNA system

60 ums. Although indoor navigation systems are of wide interest for many different  
61 applications, it is worth noticing that solutions for blind people have stricter require-  
62 ments than general systems, in terms of accuracy and reliability. For example, visually  
63 impaired people are used to a continuous reference signal, such as the one provided  
64 by tactile pavings, which guides the users along the path to the destination. This  
65 means that the navigation system cannot provide simple information on the direc-  
66 tions towards a destination and new interfaces have to be considered. Our solution,  
67 called ARIANNA (pAth Recognition for Indoor Assisted Navigation with Aug-  
68 mented perception) [6–9], proposes to use the smartphone as a mediation instrument  
69 between the users and the reality. The main idea of the system is represented in  
70 Fig. 1: the smartphone camera detects the tapes in the environment using computer  
71 vision and provides user feedback in terms of vibration signals for identifying the  
72 paths. The system has been tested in permanent and temporary exhibitions in various  
73 cultural sites, such as the Farm Cultural Park (Favara, Italy), the GAM (modern art  
74 gallery) and the Branciforte Palace in Palermo (Italy), Expo 2015 in Milan, as well  
75 various other scientific events. The system has been also installed in the Blind insti-  
76 tute of Palermo and tested by many low vision users. In the rest of the chapter, after  
77 a brief description of other possible solutions, we describe the technical features,  
78 localization performance and user experience results of ARIANNA.

## 79 2 Navigation Technologies for Blind People

80 Due to the pervasive availability of ICT technologies for localization, in recent years  
81 there was a proliferation of interesting solutions devised to improve the indepen-  
82 dence and social inclusion of visually impaired people [10]. In most cases, these  
83 solutions are focused on the design of specific user interfaces, rather than innovative  
84 localization solutions taking into account requirements for blind people. For exam-  
85 ple, Wayfinder offers an audio interface to a navigation system based on traditional  
86 GPS, providing directions and general descriptions about the outdoor places mapped  
87 by the application. Other systems working in indoor, where GPS cannot be used, are  
88 also based on general-purpose technological solutions, which that can be generally  
89 categorized into three approaches: triangulation of RF signals (mainly WiFi), direct  
90 sensing of reference points (implemented with RFIDs, ultrasound, bluetooth, etc.),  
91 ego-motion estimate provided by dead reckoning algorithms using *Inertial Measure-*  
92 *ment Units* (IMU, i.e., accelerometers, magnetometers, and gyroscopes). Examples  
93 of systems following these approaches and designed for blind people are: e-White,  
94 that uses WiFi or Bluetooth signals to coarsely locate the user's position and provide  
95 information on the nearest point of interest; RF-PATH-ID and Sesamonet, based  
96 on the detection of reference sensors whose presence is signaled by means of alert  
97 messages; Navatar [11], based on dead reckoning, where the user can provide refer-  
98 ences (such as a door in proximity) to improve the estimate of the position in a  
99 known map.

100 All these solutions have well known accuracy and practical limitations, which  
101 may represent a significant barrier for their adoption in museum itineraries. On one  
102 side, distance estimates by means of WiFi signals, which are available in most indoor  
103 environments for offering wireless connectivity, are affected by intrinsic positioning  
104 errors due to multipath; on the other side, reference points such as RFID or iBeacons  
105 may suffer of collisions in case of dense deployments and require a rigid environment  
106 instrumentation [12], not suitable for temporary exhibitions and frequent itinerary  
107 updates. In some cases, reference points can be represented by WiFi radio maps  
108 (also called fingerprinting), which need long and periodic calibration phases [13,  
109 14]. Pedestrian Dead Reckoning (PDR) solutions for tracking user positions between  
110 consecutive reference points suffer from drift due to noise [15] on long itineraries,  
111 which can be only partially mitigated by filtering techniques [16], exploiting activity  
112 recognition [17], or periodic resets at the detection of reference points [12]. In other  
113 words, no system is currently able to provide a reliable and continuous reference  
114 signal along a museum itinerary, which can be considered equivalent to the tactical  
115 pavings.

116 Assistive technologies may also include other types of services for blind people,  
117 such as scene analysis and detection of obstacles. Obviously, these services are com-  
118 pletely different from providing orientation signals towards a desired destination.  
119 Examples of systems working on obstacle detection are SmartCane [18] and Ultra-  
120 Cane/Batcane [19], which integrate sonars and cameras. Other systems, such as the  
121 ones described in [20], offer robot-assisted navigation, in which decision-making  
122 is not left to the user, but it is rather performed by an artificial intelligence agent.  
123 Researchers have also evaluated novel interfaces for enabling such a guidance of  
124 a human user. For example, in [21] it is proposed the use of a vibration belt with  
125 distinct vibration patterns to communicate directional and rotational commands for  
126 navigation.

127 Our contribution is focused on the guidance service towards a desired destination,  
128 without any additional service on obstacle detection. We also propose an innovative  
129 interface for providing orientation information and a continuous reference signal  
130 along the paths. However, decision making is left to blind users, which are free to  
131 plan their visit in the museum itineraries according to their needs and experience.

