

A Mobile Application as an Unobtrusive Tool for Behavioural Mapping in Public Spaces

Alfonso Bahillo¹(✉), Barbara Golčnik Marušić², and Asier Perallos¹

¹ Deusto Institute of Technology (DeustoTech), University of Deusto,
48007 Bilbao, Spain

{alfonso.bahillo,perallos}@deusto.es

² Urban Planning Institute of the Republic of Slovenia, 1127 Ljubljana, Slovenia
barbara.golicnik-marusic@uirs.si

Abstract. In any man-made environment, discrepancies may exist between the intent of its design and how it is actually used. Behaviour mapping allows researchers to determine how participants use a designed space by recording participant behaviours and/or tracking their movement within the space itself. Not only the participants' movements, other characteristics referring to users (e.g. age, gender, cultural background) and variety of circumstantial factors -including the time of a day, the day of the week, the season or weather conditions - may have a dramatic impact on the types of participant behaviours displayed. This paper highlights a new unobtrusive tool for helping behaviour mapping to easily identify patterns of engagements, gather suggestions and environmental factors within public spaces. The tool mainly consists of a smartphone application (app) and a web service. The app, on one hand tracks the way participants use the space, allowing them to get contextual information, answer contextual questions, and to send augmented reality suggestions or complaints. On the other, the web monitors the way participants use the space allowing to visualize participants' suggestions, answers, or their traces. The tool features and its research ability have been discussed as well as some lessons are expected to be drawn towards building a more participatory and collaborative processes of planning, designing, maintaining and monitoring of urban spaces.

1 Introduction

As part of actual transport and urban development activities, this paper is concerned with a niche addressing development and research of the applicability of ICT tools in public spaces which serve as the interface between the public space and the people. On the one hand, such interfaces could help public space designers and decision-makers to catch the perception, demand, attention or complaints of people using a space. On the other, the people could use these interfaces to enhance their participation in places with contextual information, games or socialising. Addressing various aspects of people-place relations, and focusing on actual uses in real places, the concept of behaviour mapping,

a method which allows researchers to determine how people use a designed or natural space by recording their behaviours and/or tracking their movement within the space itself, seems relevant. It can be particularly useful to help identifying underlying patterns of users' behaviour within a given environment. In travel behaviour studies most of behaviour mapping methodologies have followed the process individual-centred, i.e. tracing people across times and locations, using various technologies. But, when focusing on one location and variety of users there, the attention is paid to many users at the same time, and in such situation manual mapping is tiring and time-consuming, especially taking into account all further activities concerned with database settings and data analysis and evaluations. However, such approach is unobtrusive (done "at a distance") and often undertaken in public areas, so participant consent may not be required. The purpose of this work is to develop a new fairly unobtrusive ICT tool for helping behaviour mapping to easily identify and automatically track patterns of engagements, gather suggestions and environmental factors within public spaces.

Today, with the advent of global navigation satellite systems (GNSS) global positioning in the earth's surface is a successfully overcome problem. Nonetheless, local positioning in indoor environments is still a matter of active research, since GNSS signals get severely degraded in this type of environments due to multipath and attenuation losses, and thus they cannot be used to track people or objects with acceptable accuracy [24]. Many local positioning systems have been developed during the past two decades based on different technologies that include ultrasound [9,10,20], radio-frequency [1,13,15,22], vision cameras [19,23] and magnetic [2,3], among others. After all this research effort, it is becoming clear that none of these technologies clearly outperforms the others, and it is expected now a new tendency to design systems that combine some of them to benefit from their complementary strengths. The tool described here is based on a localization engine which performs seamless localization estimation of the participant's smartphone in real time by fusing heterogeneous signals. This localization engine would be the ideal platform for location based services (LBS) that provides the participant with context based information [18]. Therefore, this work shows a combination of two original approaches, a seamless localization engine and GIS behaviour mapping [5], both presented within the COST Action TU1306¹, which main objective is to create a research platform on the relationship between ICT and the production of public open spaces, and which offers a frame for a joint further development and improvements of the proposed monitoring tool. This tool, easy to use and unobtrusive, is an attempt to better understand how participants use public open spaces and to investigate the crucial elements to be responded by design, research, and policy-making aiming to produce more responsive, stronger, safer and inclusive cities.

The paper is organized as follow: Sect. 2 introduces the related work with regards to behavioural mapping methodologies, Sect. 3 describes the monitoring tool, Sect. 4 draws the tool features and its research ability, and Sect. 5 summarizes the work and introduces some future work.

¹ http://www.cost.eu/COST_Actions/tud/Actions/TU1306.

2 Behavioural Mapping Methodology

Originally, behaviour mapping, grounded and well used in the field of environmental psychology [11], is focused on recording behaviour as it occurs in a designed setting. Chronologically, some of the most common ways, usually applied in indoor spaces, were systematically writing notes and filling formatted tables, mostly having no connection to actual layout of the observed place. The development of photo-video techniques influenced the latter methods of recording and map production. Nowadays ICT development is forthcoming, offering various ways of recording people's engagement with places. Behaviour map is a product of observation and a tool for place analysis and design at the same time, where spatial features and behaviours are linked in both time and space. There are two main approaches to behaviour mapping known: place-centred mapping and individual-centred mapping [17].

In public open space researches (e.g. [6, 7]) usually follow the place-centred mapping, a process for recording location-based observations of people activities in places through the annotation of manual or digital maps. It is the approach, where information is recorded on layouts of the settings that reflect physical characteristics of the particular environment. In such approach [8], it is necessary to clearly define the area of observation, the types of activities and details of behaviours to be observed, to schedule specific times and their repetitions for observation, to provide a system for recording, coding, counting and analysing, and an accurate scale map of the area to be observed. Finally, the process, using GIS supported software, provided data organised into thematic layers in which original information collected on the field is listed in the attached table and based on that finally visualised on the map.

The value of behaviour maps for place analysis, design and decision-making is in empirical knowledge about dimensions, spatial requirements of uses and understanding of co-habitation of uses in places.

3 The Monitoring Tool

The main motivation behind the monitoring tool is to get to know how participants use a designed space by recording their behaviours and/or tracking their movement within the space itself. Not only the patterns of participants' movements or other engagements in places, from various passive (e.g. sitting and observing) to active activities (e.g. playing) there, but other factors such as the time of a day, the day of the week, the season, the weather conditions, or even allowing participants to send suggestions, may help urban planners and decision-makers to investigate the crucial elements aiming to produce more responsive, stronger, safer and inclusive cities.

To achieve this goal, this paper highlights a new methodology for behaviour mapping based on a monitoring tool consisting of three main elements: a smart-phone application, a set of web services and the cloud (see Fig. 2). The relation among these elements is as follows. The participant's smartphone uses its sensors

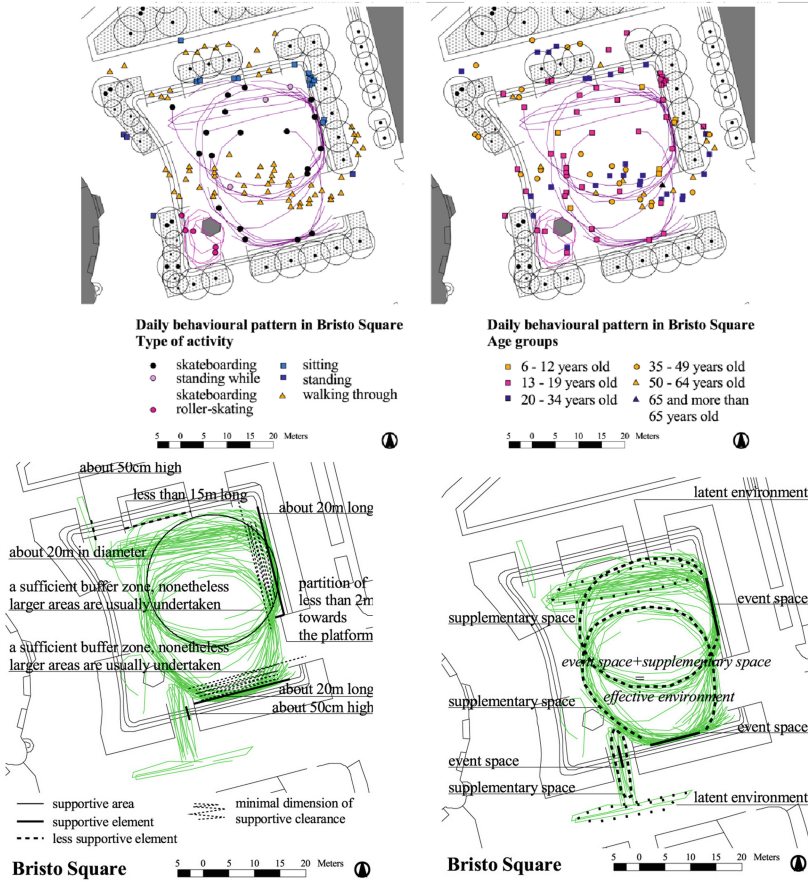


Fig. 1. Examples of behaviour maps and relevant empirical knowledge derived from them.