### 132 3 The ARIANNA Navigation System

133 The ARIANNA navigation system allows autonomous mobility of blind people in  
134 public spaces, adopting a solution that is based on ICT (robotic and vision) technol-  
135 ogies to mediate between users and environment. The system is especially designed  
136 for indoor scenarios, where GPS-based solutions are unavailable, and exploits the  
137 visual sensor and vibration signals of commodity smartphones. The system per-  
138 mits to find some points of interests in an indoor environment by following a path  
139 painted or stucked on the floor. The path is detected by the camera of the smartphone  
140 which also generates a vibration signal providing a feedback to the user for correct-

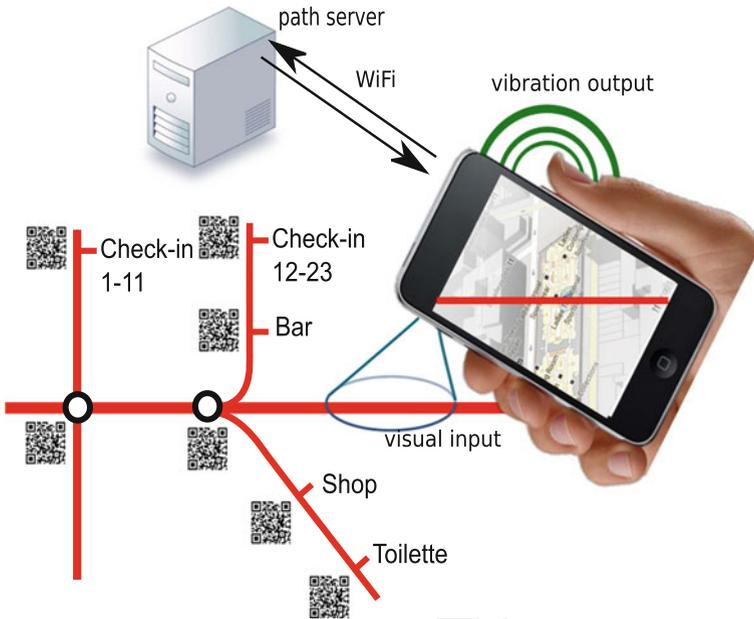


Fig. 2 ARIANNA navigation system description

141 ing his/her direction. Some special landmarks (e.g. QRcodes or iBeacons) can be  
 142 deployed along the path for coding additional information detectable by the camera.  
 143 All the computations and the computer vision algorithms run on the smartphone in  
 144 real time.

145 Figure 2 highlights the different components of the system in an airport scenario.  
 146 The paths of interest are marked with colored lines on the floor. This is the only  
 147 dedicated instrumentation applied to the environment and is a quite simple and low  
 148 cost solution; QRcodes are settled close to points of interest, on line intersections and  
 149 are also used for landmarking. They provide information on the right line to follow  
 150 in order to get to the desired destination. The user interface employs tactile stimuli  
 151 to receive feedback on the heading corrections to be employed, as better described in  
 152 the following. The systems itself is composed by five main components: (A) ambient  
 153 instrumentation; (B) sensors; (C) data transport network; (D) path server; (E) tactile  
 154 interface.

155 *Ambient instrumentation.* The ambient instrumentation is composed of colored  
 156 tapes which can be easily stucked on the floor or carpets to define different paths. This  
 157 is the only dedicated instrumentation applied to the environment. Paths can intersect  
 158 each other forming a planar graph where intersections are nodes of the graph. To  
 159 add information on the paths, any segment (the graph edges) may be deployed with  
 160 two parallel strips with different colors, so the ordered couples (color1, color2) and  
 161 (color2, color1) encode both direction and orientation. Additionally, using bar codes  
 162 or QRcodes it is possible to encode relevant information regarding the edges (as

163 for example the distance from/to the extremes of the segment) and for landmarking.  
164 Another possible solution is to deploy iBeacons to provide proximity information  
165 close to intersections or points of interests. QRcodes are generally more precise in  
166 terms of positioning, although aesthetically more visible.

167 *Sensors.* The main sensor used in the ARIANNA system is the camera, which most  
168 smartphones on the marketplace are equipped of. The camera is used to reveal the  
169 presence of lanes on the floor and acts as a visual control for the haptic transducer.  
170 We also use the embedded compass and accelerometer sensors to help maintain  
171 or recover the visual control of the line. All these sensors are available on most  
172 commodity smartphones: this is a key aspect for keeping the system low-cost and  
173 affordable for a vast public.

174 *Data transport network.* We assume that a data network connection is available  
175 for downloading the ambient map (e.g. via a WiFi or cellular network). The data  
176 transport network does not require specific adaptations but is a facility that permits  
177 communication between the phone and the ARIANNA server. The server is used to  
178 provide localization information, correlation between paths and points of interest,  
179 routing towards the destination. The presence of the server and the wireless network  
180 is necessary only in case the application is unaware about the building topology and  
181 its deployed paths. On the contrary, if the application loaded on the phone has such  
182 information locally available, the presence of network and server is optional (even  
183 if flexibility is possible only with those elements, as explained below).

184 *The path server.* The path server stores and retrieves information from a path  
185 repository via the url printed into the QRcode or provided by the iBeacon. The content  
186 pointed out by the (fixed) url can be changed on the fly with a simple update on the  
187 server. Such flexibility permits path adaptation required by topological changes due  
188 to maintenance or load balancing. When the smartphone detects a QRcode/iBeacon  
189 on the path, it immediately runs an http request to the server using the detected url.  
190 The server knows the position of the user (because of its proximity to the tag position)  
191 and sends back to the smartphone the next edge to follow. In fact, among all paths  
192 deployed in the building, thanks to the indications provided by the path server, the  
193 smartphones provides haptic feedback only towards the “enabled” paths according  
194 to the server indication.