to collect the so called signals of opportunity (SoOP) which are transmitted for localization or non-localization purposes but may be exploited to this end. The smartphone app is in charge of computing its own position by fusing those SoOP according to a localization engine which is explained below. Also, the smartphone app allows the participants to set their profile, get contextual information, answer contextual questions, and send augmented reality suggestions. All this information -participant profile, position, answers and suggestions- is sent and stored into the cloud. On the other hand, the web services get the information from the cloud allowing to visualize participants' suggestions, answers, weather conditions, real time positions, or the paths filtered by the participants profile characteristics among others. The following subsections discuss the smartphone app, its localization engine, and the web services in more detail.

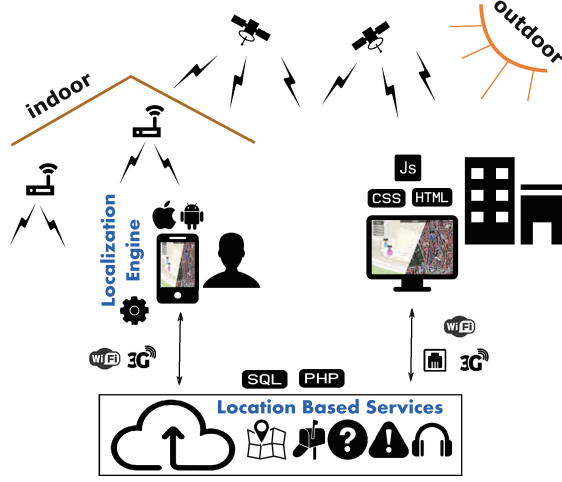


Fig. 2. Logical architecture diagram of the tool.

3.1 The Mobile Application

The core of the mobile application is the localization engine which performs seamless localization estimation of the participant’s smartphone in real time by fusing several SoOP. Once the participant’s position is estimated, several functionalities based on the context are implemented.

The localization engine is thought as a modular system for commercially available smartphones where SoOP coming from their sensors could be easily fused. Nowadays, the smartphones already integrate a GNSS receiver, a WiFi and Bluetooth adapter, a camera, and shortly, most of them will integrate other sensors such as the barometer, inertial sensors or the proximity contactless technology NFC. Bayesian filters are a theoretically sound way to combine multiple and different SoOP. Bayes filters probabilistically estimate a dynamic system’s state from noisy observations. They represent the state at time k by random variables \mathbf{x}_k . At each point in time, a probability distribution over \mathbf{x}_k , called *belief*, represents the uncertainty. Bayes filters aim to sequentially estimate such beliefs over the state space conditioned on all information contained in the observations [4]. In this paper, the state is the participant’s location, $\mathbf{x}_k = [x_k, y_k, z_k]^T$, while the SoOP provide observations about the state. Among the different Bayes filters, Kalman filters are the most widely used. They are optimal estimators, assuming the initial uncertainty is Gaussian, the observation model and system dynamics are linear functions of the state, and the measurement and process noise distributions are Gaussian. However, the lack of linearity in the models that relates most of the SoOP to the participant’s location implies the usage of a suboptimal solution, where the most common is to use the EKF. Nevertheless, the unscented Kalman filter (UKF) better captures the higher order moments caused by the non-linear transformation and avoids the computation of Jacobian and Hessian

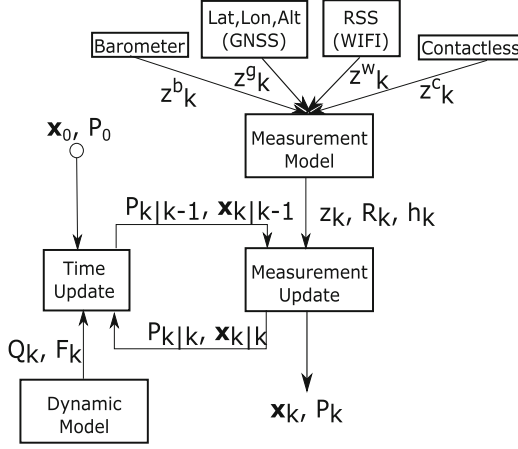


Fig. 3. Flowchart of the localization engine.

matrices [12]. Furthermore, the overall number of computations performed by the UKF are the same order as the EKF, and much lower than solutions such as the particle filter which better represents the belief but needs a number of computations unacceptable for most smartphones. Therefore, in the localization engine the SoOP will be fused by means of an UKF.

Consider the following non-linear system, described by the *dynamic* and *measurement* models with additive noise:

$$\mathbf{x}_k = \mathbf{f}(\mathbf{x}_{k-1}) + \mathbf{w}_{k-1} \quad (1)$$

$$\mathbf{z}_k = \mathbf{h}(\mathbf{x}_k) + \mathbf{v}_{k-1} \quad (2)$$

where \mathbf{w}_k and \mathbf{v}_k are the process and observation noise which are both assumed to be zero mean multivariate Gaussian noise with covariance \mathbf{Q}_k and \mathbf{R}_k , respectively. The function f can be used to compute the predicted state from the previous estimate and similarly the function h can be used to compute the predicted measurement from the predicted state.

On the one hand, the dynamics of the system can be represented as

$$\mathbf{x}_k = \mathbf{x}_{k-1} + \dot{\mathbf{x}}_{k-1} \Delta t + \mathbf{w}_{k-1} \quad (3)$$

where $\Delta t = (t_k - t_{k-1})$ is the time step and $\dot{\mathbf{x}}_k$ is the first derivative of the state, in this case, the user's velocity. Finally, \mathbf{w}_k is assumed to be a zero-mean Gaussian variable with covariance matrix \mathbf{Q}_k . The values of \mathbf{Q}_k depend on the dynamic of the target, in this paper for example, a walking person. In practice, \mathbf{Q}_k is a diagonal matrix whose in-diagonal elements represent the variance of the user's position and velocity [21].

On the other hand, the function h depends on the SoOP. In the GNSS case, the measurement model, called h^g , can be represented as

$$\mathbf{z}_k^g = \mathbf{x}_k + \mathbf{v}_{k-1}^g \quad (4)$$

where \mathbf{z}_k^g is the GNSS position estimation and \mathbf{v}_k^g represents the GNSS noise which can be assumed to be zero-mean Gaussian variable with covariance matrix \mathbf{R}_k^g . In practice, \mathbf{R}_k^g is a diagonal matrix whose in-diagonal elements represent the variance of the measurements coming from the satellites, and its value depends on the number of satellites in line-of-sight. The more satellites with good GDOP (Geometric Dilution of Precision), the more reliable the GNSS data. There is a benefit from the GNSS data only in open areas where it accurately reports the participant's position.

In the barometer case, the measurement model, called h^b , can be represented as

$$\mathbf{z}_k^b = p_0 \cdot \left(1 - \frac{\lambda}{T_0} \mathbf{x}_k[3]\right)^{\frac{g}{\lambda R_{air}}} + \mathbf{v}_{k-1}^b \quad (5)$$

where \mathbf{z}_k^b is the air pressure, $\mathbf{x}_k[3]$ is the third element of the state, $T_0 = 288, 15$ K is the temperature at sea level, $\lambda = -0.0065$ K/m is the temperature gradient, $p_0 = 1013.25$ mbar is the pressure at sea level, $R_{air} = 287$ m²(s²K)⁻¹ is the atmosphere gas constant, and $g = 9.8$ m/s² is the earth gravity. \mathbf{v}_k^b represents the air pressure noise which can be assumed to be zero-mean Gaussian variable with covariance matrix \mathbf{R}_k^b . This measurement model is not exact because it assumes some variables as constants, and it does not take into account other factors such as humidity, temperature, or the presence of air conditioning systems. However, not the absolute but the relative altitude is used. The estimated relative altitude is used to compensate GNSS errors in altitude.