195 *Tactile Interface.* The tactile interface is a key point of the system. The behavior of  
196 the haptic feedback can be summarized as follows: the camera continuously grabs the  
197 scene in front of the person. The tracking system incorporates the information on the  
198 line (together with the compass and accelerometer data) and provides feedback with  
199 the phone vibration. The intensity and type of the vibration is based on the output  
200 of the EKF and is designed to keep the camera always in contact with the line or to  
201 bring back the visual contact when it is lost. Vibration is a native functionality of the  
202 phone obtained through a rotating eccentric mass. It has been shown that the current  
203 consumption of typical vibration motors has a limited impact on the battery life of  
204 commercial smartphones [22] and that the energy savings coming from switching  
205 off the screen are higher than the costs introduced by vibrational cues [23]. Unlike  
206 other approaches in haptic interfaces, our solution does not need a selective vibration

207 of the touched point (that is also difficult to obtain and requires special piezo-electric  
208 materials, etc.).

## 209 4 Computer Vision Algorithms

210 The main idea of ARIANNA is exploiting computing vision and vibration signals  
211 for replacing the special tiles deployed along the tactile pavings with easy to deploy  
212 colored tapes. There are many different computer vision functions that can be com-  
213 bined for the identification of a painted line, taking into account the constraints of  
214 our problem: (i) the path identification has to be prompt and reliable, without per-  
215 ceivable latencies for the users, which could correspond to discontinuous signals; (ii)  
216 the lifetime of the smartphone battery has to be compatible with the timing required  
217 for a complete museum visit, in order to guarantee the practical usage of the system.  
218 These constraints correspond to the identification of robust solutions, with limited  
219 complexity, able to work in real-time.

220 There are two main features that can be exploited for detecting the paths: the  
221 geometry of the tapes (which in the end are given by piecewise lines), and the col-  
222 ors of the tapes (which combine two different colors for representing a direction  
223 without ambiguity). We developed two different solutions, focused on both the geo-  
224 metric factors and the color identification, with different complexity and additional  
225 information that can be exploited by ARIANNA, as detailed in the following.

### 226 4.1 Geometry-Based Path Identification

227 An obvious solution for detecting a path is searching lines into the images, by using  
228 the well-known Canny algorithm, which is able to identify a set of edge points in  
229 an image delimiting areas with large luminance changes. This set of points can be  
230 associated to a path whenever they result aligned. Moreover, this kind of analysis  
231 allows to detect the slope of the identified path, which can be mapped into an heading  
232 measurement of the user movements along the path. In case a map of the paths is  
233 known and the user can be positioned (even roughly) on this map, the relative heading  
234 of the user can be converted into an absolute orientation.

235 To identify the line seen by the camera, we implemented three different steps: (i)  
236 filtering the image, for reducing the noise and the details of the image background;  
237 (ii) applying the Canny algorithm, for detecting the edges of the objects in the image;  
238 (iii) identifying the sub-set of edges which can be considered as a line using the  
239 Hough transform.

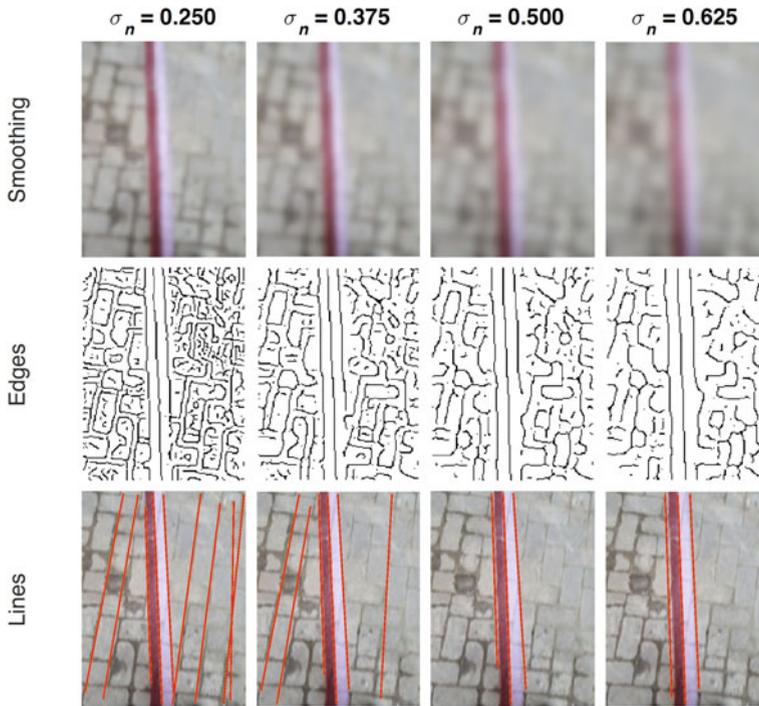
240 *Eliminating image details.* The first step is performed by using a Gaussian smooth-  
241 ing filter, whose main goal is defocusing the image for avoiding that some regular  
242 patterns of the floor (e.g., such as the edges of squared tiles) can be erroneously  
243 considered as a path trace. Since the lines deployed on the floor are very thick in

244 comparison with the tiles' edges, such a filtering operation does not affect the identifi-  
245 cation of the line edges. The filter is characterized by a parameter  $\sigma$  which represents  
246 the standard deviation of the Gaussian function used for smoothing the image details.  
247 Higher values of  $\sigma$  lead to a more evident loss of image details.