In the contactless technologies cases, such as NFC tags and QR codes, the measurement model, called h^c , can be represented as

$$\mathbf{z}_k^c = \mathbf{x}_k + \mathbf{v}_{k-1}^c \quad (6)$$

where \mathbf{z}_k^c is the position of the NFC tag or QR code. \mathbf{v}_k^c represents the observation noise which can be assumed to be zero-mean Gaussian variable with covariance matrix \mathbf{R}_k^c . As the SoOP gather by the contactless technologies have to be read at few centimeters from the tag or code, in practice, \mathbf{R}_k^c is a diagonal matrix whose in-diagonal elements are lower than 1 m. These proximity contactless technologies work anywhere and they can update the location algorithm with accurate position information.

Finally, in those places where the GNSS signals are blocked -inside buildings or in dense urban environments-, the localization engine could take advantage of WiFi signals which predominate in most cities. In the WiFi (and Bluetooth) case the measurement model, called h^w , can be represented as

$$\mathbf{z}_k^w = \alpha - 10n\log_{10}(\|\mathbf{x}_k - \mathbf{AP}\|) + \mathbf{v}_{k-1}^w \quad (7)$$

where \mathbf{z}_k^w is the RSS measured value; α is a parameter that remains constant in those scenarios where the antennas gain and the power transmitted from the access points are also constant, a situation typically found in most WiFi WLANs, (in practice, this value can be known beforehand from experimental measurements taken in a generic environment similar to that where the location system

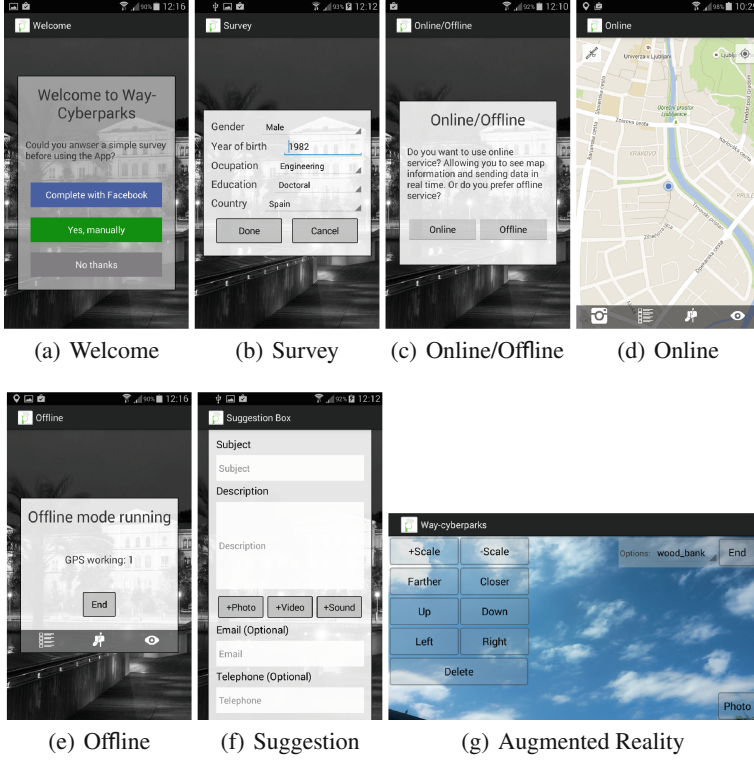


Fig. 4. Main screenshots of the smartphone application.

is going to operate) [14]; \mathbf{AP} is the position of the WiFi access point; and n is the path-loss exponent corresponding to the actual propagation environment. In free space $n = 2$, however in practice, depending on the environment the path-loss exponents ranging from 1.5 to 4.5 [14, 16]. \mathbf{v}_k^w represents the RSS noise and it can be assumed to be zero-mean Gaussian variable with covariance matrix \mathbf{R}_k^w . In practice, there is h_i^w with $i = 1, 2, \dots, M_k$ functions, where M_k is the number of WiFi access points in range at each time step k . Accordingly, \mathbf{R}_k^w is a diagonal matrix whose in-diagonal elements represent the variance of the measurements coming from each WiFi access point.

As shown in Fig. 3, and it is well described in [12], once the dynamic and measurement models, and their noise covariance matrices are described, the UKF is straightforward to implement. Notice that the initial values of the state covariance matrix, P_0 , depends on the initial state confidence. UKF main advantage is their computational efficiency (same as EKF and lower than particle filters), better linearization than EKF (accurate in the third-order Taylor series expansion), and derivative-free (no Jacobian and Hessian matrices are needed) [12].

This localization engine would be the ideal platform for LBSs that provides the participant with context based information [18]. Currently, the smartphone

app has different functionalities already implemented in Android and iOS mobile based platforms. These are summarized in Fig. 4. At first the app welcomes the participants and invites them to complete a short survey that will define their profile -they could do it typing the answers or it can be filled in automatically by logging to their Facebook account-. After that the app asks the participants to work in online or offline mode. In the online mode the app regularly sends the participant's position through the data communication link (4G, 3G, 2G or WiFi) to the cloud. In the offline mode the app stores all the participant's positions in the smartphone memory card. When finishing the track, the app asks the participant to send all the positions stored together to the cloud. Based on the working mode, the participant could send or save (to be sent later) suggestions to the cloud attaching text, photos, videos and/or audio records. The participant could enhance also the photo to be attached creating a virtual world adding virtual objects using the augmented reality engine. Finally, the participant could get contextual information in different formats: text notifications, audio tracks, video files or internet links. All of them are related to the context and based on the participant's position.

3.2 The Web Services

The aim of the web service is to help urban planners, designers or decision-makers to view how participants use the designed space. It is hosted in <http://services.cyberparks-project.eu/>, and at the moment it provides a few different pilot case studies in Europe. Figure 5 shows a general view of the web service. It consists of three main elements, the main menu on the right, the filter on the left and the map in between.

The filter is used to select the participants' path that one wants to view based on several profile characteristics such as the gender, occupation, education and age. The main menu has the following five sections:

- Current case study: it denotes the case study results one is viewing, and allows to select also other case studies to see the results.
- Positions: it denotes the participants' positions in real or past time, the position of the points of interest, and allows to see the participants' positions in real time or to search for a specific period of past time. It also allows to see the points of interest of the case study on the map.
- User data: it denotes the questions and participants' answers, suggestions and alarms; allowing to see on the map where are the questions related to the case study, their radius of influence and the answers of the participants; where participants' suggestions have been taken including their content -subject, description, photos, videos, audio, email, telephone - and the weather conditions reported by the nearer weather forecast station; and finally, where are the alarm zones, its shape, who enters and when, the time spend inside the alarm zone, and when leaves the zone.
- Edition: it denotes the edition of points of interest, questions, alarm zones, audio tracks and buildings allowing to add/edit/delete points of interest on

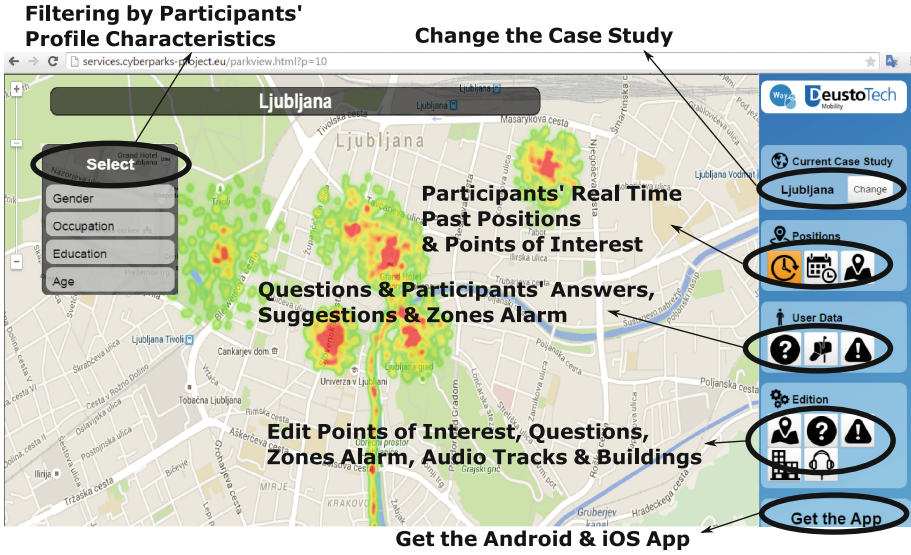


Fig. 5. Location based services and places more crowded.

the map characterized by a name, url and short description; add/edit/delete questions on the map characterized by a radius of influence, a short description of the question and several optional answers; add/edit/delete alarm zones on the map with irregular shapes characterized by a name and several actions to perform just in case a participant goes into the zone sending email, SMS or activating some sensors; add/edit/delete audio tracks on the map characterized by a radius of influence and the text describing the track that is going to be reproduced when the participant goes into the zone of influence; and finally allowing to add/edit/delete markers inside buildings. If a building plan has been previously loaded in the web service, section edition allows to add/edit/delete contactless technology markers such as NFC or QR characterized by an identifier and a location inside the building; and WiFi and Bluetooth access points characterized by a power of reference, a mac address and a location inside the building.