248 *Detecting edges.* The second step is given by the application of the well-known  
249 Canny scheme. The output is a binary matrix, whose dimension is equal to the original  
250 frame and whose values are set to 1 for the pixels corresponding to the detected edges.  
251 These pixels are identified by computing the maximum luminosity gradient (in each  
252 possible direction) for each pixel, and by selecting the pixels for which the gradient  
253 is higher than a threshold  $T$ . Higher values of  $T$  correspond to a lower number of  
254 detected edges.

255 *Detecting lines and slopes.* The last step works on the binary image found by  
256 the Canny scheme for transforming the line identification problem in a maximum  
257 search problem. The Hough transform is used for mapping each edge point in a set of  
258 parameters  $(\rho, \theta)$  representing the bundle of lines passing through that point. When  
259 multiple edge points are aligned, there is a common  $(\rho, \theta)$  value representing the  
260 line passing through all the points. Therefore, the scheme simply works by counting  
261 the maximum number of occurrences (i.e., votes) of quantized  $(\rho, \theta)$  values com-  
262 puted for each edge point. The quantization allows compensating noise effects in the  
263 identification of the alignments. This step is critically affected by the resolution used  
264 for quantization and by the threshold used for assuming that a given  $(\rho, \theta)$  value  
265 corresponds to a line in the image. We chose to only consider the global maximum in  
266 the parameter space, i.e., a single  $(\rho, \theta)$  value receiving the greatest number of votes,  
267 because we assume that the greatest number of aligned points always correspond to  
268 the thickly painted line. However, since the painted line is actually implemented  
269 with a bi-colored stripe, such a choice implies that we are only able to detect one of  
270 three parallel linear edges along the stripe. In proximity of a turning point, such as  
271 L-like junction points, the number of path segments with a different orientation is at  
272 least equal to two. However, by always choosing the line with the highest number of  
273 votes, which usually correspond to the longest detected line, we avoid ambiguity in  
274 the reference orientation for the user.

275 The above scheme can be optimized by considering the effects of the image  
276 resolution, the smoothing factor of the Gaussian filter, and the threshold values of  
277 the Canny schemes on the accuracy of line detection. Figure 3 visualizes the effects  
278 of different smoothing factors on a real image of a path trace. The standard deviation  
279 is normalized as a function of the image resolution (for representing the portion of  
280 the area involved in the filtering operations). As the standard deviation increases,  
281 the image loses details as evident in the reduction of the number of edges identified  
282 by the Canny algorithm. This, in turns, corresponds to a lower number of detected  
283 lines (from 9 lines for  $\sigma = 0.25$  to 3 lines for  $\sigma \in [0.5, 0.625]$ ), which are likely  
284 to coincide with the path trace, rather than with the floor regular patterns. Image  
285 resolutions have a similar effect on line detection accuracy: too high resolutions  
286 (apart from complexity issues) include too many details, which can correspond to  
287 the detection of wrong lines; too low resolutions imply rough estimates of the line  
288 orientation. We also noticed that the threshold of the Canny scheme has a limited



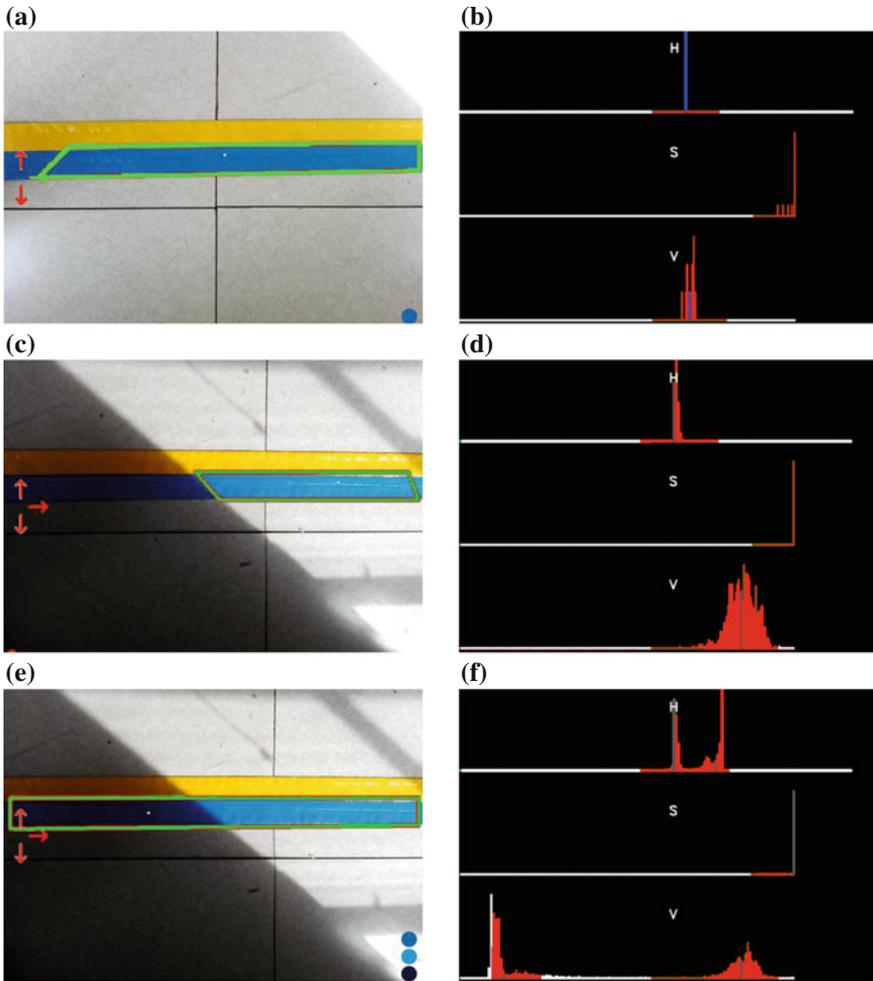
**Fig. 3** Effects of the Gaussian smoothing filter on the capability of detecting the correct path trace

289 impact on the error metric. In the next experiments discussed in the paper, we used  
 290 the optimal configurations found on the basis of these considerations.

## 291 4.2 Color-Based Path Identification

292 Another possible solution for identifying the path is to detect areas with the expected  
 293 tape colors into the image. Image colors can have different representations, among  
 294 which the HSV (hue, saturation, value) representation is more robust to luminance  
 295 changes. In principle this approach can be quite simple, because it works by applying  
 296 conditional statements on each image pixel, in order to verify if it belongs to the  
 297 desired intervals of hue, saturation and values. The complexity required by this filtering  
 298 operation is much lower than the complexity required by the previous approach,  
 299 which requires many operations on the image matrices. Moreover, the direction information  
 300 can be easily extracted from the blob of points identified as belonging to the  
 301 path, by evaluating the second-order moments of the blob.

302 Despite of these considerations, the approach based on color searches has the  
 303 drawback of being potentially affected by the light conditions in which the camera



**Fig. 4** Effects of the dynamic resampling of HSV filtering values

304 works. Indeed, it is not obvious how to define absolute HSV intervals for identifying  
 305 the path under variable (even on a day-basis) light conditions. Schemes removing  
 306 shadows on the images or correcting luminance changes can be more complex than  
 307 edge-based solutions. We therefore implemented a mixed algorithm, in which the two  
 308 schemes are opportunistically combined: ARIANNA normally works by applying a  
 309 simple color-based detection, but at regular time intervals the geometry-based scheme  
 310 is executed for delimiting the tapes and re-sampling the color intervals.

311 Figure 4 shows an example of dynamic resampling of the HSV values used by  
 312 the color-based path identification approach. In the left part of the figure, we can see  
 313 the bi-colored tape under three different light conditions. A red delimiter is used for  
 314 segmenting the image area recognized as belonging to one color of the path. In the

315 right part of the figure, we also show the HSV distributions of the points belonging to  
316 the segmented area. In the top case, when the light conditions are almost uniform, we  
317 can see that the HSV distributions are very narrow and color recognition by means  
318 of HSV filtering works well. In the middle case, we see that the HSV filtering allows  
319 to recognize only one part of the path, not covered by the shadowed area. Only after  
320 the execution of the geometric-based path identification function, the whole path  
321 captured in the image is correctly identified and the HSV values can be resampled,  
322 leading to the bi-modal distributions shown in the bottom case of the figure. These  
323 distributions can be used for applying the color filters to the subsequent image frames,  
324 until the user moves completely to the shadowed area. At this point, the next execution  
325 of the geometric-based identification function will update the HSV values to new  
326 single-modal distributions typical of the shadowed image.

## 327 **5 Extending ARIANNA with IMU-Based Tracking**

328 A possible question that could arise from the description of ARIANNA is understand-  
329 ing what happens whenever the user loses the path. If the camera is no more able to  
330 capture the colored tape, in some cases it is enough to sweep the smartphone around  
331 for finding it again. However, we cannot exclude that users accidentally abandon  
332 the path. In this case, our idea is exploiting the inertial sensors of the smartphone,  
333 i.e. the IMU systems, for supporting PDR solutions, able to localize the user in  
334 the space and provide information for bringing him/her back to the path. Basically,  
335 the IMU systems are utilized at regular time intervals for providing a direction and  
336 velocity measurement, by reading the measurements provided by the gyroscope and  
337 accelerometers of the smartphone. It is also important to estimate the user activity, in  
338 order to stop the measurement acquisition whenever the user stops walking. Indeed,  
339 when the user stands in front of an artwork, for example experiencing a tactile fruition  
340 of a 3D model, IMU measurements could be very noisy and lead to positioning errors.

341 PDR solutions can be executed also when the camera correctly captures the colored  
342 tapes. In this case, the measurements provided by the IMU system can be aggregated  
343 to the heading information provided by the computer vision algorithms, in order to  
344 improve the accuracy of the estimated user position along the path.

### 345 **5.1 Activity Recognition**

346 The *Activity Recognition* is devoted to classify the human motion. This step is crucial,  
347 since according to the output of this subsystem, different models are applied to track  
348 the displacement of the user. This step is also difficult to be performed when the  
349 number of motions to be identified is high, however, in this set up only a limited  
350 number of activities are required.

351 Most of the cultural sites, indeed, are organized in planar environments connected  
352 by stairs and/or elevators. The user walks in this environment and stops to appreciate

353 the artworks. Using markers to identify the floor or the area, the user moves in a two-  
 354 dimensional space and only 2 activities, i.e., *standing still* and *walking* need to be  
 355 recognized. These two activities can be easily detected by exploiting the accelerations  
 356 recorded by the IMU, as proposed in [24–26].