- Get the app: it allows to get the Android and iOS based smartphone app through Google Play and Apple Store, respectively.

4 Discussion

The last version of the app has been successfully tested in the city of Ljubljana; Slovenia, where various types of public spaces from natural green and hilly areas to paved flat surfaces of various articulation and equipment are at hand in the time distance of 10 minutes. Testing phase paid attention mostly on technical capability of the app. However, having discussions with representatives of various

user groups, the app seems interesting to them to get informed about places and to let others know about places in relation to their presence there, not only via behavior pattern which occurred running the app, but also via other means of communication the app offers (e.g. photo, video, message etc.). Besides, pilot actions also revealed that quite some effort will have to be made to attract various users to use the app, to finally get a comprehensive picture of dynamic patterns of public spaces of studied cities.

Advantages using the new app as a monitoring tool, discussed in this paper, are in precise and fast data collection, simultaneous and evolving analytics and valorisations. However, one must bear in mind that such app reaches only people who are familiar with smartphones and their advanced use, but left aside other users who are not. For this reason, when addressing place occupancies and co-habitation and compatibility of uses and user groups, combinations of methods, from using the proposed app, simulations it offers based on previous empirical knowledge, to traditional field observations would still need to be applied. In this respect, triangulation of such various behavior mapping techniques offers insights into advantages and disadvantages of the tool and opens discussion for possible further development of the tool and its compatibility with other (new coming) tools and approaches.

5 Conclusions

The unobtrusive tool that has been presented in this paper shows a new methodology for helping behaviour mapping to easily identify patterns of engagements, gather suggestions and environmental factors within public spaces. The combination of this localization engine, thought as a modular system for commercial available smartphones where heterogeneous signals can be easily fused, and behaviour mapping provides a powerful tool to support designers with empirical evidence of the relationship between environmental design and use of open space that is presented in a spatial and visual language familiar to designers. Future work goes towards (1) including in the localization engine the difference between the measured GNSS pseudoranges and actual pseudoranges measured at fixed, ground-based reference stations which positions are known. This way the accuracy in open spaces will improve from the 10-m nominal GNSS accuracy to lower than 1 meter, and (2) performing a case study with focused user groups of urban spaces (e.g. skateboarders) to create research and working environment where communication between users and tool developers is easy, to be able to adopt and refine the tool as useful for both, place and app users as well as for spatial planning and design related professionals, who want to understand users relations with places, encourage and produce better places than they would otherwise be produced.

Acknowledgements. This work has been supported by the Spanish Ministry of Economy and Competitiveness under the ESPHIA project (TIN2014-56042-JIN), by Slovenian Research Agency within Programme Spatial Planning (P5-0100), and by the

Cost Action TU1306, called CYBERPARKS, with special thanks to Mrs. Ina Šuklje Erjavec for encouraging the short time scientific mission.