## 357 5.2 Heading Estimation

358 The *Heading Estimation* aims at computing the direction of the user when visiting  
 359 the cultural sites. It is related only to the *walking* activity since when the user stops  
 360 is supposed standing still in front of an artwork.

361 The heading estimate is calculated with respect to the fixed Cartesian reference  
 362 frame (i.e., the *Navigation Frame*, NF) and it is performed using data from gyroscopes  
 363 and accelerometer merged with the information provided by the camera in a two-step  
 364 procedure:

- 365 • The *Attitude Estimation*;
- 366 • The *Heading Refinement*.

367 The *Attitude Estimation* exploits the measurements collected from gyroscopes,  
 368 accelerometers and magnetometers to provide the attitude of the smartphone refer-  
 369 ence frame (i.e., the Body frame) with respect to the NF. The attitude is computed  
 370 as quaternions and an Extended Kalman Filter is applied to merge the data from  
 371 the different sensors as detailed in [26, 27]. Once the quaternions are updated, both  
 372 the rotation matrix  $\mathbf{R}_b^n$  from the Body frame to the NF and the heading  $\gamma_k$  with its  
 373 uncertainty  $\Gamma_k$  can be easily retrieved. The initial condition  $q_0$  is obtained from the  
 374 acceleration and the data provided by the camera considering the user standing still  
 375 when the system is activated as in [26].

376 Data from gyroscopes and accelerometers are affected by bias that downgrade  
 377 the accuracy of the estimate. To reduce this effect, the bias is recalculated when the  
 378 *standing still* activity is detected. Furthermore, the *Heading Refinement* uses the data  
 379 from the camera to bound the drift error. Specifically, the only the heading  $\gamma_k$  and  
 380 the related uncertainty  $\Gamma_k$  feed the correction step and the following simple update  
 381 is performed

$$382 \quad \phi_k = (1 - W_k)\gamma_k + W_k\gamma_{C,k} \quad (1)$$

where  $W_k$  is a gain computed according to EKF equation as

$$W_k = \frac{\Gamma_k}{\Gamma_k + R}$$

383 where  $R$  is the uncertainty related to the heading measurement  $\gamma_{C,k}$  performed by  
 384 processing data from the camera and is supposed known and time-invariant.

### 5.3 Position Estimation

The *Position Estimation* computes the position  $(x, y)$  of the user with respect to the *Navigation Frame* NF. To this end, the rotation matrix  $\mathbf{R}_b^n$  provided by the Heading Estimation is used to project the accelerometer data in the the NF: in this way the acceleration along the  $z$ -axis lies on the sagittal plane of the user, perpendicular to the floor. This signal is fundamental during the *walking* activity, since it is analyzed to identify the step event. Specifically, the local minima and the local maxima of the vertical acceleration signal is retrieved to perform both peak detection and zero crossing detection. The sharp changes to the vertical acceleration associated with the heel strike. These features are also exploited to compute the cardinality  $c_i$  of the set of samples to be processed to cope with different walking speed. During *walking* activity, the displacement  $l_i$  is estimated as proposed in [28].

The initial position is supposed known while the position (i.e., the position of the first marker met by the user when approaching an artwork) of the user during *walking* is recursively computed, by estimating the length of the stride on step event detection  $i$

$$\begin{bmatrix} x_i \\ y_i \end{bmatrix} = \begin{bmatrix} x_{i-1} \\ y_{i-1} \end{bmatrix} + l_i \begin{bmatrix} \sin \bar{\phi}_i \\ \cos \bar{\phi}_i \end{bmatrix} \quad (2)$$

where  $l_i$  is the displacement of the user between two step events with respect to the NF and  $\bar{\phi}_i$  is the average heading in the same time interval. Finally, the user displacement is  $l_i = [0 \ 0]^T$  when the output of the classification phase is the *standing still*.

## 6 Experimental Validation

To evaluate the performance of the proposed system, several experiments have been carried out. Specifically, two different types of trials have been considered. The first set aims at assessing the performance of the system comparing the tracking results with a ground truth. The second set is devoted to prove the effectiveness of the approach in a real scenario. In both cases a Samsung Galaxy S6 (SM-G920F), running Android 6.0.1 is used: it is equipped with an IMU-MPU6500 by Invensense and an IMX240 camera by Sony. Data from IMU are available at sampling frequency 100Hz, while the images from the camera are acquired at 20Hz.

In Table 1, the parameters used to initialize Tracking System (TS) during the experiments are shown.

**Table 1** Parameters initialization

Param init val	
$\beta$	0.48
$\alpha_x$	0.02
$\alpha_y$	0.01
$\alpha_z$	0.03

416 The parameter  $\beta$  is related to the human gait and has been calibrated on the  
 417 user adopting the procedure introduced in [27]; the covariances associated to the  
 418 accelerations  $\{\alpha_x, \alpha_y, \alpha_z\}$  are used to discriminate between different human activities  
 419 and are computed at the beginning of the experiment when the user is supposed  
 420 standing still for 10 s.

421 To assess the performance of the system, the optical motion capture system Opti-  
 422 Track has been used to compute the ground truth (GT). The system for motion capture  
 423 exploits 10 infrared cameras to detect the position of markers in a limited area: it  
 424 reach the accuracy of  $10^{-4}$  m. To build the GT, the smartphone has been equipped  
 425 with 4 markers: the CoM of the markers corresponds to the CoM of the smartphone.  
 426 The accuracy of the proposed system is evaluated according to the estimated error on  
 427 checkpoints. Specifically, the considered key performance indicator is represented by  
 428 the Euclidean distance between the estimate (i.e., PDR or TS) and the corresponding  
 429 points on the GT.

430 In the first trial, the user walks on an *S shaped* path, (10 m) long. Both the results  
 431 obtained using PDR-only and the complete tracking system are compared with the  
 432 GT and reported in Fig. 5. Considering PDR-only approach, the error accumulated is  
 433 relevant, although the path is short and the opposite curves partially compensate the  
 434 drift. Using the Tracking System, the error is reduced to 0.54 cm in the worst case.

435 The second experiment aims at evaluating the accuracy of the estimate when a  
 closed loop is executed. To this end the user is required to repeat a square-path 5

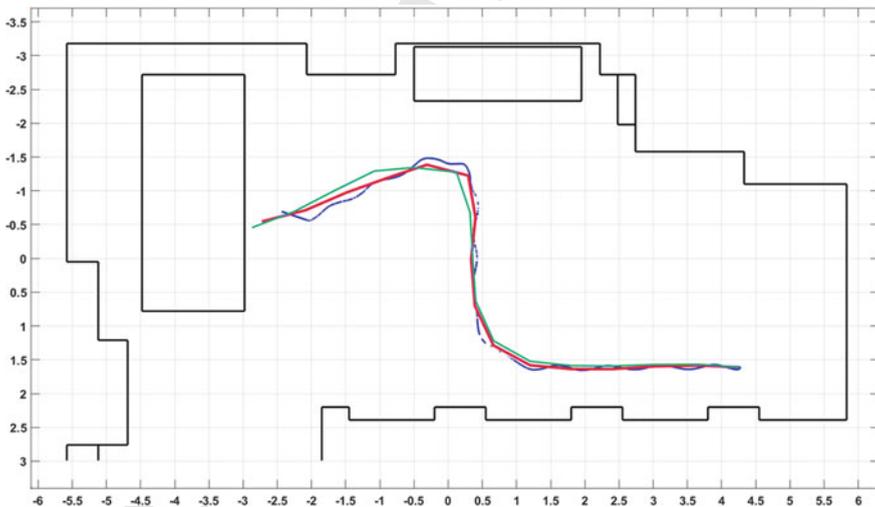


Fig. 5 Results of the S-path experiments: the  $(x-y)$  axes represent the NF [m]

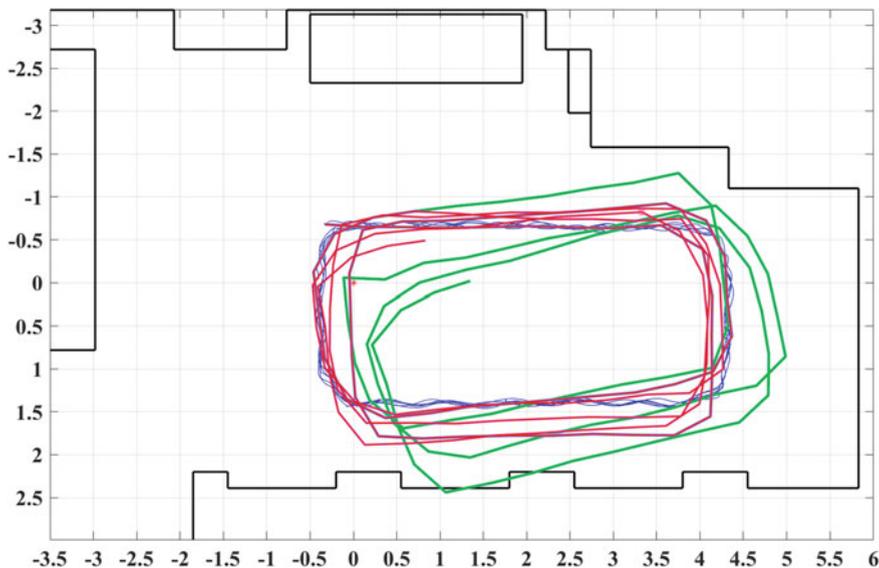


Fig. 6 Results of the Q-path experiments: the  $(x-y)$  axes represent the NF [m]

Table 2 S and square-path: performance index

	Mean err [m]	Min err [m]	Max err [m]	Std dev [m]
S-path				
PDR	0.21	0.01	1.25	0.09
TS	0.10	0.001	0.54	0.02
Square-path				
PDR	0.66	0.15	1.77	0.22
TS	0.34	0.15	0.61	0.02

436 time without stops (see Fig. 6). The user walks for 130m: since the user turns in the  
 437 same direction, the shape of the path does not compensate the drift. The heading  
 438 drift makes the PDR error unbounded, thus the covariance of the error is larger than  
 439 the one obtained in the previous trial. When the heading is continuously corrected  
 440 by the vision system the corresponding covariance does not change.

441 The values of the key performance indicator selected to assess the accuracy of the  
 442 proposed system are collected in Table 2.