References

1. Bahillo, A., Mazuelas, S., Lorenzo, R.M., Fernández, P., Prieto, J., Durán, R.J., Abril, E.J.: Hybrid RSS-RTT localization scheme for indoor wireless networks. *EURASIP J. Adv. Signal Process* **2010**, 1–12 (2010)
2. Blankenbach, J., Norrdine, A., Hellmers, H.: Adaptive signal processing for a magnetic indoor positioning system. In: *Proceedings of the 2011 International Conference on Indoor Positioning and Indoor Navigation* (2011)
3. Chung, J., Donahoe, M., Schmandt, C., Kim, I.J., Razavai, P., Wiseman, M.: Indoor location sensing using geo-magnetism. In: *Proceedings of the 9th International Conference on Mobile Systems, Applications and Services (MobiSys 2011)*, pp. 141–154 (2011)
4. Fox, D., Hightower, J., Liao, L., Schulz, D., Borriello, G.: Bayesian filters for location estimation. *IEEE Pervasive Comput.* **2**, 24–33 (2003)
5. Goličnik, B., Thompson, C.: People in place: a configuration of physical form and the dynamic patterns of spatial occupancy in urban open public space. Submitted for the Degree of Doctor of Philosophy, B. Goličnik (2005)
6. Goličnik, B., Thompson, C.W.: Emerging relationships between design and use of urban park spaces. *Landscape Urban Plan.* **94**(1), 38–53 (2010)
7. Goličnik Marušić, B.: Analysis of patterns of spatial occupancy in urban open space using behaviour maps and GIS. *Urban Des. Int.* **16**, 36–50 (2011)
8. Goličnik Marušić, B., Marušić, D.: Behavioural maps and GIS in place evaluation and design. In: *Application of Geographic Information Systems*, 31 October 2012
9. González, J.R., Bleakley, C.J.: High-precision robust broadband ultrasonic location and orientation estimation. *IEEE J. Sel. Top. Signal Process.* **3**(5), 832–844 (2009)
10. Hazas, M., Ward, A.: A novel broadband ultrasonic location system. In: Borriello, G., Holmquist, L.E. (eds.) *UbiComp 2002. LNCS*, vol. 2498, p. 264. Springer, Heidelberg (2002)
11. Ittelson, W.H., Rivlin, L.G., Proshansky, H.M.: *The Use of Behavioral Maps in Environmental Psychology*. Holt, Rinehart and Winston, New York (1970)
12. Julier, S., Uhlmann, J.K., Durrant-Whyte, H.F.: A new method for the nonlinear transformation of means and covariances in filters and estimators. *IEEE Trans. Automat. Contr.* **45**(3), 477–482 (2000)
13. K, A., Adepoju, F.: A model for estimating the real-time positions of a moving object in wireless telemetry applications using RF sensors. In: *Proceedings of the IEEE Sensors Applications Symposium* (2007)
14. Li, X.: RSS-based location estimation with unknown pathloss model. *IEEE Trans. Wireless Commun.* **5**(12), 3626–3633 (2006)
15. Mazuelas, S., Bahillo, A., Lorenzo, R.M., Fernández, P., Lago, F., García, E., Blas, J., Abril, E.J.: Robust indoor positioning provided by real-time RSSI values in unmodified WLAN networks. *IEEE J. Sel. Top. Signal Process.* **3**(5), 821–831 (2009)
16. Pahlavan, K., Levesque, A.H.: *Wireless Information Networks*. Wiley, New York (1995)
17. Sommer, R., Sommer, B.: *A Practical Guide to Behavioural Research*. Oxford University Press, New York (2002)

18. Steiniger, S., Neun, M., Alistair, E.: Foundations of Location Based Services. CartouCHE1-Lecture Notes on LBS 1 (2006)
19. Tilch, S., Mautz, R.: Current investigations at the ETH Zurich in optical indoor positioning. In: Proceedings of the 7th Workshop on Positioning Navigation and Communication, vol. 7, pp. 174–178 (2010)
20. Ureña, J., Hernández, A., Villadangos, J.M., Mazo, M., García, J.C., García, J.J., Álvarez, F.J., de Marziani, C., Pérez, M.C., Jiménez, J.A., Jiménez, A., Seco, F.: Advanced sensorial system for an acoustic LPS. *Microprocess. Microsyst.* **31**, 393–401 (2007)
21. Wakim, C.F., Capperon, S., Oksman, J.: A Markovian model of pedestrian behavior. In: SMC, vol. 4, pp. 4028–4033. IEEE (2004)
22. Whitehouse, K., Karlof, C., Culler, D.: A practical evaluation of radio signal strength for ranging-based localization. *ACM SIGMOBILE Mob. Comput. Commun. Rev.* **11**(1), 41–52 (2007)
23. Willert, V.: Optical indoor positioning using a camera phone. In: Proceedings of the 2010 International Conference on Indoor Positioning and Indoor Navigation (2010)
24. Zandbergen, P.: Accuracy of iPhone locations: a comparison of assisted GPS, Wifi and cellular positioning. *Trans. GIS* **13**(s1), 5–25 (2009)

Ubiquitous Computing and Ambient Intelligence.
Sensing, Processing, and Using Environmental
Information

9th International Conference, UCAmI 2015, Puerto
Varas, Chile, December 1-4, 2015, Proceedings

García-Chamizo, J.M.; Fortino, G.; Ochoa, S.F. (Eds.)

2015, XV, 507 p. 198 illus. in color., Softcover

ISBN: 978-3-319-26400-4