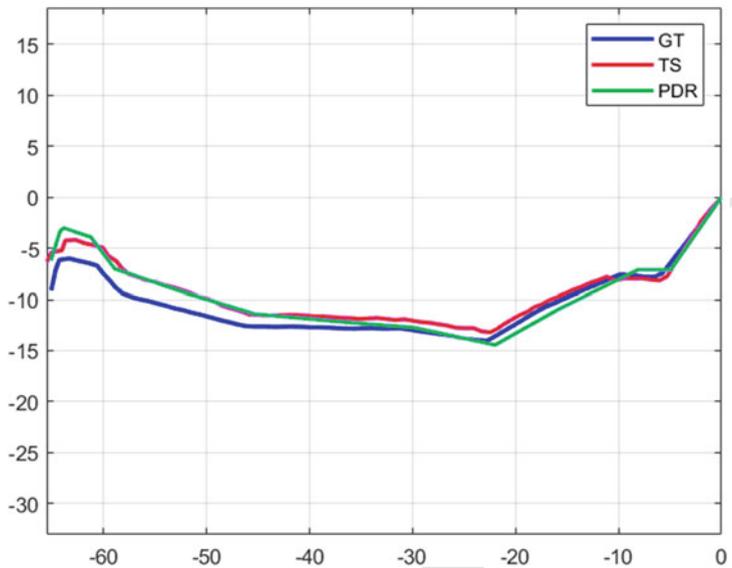
443 To prove the effectiveness of the approach in a real scenario, the ARIANNA  
 444 system has been tested in the Farm Cultural Park, an open-air museum in city center  
 of the Favara (AG), Italy. The project of the Farm Cultural Park has involved

**Fig. 7** ARIANNA  
installation at Farm Cultural  
Park, Favara, Italy



445 several semi-abandoned buildings that were completely renovated. They host expo-  
446 sitions, exhibitions by international and local artists. The system ARIANNA has been  
447 installed to help the visually impaired people visit the outdoor museum, as shown in  
448 Fig. 7.

449 In the trial, the user travels among the buildings, exploiting the path shown in  
450 Fig. 8. The path is about 76 m: in this case, the ground truth is not available, so the  
451 key performance indicator is represented by the error accumulated at the end of path.  
452 Considering PDR, the final positioning error is 3.1 m, that represents about 4% of  
453 the distance traveled. This error is limited, since the path is almost straight, however,  
454 using the correction provided by the camera, the error is reduced to 0.41 m, that  
455 represents less than the 1% of all the distance traveled.



**Fig. 8** Real and estimated path in a real installation: the  $(x-y)$  axes represent the NF [m], GT (blue line), PDR (green line), and TS (red line)

## 7 Conclusions

In this chapter we have presented ARIANNA, an innovative smartphone-centric tracking system for indoor and outdoor environments, based on the joint utilization of dead-reckoning and computer vision techniques. The system is explicitly designed for visually impaired people and has been tested in collaboration with key institutions such as the Italian Blind Association (Unione Italiana Ciechi). Many have been the installations (permanent or temporary) that have been provided to the users to be tested. In the occasion of these events, we interviewed 20 visual impaired people (10 low vision users and 10 blind users), asking them to answer to an assessment questionnaire. In both cases, the answers were very encouraging, with a satisfaction grade of 90%. A summary of the users' feedback is provided in Tables 3 and 4.

In real outdoor tests, such as the one carried in the installation present in the Farm Cultural Park, the system is able to suitably reduce the navigation error with respect to the results obtained using PDR only, as demonstrated by the trial carried out using the precise optical tracking system as GT. Future development of the system will include also a model of the hand movement and possibly the design of a vibration feedback to tell the user how to correct its location. Based on the presented tests and experiments, we have implemented and embedded all the algorithms into an app available for both Android and iOS platforms.

**Table 3** Answers by low vision people

Question		Answer			
		Yes	No		
1	Have you understood the shape of the path?	9	1		
		None	Mild	Moderate	Very
2	Have you found difficult the change in direction?	2	2	6	0
3	How easy was to follow the path?	0	2	6	2
4	Do you need a learning phase?	1	3	4	2
5	The vibration is useful?	0	0	4	6
6	Have you noticed delays?	6	2	1	1
		Unusable	Not good	Satisfactory	Good
7	What's about the haptic interface operation?	0	3	4	3
		None	Mild	Moderate	Very
8	Do you think this app can substitute tactile paving?	0	1	2	6
9	Do you think interactive information are useful?	0	1	3	6
10	Do you think ARIANNA will increase your independence?	0	0	4	6
		With direction	Without direction	Both	
11	Which operaton mode do you prefer?	6	2	2	
		Indoor	Outdoor		
12	In which context is ARIANNA useful?	8	9		
		None	Mild	Moderate	Very
13	Have you found difficulties in the use of ARIANNA?	0	0	6	3

**Table 4** Answers by blind people

Question		Answer			
		Yes	No		
1	Have you understood the shape of the path?	6	4		
		None	Mild	Moderate	Very
2	Have you found difficult the change in direction?	3	6	1	0
3	How easy was to follow the path?	0	4	6	1
4	Do you need a learning phase?	0	3	4	2
5	The vibration is useful?	0	1	6	3
6	Have you noticed delays?	6	3	1	0
		Unusable	Not good	Satisfactory	Good
7	What's about the haptic interface operation?	0	1	7	2
		None	Mild	Moderate	Very
8	Do you think this app can substitute tactile paving?	0	0	2	8
9	Do you think interactive information are useful?	2	1	2	5
10	Do you think ARIANNA will increase your independence?	1	0	6	3
		With direction	Without direction	Both	
11	Which operaton mode do you prefer?	3	5	2	
		Indoor	Outdoor		
12	In which context is ARIANNA useful?	5	8		
		None	Mild	Moderate	Very
13	Have you found difficulties in the use of ARIANNA?	4	6	0	0

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 477 sibility to Urban Historic Center’s Use and Knowledge”



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